2019

Transformation through Big Data Analytics: a Qualitative Enquiry in Healthcare

Kasuni Weerasinghe
Massey University, w.m.k.g.weerasinghe@hotmail.com

Transformation through Big Data Analytics: a Qualitative Enquiry in Healthcare

Full Paper

Kasuni Weerasinghe
School of Management
Massey University
Auckland, New Zealand
Email: w.m.k.g.weerasinghe@hotmail.com

Abstract

With an aim to understand transformation around big data analytics, this paper first investigates the literature to explore elements of change around big data. The research comprises a qualitative enquiry in the New Zealand healthcare context to understand how professionals across the sector view this transformation. Healthcare sectors are increasingly adopting big data technologies to improve healthcare delivery and management. However, for sectors like healthcare, big data brings significant changes in terms of technology architecture, infrastructure, skills, and organisational structure changes. Security measures and policy changes are also apparent. Using a deductive approach to data analysis, it confirms the important elements identified in the literature around big data transformation and highlights the relationships between these elements of change. The paper uses Sociotechnical Systems Theory as the underlying theoretical foundation for this study. The findings of this research contribute to policy and practice in healthcare.

Keywords: big data analytics, qualitative research, big data transformation, healthcare

1 INTRODUCTION

'Big data' is a popular topic both in industry (Bennett 2015; Burton 2013) and academia (Davenport 2013; Pentland and Berinato 2014). Articles in the popular press like the New York Times (Lohr 2019) also contribute to this trend. Identified by Girard (2019) as "the new oil" (p.1) interest around big data is spreading across the areas of business, computer science, information systems, finance, statistics and many other fields (Watson 2014). In the field of Information Systems (IS) it is evident that big data is an important field of study, due to the increasing discussions in IS journals and conferences (Abbasi et al. 2016; Baesens et al. 2014).

Halevi and Moed (2012) review of the big data literature found that research on the term 'big data' dates back to the 1970s. The earliest definitions of it included large amounts of complex data, and were typically related to computer modelling and development of hardware and software to handle large data sets in the fields of linguistics, geography and engineering (Halevi and Moed 2012). However, an explosion of publications on big data was noted from 2008 onwards (Halevi and Moed 2012). The reason behind this was the launch of social networking companies during the mid-2000s. When these internet-based companies were first introduced, a new kind of information emerged – rapidly aggregating chunks of unstructured data, later identified as big data (Davenport 2013; Davenport and Dyché 2013). Since then big data has been a reason for many technological developments and has increased its presence in both business and academia. A preliminary search for articles with "big data" in the title on Google Scholar found 9,410 results in 2012, 60,100 in 2015 and 80,600 in 2018. This shows a huge growth of interest in the term 'big data'.

In simple terms big data refers to enormous amounts of unstructured and complex data produced by a wide range of computer applications (Emani et al. 2015; Wang and Huang 2015). There is no universally agreed upon definition for big data (Herland et al. 2014). Phrases such as "massive amounts of data", "enormous growth of data" and "large data sets" are typically seen across the literature as defining big data (Chen et al. 2014; Shin 2015). Three characteristics, known as the 3Vs – volume, variety and velocity – are generally used to define big data and distinguish it from standard data (McAfee and Brynjolfsson 2012; Russom 2011). Two additional Vs – value and veracity – are also commonly seen extending the characteristics of big data to 5Vs (Saporito 2013; Weerasinghe et al. 2019). Based on the 5V characteristics Emani et al. (2015) say "dealing effectively with big data requires one to create value against the volume, variety and veracity of data while it is still in motion (velocity), not just after it is at rest" (p.72). Additionally Weerasinghe et al. (2019) highlights that volume, variety and velocity are more objective characteristics of big data while veracity and value are seen as more subjective depending on the need and application.

Analytics is the use of applications/algorithms to analyse data (Watson 2014). It is apparent that advanced analytical techniques are required to deal with data that is high in volume, variety and velocity (Emani et al. 2015). Only with such advanced analytics techniques will companies be able to create value from big data by managing uncertainty (Wang and Huang 2015). Traditional analytic capabilities are not sufficient to process big data. Additionally, big data sets which have not been utilised through analytics create no value (Saporito 2013). Using advanced analytical techniques to make use of big data is often referred to as 'big data analytics'. Knowledge created through big data analytics is central to discussions around big data technologies (Pauleen and Wang 2017). Such knowledge derived from big data analytics has the potential to transform business as business decisions based on 5V-based data should lead to better decisions. Therefore, big data analytics can be identified as central to the revolution brought by big data to the modern business world (Davenport 2013).

With the aim to further understand this transformation, this paper presents a study conducted within the New Zealand healthcare context to explain how professionals across the healthcare sector perceive how big data analytics drives change. The research question addressed in this paper is *how is big data perceived to change the healthcare sector and organisations within the sector?* Understanding the elements of change driven by big data to transform traditional environments will allow organisations to understand the requirements and prepare themselves for the transformation brought about by technologies around big data analytics. The paper presents a review of the healthcare context, background literature around big data transformation, the methodology undertaken for this research and the findings with a discussion around these findings, followed by the conclusions.

2 HEALTHCARE CONTEXT

The healthcare sector is under pressure to perform and advances in information technology are seen as one significant means to improve patient care (Paré et al. 2008; Roski et al. 2014). As such, a wide range of clinical and operational information systems have been adopted by healthcare systems around the world (Menon et al. 2009). The accelerated use of information systems, on top of increasing patient populations, complex diseases, sophisticated medications and diagnostic testing, generates complex and unstructured data that have the characteristics of 'big data' (Burns 2014; Ward et al. 2014). As technology itself was not mature enough to cope, it was considered difficult, if not impossible, to use data-driven approaches in healthcare to make use of large and complex healthcare data (Wyber et al. 2015). However, recent developments in technology around big data analytics have opened promising avenues for healthcare to make use of big-healthcare-data for improved healthcare delivery (Weerasinghe et al. 2018a). Big data in the healthcare system is generated through traditional healthcare data as well as genomic data, patient-generated data and population health data (Weerasinghe et al. 2019). Precision medicine, discovering the most effective treatments, identifying patterns in health, and advances in pharmaceutical research are some notable examples of big data applications in health (Groves et al. 2013; Nash 2014; Tormay 2015).

Unlike other sectors, internationally healthcare has not been an early adopter of big data analytics (Groves et al. 2013; Ward et al. 2014). However, developed countries like New Zealand (NZ) have demonstrated a great interest in the potential to improve healthcare planning and service delivery through the use of analytics (Orion Health 2016). NZ healthcare is an early adopter of electronic devices and computer systems in comparison to other parts of the world (Protti and Bowden 2010). This habit of early adoptions has now resulted in huge amounts of data and this will increase exponentially. With electronic data having been generated for nearly 30 years, traditionally collected health data is perceived to be big data. On top of this, new types of data like genomics and patient-generated data require application of big data technologies to facilitate improved healthcare delivery and management in NZ (Weerasinghe et al. 2019). Therefore NZ was selected as the context for this research.

3 ASPECTS OF CHANGE AROUND UTILISING BIG DATA

While big data is not an off-the-shelf product, utilising big data demands a specific combination of tools, techniques, and skills (Loshin 2013). Companies such as Google, Facebook and eBay, which were started in the internet era, are implicitly built around big data and are well equipped with necessary capabilities to handle such large and complex data (Davenport and Dyché 2013). While these companies have only had to deal with big data, traditional businesses and sectors that existed before the internet era are also looking into opportunities and ways of making use of big data technologies with great challenges around transforming their business (Weerasinghe et al. 2018a). Traditional businesses need to consider making changes to their existing IT ecosystem to integrate big data and related technologies (Weerasinghe et al. 2018b). They will not only be working with big data but also with standard small datasets, they will have Hadoop[1] clusters running along with their IBM mainframes, big data analytics will be used to complement traditional analytics, and their data scientists will be working together with quantitative analysts (Davenport and Dyché 2013). Therefore, it is a huge challenge for the traditional businesses to integrate the new (implementation of big data analytics) with the known (traditional data technologies in the IT ecosystem) (Bean and Kiron 2013; Davenport and Dyché 2013).

The new environment, which is the implementation of big data analytics, calls for changes in the technical aspects as well as social aspects of the organisation (Coyne et al. 2018). The literature has noted that technology architecture, IT infrastructure, security measures and analytics platforms can be identified as technical aspects affected by big data implementation (Davenport 2013; Davenport and Dyché 2013). Social aspects of the organisation such as skills (Davenport 2013; Watson 2014), organisational roles and structure are also affected when integrating big data into an existing IT ecosystem (Bean and Kiron 2013; Davenport and Dyché 2013). In addition, in sectors like healthcare, policy and regulations are identified as necessary areas of change with adoption of big data technologies (Roski et al. 2014). The following sections present these areas in detail.

3.1 Analytics

Analytics is central to implementing big data technologies. Advanced analytical capabilities are required to create value from big data and these capabilities are more sophisticated than traditional analytical capabilities (Emani et al. 2015; Watson 2014). Only with such advanced analytics techniques will companies be able to create value from big data by managing uncertainty (Wang and Huang 2015). Traditional businesses should implement big data analytics in conjunction with the analytics of standard data (Davenport 2013; Davenport and Dyché 2013). There are four main variations of analytics that can

[1] Hadoop is an open source software framework for distributed storage and distributed processing of large data sets.

be used with big data: (i) descriptive, (ii) diagnostic, (iii) predictive, and (iv) prescriptive. Descriptive analytics reveal what has occurred, diagnostic analytics investigate why something has occurred, predictive analytics forecast what will occur, and prescriptive analytics suggest what to do (Khalifa 2018; Watson 2014). These variations influence the technologies and architectures used to perform big data analytics (Watson 2014).

3.2 IT architecture

IT architecture refers to the methods, models and technologies that guide the data environment of the organisation. The existing IT architecture needs to be extended to cater to technical requirements of big data in order to deal with volume, variety, velocity and veracity (Abbasi et al. 2016; Sathi 2012). Unlike traditional data analytics environments, implementation of big data analytics requires methods such as MapReduce[2], in-memory analytics[3], and in-database processing[4] (Davenport and Dyché 2013; Wang and Huang 2015). On top of these defined standards around data integrity, security, platforms and tools, other design methods need to be rethought (Girard 2019). Thus, when integrating big data analytics into the existing IT ecosystem, such measures in an organisation's IT architecture need careful integration.

3.3 IT infrastructure

IT infrastructure is the required hardware, software, data warehouses and networking capabilities. Arguably, the introduction of big data analytics requires significant changes to the IT infrastructure of an organisation. To deal with the sheer volume of data, Hadoop clusters need to be integrated with existing servers (e.g. IBM mainframes) (Davenport and Dyché 2013). Additionally, networking requirements and data warehouse requirements are significantly different for big data compared to traditional data (Demchenko et al. 2012). Use of sensors and Internet of Things technologies are also changing IT infrastructures in the big data era (Yaqoob et al. 2019). Roski et al. (2014) also acknowledged the use of cloud storage as well as data 'lakes' that can store and manage many different types of structured and unstructured data as infrastructure changes organisations can utilise in the big data domain. Other cloud services such as infrastructure-as-a-service (IaaS), platform-as-a-service (PaaS) and database-as-a-service (DBaaS) are being increasingly utilised in the big data era, influcencing changes to the IT infrastructure of organisations (Abbasi et al. 2016).

3.4 Security

Security can be seen as a general concern when making use of big data. Because of the availability of such large amounts of data, security breaches could bring more severe consequences and losses to an organisation (Kshetri 2014). Roski et al. (2014) argue that current practices, policies and security measures around the use of data need to be revisited by policy makers in order to facilitate better data security in the big data era. Tightening the security controls and taking adequate safeguards to ensure security of big data is paramount to the success of big data implementations and use (Zhang 2018).

3.5 Skills

Skills in this context are capabilities of people who deal with data to create value. Traditional data processing is typically done by quantitative analysts with mathematical and statistical skills. However, the analysts need to have both computational and analytical skills to process big data; specifically they need to be capable of manipulating big data technologies with skills in text mining, video image analytics, coding in scripting languages and so forth (Davenport and Dyché 2013). Organisations integrating big data may need to hire people with these skills, who are commonly identified as data scientists (Davenport 2013). Data science is an emerging area of expertise that has the ability to address the challenges of big data. It is the coming together of skills around technologies like single processing, statistics, machine learning, text retrieval and natural language processing for the means of analysis and interpretation (Roski et al. 2014). Acquiring data science skills is critical for the effective utilisation of big data in any context (Halamka 2014). In the big data era, there is a greater reliance on data science skills around utilising big data for real time decision support (Abbasi et al. 2016).

3.6 Organisational Structure and Roles

Organisational Structure and Roles refers to the groups involved in big data processing and IT decision making roles in an organisation. The analytics groups (often with the title "operations research"), innovations groups, or architectural groups within the IT structure are typically initiated to face the big

[2] MapReduce is a programming model used for creating and processing very large datasets.
[3] In memory analytics are used to query data that resides in random access memory, opposed to stored data.
[4] In database processing/analytics refers to integrating analytics into data warehouses.

data revolution (Davenport and Dyché 2013). The Chief Information Officers (CIO) and Chief Data Officers (CDO) at the MIT Chief Data Officer Forum envisioned that in 10 years' time the CIO role will be taken over by the CDO (Bean and Kiron 2013). Other executive roles like Chief Analytics Officer and Chief Science Officer are also emerging roles with big data technologies (Davenport and Dyché 2013).

3.7 Policy

In the healthcare literature, policy was seen as a particularly important element that requires changes/revision in the big data era. The reason behind this was that the sheer volume of data collected and stored about people needs better governing policies and practices to ensure security (Roski et al. 2014).

The above discussion in sections 3.1-3.7 shows that making use of big data goes beyond analytics or infrastructure when handling massive volumes of data. It shows that implementing big data analytics is associated with a wide range of sociotechnical aspects, making it a whole new technology phenomenon. Thus big data analytics is a revolution; implementing big data analytics triggers organisational transformation. When an organisation is integrating big data with its existing IT ecosystem, these aspects need to be carefully managed and changed appropriately. This paper presents an attempt to bring together past literature and conduct a qualitative study within the NZ healthcare context to understand whether the relevant professionals see these areas as important elements of change and whether there are differences or new areas which can be identified.

4 THEORETICAL FOUNDATION: SOCIOTECHNICAL SYSTEMS THEORY

Grounded in sociotechnical perspectives to acknowledge the importance of understanding interdependencies of people and technology, this paper examines the research question: *how is big data perceived to change the healthcare sector and organisations within the sector?* Sociotechnical Systems Theory (SST) (Emery and Trist 1965) is used as the underlying theoretical basis for this research. In simple terms, SST identifies social and technical subsystems as two interdependent subsystems that interact and influence each other (Bostrom and Heinen 1977). While the technical subsystem includes the technological system, machinery, technology and business processes, the social subsystem is about roles and responsibilities of people involved in making use of the technical subsystem (Bostrom et al. 2009; Fox 1995). Typically SST is used as an underlying perspective for IS research to understand that use of technology cannot be separated from its stakeholders. The use of SST acknowledges that work systems are mutually shaped by social and technical systems (Winter et al. 2014) and therefore was considered ideal to understand how people see big data driving organisational change in this research. The use of the SST perspective as the theoretical foundation allows framing the research to understand people and their understanding of big data analytics.

5 METHODOLOGY

The research procedure undertaken is shown in Figure 1. The research question and literature along with the theoretical foundations provided through SST influenced the selected research methodology. SST was used as an underlying perspective to understand social and technical interdependencies of technological phenomenon such as big data. Ontological assumptions and epistemological views of the researcher as a social constructionist also influenced the selected research methodology as a qualitative study. The interview schema was piloted prior to actual data collection. Preliminary analysis of the initial five interviews also shaped the researcher's thinking and refined the interview schema to carry data collection forward.

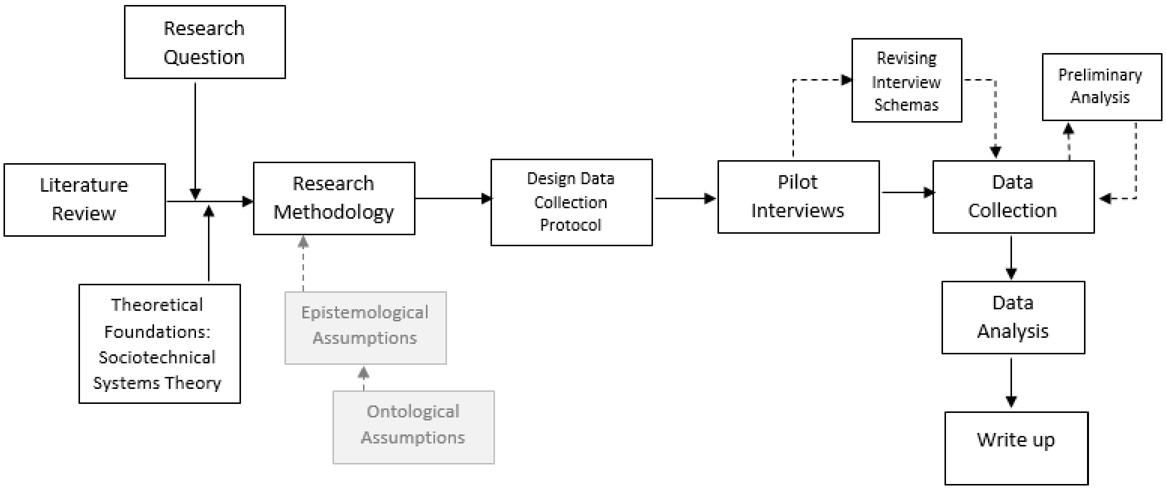

Figure 1: Research Process

In-depth interviews were conducted to gather rich data from participants (Liamputtong 2009), using semi-structured interview schemas (Merriam 2009). The in-depth interview approach acknowledges that knowledge about the social world that participants are involved in can be articulated through verbal communication between the researcher and the participants (Liamputtong 2009). Purposive sampling techniques were used as the research required gathering data from informants who are involved in constructing policies about, planning, funding and implementing, or researching the topic (Miles et al. 2014; Patton 2015). A snowball sampling strategy was also used to ask informants to direct the researcher to other possible participants (Miles et al. 2014). Table 1 provides an overview of the types of organisations and participants that were involved in this research. Twenty-three interviews were conducted with policy makers, planners, funders, implementers, and technology vendors as well as academics.

Types of Organisations	Types of Participants	Number of Participants
Macro Organisations Ministry of Health (MoH) and Business units of MoH	Policy makers in the NZ healthcare sector (e.g., the directors, senior executives)	6
Meso Organisations District Health Boards (DHBs) Primary Health Organisations (PHOs) Universities Technology Vendor Organisations	Senior executives Managers (Health focus, IT focus) Academics	17

Table 1: Types of organisations and participants

Data were collected between March 2016 and June 2018. Interviews were audio recorded and transcribed verbatim. Data was analysed using thematic analysis, with a deductive approach to understand participants' perceptions around aspects of change with reference to the findings from the literature. NVivo 11 software was used for coding.

6 FINDINGS AND DISCUSSION

Data was analysed under seven themes (in Table 1) found in the literature: analytics, security measures, IT architecture, IT infrastructure, skills, organisational structure and roles, and policy. Data was coded into these seven themes, and no new theme was identified. By and large, the findings[5] confirmed the literature. However, some differences from the literature were observed. In addition, relationships between these themes that were not apparent in the literature were found and are discussed below.

[5] This is part of a larger study that investigated big data in the New Zealand healthcare context.

Most participants agreed that changes brought by big data (and advanced analytics) involve skills, organisational structure, and IT infrastructure. Security measures were seen as a key influencer and key challenge around big data analytics and seem to be driving change in policy, IT infrastructure, and skills. While these findings largely agreed with the literature, very little information came from participants around IT architecture. A conceptual framework (Figure 2) was created through the researcher's understanding and interpretation of the findings to present the areas of change and how these different areas may affect each other's transformation.

While participants talked about the evolving nature of analytics around big data, the discussions showed that analytics is central to this transformation. This centrality is depicted in Figure 2 with big data analytics (techniques and tools) transforming and influencing changes in security measures, IT architecture and infrastructure, skills, organisational structure and roles as well as policy and governing regulations.

Participants agreed that big data requires large processing power, and the storage requirements are getting more demanding. Therefore they commented that "there is now a big move towards cloud" (MES10), referring to the infrastructure changes promoted by big data. The participants also highlighted that while technology requirements are evolving, due to a lot of advanced analytics in healthcare, there are still challenges around accessing required IT infrastructure in the NZ healthcare context. Participants talked about how technology around retaining big data as well as analytics and related technologies are increasingly evolving, and some participants were even reluctant to use the term 'big data', as they argue it is a part of technology developments. Participants also expressed concerns around the use of data lakes with the increasing amounts of data being pooled in the cloud, without a specific purpose. A policy-level participant emphasised this concern:

> "I think there's something about, people are getting too confident about, that you can just roll your data into these large, cloud-based big data environments and everything will be sweet." (MAC2)

Most of the participants identified that access to necessary skills is increasingly becoming a challenge. They argued that while big data brings a lot of opportunities for the healthcare sector, finding people with such skills is increasingly becoming difficult. One of the policy makers talked about limited access to skills:

> "I think there is a capability and capacity gap. We don't have [a] lot of smart data analysts who really understand how to get value out of data." (MAC2)

Looking further into comments from the participants, it was found that while there are issues around accessing skills (i.e. data science skills), there are also increasing demands for training and updating existing skills within the existing workforce. While the required skills seem to be drastically changing in the domain of big data, organisational structure and people's roles are also influenced to undergo a major change. Explaining this, MES10 highlighted:

> "I know Chief Data Officer[s have been] appointed in organisations recently; it's very new for New Zealand." (MES10)

Similarly, MES 11 explained how the organisation landscape is changing and how new departments are evolving within their organisations around the transformation of data. He highlighted that:

"If you look into the title of our department, knowledge management, we are geared actually towards the changing landscape of information analysis and information processing. It is all about analytics and trying to transfer that information to decision making and also educating. What I am saying is I think the organisation has a vision over there because otherwise it could have been [called] data processing unit [or] data processing department." (MES11)

While policy was something that was identified by most participants as an important element in big data, there was a clear understanding that the policies around data need changing in the era of big data. Big data literature also asserts the importance of revisiting policy in the big data domain (Roski et al. 2014). In the NZ healthcare context, participants saw the NZ health policy as driving the change around big data in a positive way, by requiring the health system to be a "smart system" (MAC1, MES5, MES14). While there may be areas that still need improvements (i.e. policy around collecting data from patient wearable devices), participants highlighted that it has taken the first steps, claiming "it gives us licence" (MES14) to do big data analytics.

Security measures were seen rather as an umbrella governing change in most of these areas. Measures around data security are seen as an absolute necessity within the healthcare sector. Therefore, while security measures were changing in the big data domain, it was also seen to govern changes to most of the other areas. For example, policies need changes (and have changed) to enable better protection of privacy for healthcare data. There were some discussions and concerns around moving data to the cloud (security measures affecting IT infrastructure changes/decisions). There was an evident relationship between organisational structure and roles with changing skills of the workforce around data. These relationships between the themes have been conceptualised into a framework and shown below in Figure 2.

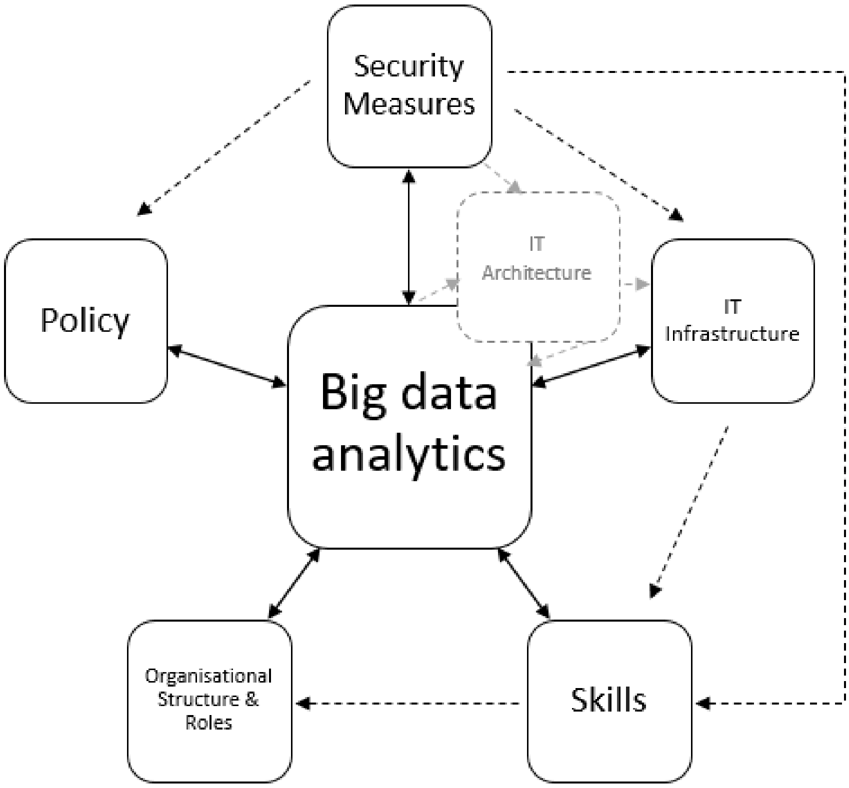

Figure 2: Conceptual Framework: Big Data Transformation

IT architecture is shown in grey because the data on architecture from the participants were limited, and it seemed that architecture is more embedded in analytics than any other element. However, further research may be needed to confirm this. Because of its view on work systems as mutually dependent systems, use of Sociotechnical Systems Theory influenced the researcher to look into the relationships between the elements identified in the data analysis. The arrows across the conceptual framework denote these relationships. All arrows from big data analytics to other themes are two-way arrows representing the changes as interdependent. For example, advancements in big data analytical techniques will influence transforming and improving IT infrastructure capabilities. However, at the same time modern technological infrastructure advancements promote change and better use of big data analytics. The dashed arrows shows the relationships seen in data across these elements. They are not always two-way relationships: for example, while infrastructure changes promoted changes to required skills, changes in skills will not have an impact on transforming infrastructure.

7 CONCLUSIONS

In the modern era, known as the fourth industrial revolution (Industry 4.0), it is inevitable that almost every industry transforms into using advanced technologies. While artificial intelligence (AI) is the most dominant area at present, big data is a close second. For AI to be more reliable and more effective, successful use and application of big data technologies is the key. Therefore, this is timely research conducted to better understand transformation in the era of Industry 4.0, with a focus on the revolution around big data technologies. Specifically the research was conducted in the healthcare context, as healthcare is identified as a field where there is considerable potential around the use of big data technologies, but at the same time is not an early adopter of big data (Groves et al. 2013).

This paper looked into the areas of change facilitated by big data analytics and related technologies of big data in the healthcare sector. It identified that IT infrastructure, IT architecture, skills, organisational structure and roles, security measures and policy are major elements changing within the healthcare sector in relation to technological advancements around big data analytics. This paper confirms the literature in identifying areas of change, and complements the literature by identifying relationships between these areas. Grounded on sociotechnical views, the findings also make a practical contribution to policy and practice, identifying anticipated change for the future. This is timely research on the essence of health policy and health services in the era of modern technology. Although this research was done in the healthcare context, the findings are anticipated to have wider applicability into other areas. However, further research may be needed to confirm applicability in different areas. One of the key future studies planned is a quantitative study confirming these findings, which may allow developing the conceptual framework further.

8 REFERENCES

Abbasi, A., Sarker, S., and Chiang, R. H. 2016. "Big Data Research in Information Systems: Toward an Inclusive Research Agenda," *Journal of the Association for Information Systems* (17:2), pp. i – xxxii.

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., and Zhao, J. L. 2014. "Transformational Issues of Big Data and Analytics in Networked Business," *MIS quarterly* (38:2), pp. 629-631.

Bean, R., and Kiron, D. 2013. "Organizational Alignment Is Key to Big Data Success," *MIT Sloan Management Review Big Idea: Data & Analytics* (54:3).

Bennett, D. 2015. "From Big Data to the Big Picture: The Power of an Open Platform in Healthcare," *Orion Health - White Paper*).

Bostrom, R. P., Gupta, S., and Thomas, D. 2009. "A Meta-Theory for Understanding Information Systems within Sociotechnical Systems," *Journal of Management Information Systems* (26:1), pp. 17-47.

Bostrom, R. P., and Heinen, J. S. 1977. "Mis Problems and Failures: A Socio-Technical Perspective, Part Ii: The Application of Socio-Technical Theory," *MIS Quarterly* (1:4), pp. 11-28.

Burns, W. A. 2014. "Healthcare Data's Perfect Storm: Why Healthcare Organizations Are Drowing in the Data They Are Creating and Why They Need Even More Data to Weather This Storm [White Paper]."

Burton, T. 2013. "The Best Approach to Healthcare Analytics." *Analytics in Healthcare* Retrieved 05 Mar 2015, from https://www.healthcatalyst.com/wp-content/uploads/2013/10/The-Best-Approach-to-Healthcare-Analytics-TOM-BURTON-final.pdf

Chen, M., Mao, S., and Liu, Y. 2014. "Big Data: A Survey," *Mobile Networks and Applications* (19:2), pp. 171-209.

Coyne, E. M., Coyne, J. G., and Walker, K. B. 2018. "Big Data Information Governance by Accountants," *International Journal of Accounting & Information Management* (26:1), pp. 153-170.

Davenport, T. H. 2013. "Analytics 3.0: In the New Era, Big Data Will Power Consumer Products and Services," *Harvard Business Review*:12), p. 64.

Davenport, T. H., and Dyché, J. 2013. "Big Data in Big Companies," *International Institute for Analytics*).

Demchenko, Y., Zhao, Z., Grosso, P., Wibisono, A., and De Laat, C. 2012. "Addressing Big Data Challenges for Scientific Data Infrastructure," *4th International Conference on Cloud Computing Technology and Science (CloudCom) 2012*: IEEE, pp. 614-617.

Emani, C. K., Cullot, N., and Nicolle, C. 2015. "Understandable Big Data: A Survey," *Computer Science Review* (17), pp. 70-81.

Emery, F. E., and Trist, E. L. 1965. "The Causal Texture of Organizational Environments," *Human Relations* (18:1), pp. 21-32.

Fox, W. M. 1995. "Sociotechnical System Principles and Guidelines: Past and Present," *The Journal of Applied Behavioral Science* (31:1), pp. 91-105.

Girard, M. 2019. *Big Data Analytics Need Standards to Thrive: What Standards Are and Why They Matter*. Canada: Center for International Governance Innovation.

Groves, P., Kayyali, B., Knott, D., and Van Kuiken, S. 2013. "The 'Big Data' Revolution in Healthcare: Accelerating Value and Innovation," *McKinsey Quarterly*).

Halamka, J. D. 2014. "Early Experiences with Big Data at an Academic Medical Center," *Health Affairs* (33:7), pp. 1132-1138.

Halevi, G., and Moed, H. 2012. "The Evolution of Big Data as a Research and Scientific Topic," in: *Research Trends*. Elsevier, pp. 1-34.

Herland, M., Khoshgoftaar, T. M., and Wald, R. 2014. "A Review of Data Mining Using Big Data in Health Informatics," *Journal of Big Data* (1:1), pp. 1-35.

Khalifa, M. 2018. "Health Analytics Types, Functions and Levels: A Review of Literature," *Studies in health technology and informatics* (251), pp. 137-140.

Kshetri, N. 2014. "Big Data׳S Impact on Privacy, Security and Consumer Welfare," *Telecommunications Policy* (38), pp. 1134-1145.

Liamputtong, P. 2009. *Qualitative Research Methods*, (3rd ed.). Australia and New Zealand: Oxford University Press.

Lohr, S. 2019. "Calls Mount to Ease Big Tech's Grip on Your Data," in: *The New York Times*.

Loshin, D. 2013. *Big Data Analytics : From Strategic Planning to Enterprise Integration with Tools, Techniques, Nosql, and Graph*. Amsterdam: Morgan Kaufmann.

McAfee, A., and Brynjolfsson, E. 2012. "Big Data: The Management Revolution. (Cover Story)," *Harvard Business Review* (90:10), pp. 60-68.

Menon, N. M., Yaylacicegi, U., and Cezar, A. 2009. "Differential Effects of the Two Types of Information Systems: A Hospital-Based Study," *Journal of Management Information Systems* (26:1), pp. 297-316.

Merriam, S. B. 2009. *Qualitative Research: A Guide to Design and Implementation*. San Francisco: Jossey-Bass.

Miles, M. B., Huberman, A. M., and Saldana, J. 2014. *Qualitative Data Analysis: A Methods Sourcebook*, (Third ed.). Thousand Oaks, Califorinia: SAGE Publications.

Nash, D. B. 2014. "Harnessing the Power of Big Data in Healthcare," *American Health & Drug Benefits* (7:2), pp. 69-70.

Orion Health. 2016. "How Precision Medicine Is Radically Improving Healthcare ". Orion Health Newsroom.

Paré, G., Sicotte, C., Jaana, M., and Girouard, D. 2008. "Prioritizing Clinical Information System Project Risk Factors: A Delphi Study," in: *41st Hawaii International Conference on System Sciences*. p. 242.

Patton, M. Q. 2015. *Qualitative Research & Evaluation Methods : Integrating Theory and Practice*, (4 ed.). Los Angeles: SAGE Publications.

Pauleen, D. J., and Wang, W. Y. 2017. "Does Big Data Mean Big Knowledge? Km Perspectives on Big Data and Analytics," *Journal of Knowledge Management* (21:1), pp. 1-6.

Pentland, A. S., and Berinato, S. 2014. "With Big Data Comes Big Responsibility," *Harvard Business Review* (92:11), pp. 100-104.

Protti, D., and Bowden, T. 2010. "Electronic Medical Record Adoption in New Zealand Primary Care Physician Offices," *Commonwealth Fund: Issues in International Health Policy* (96).

Roski, J., Bo-Linn, G. W., and Andrews, T. A. 2014. "Creating Value in Health Care through Big Data: Opportunities and Policy Implications," *Health Affairs* (33:7), pp. 1115-1122.

Russom, P. 2011. "Big Data Analytics," *TDWI Best Practices Report, Fourth Quarter*).

Saporito, P. 2013. "The 5 V's of Big Data: Value and Veracity Join Three More Crucial Attributes That Carriers Should Consider When Developing a Big Data Vision," in: *Best's Review*. A.M. Best Company, Inc., p. 38.

Sathi, A. 2012. *Big Data Analytics: Disruptive Technologies for Changing the Game*. Boise: Mc Press.

Shin, D.-H. 2015. "Demystifying Big Data: Anatomy of Big Data Developmental Process," *Telecommunications Policy* (40:9), pp. 837-854.

Tormay, P. 2015. "Big Data in Pharmaceutical R&D: Creating a Sustainable R&D Engine," *Pharmaceutical Medicine - New Zealand* (29:2), pp. 87-92.

Wang, X., and Huang, J. Z. 2015. "Editorial: Uncertainty in Learning from Big Data," *Fuzzy Sets and Systems* (258:1), pp. 1-4.

Ward, M. J., Marsolo, K. A., and Froehle, C. M. 2014. "Applications of Business Analytics in Healthcare," *Business Horizons* (57:5), pp. 571-582.

Watson, H. J. 2014. "Tutorial: Big Data Analytics: Concepts, Technologies, and Applications," *Communications of the Association for Information Systems* (34:1), pp. 1247-1268.

Weerasinghe, K., Pauleen, D., Scahill, S., and Taskin, N. 2018a. "Development of a Theoretical Framework to Investigate Alignment of Big Data in Healthcare through a Social Representation Lens," *Australasian Journal of Information Systems* (22).

Weerasinghe, K., Scahill, S. L., Taskin, N., and Pauleen, D. J. 2018b. "Development of a Taxonomy to Be Used by Business-It Alignment Researchers," in: *22nd Pacific Asia Conference on Information Systems*. Yokohama, Japan: AIS Electronic Library.

Weerasinghe, K., Taskin, N., Pauleen, D. J., and Scahill, S. L. 2019. "Big Data in Health: Perceptions of Professionals across the Healthcare Sector," in: *2019 International Conference on Digital Health and Medical Analytics*. Zhengzhou, China.

Winter, S., Berente, N., Howison, J., and Butler, B. 2014. "Beyond the Organizational 'Container': Conceptualizing 21st Century Sociotechnical Work," *Information and Organization* (24:4), pp. 250-269.

Wyber, R., Vaillancourt, S., Perry, W., Mannava, P., Folaranmi, T., and Celi, L. A. 2015. "Big Data in Global Health: Improving Health in Low- and Middle-Income Countries," *Bulletin of the World Health Organization* (93:3), pp. 203-208.

Yaqoob, I., Salah, K., Imran, M., Jayaraman, P. P., and Perera, C. 2019. "The Role of Big Data Analytics in Industrial Internet of Things," *Future Generation and Computer Systems*).

Zhang, D. 2018. "Big Data Security and Privacy Protection," *8th International Conference on Management and Computer Science (ICMCS 2018)*: Atlantis Press.

Acknowledgements

This paper was developed as a part of a PhD study and the author would like to acknowledge her supervisors, Prof David J Pauleen, Associate Prof Shane L Scahill and Dr Nazim Taskin, for their comments on this paper and their guidance on completion of the research.