A Review on Factors for Big Data Adoption towards Industry 4.0

* Miza Shawani Kamarulzaman¹; Noor Hafizah Hassan¹; Sulfeeza Md. Drus²; Saiful Adli Ismail¹
Razak Faculty of Technology and Informatics, Universiti Teknologi Malaysia¹
College of Computing and Informatics, Universiti Tenaga Nasional²
miza1994@graduate.utm.my¹,noorhafizah.kl@utm.my², sulfeeza@uniten.edu.my³,saifuladli@utm.my⁴

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*Corresponding author noorhafizah..kl@utm. my

Abstract

The amount of data being collected and stored is expanding rapidly in digital form in term of volume, variety, velocity and veracity and known as big data phenomenon. The use of Internet of Things (IoT) in energy industry in creating a new industrial paradigm creating a comprehensive data capture through smart energy and smart meter in embarking Industry 4.0. However, organization seems left behind to catch up with the big data adoption and the use of it. Therefore, it is important to identify the issues and hurdles surround in big data adoption in organization especially in energy industry. This study was conducted to investigate factor for big data adoption in energy in facing industry 4.0. A literature review was conducted in identifying the factors and issues surround and a conceptual model was proposed. The factors found from previous literature in big data adoption will be replicated and adopted in energy sector. Findings of this study focused on improving current implementation adoption for organization in understanding organizational perspectives underpinning of Technology Organisation Environment (TOE) framework.

Keywords: TOE, energy, big data adoption.

1. Introduction

The implementation of big data analytics in organisation has been rapidly increasing. Big data analytics has proven to improved decision making process and provide greater solution in the business. Organisation has make use the data that they have to a meaningful information. Increasing needs of Industry 4.0 initiated by the government have increased the awareness in managerial level to adopt big data in their sector. Big data analytics have been widely used in many industry such as in education (Miftachul et al., 2018), supply chain management (Lai, Sun, & Ren, 2018), healthcare (Youssef, 2014) and energy (Zhou & Yang, 2016), transportation, automotive, oil and gas industry and many more.

Big data analytics can serve different purpose in variety of domain. The massive amount of data generated in industry can helps decision makers to understand their

^{*} Corresponding author. noorhafizah.kl@utm.my

customer better. Big data analytics includes descriptive, diagnostic, predictive, prescriptive analytics modelling. Descriptive modelling is defined as 'what' describing current the business-problems and opportunities comprehensively through visualisation, while diagnostic modeling explain the concept of 'why' on the root cause and isolate co-founding information. Meanwhile, predictive modelling presents the future on 'what will happened' based on the datasets that has been analyse based on historical pattern used to predict outcome using certain algorithm. For prescriptive modeling, it tells the organisation the recommendation of actions and strategies of business decision 'what should I do next'.

With the innovative technology that has been embracing organisation in terms of big data analytics, energy industry has to follow the needs of this trend. The evolution of smart meter and smart grid towards energy efficiency has create a hurdle to the management to adopt big data in the organisation. Despite of growing needs and trends, energy industry has been lagging behind in big data analytics especially in terms of integration. There have been significant efforts over the last decade to define appropriate standards and best practices and implement energy saving efficiency. Using big data analytics can help to improve energy efficiency (Koseleva & Ropaite, 2017). Various significant efforts have been reported from previous literature (Sun, Cegielski, Jia, & Hall, 2018) to study the factors associated with the adoption of big data analytics in various industry. However, there still limited study found that replicate the adoption factors found in energy industry. Therefore, this paper investigates factors associated of big data adoption in organisation to be further evaluated in selected energy industry using Technology, Environment, Organisational (TOE) framework.

This paper is organised as follows, the first section will briefly have described big data analytics in energy, following that, factors associated with big data analytics in organisation will be presented. A proposed conceptual model will be further described in the later section. Finally, future recommendation and conclusion will be presented.

2. BIG DATA ANALYTICS IN ENERGY

The transformation of energy industry in digitization of their operation have increase the demand of automation in the energy infrastructure especially in Industry 4.0. Industry 4.0 is a term related to the concept of Internet of Things (IoT) and Cyber Physical System (CPS), information and communications technology (ICT), Enterprise Architecture (EA), and Enterprise Integration (EI). IoT become one of the agenda of Industry 4.0 that stimulated government to launch this evolutionary journey to ensure the maximum production and volume of the business operation in energy industry. Besides that, underlying physical system in the IoT is closely related towards big data as this physical system have a potential to create massive amount high-volume and velocity of the data.

Energy industry is undergoing radical change as renewable energy has taken place to ensure the effective usage of electricity. With a proper planning and management, power optimisation can be utilised through the implementation of big data analytics. Besides, it can help to reduce the cost of energy towards utilising the resources and make use of the IoT to gather the data. Leverage energy efficiency data from internet of things and smart meters for big data management and analytics may deliver operational reliability and profitability. Big data can also help to shape future renewable energy through smart grid and smart metering system. In the context of consumer perspective, using the concept of smart analytics can help the consumer in managing the energy at their home by monitoring their usage based on the smart meter installed in their house. Understanding the consumer usage pattern based on their historical data can help them to use the energy efficiently. Through the identification of consumer usage patterns, Chou & Ngo (2016) designed a smart decision support system (SDSS) and smart energy management system (SMES) by Al-Ali, Zualkernan, Rashid, Gupta, & Alikarar (2017) that may help to enhance energy use efficiency by letting the consumer to reduce their electricity cost by implementing the optimal operating schedule for electricity appliances.

The development of big data processing technique in smart grid application, supervisory control and data acquisition (SCADA) becomes a core decision making for collecting data from sensor nodes and perception devices and might burden utilities companies with the growing size of power grids to capture massive amount of data (Jaradat, Jarrah, Bousselham, Jararweh, & Al-Ayyoub, 2015). This require advanced analytics technique for upgrading the infrastructure to handle the growth in smart grid environment (Shyam R., Ganesh H.B., Kumar S., Poornachandran, & Soman K.P., 2015). (Munshi & Mohamed, 2017a) has proposed a framework on a secure-cloud based platform for big data processing in smart meter data in a massive amount and can be collected through real time from big data analytics approaches.

3. METHODOLOGY

This paper use a conventional literature review by reviewing related literature in big data adoption. This study use technology, organization and environment (TOE) framework considering related factors for basis in designing the proposed conceptual model.

4. TECHNOLOGY ORGANISATION ENVIRONMENT (TOE) IN BIG DATA ADOPTION

In understanding big data adoption in energy industry, Technology Organisation Environment (TOE) framework (Tornatzky, Fleischer, & Chakrabarti, 1990)by will be use to examine big data adoption in energy sector. A related work of TOE in big data adoption has been widely use in security and privacy context (Ahmad Salleh, Janczewski, & Beltran, 2015; Salleh & Janczewski, 2016); South African Telecommunication Industry (Malaka & Brown, 2015); two emerging economies of Asia –China and India(Agrawal, 2015), Korean firm (Park, Jong-Hyun; Kim, Moon-Koo; Paik, 2015) , Norway (Nguyen, 2017), manufacturing company in Malaysia (Yadegaridehkordi et al., 2018), logistic and supply chain management (Lai et al., 2018). Recently, Sun et al. (2018) have group together the factors using content analysis and come out with 26 factors. The list of most associated factors found in previous literature as depicted in Table 1.

Table 1 : Significant Factor Associated with Big Data Adoption

Factor	Sub-Factor	Domain	Author
TOE	Technological (Perceived benefits, complexity, technology resources, and big data quality and integration,	Manufacturing	(Yadegaridehk ordi et al., 2018)
	Environmental (partners pressure, government support and policy, competitive pressure), Organizational		2010)
	dimension, (management support, human resources capability, perceived costs, and change efficiency)		
Security and Privacy of (TOE)	Security and Privacy of Technology	Organisation	(Salleh & Janczewski, 2016)
System Quality and Information Quality	Technology Acceptance Model (TAM)	Indian Firms	(Verma, Sekhar, & Kumar, 2018)
Technology and Talent	Big Data Adoption Process	Radiology	(Kansagra et al., 2016)
Data quality management, usage benefits, and the pro-IT culture	capability through data quality management and rewarding usage experience has a positive effect in shaping intention to adopt big data analytics at a firm.		(Kwon, Lee, & Shin, 2014)
Big Data Understanding	Uncertainty about the meaning of the new technology and uncertainty about how to adapt organizational processes to the new technology.	home appliance manufacturer , retail company, gambling, insurance firm	(Caesarius & Hohenthal, 2018)
Data security, privacy and protection	Data quality of construction industry datasets, cost, internet connectivity	Construction	(Bilal et al., 2016)
Privacy and security	Lack of Information System and infrastructure support; Capital outlay with no guarantee of likely returns, Minimal IT expertise, Technical uncertainty, Reluctance of employees to adapt to changes, Uncertainty about how to measure potential benefit	Manufacturing, Construction, Services, Retail	(Raguseo, 2018)
Associated cost, privacy and policy	Investigation on BDA's benefits (BDA's benefit for firms and consumers and BDA efficiency) negative influence (BDA's privacy risk).	Healthcare	(Wu, Li, Liu, & Zheng, 2017)
Data and technology related barriers	The findings of this research are as follows: (i) data-related barriers are most important, (ii) technology- related barriers are second, and (iii) the five most important components of these barriers are (a) lack of infrastructure, (b) complexity of data integration, (c) data privacy, (d) lack of availability of BDA tools and (e) high cost of investment.	Manufacturing	(Moktadir, Ali, Paul, & Shukla, 2018)
Lack of infrastructure readiness,	Advancing immature technology, resolving the complexity of data management, lack of skilled labour, and legal and ethical challenges.	Literature review	(Shukla & Mattar, 2018)

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Lack of skilled labour			
Amount of Data	Developing application to handle amount of data created by smart grid	Smart Grid	(Munshi & Mohamed, 2017b)
Clear understanding of the business problem, a detailed and well planned step-by-step project ma	Culture of innovation within the organization, patronage and active involvement of senior management in such initiatives, a step by step logical approach as postulated earlier, an enthusiastic, highly skilled in- house team, a cooperative ERP vendor and availability of sufficient budget and infrastructure	Cement manufacturing	(Dutta & Bose, 2015)
Data Quality	Poor quality data impacting the decision-making without the knowledge of the operator. This could happen if critical sensors failures are not detected by the data cleansing routines and the state estimation applications, privacy and data protection.	Power Distribution System	(Nanpeng et al., 2016)
Technological and Business	Business, Planning, Sustainability, Sources of market and customers, Cost, Data Integration	Smart City	(Abaker et al., 2016)
The perception of benefits from big data and technological capability	Compatibility with existing system, data quality and integration, security and privacy. Management support and financial investment competence for the implementation and utilization of big data, and the government support and policy	Korean	(Park, Jong- Hyun; Kim, Moon-Koo; Paik, 2015)
TOE	Data Integration; Data Privacy; Return on Investment; Data Quality; Cost; Data Integrity; and Performance and Scalability. Ownership and Control; Skills Shortages; Business Focus and Prioritisation; Training and Exposure; Silos; and Unclear Processes	South African Telecommunicatio Industry	(Malaka & Brown, 2015)
TOE, Supply Chain Characteristic	Perceived benefits and top management support can significantly influence the adoption intention, competitors' adoption, government policy, and SC connectivity,	Supply Chain	(Lai et al., 2018)
TOE	Complexity, compatibility, regulatory support, organizational size, competition intensity, environmental uncertainty	Firms in China and India	(Agrawal, 2015)
Organisational Process, Fit with Business Model	IT Fashion, Relative Advantage, Business with IT alignment, Fear of Missing Out, Innovative Dilemma, Desire for Innovation, Fear of Uber effect	Different type of organisation	(Chen, Kazman, & Matthes, 2015)

5. PROPOSED CONCEPTUAL MODEL

Based on previous study conducted, this research will be based on the theoretical TOE three-dimensional framework to be adopted in the proposed conceptual model. Antecedents identified in the TOE will be based on the most significant factors that influence BDA adoption in previous study based on Table 1. Figure 1 shows the proposed conceptual model for this study that leveraging on TOE framework with eight construct identified.

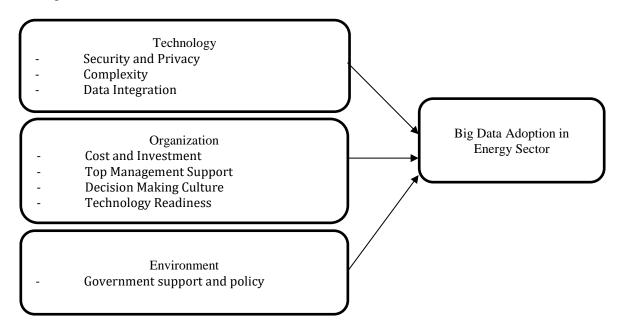


Figure 1 : Proposed Conceptual Model

5. Conclusion

Big Data Analytics known as a platform that can enhanced decision making process. In energy sector, consumer can gather advantage through smart energy monitoring and provide efficient energy management for the utility company. Following the skeleton of TOE framework, eight identified factors through that may influence the big data adoption energy is conceptualized in the research model proposed. The proposed model will be evaluated with respondents from utility company for further evaluation.

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