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# Big Data Based Knowledge Management vs. Traditional Knowledge Management: A People, Process and Technology Perspective

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Value creation is one of the core aspects of Big Data. This concept of value creation can be linked to the efficient knowledge management within the organizations, in terms of knowledge creation, sharing and application, through which organizations can enhance their organizational performance. Little work has been done on the linkage of value creation from big data and the knowledge management capability of the organizations in terms of people, processes and technology which play a crucial role in effective knowledge management. This study contributes towards the existing body of knowledge by exploring this linkage of people, process and technology in relation to big data through the lens of knowledge management, by conducting a qualitative study in the oil and gas industry. The findings reveal that the KM capability of the organizations through big data can be explained through the Complex domain of Cynefin framework which involves probing, sensing and responding in which there are no right answers and instructive patterns (predictive knowledge) emerging from big data could be right or wrong depending upon the complexity of the situation. The useful and tested predictive knowledge by experts (people) can then emerge as good or best practice falling into complicated and simple domains of Cynefin framework.

***Keywords:*** big data, knowledge management, knowledge creation, knowledge application, technology, Cynefin framework

## 1. INTRODUCTION

The advent of big data has created huge opportunities for the organizations to flourish their businesses [26]. Because of the rapid advancements in the technology, we are living in *e*-world where huge volumes of data both in structured and unstructured format are

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continuously being generated within the organizations [15]. The main challenges in its utilization include understanding the data, filtration and removal of noise, integration of data and finally processing of this data to understand the hidden patterns which can provide useful insights to improve the businesses, finding the loopholes in the processes and rectifying the problems [4]. Building on resource based theory of the firm, big data, thus, can be a resource for the organizations, which is very unique and inimitable [28, 29]. Valuable knowledge can be created from this resource which can lead to gaining competitive edge over the competitors. When we talk about valuable knowledge creation from big data, the knowledge based theory of the firm states that data can be seen as a knowledge asset for the organizations and through predictive knowledge generated from this data, this knowledge can be used to make important decision within the organization [28, 29].

A review of literature indicated the dearth of knowledge especially empirical studies on this linkage of big data to knowledge creation and effective decision making seen through the lens of knowledge management. Some of the studies conducted in this domain focused on predictive knowledge (machine focused) versus tacit knowledge (human focused) [29]; intellectual capital, big data and KM [22]; big data as an element of knowledge management [30]; KM theory role in big data systems installation [22]; Integrating big data to foster organizational knowledge [19], managerial capabilities to transform big data into value [8, 33] and knowledge guided big data project planning and new product innovation [32]. Most of these studies are conceptual in nature and lack empirical evidence. Technology, culture, processes and people have been discussed in the previous studies in terms of issues and challenges regarding big data implementation [14, 22, 26] however, these aspects haven't been discussed in terms of comparison between traditional knowledge management and big data based knowledge management. Using the 3 main pillars of knowledge management *i.e.* people, technology and process [2], this study makes an attempt to extend this stream of research and argumentation on the similarities and differences between big data based knowledge management and traditional knowledge management.

## 2. BACKGROUND

### 2.1 Big Data

With the increased competition in the market, companies are moving towards advanced digitalization to achieve the competitive advantage and those not following this trend are on the edge of losing sustainability [16]. Digitalization has made the data and knowledge valuable and important within organizations by suggesting that big data analytics throughout value chain is important for developing business strategies and for increasing firm's performance [23]. Big data is considered to be the "next big thing in innovation" [11] as it has the power for value creation. Big data is traditionally understood through 4 vs. volume, variety and velocity, veracity [3]. Volume represents the huge amount of data in terms of its sheer size. Variety represents the existence of data in various formats and structures. Velocity indicates the pace at which data is being generated within the organizations and finally veracity tell us about the quality of data if some useful knowledge can be extracted out of this data.

Companies have largely become aware of the importance of big data in the past few years. A lot of big companies are using this big data for increased business performance whereas smaller companies have started experimenting with their data to create some value out of it useful for the organizations [33]. Big data analytics improve the flexibility and intensify the operational agility [10] as well as improve the internal business processes [6]. Overall, big data plays an important role in two ways; (i) improving exploitative processes through problem identification and problem solving, improved risk management, decision-making processes and efficiency, individual processes performance measurements and (ii) improving explorative processes through tapping into opportunities like service innovation, network management, responsiveness to market changes, improved customer centricity and agility, knowledge acquisition and business model experimentation [7]. The initial issues on big data mostly revolved around the infrastructure and technology related issues *i.e.* storage, processing and visualization. Majority of these concerns have been resolved with the advent of cheap technological solutions for data handling and processing. The current issues revolve around the soft side *i.e.* management and executives realizing the importance of big data, creating an organizational culture to incorporate big data within the organizations, understanding the importance of data scientists and analysts, understanding the trends, issues and challenges in effective utilization of big data for improved business performance [32].

**2.2 Big Data and Knowledge Management**

The traditional DIKW model [1] states that knowledge is the 3$^{rd}$ highest level starting from data. Data represents the raw figure and stats. When this data is presented with some context, it becomes information. This information then converts into knowledge when it can be used to answer the why and how questions for effective decision making. Against this traditional view, the big data concept is directly linked with knowledge management where data can be analyzed and processed with machine learning algorithms to create valuable predictive knowledge. This knowledge then can be used for effective decision making. In this new concept the hidden knowledge residing in the structured and unstructured patterns is identified. Thus, in terms of knowledge based theory of the firm [12], data is an inimitable heterogeneous resource for organizations that can contribute towards sustainable competitive advantage [24]. Knowledge presides in many forms in the organizations and also flows through different ways in the organizations. It is managed through a structured process that helps to achieve organizational goals [13] with the help of either technology or individuals. Thus, managing knowledge involves creation, sharing and utilization of knowledge for competitive advantage [29].

The purpose of big data and knowledge management is, however, similar *i.e.* to enhance organizational performance. The difference exists in the way; they are carried out. Big data in raw form is available from different sources. By analyzing that data, some patterns are generated and then by interpreting data through data analysts and business intelligence tools; some insightful knowledge is drawn which we call as knowledge management [19]. Big data becomes useful when it is analyzed by individual and some deep insight is drawn from it and data analytics performs this function. It is a process of generating meaning in data by "producing trends and patterns" with the help of data analysts (people) or business intelligence models (technology). In this whole process, human interpretation or reflection plays an important part because it sheds light according to contextual information that creates business value [4, 26]. Rusly (2017) has created the conceptual model for leveraging big data through KM processes. He suggested that KM can provide relevant data for big data analytics which can be referred to as knowledge acquisition. It can then be converted as a knowledge conversion process into useful knowledge to enhance its value and further this useful knowledge derived from data analytics can be utilized as a knowledge utilization process. The way people, process and technology interact is the foundation for traditional knowledge management. The current study attempts to explain this perspective through big data based knowledge management where technology is the central part in combination with people and processes leading to value creation. This three factor perspective hasn't been discussed in literature before particularly in connection with the KM models such as the SECI model and Cynefin model which this study tries to address to have a deeper understanding of the connection between big data and knowledge management.

## 3. METHODOLOGY

Qualitative research design was followed as the purpose was to gain an in depth insight of the phenomenon. Moreover, as big data is an emerging field, not much knowledge is available as companies are trying to understand how to utilize big data, very few people within the organizations directly working with big data can understand and explain its relevance and connection with respect to value creation. Thus, in such scenarios, qualitative research is preferred to understand the phenomenon. 10 semi-structured interviews were conducted from big data experts in oil and gas industry (Table 1). These big data experts were the key informants and were selected according to the following criteria: (i) Extensive experience of working in oil and gas industry. Majority of these experts had more than 10 years of experience in oil and gas sector; (ii) Involved directly in big data related activities; (iii) Managing projects and teams in relation to big data and knowledge management activities. Hence, the participants were selected based on their expertise related to knowledge management and big data and their overall experience of working in the oil and gas sector. The participants were primarily contacted through their LinkedIn profiles and personal contact points of the research team. Further, snow ball sampling technique was used and participants were requested to nominate some of their colleagues or friends working in oil and gas industry whom they deem appropriate for the study. The research team then went through the profiles of these candidates to select the most suitable candidates. The purpose of the interviews was explained to the participants and how the collected data will be used. Moreover, consent of the participants was obtained prior to the interviews. Using an interview guide prepared by the research team, open ended and probing questions related to big data and KM were asked from the participants. Interview questions were sent in advance to the participants so that they can prepare and also provide their feedback regarding the suitability of the questions. As the interviews progressed, some changes were also made in the interview guide based on the responses of the participants. The average duration of the interviews was about 40 minutes and all the interviews were conducted in English. Data collection stopped when saturation was achieved in the obtained results and further interviews were adding no new information. The data was analyzed using CAQDAS ATLAS.ti

(Friese, 2014). The interviews were transcribed and uploaded in ATLAS.ti for coding purposes. Initial and focused coding was performed to sort out the main categories that emerged from the data. In the initial coding, everything was coded whereas in the focused coding, codes related to the study were separated to generate the categories for example the process perspective, technology perspective and people perspective. All these categories were combined under the theme; "PPT (People, Process and Technology) Perspective of Big Data based KM". The generated theme was used to explain the linkage of big data to KM in relation to people, processes and technology.

## 4. RESULTS

In this section we will discuss and analyze the various examples provided by the participants on big data utilization in oil and gas industry and how the people process and technology are being used for efficient knowledge creation, sharing and application through big data.

**Table 1. Details of participants in the study.**

| Sr. No. | Participant | Location | Position | Experience in Oil and Gas Industry |
|---|---|---|---|---|
| 1 | Participant 1 | USA | Chief Knowledge Officer / Consultant | 12 |
| 2 | Participant 2 | Australia | Team Lead, Information and knowledge management Systems | 10 |
| 3 | Participant 3 | USA | Technology Manager | 13 |
| 4 | Participant 4 | Australia | Director IT and Knowledge Management | 18 |
| 5 | Participant 5 | Norway | Engineering Lead | 20 |
| 6 | Participant 6 | Russia | Project Engineer, Knowledge Management Coordinator | 6 |
| 7 | Participant 7 | USA | Senior Project manager and Technology Manager | 14 |
| 8 | Participant 8 | UK | Data and Information Systems Manager | 10 |
| 9 | Participant 9 | UK | Chief Knowledge Management Manager | 18 |
| 10 | Participant 10 | Netherlands | KM Manager | 12 |

### 4.1 PPT (People, Process and Technology) Perspective of Big Data Based KM

First example of big data is related to detecting the potential leakages in underwater oil and gas installations. Underwater pipelines are used to transport oil from sea to land. A large number of satellite images of these pipelines are collected regularly and then analyzed in real time for any potential leakages. These images are very huge in number and not possible to analyze manually. Using advanced image processing techniques and machine learning, these images are automatically analyzed for any potential leakages in the underwater pipelines. If any potential leakages are detected, in time measures are taken to avoid the damages through oil spill in the water thus saving the marine environment on one hand, and avoiding costs of repairing in the long run. Participant 6 stated this as:

"*We have collection of satellite images; we use these images to take decisions related to pollution. Idea for this is to monitor the pollution of our assets, like oil traces in the* *water, like we have a lot of installations under water. So for this we need to monitor and automatically detect leakage of oil pipelines through processing these images.*"

Second example provided by the participants is the predictive maintenance of machines. A lot of oil and gas companies are using data generated from a variety of sensors for predictive maintenance of machines. The data generated from these sensors on the machines is analyzed autonomously to check for any faults and if any maintenance is required by the machine. This helps in getting to know in advance about the maintenance apart from the regular schedule of the machines thus saving the companies a lot of time and money by taking timely measures to avoid wear and tear of the machines. Participant 7 explained this as:

"*We have a large data analytics team in our company. One example is predictive maintenance of hardware. We can use big data to predict in advance when a piece of equipment is going to fail… Thus, it provides enhanced knowledge in advance other than the regular or scheduled maintenance if some fault occurs thus saving time and money.*"

Another important application revealed from the interviews is finding the optimal parameters for the compressors at various locations in the oil and gas fields. Compressors have variety of purposes in oil and gas industry mainly to adjust gas pressures. By collecting the data from large amounts of compressors and analyzing it, the oil and gas companies try to estimate the optimal parameters for the compressors. By integration and analysis of all the data in recent years, it has become possible to compare and understand the parameters under which the compressors can provide an optimal performance. It can also help compare the performances of the compressors under different working conditions.

Fracturing process carried out in oil and gas is another example of big database knowledge management as revealed by the participants. Fracturing is a process which involves the injection of high-pressure fluids to cause cracks in the rocks which helps in easy extraction of the oil and gas. By doing experiments and analyzing the data, the optimal parameters for the fracturing process can be found. Moreover, one of the companies found that these parameters vary for different surfaces. It became only possible to understand this phenomenon after analyzing the data through large number of experiments. Participant 3 explained this as:

"*We did a project a year ago and we got a lot of data. We decided to put together the data. The idea was they wanted to know what created a good fracturing job. It is not how much data but it is the variety of data. Many of the elements in big data haven't been compared to each other for correlations, and that's where the power of big data lies … having the right knowledge and using it for analysis of data is extremely valuable and people don't realize it that much.*"

Reservoir management is the final example related to knowledge creation through big data. Using a variety of sensors installed in the reservoirs, knowledge related to the functioning of reservoir is generated. Permanent monitoring of reservoir became possible due to continuous data generation which helps in setting the suitable production parameters, understanding the capacity of the reservoir, resolving the variance between the actual and expected production of the reservoir and to get a complete picture of the strengths and weaknesses of the reservoir. On the whole, big data was considered as a way of intelligent automation especially for operational purposes. Most of the operations can be automated through use of smart algorithms and the processes could be optimized for improved performance for example reservoir management is carried out through big data. Participant

1explained this as:

"*Yes, absolutely, if you want to say big data is an extension of automation, I say, automation, especially; intelligent automation will be a replacement in some areas, specifically in the operational sense. Analytics is leveraging the optimization point of view. The way in which you are optimizing the reservoirs or other operations is good.*"

In all these examples, a combination of people, process and technology has been used to create value out of big data. This value creation is basically linked to knowledge creation at first stage and knowledge application at the second stage. This linkage will now be discussed in the next section of Analysis and Discussion in the light of examples provided by the participants.

## 5. ANALYSIS AND DISCUSSION

From the findings in the form of examples, we can see that people, technology and process play a key role for value creation and enhanced organizational performance [33]. Technology is used to collect, integrate and analyze the data for example in case of predictive maintenance, state of the art sensors are used to collect data regarding different parameters of the machines. In case of underwater installations, satellite images are collected and then analyzed using image processing techniques. Similarly, for reservoir management, again the sensors based on advanced technology are used to collect data. Same is the case for the fracturing process and collecting data of compressors from various parts of the world for analysis and comparison. So, technology is at the heart of value creation from big data as useful patterns are generated from the data analysis using technology and that is the first part *i.e.* knowledge is created from the structured and unstructured data formats falling in line with the findings of Rialti *et al*. [20] and Sumbal *et al.* [28]. We can say that technology is essential part in knowledge creation through big data, however, in the traditional knowledge management approaches; technology is just an enabler for knowledge management and more used for knowledge sharing purposes as stated by early researchers for example Dalkir [5] and O'Dell and Hubert [18]. In fact, it has been argued that most of the knowledge is tacit knowledge that is shared using face to face interaction [27] and only a small percentage of the knowledge resides in the explicit form for which technology can be used. The usage of the technology was not the prime focus in traditional knowledge management approaches as most of the literature believed that people rely more on face to face interactions rather than using databases and portals for valuable knowledge generation and knowledge sharing. However, technology is the prerequisite for knowledge creation through big data as explained by Corte-Real *et al.* (2019). The predictive knowledge cannot be generated without the use of technology. Thus, technology has been used in big data for both knowledge creation and knowledge sharing. Moreover, integration and collection of data is first step in big databased knowledge management which is not possible without technology as per findings of Sumbal *et al*. [29].

In the second phase, this knowledge is shared with the experts and applied in relevant contexts. Here the involvement of people can be observed at 2 stages if we look at the findings. First, at analysis level, where data scientists and engineers collect the data and run the analytics; second is at the decision-making level after the analysis. Thus, after the experts make the decision, finally this knowledge is then applied in real settings and context for improved performance as is evident from the results thus falling in line with the findings of Sumbal *et al.* [26]. Regarding people, previous literature indicates that it's the people from where the knowledge originates [12]. People socialize and they share knowledge which leads to the stages of externalization, combination and internalization in Nonaka's SECI Model [17]. In case of predictive knowledge, the machines generate or create the knowledge at first stage without the involvement of people. The involvement of people could be necessary at the vetting stage to see if the predictive knowledge could be useful or not [26]. This also depends how efficiently the machines can learn from the data and what is the authenticity of the predictive knowledge. In certain scenarios, the human intervention might not be necessary at all and thus generated predictive knowledge leads to knowledge sharing and knowledge application eventually [26]. An important thing to understand here is that machines need some time to mimic the human behavior and thus the predictive knowledge generated might not be accurate all the time [26]. The tacit knowledge of employees gained through years of experience cannot be replaced by machines in a short span of time [21]. For simple tasks such as the example of predictive maintenance of machines discussed above, it might be easier for the machines to learn and also might not involve high degree of tacitness; however, for complex and risky tasks having huge financial and human impact, the human involvement cannot be compromised. Moreover, it can also be argued that with the passage of time, as more organizations work on big data and learning algorithms become smarter, majority of the tasks from knowledge generation to knowledge application could be completed without human intervention.

Talking about the process perspective in big databased KM, the traditional knowledge management is best described by Nonaka's SECI Model starting from Socialization and then going through externalization, combination and internalization. However, this cycle of processes does not work in a linear way in big databased knowledge management just as discussed above. The Cynefin framework [25] best describes this relationship of knowledge management and big data. This framework has four domains namely Simple, Complicated, Complex and Chaotic. In "Simple" domain, we categorize the best practices already being followed in the organization, in "Complicated" domain, expert judgements and systems thinking approach can be used to determine if something known can be categorized as a good practice for the organization. The third domain "Complex" represents the domain when the cause and effect are not obvious and through experimentation, "instructive patterns" can emerge. According to Cynefin model, this stage is "probe-sense-respond" which matches with the predictive knowledge creation from big data when patterns emerge from data. Thus, according to above discussion, big data can fall in the Complex domains in which there are no right answers and instructive patterns can emerge. This is similar to how the predictive patterns emerging from big data could be right or wrong depending upon the complexity of the situation for example in case of predictive maintenance of machines, the emerging patterns could be reliable how-ever, in case of predicting leakages of underwater oil pipelines through satellite images, proper vetting needs to be performed on those predictions to determine their accuracy. Thus, the outcomes tend to be emerging practices as described by [25]. This vetted knowledge after application can be categorized into the complicated and simple domains as good and best practice respectively. The final chaotic domain will apply when the situations are more complex such as force majeures in which the organizations act first to contain the situation and later on use data to analyze the situations such as the recent pandemic of COVID-19. Chaotic domain is the next step process in which activities such as fall of oil prices and other market trends can be analyzed to decide for the explorations and stuff. In the current findings, the chaotic domain does not apply and further case studies can be conducted to strengthen this argument.

## 6. CONCLUSION

Value creation comprises of three levels where the technology plays its part at first step, and then the process and people together combine to create value out of big data. First step is knowledge creation, and then it is disseminated across the people and within the organization. Then, this knowledge is applied in given contexts for enhanced performance. The relevant knowledge is also stored for reuse purpose as well. In order to create value, organizations need to understand the importance of all these three aspects of knowledge management (technology, process and people) that can help in optimal utilization of big data. Technology plays the most important role in big databased knowledge management and is a pre-requisite to initiate the big databased activities. The knowledge people or "deep smarts" in the organizations are important for effective decision by vetting the predictive knowledge obtained using the technology, however, their role might become obsolete as algorithms become smarter and the world is on its way from Industry 4.0 to Industry 5.0 systems. Moreover, generating predictive knowledge from big data is just the first step, this knowledge needs to be shared within the organization for reuse and to be applied in relevant contexts. Here again technology plays it part to decide on how to share and store this knowledge. Finally, the process perspective of knowledge creation up to knowledge application can be best described by the Cynefin framework as there is more disorder in big data and the aim is to generate patterns through probing, sensing and responding. Based on the outcome, the generated patterns can then become useful knowledge and become a good or best practice falling into the complicated and simple domains of the Cynefin framework.

This study contributes to the literature on the linkage of big data and knowledge management by focusing on the three main pillars of knowledge management *i.e.* people, processes and technology and tries to explain the difference between traditional and big data-based knowledge management using the Cynefin framework which has not been discussed before. Moreover, the study has important implications for managers and executives. It provides insights regarding different factors important in big databased knowledge management such as utilization of technology, people and understanding the process of knowledge creation to knowledge application in the context of big data. The study focused on only oil and gas industry and, thus, results may lack generalizability. Future studies on this topic can be conducted in other knowledge intensive industries to understand the big databased knowledge management. The usage of technology for big data might be same however; the people and process perspective might vary across different industries. Thus, it would be interesting to explore this PPT perspective in other knowledge intensive industries. Also, the context of big data regarding Industry 4.0 seems to be a promising avenue for further research regarding PPT perspective.

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