An application of the dynamic knowledge creation model in big data

Jestine Philip

PII: S0160-791X(17)30262-2

DOI: 10.1016/j.techsoc.2018.04.001

Reference: TIS 1050

To appear in: *Technology in Society*

Received Date: 6 November 2017

Revised Date: 23 March 2018

Accepted Date: 3 April 2018

Please cite this article as: Philip J, An application of the dynamic knowledge creation model in big data, *Technology in Society* (2018), doi: 10.1016/j.techsoc.2018.04.001.

TITLE PAGE

Title

AN APPLICATION OF THE DYNAMIC KNOWLEDGE CREATION MODEL IN BIG DATA

Contact Information of Author

Jestine Philip
Doctoral Student, 379J, Business Leadership Building,
College of Business, University of North Texas, 1307 West Highland Street, Denton, TX 76201.
Phone No: 213-400-9330. *Email Id*: Jestine.Philip@unt.edu

ABSTRACT

The recent surge in big data is unavoidable. In order to efficiently utilize voluminous data being constantly created, managers face the uphill task of having to convert this data into useful information. With increasing importance being given to actionable knowledge both from a practice as well as research perspective, a well-established framework of knowledge creation can help managers and researchers understand the conversion of big data into useful knowledge. With a focus of applying a knowledge-perspective to big data, I propose using elements of the knowledge creation model, namely *Ba*, the SECI process, and Knowledge Assets, to understand the conversion of big data into explicit and tacit employee knowledge. Additionally, an argument for enhancing a firm's dynamic capabilities using big data is also proposed.

KEYWORDS: Big data, Knowledge**,** Knowledge creation process, Sensing, Seizing

1. INTRODUCTION

Big Data. Data Analytics. Data Mining. These are some common buzzwords we have all been hearing recently. In the past few years, there has been a huge emphasis on big data and business analytics. In simple words, 'big data' refers to the vast volumes and types of data that companies can collect from a variety of sources - both internal and external - such as employees, customers, suppliers, and the market (Harvard Business Review, 2014) [64]. Big data can be both structured such as employee performance data or customer sales data and unstructured such as internet clicks or social media content. Data is generated every second by both humans and machines alike; about 90% of the world's data were generated just between 2010 and 2013 (SINTEF, 2013) [57]. Organizations are now trying to analyze these huge amounts of data so that they can be successfully interpreted to make smarter strategic decisions for positive value creation (Hargrave, 2013 [26]; McKinsey Global Institute, 2011 [42]).

Erik Brynjolfsson, an economist at MIT's Sloan School of Management, explains how companies will increasingly make strategic decisions based on data and analytics in the coming years rather than on experience. His study of 179 firms found that companies that adopted data-driven decision-making were able to achieve 5% higher productivity and profitability than their competitors (Brynjolfsson, Hitt, & Kim, 2011) [9]. Numerous business case studies have also indicated that data-driven companies make better decisions, are able to improve performance, and thus able to generate more value (McAfee & Brynjolfsson, 2012) [41]. Big data can enable organizations to accurately foresee potential business problems. Organizations can now perform 'predictive' and 'prescriptive' analyses, through which potential issues could be mitigated or even entirely avoided. Whereas predictive analytics can forecast future trends by performing statistical modelling on past data to help answer the question, "what could happen?" (Grillo &

Hackett, 2015) [24], prescriptive analytics can help determine cause and effect among business processes for model optimizations (Bihani & Patil, 2014) [6], provide the foresight to ask, "what should we do?", and offer prescriptions for moving forward.

The following are two specific examples where big data analytics can be particularly useful for organizations. Researchers have found that during the flu season, there are higher Google searches for terms like 'flu treatments' and 'flu symptoms' just a few weeks before an increase in the number of patients visiting hospitals for flu-related sicknesses (Lohr, 2012) [37]. By using predictive analytics in such scenarios, hospitals can be better prepared to deal with patient influxes during epidemic seasons. From a marketing perspective, many companies are now trying to understand, through real-time monitoring of social media & even customers in store, any changes in customer-buying behavior globally about their brands and products such that even a slight deviation from previously observed patterns could immediately flag action for that brand or product (Datoo, 2014) [18]. Such vast amounts of continuous and specific customer data can help companies effectively track product trends over time, monitor customer engagement both inside the store and on their website, as well as attract new consumers through customized marketing campaigns. Prescriptive data analytics provides a wealth of new information for making smarter decisions to stay ahead of competition. Hence, the ability to convert these massive amounts of data into useful information and knowledge is increasingly becoming a key source of competitive advantage for organizations (Oracle, 2015) [51].

From a research perspective, big data has been primarily studied from an information systems and business analytics perspective. Most research focus has been on big data technologies (both physical, in-house technologies such as Hadoop and on premise, in cloud technologies such as Amazon's RedShift & Google's Big Query) and on data management in

Business Intelligence and Analytics (BI&A) (Chen, Chiang, & Storey, 2012) [12]. Although a few streams of research in BI&A have tied in data analytics to strategy and planning (Butler & Murphy, 2007) [10], efficiency and productivity (Wikoff, 2008) [69], and availability of resources (Knight, 1998) [34], there appears to be an opportunity to study the impact of big data for organizations using management theories. Scholars are beginning to encourage future research in big data from management and organizational scholarship perspectives. Big data have been emphasized as a potential "stage-setter for further work and to open up fresh, new areas of inquiry for management research" (George, Haas, & Pentland, 2014, p. 321) [23]. Recent works in management research include addressing the challenges associated with big data research (Jin, Wah, Cheng, & Wang, 2015) [31] and methodological & data analytic techniques in big data (Tonidandel, King, & Cortina, 2016) [66].

In this paper, I look to adopt and incorporate a knowledge-based theoretical approach in understanding the usefulness of big data. We are now living in a technology- & data-driven world, where knowledge is considered one of the most important strategic resources for competitive success (Hao & Song, 2016) [26]. With companies constantly trying to enhance their data collection and data processing capabilities and the increasing importance being given to actionable knowledge that can be created using big data, strategic management theories can help provide a solid foundation for better understanding the knowledge creation process in this field. There is substantial, foundational research done on knowledge creation and knowledge management. Hence, there is scope for studying big data using a management theoretical lens - that of knowledge creation. Introducing the aspect of knowledge into big data would also help advance current research in knowledge management. Hence, the goal of this paper is to help further both big data and knowledge creation research.

The knowledge created in big data will depend not on the size of available data but on how much of that data organizations are able to successfully harness into information. Organizations today have an abundance of digital data that they can effectively make use of to remain competitive. Not just the volume, even the complexity and diversity of data have been constantly increasing (Barton & Court, 2012) [3]. Senior management is right in taking note of these evolving dynamics of digital data. However, in order to efficiently utilize these vast amounts of data, organizations must be able to convert the data into applicable information and knowledge. Most companies are shying away from investing in big data and advanced business analytics simply because they do not feel confident enough to be able to 'create' useful knowledge from them. Although the importance of knowledge creation has been widely recognized and emphasized time and again in practice and in research, the concept has not been applied in its entirety to newer, more recent technological advancements such as big data (Hota, Upadhyaya, & Al-Karaki, 2015) [29]. Hence, the research question: *How can organizations utilize big data to create useful knowledge?*

We need a better understanding of the knowledge creation process in big data. Specifically, a model that captures the flow and conversion of big data to knowledge. Prior research has shown the flow from data to information, knowledge, learning, and ultimately improved decision-making to be sequential (Figure 1).

Figure 1. Adopted from Liew's (2007) [35] diagram of Knowledge, Information, and Data

Data → Information → Knowledge → Learning → Better Strategic Decisions; Cost Reductions; Time Reductions; New Product Developments

This paper contributes to academic literature and practice in two ways. First, it extends the current literature on knowledge management to incorporate a new and emerging research phenomenon in both management & information sciences. By using an established framework of the knowledge creation process, a management theory is being used to understand the impact of big data in organizations rather than limiting our understanding of big data to an information systems perspective. Second, organizations can utilize the knowledge creation model towards improved learning from big data. An explanation of how organizations might achieve improved learning is provided in propositions (using examples of customer service representatives and marketers).

From a practical standpoint, this paper aims to build the argument that organizations would achieve competitive success by applying the knowledge creation model in big data. The model captures the flow from data to information to the creation of increased knowledge, which can then be used for better decision-making. The outline of the paper is as follows. The following section provides a literature review of big data and knowledge (specifically, knowledge creation). The next section includes proposition development. Next, the discussion section follows which includes theoretical and practical implications, limitations, and future directions. Lastly, the conclusion section is presented.

2. LITERATURE REVIEW

2.1. Big Data

Although the term ‘big data is fairly new in research streams, several researchers and practitioners have previously referred to the concept in literature. For example, McKinsey defines big data as huge “datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze” (McKinsey Global Institute, 2011, p. 1) [42].

Originally introduced by Gartner, big data is often characterized by the several V’s – including, volume (large amounts of data), variety (different types of data), and velocity (speed and continuity of data generated) (Zikopoulos, Parasuraman, Deutsch, Giles, & Corrigan 2012 [72]; Berman, 2013 [5]) as well as by the degree to which it is structured (highly organized and searchable) or unstructured (such as images, audio, or video) (Gandomi & Haider, 2015) [22]. In their book, *Big Data: A Revolution That Will Transform How We Live, Work, and Think*, Viktor Mayer-Schönberger and Kenneth Cukier (2013) [40] offer a definition in terms of its size and what could be done with the data: “The ability to … harness information in novel ways … to extract new insights or create new forms of value” (p. 6). Whether it is in terms of transactional data to understand consumer choices or online search behaviors to predict outbreaks of diseases, big data analytics is gaining great momentum in both business and scientific domains. Data analytics is applicable in almost every industry and any organization that operates digitally. Baesens (2014) [2] lists several examples of analytics applications in functions like marketing (for customer segmentation and market-based analysis), logistics (for supply chain analysis), risk management (for market risk modeling and fraud detection), and even for government organizations (to investigate social security fraud, money laundering etc.).

Analysis of big data would require methodologies beyond statistical approaches like regression and would include techniques like data mining, cluster analysis, machine learning, and time series analysis (McKinsey Global Institute, 2011) [42]. Methods-related literature on big data includes accepted forms of data descriptions (i.e., what is the right way to describe the data), syntax of data description (e.g., XML), and semantics (i.e., how to write computer language codes that convey meaning) (Berman, 2013) [5].

To apply big data in management research would mean management scholars trying to 'unpack' the voluminous amounts of diverse data in order to create new sources of value for organizations and to provide mechanisms or channels for value creation (George, Haas, & Pentland, 2014) [23]. Since the nature of data is continuous (spreading over multiple time periods ranging from micro-seconds to years) and ubiquitous, researchers have abundant opportunities to focus on various aspects of management such as micro foundations of firm strategies, longitudinal studies about firms/markets, and even real-time predictions of individual and team behaviors. From a knowledge management perspective, big data research could change the very definition of knowledge. Because big data can create such a radical change in the way we see data, information, and reality, it can lead to new "methods of knowing" and "meaning of learning" (Boyd & Crawford, 2012, p. 665) [8]. The capability of organizations to decode big data and assess its quality in order to create useful knowledge will have great implications on management theory and practice. Since big data comprises of multidimensional data, there is scope in management research for converging data from multiple, unrelated sources to derive strong interpretations and conclusions, thereby producing unparalleled new knowledge (Hota et al. 2015 [29]; Wilson, 1999 [70]).

2.2. Knowledge

The vast majority of literary work on knowledge has been from a positivist viewpoint, according to which, all rational knowledge or "justified true belief" is derived from scientific and systematic analyses of our understanding of reality (Spender, 1996, p.47) [58]. Although we are confident of most of the knowledge we create, we also recognize that this knowledge is temporary and subject to dynamic change and that we must be open to empirical falsification as illustrated by Popper (1969) [53]. In their study of organizations as entities that continuously create knowledge, Nonaka, Toyama, and Konno (2000) [49] adopted the justified true belief definition of knowledge, giving special emphasis to it being 'justified'. Epistemologies on knowledge correspond to views by realists (who validate the existence of reality and the knowledge we derive from reality), empiricists (who assume that our knowledge corresponds to reality), and rationalists (who assume that reality has a logical structure) (Spender, 1996) [58]. Ultimately, the basis of our interpretation of available information is constrained within the realm of our reality.

Another stream of research on knowledge management has focused on the types of knowledge. The first type, called 'explicit knowledge' (that can be expressed in the form of words and numbers), is based on systematic structures and languages, and is shared in the form of *data*. The second type, called 'tacit knowledge' deals with routines, procedures, and human experience (Nonaka and Takeuchi, 1995 [46]; Collins, 2010 [16]). It is generally understood that while both knowledge types may involve complexities, tacit knowledge is more difficult to convey from one individual to another. The reason for this is that, while explicit knowledge is quantifiable and often standardized, tacit knowledge is highly individual-specific. Tacit knowledge is also complex because it has two sub-dimensions – the technical dimension (which includes personal skills and crafts) and the cognitive dimension (which includes personal values, beliefs, and ideals often deeply ingrained in an individual) (Nonaka & Konno, 1998) [47]. However, even with the distinctions between explicit and tacit knowledge and the complexities of tacit knowledge, knowledge management theory posits that the combination and continuous interactions between these two types is important for the creation of new knowledge.

Because the focus of this paper is to apply a *knowledge*-perspective to big *data*, a review of interrelated terminologies like data, information, and knowledge is ensued. The interactional relationships among data, information, knowledge, and learning have been studied by defining one in terms of the other: that is, data defined in terms of information, information defined in terms of knowledge, and knowledge defined in terms of learning (Liew, 2007) [35]. For instance, Tiwana (2001) [65] defined 'knowledge' as actionable information and 'information' as processed data that be packaged into a usable format. The key to understanding the complex relationships between data, information, and knowledge creation lie in the sources (or spaces) of data and information and the contexts in which they are analyzed and shared. Nonaka and Konno (1998) [47] have provided a deep theoritical and practical understanding of the concept of *Ba* (discussed in the following section), which deals with the 'shared space' in which knowledge is embedded. They explain that when knowledge is separated from this shared space, it remains as information: that is, the information never gets converted into applicable knowledge. Such distinctions have helped to solidify scholarly understanding of data, information, and knowledge and to propose ways to create value and competitive advantage for organizations by effectively utilizing each (Nomura, 2002) [44].

2.3. Knowledge Creation Process

Because the research question for this article looks to understand how big data can be used to *create* useful knowledge, a specific literature in knowledge management research, vis-à-vis the knowledge creation process, is further reviewed. The knowledge creation process involves both micro (individual) and macro (environmental) aspects. Nonaka et al. (2000) [49] proposed a model of knowledge creation that involves three elements: namely, *Ba*, the SECI process, and Knowledge Assets, suggesting that knowledge is dynamically created from a combination of these three elements.

2.3.1. *Ba*

'*Ba'* is the shared context for knowledge creation. According to Nonaka et al. 2000 [49], a context is needed for knowledge to be generated. Originating from Japanese philosophy, *Ba* is a "time-space nexus" (p. 14). In an organizational context, it would mean a concept that combines a physical space (such as a physical office) or a virtual space (such as emails) with mental space (such as ideals or values). *Ba* provides the contexts of time, energy, and place for individuals to interact among themselves and with the environment in order to facilitate new knowledge creation. As mentioned in the previous section, when knowledge is separated from this shared space, it remains as information. The most important aspect in *Ba* is the interaction between these contexts. There are four characteristics of *Ba*: i) Originating *Ba* (face-to-face individual interactions), ii) Dialoging *Ba* (face-to-face collective interactions), iii) Cyber *Ba* (virtual collective interactions), and iv) Exercising *Ba* (virtual individual interactions). The first two contexts, Originating *Ba* and Dialoging *Ba*, combine physical space/tangible platforms with a cognitive context in order for employees to gain new knowledge. Examples of such shared space include meeting rooms for face-to-face informal socialization to share experiences and feelings with team members and managers (Originating *Ba*) and sophisticated meeting facilities that are equipped with customized media (visual aids such as props, white/blackboards, paper handouts) capable of projecting information possessed by a single individual (such as a presenter or trainer) onto said media in order to help collective knowledge creation within a group (Dialoging *Ba*). On the other hand, Cyber *Ba* and Exercising *Ba* combine virtual space (rather than physical space) with a cognitive context. Cyber *Ba* provides the context or platform for employee group interactions in a virtual setting such that explicit knowledge gets transmitted to a large number of people inside the organization with the help of information technology (Nonaka, Reinmoeller, & Senoo, 1998) [48]. Virtual team spaces (often an IT-based tool/application) such as emails, internal chats, online databases, project management software, simulations, video conferencing etc. enable organizational members to share work-related documents, ideas, and comments (Eppler & Sukowski, 2000) [21]. Exercising *Ba* is narrower than Cyber *Ba*, in that it provides contexts for individual (and not group) interactions such that employees may gain tacit knowledge using the explicit knowledge communicated via Cyber *Ba*. Exercising *Ba* such as individual computers help employees review and 'internalize' virtually shared knowledge.

2.3.2. SECI

'SECI' is the knowledge conversion process, where tacit and explicit knowledge interact to create new knowledge. While *Ba* provides the platform for knowledge creation, SECI is the actual process of knowledge creation (Nonaka, 1990) [45]. There are four modes or stages in this process (the names of which make up the acronym): i) Socialization (sharing collective tacit knowledge among individuals), ii) Externalization (translating individual tacit knowledge for collective understanding), iii) Combination (integrating unstructured explicit knowledge and organized forms of explicit knowledge), and iv) Internalization (converting explicit knowledge into individual tacit knowledge). Each SECI stage is attributed to a *Ba* (Nonaka & Konno, 1998) [47]. That is, socialization is linked to Originating *Ba* (because it provides a platform for face-to-face individual interactions to share collective knowledge) and Externalization is associated with Dialoging *Ba* (because it aids in transferring individual knowledge & experience to a collective group). Because Cyber *Ba* and Exercising *Ba* involve virtual space, they provide means for converting explicit virtual knowledge into other forms of explicit knowledge (in Combination) and into individual tacit knowledge (in Internalization). Since most organizational data today is in digital formats, these virtual *Ba's* (along with Combination and Internalization) have become highly important in the knowledge creation process and have often been employed more than the other *Ba's* to understand knowledge management in information sciences (Mueller, Hutter, Fueller, & Matzler, 2011 [43]; Lindblom & Tikkanen, 2010 [36]; Wei Choo & Correa Drummond de Alvarenga Neto, 2010 [68]).

2.3.3. Knowledge Assets

'Knowledge Assets' (KA) are assets or resources specific to a firm that can aid in the knowledge creation process (Nonaka et al. 2000) [49]. These assets could either be related to explicit knowledge (such as databases, manuals, and product design) or to tacit knowledge (such as trust, organizational culture, and individual know-how). They can act as inputs, outputs, or moderators in the knowledge creation process. For example, trust can be seen both as an output as well as a moderator to the *Ba* platform and SECI process. An instance where trust can be an output is when managers create an atmosphere where members feel safe to share their knowledge. Similarly, trust becomes a moderator when individuals have to work collectively and share physical/virtual space to gain tacit knowledge. Linking the three together, one might say that with the help of its existing Knowledge Assets, an organization creates new knowledge through the SECI process, which takes place in *Ba*.

There are four types of KAs: i) Routine KAs (assist creation of tacit knowledge embedded in an organization's practices such as culture), ii) Conceptual KAs (assist creation of explicit knowledge expressed through common language and symbols), iii) Systemic KAs (assist creation of explicit knowledge that is organized and systematically stored in databases and repositories), and iv) Experiential KAs (assist creation of tacit knowledge expressed through common experiences such as know-how and skills). Each KA has been associated with an SECI process (Chou & He, 2004) [15]. Routine KAs are linked to Socialization (because they assist in sharing collective tacit knowledge to individuals through socialization tactics); Conceptual KAs are linked to Externalization (because images and common jargons help transfer individual tacit knowledge to collective groups); Systemic KAs are linked to Combination (because they aid in integrating various forms of explicit knowledge using technological assets); and Experiential KAs are linked to Internalization (because they help convert explicit knowledge into individual tacit knowledge through shared experiences).

Although it has been suggested that people/employees can act as 'knowledge carriers' of both explicit and tacit knowledge (Kalpič and Berneus, 2006) [33], there are bound to be limitations in reach and speed of knowledge transfer when utilizing individuals (Sanchez, 2004) [55]. These limitations arise from the fact that individuals can only be at one place at a time, can only work so many hours in a day, and that employees leave organizations taking their knowledge with them. On the contrary, a far more efficient and quicker way to disseminate explicit knowledge throughout an organization is by utilizing information systems as knowledge carriers. When studying knowledge creation in information sciences (which include advanced digital datasets like big data), it is more helpful to focus on the KAs associated with relevant *Ba's* and SECI processes. Hence, this study utilizes Systemic KA (associated with the Combination process, which is in turn linked to Cyber *Ba*) and Experiential KA (associated with the Internalization process, which is in turn linked to Exercising *Ba*) (Chou & He 2004) [15].

3. PROPOSITIONS

3.1. Sensing and Seizing Opportunities in Big Data

Sensing and seizing capabilities are stages of a broader concept called 'dynamic capabilities' developed by Teece, 2007 [63]. The dynamic capabilities of a firm allow it to create and apply intangible assets (such as knowledge) to improve performance and provide competitive advantages (Helfat & Peteraf, 2009) [27]. Dynamic capabilities can include enterprise capabilities that are difficult to replicate and necessary for firms to adapt during changing technological environments and customer demands. Teece (2007) [63] proposed that dynamic capabilities are created as a result of three stages, namely a firm's: i) capability to 'sense' new opportunities, ii) ability to 'seize' these opportunities, and iii) capability to 'transform' these opportunities for competitive advantage. Sensing capability enables organizations to capture data from the external environment thus, facilitating internal organizational change (Chakravarty, Grewal, & Sambamurthy, 2013) [11]. Such intra-organizational change is found to invoke the transformatory phase which leads to new processes and ideas, resulting in competitive success (Pettigrew, 1987 [52], Chia, 1999 [14]). Once these new data opportunities are identified or 'sensed', a firm must be able to seize these opportunities by using the right decision-making protocols, generating consensus among its stakeholders, and by making other strategic choices (Teece, 2007) [63]. Hence, seizing capability involves making the right investment decisions and formulating action plans to leverage captured data. Finally, the organization must be capable of transforming these seized data opportunities into assets. The transformation stage of dynamic capabilities results in continuous alignment and realignment of tangible and intangible assets that can result in competitive advantage (Teece, 2007) [63]. For a firm to be able to apply its dynamic capabilities for competitive success, it must surpass its operational competence (Schreyögg & Kliech-Eberl, 2007) [56] and not just be able to perform routine operations but it must also be able to innovate and invent in tandem in order to generate profits (Teece, 2006) [62].

Traditional analytical systems possess sensing capabilities to detect, filter, and calibrate new opportunities that exist in the firm’s external environment. Because big data is a highly evolved analytical tool with capabilities that surpass those of older information technologies (Lohr, 2012) [37], the firm would be able to capture highly specific and relevant quantifiable/structured data (such as real-time financial data of its competitors) as well as non-quantifiable/unstructured opportunities (such as customer sentiments on social media and consumer internet clicks on its web products) from its external environment. Next, in order to successfully seize and maximize these newly identified external data opportunities, the firm must have a ‘big data strategy’ in place (Davenport, 2014) [19]. Whether the firm’s objective is to effectively utilize big data tools for Business Intelligence & Analytics (BI&A) to improve performance at reduced costs or whether it is to employ the knowledge gained from big data in developing new products/services, the firm must first decide what it wants from big data. Because of its vast and complex capabilities, firms are encouraged to utilize big data for more than just one type of outcome (whether it is cost-effectiveness or innovation) (Davenport, 2014) [19]. Google is an example of a company that has put in place a thorough big data strategy, where it uses big data algorithms for both its day-to-day operations (such as in core searches and targeting ads for specific consumers) as well as in the development of innovative products like Google apps and self-driving cars (Ibarra, 2017) [30]. Such efficient utilization of data analytics advances a firm to the transformatory stage which further helps develop its dynamic capabilities. These highly advanced firm capabilities constitute the reconfiguration, realignment, leveraging, and integration of existing resources (Bowman & Ambrosini, 2003) [7] for the creation of new resources (like knowledge). From the findings of five case studies undertaken by Daniel and Wilson (2003) [17], who identified the various dynamic capabilities necessary for e-business transformations, it was found that in the competitive world of online businesses, firms are constantly required to integrate their existing resources (such as integration of IT systems of a firm's physical stores with that of its online stores) and reconfigure their processes (such as redesigning a firm's online direct sales processes to accommodate physical distribution channels). In this regard, employment of big data is a huge leap forward for a firm's tranformatory phase as this technology can be highly collaborative, integrative, and interactive with other database tools to help gather and analyze business intelligence from multiple data sources concurrently (Tableau, 2017) [61]. Such operational data can then be converted into useful information (Elbashir et al. 2013) [20], thereby generating new knowledge which could be both explicit and tacit (Kabir & Carayannis, 2013) [32].

Big data is increasingly becoming a valuable knowledge resource for competitive advantage for firms when it is utilized with the right tools and people (Zhou & Uhlaner, 2009) [71]. Hence, sensing and seizing opportunities using big data can help firms develop transformational capabilities that contribute to knowledge repositories (explicit knowledge) and employee knowledge foundations (tacit knowledge). This leads to the following proposition:

Proposition 1: Sensing and seizing extremal opportunities using big data are positively related to a firm's transformational capabilities of knowledge creation.

3.2. Transformation into Knowledge

Cyber *Ba* is the context for interactions of groups of individuals in a virtual world in a way such that explicit knowledge can be transmitted to a large number of people in an organization through information technology (Nonaka & Konno, 1998) [47]. In the Combination stage, structured or unstructured explicit knowledge that is collected from outside the firm is edited and processed into organized forms of new explicit knowledge. This new explicit knowledge is then distributed among individuals in an organization. Knowledge is created when individuals interact amongst themselves or with their environments (physical space or virtual space) in a shared time, energy, and place (Nonaka, 1990) [45]. For big data (which is explicit knowledge consisting of numbers, 3D data, audios/videos, customer log files, social media content etc.), Cyber *Ba* will offer a platform for combining and generating new forms of explicit knowledge through online databases, data analytical tools, and other computerized communication networks. Managers and employees can use Customer Relationship Management (CRM) systems to acquire new knowledge about customer demands, suppliers, and competitors (Chen & Popovich, 2003) [13]. For example, big data 'infused' CRM systems can analyze multiple sources in real time to suggest customer care representatives with promotional offers (new explicit knowledge) while they are on the phone with customers.

Exercising *Ba*, on the other hand, involves contexts for individuals to gain tacit knowledge using the explicit knowledge communicated through virtual media (Nonaka & Konno, 1998) [47]. In the Internalization stage, individuals utilize the explicit knowledge in practice or action in order to gain tacit experience. In the previous example of customer care representatives, they would develop the technical expertise, computer skills, and speed to tactfully navigate through the CRM system (and the new explicit knowledge available in it), thus reducing customer call durations. Hence, Exercising *Ba* will offer a platform for employees to interact with big data tools and other analytical software to gain the experience that will help them assist customers better. As another example, by regularly working with social media content sources of big data, marketers can gain in-depth know-how on customer choices and sentimental reactions of dissatisfied customers that cannot be obtained from merely analyzing sales numbers.

For effective knowledge management to occur in the virtual world, frequent dialog interactions are required (more than in the physical world) among internal organizational members as well as with external stakeholders such as customers. Hence, it has been found that Exercising *Ba* must be combined with Cyber *Ba* using Information & Communication Technology (ICT) (Lindblom & Tikkanen, 2010) [36]. These lead to the following propositions:

Proposition 2a: The presence of Cyber Ba is positively associated with the creation of new explicit knowledge from big data.

Proposition 2b: The presence of Exercising Ba is positively associated with the creation of individual tacit knowledge from big data.

Systemic KAs consist of systematically packaged explicit knowledge in state-of-the-art technologies, software, databases, and repositories (Nonaka & Konno, 1998) [47]. These Knowledge Assets can be easily utilized by and transformed among various organizational members. This is because Systemic KAs are tangible and their task orientation is explicit (know-what knowledge). According to Chou & He (2004) [15], Systemic KAs (than other KAs) are able to best facilitate knowledge created through Combination in a Cyber *Ba*. Additionally, because Combination involves manipulation of one form of explicit data into a new form, Systemic KAs (using their explicit or content-specific task orientation) offer the highest moderating effect compared to other KAs for Cyber *Ba* and Combination. In the example of customer care representatives being able to suggest promotional offers, the Systemic KA is the big data 'infused' CRM system which is systemized and contains explicit forms of customer information.

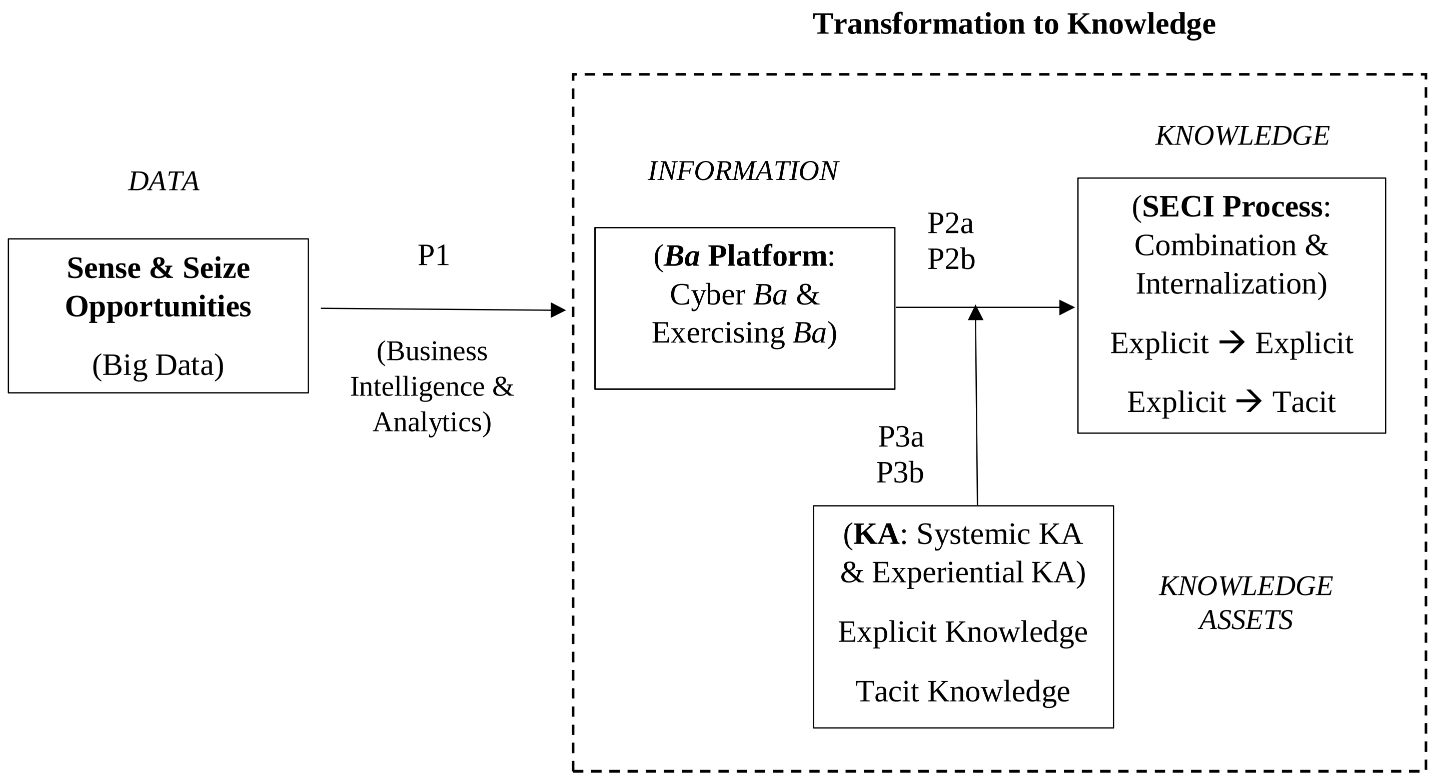
Experiential KAs consist of tacit knowledge built from hands-on experience among organizational members and with external stakeholders like customers and suppliers (Nonaka & Konno, 1998) [47]. Unlike Systemic KAs, Experiential KAs are intangible and their task orientation is tacit (know-how knowledge acquired through repeated processes). They include individual know-how, skills, and expertise. Chou & He (2004) [15] also found that Experiential KAs (than other KAs) are able to best facilitate knowledge created through Internationalization in Exercising *Ba*. Furthermore, because Internalization involves utilizing explicit knowledge to gain tacit know-how, Experiential KAs facilitate learning of process-oriented tasks through repetition and continued exposure. Thus, Experiential KAs offer the highest moderating effect compared to other KAs for Exercising *Ba* and Internalization. In the example of marketers using social media content, aspects of Experiential KAs such as improved know-how and skills would help these marketers predict customer choices and emotions better. These lead to the following propositions:

Proposition 3a: Systemic KAs strengthen the explicit knowledge creation process of big data occurring through Combination in Cyber Ba.

Proposition 3b: Experiential KAs strengthen the tacit knowledge creation process of big data occurring through Internalization in Exercising Ba.

Figure 2 shown ahead provides a representation of the proposed model.

Figure 2: Knowledge Creation Model in Big Data



4. METHODOLOGICAL APPROACH

In an attempt to offer some preliminary validation for the practicality of this model, I adopted a qualitative methodological approach to understand how big data is utilized by employees/managers and how the knowledge obtained from it is being applied/used by various other functions of their organization. Qualitative interviews have been previously used as a method to capture managerial perceptions of big data (Warkentin, 2015) [69]. While rigorous qualitative interviews and in-depth case studies combined with content analytical procedures would provide empirically validated results regarding the applicability of the model, for the purposes of this paper I only include an initiatory test.

To gain some understanding of big data and its utilization in organizations, I spoke with two software engineers and one business analytics manager from three different companies in the U.S. that use big data. The conversations generally consisted of topics on big data utilization from engineering and business analytics perspectives and its associated challenges. Furthermore, to capture the 'knowledge transformation' component of the proposed model (i.e. *Ba*, SECI, and KAs) questions pertaining to the exchange of knowledge from engineering and data analytical teams (that seize big data opportunities) to other members of the organizations (such as salespersons, executives) were also asked. From these conversations, I gathered that firms that use big data have a huge advantage to seize external customer opportunities. Big data is primarily being utilized in two crucial functions of these organizations – engineering and business analytics. Example scenarios of how big data is utilized by both these functions is described ahead. From an engineering perspective, big data allows a company to generate billions of queries obtained from user searches for the company's (or its competitors') products on search engines like Google. The big data software engineer then uses machine leaning algorithms to optimize these customer searches such that the company's most searched product would appear at the top of a search engine list when potential customers search for products online. The vast amounts of user click data and search data are useful to the company because it allows big data engineers to understand the size and nature of potential customer traffic. Such valuable information is then passed on to the company's various other functions like operations, sales, and finance so that products that have been identified as high-demand may be given priority focus across the organization. This further involves transformation and spread of newly obtained knowledge about these key market trends from one function in the company to other departments via databases, emails, trainings, meetings etc. Hence from an engineering standpoint, the model of big data utilization proposed in this paper holds well. The second example scenario is from a business analytics perspective. Big data allows the data analytics team in a company to customize and personalize external data (e.g., customer sales or competitor revenue data) or internal data (e.g., HR data on employees) specific to the needs of the requestor – something that data analytics teams historically lacked the capability to do when relying on statistics. Using big data, business analytics teams can create user-friendly dashboards in order to provide customized answers to specific questions from different internal requestors. For example, a sales team that wishes to know how many customers in a certain geographic region have expressed dissatisfaction over a specific product on the internet; or the finance department wanting to know potential losses in dollar amounts if these dissatisfied customers purchase the competitor's product they have been browsing online. Once again, the proposed model of seizing opportunities using big data and effectively spreading the acquired knowledge through dashboards within different departments of a firm is valid from a business analytics function. Finally, once this new data gathered from the external environment is transferred internally through *Ba* platforms, new explicit knowledge is generated among the various employees in the company through their access to databases, dashboards, emails, trainings, meetings etc. New tacit knowledge is created by hands-on usage of computerized systems that contain the explicit knowledge as well as through constant communication with big data engineers and data analysts.

In summary, my conversations with the software engineers and business analytics manager who work with big data offer preliminarily validation for this model. These findings serve as a pathway for future rigorous empirical testing using qualitative or quantitative methods.

5. DISCUSSION

The recent surge in big data is unavoidable. In order to efficiently utilize voluminous data being constantly created, managers face the uphill task of having to convert the data into useful information. Actionable knowledge is desired both from a practical as well research perspective: hence, a well-established framework of knowledge creation can help managers and researchers to understand the conversion of big data into explicit and tacit knowledge.

The objective of this paper was to offer a theoretically-anchored overarching framework of a practically-applicable/relevant concept (i.e., big data). By applying concepts that are deeply rooted in knowledge management literature, the intention was to focus on the phenomenon rather than constructs or variables. The papers emphasizes the application of the knowledge creation framework in big data in order to derive actionable knowledge from it. I have provided here a well-suited model that captures the flow from data to information to, finally, the generation of knowledge repositories and experiential understanding, both of which can then be used by employees and managers for better decision-making. With huge volumes of data being constantly created by both humans and machines, businesses today are increasingly finding it difficult to interpret and put these vast amounts of data to good use. The model presented here applies the theory of knowledge management to demonstrate the flow (and interpretation) from big data to usable knowledge.

5.1. Contributions to Theory and Practice

This paper contributes to academic literature and practice in the following ways. First, it extends the current literature on knowledge management to incorporate aspects of data analytics. Although knowledge management has been researched in conjunction with other areas such as organizational learning, innovation, creativity, intellectual capital, and organizational strategy (Amidon, 1997 [1]; Probst, Raub & Romhardt, 2000 [54]; Stewart, 2002 [59]), its relevance in data analytics has been fairly limited. The application of knowledge management in big data is, however, gaining traction in management research as evidenced in Sumbal, Tsui, See-to (2017) [60], O'Connor & Kelly (2017) [50], and Vishkaei, Mahdavi, Mahdavi-Amiri, & Askari (2016) [67]. Multi-disciplinary and cross functional research (such as studying data analytics in strategic management, human resource management, or marketing) should be encouraged because they help provide new theoretical lenses to understand the various opportunities and complex organizational issues that emerge in today's technological world. Hence, in the same vein, by using an established framework of the knowledge creation process, I have utilized a management theory to understand the impact of big data in organizations. Second, this paper contributes to practice. Organizations could utilize big data not only to improve operational and financial performances but also to increase learning and to enhance outcomes for their customers and employees. The framework presented in this paper is both parsimonious and practically applicable to any organization that aspires to invest in big data technologies in order to enhance their customer relations through improved employee learning. The emerging trend of governance surrounding technology systems is to have business leaders carry out most decision-making

(Griffy-Brown, 2017) [24]. In this regard, this paper (grounded in business management theory) contributes to the ongoing scholarly conversation of technology in today's society through the lens of management-driven problem-solving and decision-making. On a broader scale, such efforts could also help organizations align big data utilization and innovation to have societal implications – a concept known as Responsible Research and Innovation (RRI) (Lukovics, Flipse, Udvari, & Fisher, 2016) [38].

5.2. Limitations

Like any research study, this paper has a few limitations. First, the model was restricted to capturing only intra-organizational knowledge creation. Knowledge is created and transferred not just within the boundaries of an organization but also among different organizations. Second, the model presented here is a simplified and static version of the knowledge creation process, especially in the context of big data. Knowledge creation is a much more complex and dynamic process that can be studied at detailed levels. Third, although this study is theoretically-anchored, it is a conceptual model that is yet to be tested. It is crucial to operationalize components of the proposed framework and test it in an organizational setting. Hence, an important 'next step' for this study is to collect qualitative (interview) or quantitative (survey) data from organizations. If quantitative testing is adopted as the methodological approach, researchers must bear in mind that concepts like *Ba* and SECI do not have established scales in literature. Hence, operationalization of concepts like Cyber *Ba* would involve capturing the underlying phenomenon while also giving ample consideration to the advancements in technology since the time period these concepts were originally fathomed. Even though no established and validated scales exist to measure Cyber *Ba* or Exercising *Ba*, one particular empirical study - by Bennett (2001) [4] - employed the concepts of *Ba* and SECI to understand the creation and exchange of knowledge among salespeople (in terms of specific customers, sales leads, past experiences etc.). Consistent with literature, the scale items that capture Cyber *Ba* are linked to Combination and those that capture Exercising *Ba* are linked to Internalization. Examples of respective scale items are "This firm has computerized systems which enable employees to quickly and easily find out where knowledge on various topics is located." (Cyber *Ba* & Combination) and "Senior employees of this firm provide extensive advice, support, help, information, and mentoring to recently appointed and less experienced colleagues." (Exercising *Ba* & Internalization) (Bennett, 2001) [4]. To capture Systemic KAs and Experiential KAs, an existing scale used by Martin-de-Castro, López-Sáez, & Navas-López (2008) [39] could be employed.

5.3. Future Directions

Future directions for this study could include delving deeper into the dynamic capabilities processes (namely, sensing, seizing, and transforming) in order to understand the knowledge *process flow* from big data (an explicit and visible form of knowledge stored in repositories) all the way to employee experiential knowledge (a tacit form of knowledge gained by humans) for organizational value creation. As big data technologies gain more traction, scholars are also beginning to study its flip side. Hence, another emerging perspective of big data is that of the ethics involving in data capturing. For example, Herschel and Miori (2017) [28] proposed a taxonomy-based approach to study ethical perspectives surrounding big data. From a knowledge management perspective, incorporating ethics would mean trying to effectively differentiate between 'useful' and 'harmful' knowledge derived from big data. Constant collection of customers' actions, reviews, and sentiments by companies is often viewed as an invasion of privacy and increase of corporate control. Along with its overly positive potential, big data is also being seen as a socio-technical phenomenon which allows corporate gains to overshadow social and civil implications (Boyd & Crawford, 2012) [8].

6. CONCLUSION

Big data is a fast-paced phenomenon that can provide organizations with new and unique sources, mechanisms, and channels for information and value creation. The most recent trends in big data include: Creating highly interactive database tools that can collect information from multiple data sources (such as competitions, customers, employees, and other stakeholders) and need-based data architectures that are capable of incorporating customer factors such as individual personas (a new and innovative source of customer information) (Tableau, 2017) [61]. Hence, there is a huge scope for scholars and practitioners alike to evaluate the effects of big data on enhancing organizational capabilities.

REFERENCES

[1] Amidon, D. (1997). *Innovation Strategy for the Knowledge Economy: The Ken Awakening.* Newton, MA: Butterworth-Heinemann.

[2] Baesens, B. (2014). *Analytics in a big data world: The essential guide to data science and its applications*. John Wiley & Sons.

[3] Barton, D. & Court, D. (2012, October). Making advanced analytics for you. *Harvard Business Review*. Retrieved February 21, 2016 from https://hbr.org/2012/10/making-advanced-analytics-work-for-you

[4] Bennett, R. (2001). “Ba” as a determinant of salesforce effectiveness: an empirical assessment of the applicability of the Nonaka-Takeuchi model to the management of the selling function. *Marketing Intelligence & Planning*, 19(3), 188-199.

[5] Berman, J. (2013). *Principles of Big Data*. Boston, MA: Morgan Kaufmann.

[6] Bihani, P., & Patil, S. T. (2014). A comparative study of data analysis techniques. International *Journal of Emerging Trends & Technology in Computer Science*, 3(2), 95-101.

[7] Bowman, C., & Ambrosini, V. (2003). How the resource□based and the dynamic capability views of the firm inform corporate□level strategy. *British Journal of Management*, 14(4), 289-303.

[8] Boyd, D. & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication & Society*, 15(5), 662-679.

[9] Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in numbers: How does data-driven decision making affect firm performance? In *Social Science Research Network (SSRN)*.

[10] Butler, T. & Murphy, C. (2007). Understanding the Design of Information Technologies for Knowledge Management in Organizations: *A Pragmatic Perspective. Information Systems Journal*, Vol. 17(2), p. 143-163.

[11] Chakravarty, A., Grewal, R., & Sambamurthy, V. (2013). Information technology competencies, organizational agility, and firm performance: Enabling and facilitating roles. *Information Systems Research*, 24(4), 976-997.

[12] Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, 36(4), 1165-1188.

[13] Chen, I. J., & Popovich, K. (2003). Understanding customer relationship management (CRM) People, process and technology. *Business Process Management Journal*, 9(5), 672-688.

[14] Chia, R. (1999). A ‘rhizomic’model of organizational change and transformation: Perspective from a metaphysics of change. *British Journal of Management*, 10(3), 209-227.

[15] Chou, S. W., & He, M. Y. (2004). Knowledge management: The distinctive roles of knowledge assets in facilitating knowledge creation. *Journal of Information Science*, 30(2), 146-164.

[16] Collins, H. (2010). *Tacit and explicit knowledge*. University of Chicago Press.

[17] Daniel, E. M., & Wilson, H. N. (2003). The role of dynamic capabilities in e-business transformation. *European Journal of Information Systems*, 12(4), 282-296.

[18] Datoo, S. (2014). How tracking customers in-store will soon be the norm. *The Guardian*, 10.

[19] Davenport, T. (2014). Big data at work: dispelling the myths, uncovering the opportunities. *Harvard Business Review Press*.

[20] Elbashir, M. Z., Collier, P. A., Sutton, S. G., Davern, M. J., & Leech, S. A. (2013). Enhancing the business value of business intelligence: the role of shared knowledge and assimilation. *Journal of Information Systems*, 27(2), 87-105.

[21] Eppler, M. J. & Sukowski, O. (2000). Managing team knowledge: core processes, tools and enabling factors. *European Management Journal*, 18(3), 334-341.

[22] Gandomi, A. & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137-144.

[23] George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal*, 57(2), 321-326.

[24] Griffy-Brown, C. (2017). The changing discourse of technology in society in the 21st century-Identifying themes and broader questions. *Technology in Society,* (49), A1-A4.

[25] Grillo, M., & Hackett, A. (2015). *What types of predictive analytics are being used in talent management organizations?*. Retrieved from Cornell University, ILR School.

[26] Hao, S., & Song, M. (2016). Technology-driven strategy and firm performance: Are strategic capabilities missing links? *Journal of Business Research*, 69(2), 751-759.

[27] Hargrave, B. (2013, July). Dean's corner: Volume, variety, and velocity: Big data is here to stay. *eNewsline Global Business Education News and Insights*. Retrieved February 18, 2016 from http://enewsline.aacsb.edu/deanscorner/hardgrave.asp

[28] Helfat, C., & Peteraf, M. (2009). Understanding dynamic capabilities: progress along a developmental path. *Strategic Organization*, 7(1), 91.

[29] Herschel, R., & Miori, V. M. (2017). Ethics & Big Data. *Technology in Society*, 49, 31-36.

[30] Hota, C., Upadhyaya, S., & Al-Karaki, J. N. (2015). Advances in secure knowledge management in the big data era. *Information Systems Frontiers*, 17(5), 983-986.

[31] Ibarra, F. (2017, March 9). *Google Cloud Platform adds new tools for easy data preparation and integration*. Google Cloud Platform. Retrieved January 1 from https://cloud.google.com/blog/big-data/2017/03/google-cloud-platform-adds-new-tools-for-easy-data-preparation-and-integration

[32] Jin, X., Wah, B. W., Cheng, X., & Wang, Y. (2015). Significance and challenges of big data research. *Big Data Research*, 2(2), 59-64.

[33] Kabir, N., & Carayannis, E. (2013, January). Big data, tacit knowledge and organizational competitiveness. *In Proceedings of the 10th International Conference on Intellectual Capital, Knowledge Management and Organizational Learning*: ICICKM (p. 220).

[34] Kalpič, B., & Bernus, P. (2006). Business process modeling through the knowledge management perspective. *Journal of Knowledge Management*, 10(3), 40-56.

[35] Knight, F.S. (1998). The Internet and Web Go Mainstream. *Business Communications Review*, Vol. 28(10), p. 42-46.

[36] Liew, A. (2007). Understanding data, information, knowledge and their inter-relationships. *Journal of Knowledge Management Practice,* 8(2), 1-16.

[37] Lindblom, A., & Tikkanen, H. (2010). Knowledge creation and business format franchising. *Management Decision*, 48(2), 179-188.

[38] Lohr, S. (2012, February 11). The age of big data. *The New York Times*. Retrieved March 12, 2016 from http://wolfweb.unr.edu/homepage/ania/NYTFeb12.pdf

[39] Lukovics, M., Flipse, S. M., Udvari, B., & Fisher, E. (2017). Responsible research and innovation in contrasting innovation environments: Socio-Technical Integration Research in Hungary and the Netherlands. *Technology in Society,* 51, 172-182

[40] Martin-de-Castro, G., López-Sáez, P., & Navas-López, J. E. (2008). Processes of knowledge creation in knowledge-intensive firms: Empirical evidence from Boston's Route 128 and Spain. *Technovation*, 28(4), 222-230.

[41] Mayer-Schönberger, V. & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. New York: Houghton Mifflin Harcourt.

[42] McAfee, A. & Brynjolfsson, E. (2012, October). Big data: The management revolution. *Harvard Business Review*. Retrieved February 18, 2016 from https://hbr.org/2012/10/big-data-the-management-revolution/ar.

[43] McKinsey Global Institute. (2011). Big data: *The next frontier for innovation, competition, and productivity*. June 2011. Lexington, KY: McKinsey & Company.

[44] Mueller, J., Hutter, K., Fueller, J., & Matzler, K. (2011). Virtual worlds as knowledge management platform–a practice□perspective. *Information Systems Journal*, 21(6), 479-501.

[45] Nomura, T. (2002). Design of ‘Ba’ for successful Knowledge Management—how enterprises should design the places of interaction to gain competitive advantage. *Journal of Network and Computer Applications*, 25(4), 263-278.

[46] Nonaka, I. (1990). Redundant, overlapping organization: A Japanese approach to managing the innovation process. *California Management Review,* 32(3), 27-38.

[47] Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. New York: Oxford University Press.

[48] Nonaka, I., & Konno, N. (1998). The concept of" Ba": Building a foundation for knowledge creation. *California Management Review,* 40(3), 40-54.

[49] Nonaka, I., Reinmoeller, P., & Senoo, D. (1998). The ART 'of knowledge: Systems to capitalize on market knowledge. *European Management Journal*, 16(6), 673-684.

[50] Nonaka, I., Toyama, R., & Konno, N. (2000). SECI, Ba and leadership: a unified model of dynamic knowledge creation. *Long Range Planning*, 33(1), 5-34.

[51] O'Connor, C. & Kelly, S. (2017). Facilitating knowledge management through filtered big data: SME competitiveness in an agri-food sector. *Journal of Knowledge Management*, 21(1), 156-179.

[52] Oracle. (2012). *Improving Retail Performance with Big Data*. Retrieved from http://www.oracle.com/us/technologies/big-data/big-data-retail-2398957.pdf

[53] Pettigrew, A. M. (1987). *The Management of Strategic Change*. Oxford: Basil Blackwell.

[54] Popper, K. R. (1969). *Conjectures and Refutation: The Growth of Scientific Knowledge* (3rd Ed.). London: Rout- ledge & Kegan Paul.

[55] Probst, G., Raub, S., & Romhardt, K. (2000). *Managing Knowledge: Building Blocks for Success.* Chichester, UK: John Wiley& Sons.

[56] Sanchez, R. (2004). *"Tacit Knowledge" versus "Explicit Knowledge" Approaches to Knowledge Management Practice* (No. 2004-01). Department of Industrial Economics and Strategy, Copenhagen Business School.

[57] Schreyögg, G., & Kliesch□Eberl, M. (2007). How dynamic can organizational capabilities be? Towards a dual□process model of capability dynamization. *Strategic Management Journal*, 28(9), 913-933.

[58] SINTEF, (2013, May 22). Big data, for better or worse: 90% of world's data generated over last two years. *Science Daily*. Retrieved February 18, 2016 from www.sciencedaily.com/releases/2013/05/130522085217.htm

[59] Spender, J. C. (1996). Making knowledge the basis of a dynamic theory of the firm. *Strategic Management Journal*, 17(S2), 45-62.

[60] Stewart, T.A. (2002). *The Wealth of Knowledge: Intellectual Capital and the Twenty-First Century Organization.* London: Nicholas Brealey Publishing.

[61] Sumbal, M. S., Tsui, E., & See-to, E. W. (2017). Interrelationship between big data and knowledge management: an exploratory study in the oil and gas sector. *Journal of Knowledge Management*, 21(1), 180-196.

[62] Tableau. (2017). *Top 10 Big Data Trends 2017*. https://www.tableau.com/resource/top-10-big-data-trends-2017

[63] Teece, D. J. (2006). Reflections on "profiting from innovation". *Research Policy*, 35(8), 1131-1146.

[64] Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-1350.

[65] The Explainer: Big Data and Analytics. (2014, August 26). *Harvard Business Review*. Retrieved from https://hbr.org/video/3633937151001/the-explainer-big-data-and-analytics.

[66] Tiwana, A. (2001). *The Essential Guide to Knowledge Management – E-Business and CRM Application.* Upper Saddle River, NJ: Prentice Hall.

[67] Tonidandel, S., King, E. B., & Cortina, J. M. (2016). Big Data Methods: Leveraging Modern Data Analytic Techniques to Build Organizational Science. *Organizational Research Methods*, 1094428116677299.

[68] Vishkaei, B. M., Mahdavi, I., Mahdavi-Amiri, N., & Askari, M. (2016). Optimizing Employment and Learning System Using Big Data and Knowledge Management Based on Deduction Graph. *Journal of Information Technology Applications & Management*, 23(3), 13-23.

[69] Warkentin, M. (2015). Models and Applications in the Decision Sciences. *Best Papers from the 2015 Annual Conference*. FT Press.

[70] Wei Choo, C., & Correa Drummond de Alvarenga Neto, R. (2010). Beyond the ba: managing enabling contexts in knowledge organizations. *Journal of Knowledge Management*, 14(4), 592-610.

[71] Wikoff, L. (2008). The Importance of Process in IT Organizations. *Journal of Computing in Civil Engineering*, Vol. 22(2), p. 71-73.

[72] Wilson, E. O. (1999). Consilience: *The unity of knowledge*. Vol. 31. New York: Vintage.

[73] Zhou, H., & Uhlaner, L. M. (2009). Knowledge Management as a Strategic Tool to Foster Innovativeness of SMEs. *Social Science Research Network*.

[74] Zikopoulos, P. & Parasuraman. K., Deutsch, T., Giles, J. & Corrigan, D. (2012). *Harness the Power of Big Data: The IBM Big Data Platform*. New York: McGraw Hill.

HIGHLIGHTS

The knowledge creation model is a means of converting big data into useful knowledge

Sensing and seizing big data opportunities can build knowledge repositories

Cyber Ba and Exercising Ba create new explicit and tacit knowledge from big data