Alignment of Big Data Perceptions in New Zealand Healthcare

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Abstract

The growing use of information systems (IS) in the healthcare sector, on top of increasing patient populations, diseases and complicated medication regimens, is generating enormous amounts of unstructured and complex data that have the characteristics of 'big data'. Until recent times data driven approaches in healthcare to make use of large volumes of complex healthcare data were considered difficult, if not impossible, because available technology was not mature enough to handle such data. However, recent technological developments around big data have opened promising avenues for healthcare to make use of its big-healthcare-data for more effective healthcare delivery, in areas such as measuring outcomes, population health analysis, precision medicine, clinical care and research and development.

Being a recent IT phenomenon, big data research has leaned towards technical dynamics such as analytics, data security and infrastructure. However, to date, the social dynamics of big data (such as peoples' understanding and their perceptions of its value, application, challenges and the like) have not been adequately researched. This thesis addresses the research gap through exploring the social dynamics around the concept of big data at the level of policy-makers (identified as the macro level), funders and planners (identified as the meso level), and clinicians (identified as the micro level) in the New Zealand (NZ) healthcare sector. Investigating and comparing social dynamics of big data across these levels is important, as big data research has highlighted the importance of business-IT alignment to the successful implementation of big data technologies.

Business-IT alignment is important and can be investigated through many different dimensions. This thesis adopts a social dimension lens to alignment, which promotes investigating alignment through people's understanding of big data and its role in their work. Taking a social dimension lens to alignment fits well with the aim of this thesis, which is to understand perceptions around the notion of big data technologies that could influence the alignment of big data in healthcare policy and practice. With this understanding, the research question addressed is: *how do perceptions of big data* *influence alignment across macro, meso, and micro levels in the NZ healthcare sector*? This thesis is by publication with four research articles that answer these questions as a body of knowledge.

A qualitative exploratory approach was taken to conduct an empirical study. Thirty-two in-depth interviews with policy makers, senior managers and physicians were conducted across the NZ healthcare sector. Purposive and snowball sampling techniques were used. The interviews were transcribed verbatim and analysed using general inductive thematic analysis. Data were first analysed within each group (macro, meso, and micro) to understand perceptions of big data, then across groups to understand alignment. In order to investigate perceptions, Social Representations Theory (SRT), a theory from social psychology, was used as the basis for data collection. However, data analysis led to the decision to integrate SRT with Sociotechnical Systems Theory (SST), a well-known IS theory. This integration of SRT with SST developed the Theory of Sociotechnical Representations (TSR), which is a key theoretical contribution of this research. The thesis presents the concept and application of TSR, by using it to frame the study's findings around perceptions of big data across macro, meso and micro levels of the NZ healthcare sector.

The practical contribution of this thesis is the demonstration of areas of alignment and misalignment of big data perceptions across the healthcare sector. Across the three levels, alignment was found in the shared understanding of the importance of data quality, the increasing challenges of privacy and security, and the importance of new types of data in measuring health outcomes. Aspects of misalignment included the differing definitions of big data, as well as perceptions around data ownership, data sharing, use of patient-generated data and interoperability. While participants identified measuring outcomes, clinical decision making, population health, and precision medicine as potential areas of application for big data technologies, the three groups expressed varying levels of interest, which could cause misalignment issues with implications for policy and practice.

This thesis is dedicated to the memory of my beloved parents, Suminda and Veronica Weerasinghe, for being my inspiration to come this far. Thank you for bringing me up to be strong and capable, even in your absence.

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Publications

[1] Weerasinghe, K., Taskin, N., & Scahill, S., "A Conceptual Framework to Explore the Influence of Big Data on Business-IT Alignment in Healthcare", Presented at the 14th Annual Health Informatics New Zealand (HiNZ) Conference, 19-22 October 2015, Christchurch, New Zealand.

[2] Weerasinghe, K., Pauleen, D., Scahill, S., & Taskin, N. (2018). Development of a Theoretical Framework to Investigate Alignment of Big Data in Healthcare through a Social Representation Lens. Australasian Journal of Information Systems, 22. doi:http://dx.doi.org/10.3127/ajis.v22i0.1617

[3] Weerasinghe, K., Scahill, S. L., Taskin, N., & Pauleen, D. J. (2018) Development of a Taxonomy to be used by Business-IT Alignment Researchers, in proceedings of the Twenty Second Pacific Asia Conference on Information Systems, 26th to 30th June 2018, Yokohama, Japan.

[4] Weerasinghe, K., Taskin, N., Pauleen, D. J., & Scahill, S. L. (2019) Big data in Health: Perceptions of Professionals across the Healthcare Sector, in proceedings of the 2019 International Conference on Digital Health and Medical Analytics, 23-25 August, Zhengzhou, China.

Papers under review

[1] Weerasinghe, K. "Transformation through Big Data Analytics: a Qualitative Enquiry in Health" at the Australasian Conference on Information Systems, Perth, Australia.

Papers Awaiting Submission

[1] Weerasinghe, K., Pauleen, D., Scahill, S., & Taskin, N., Theory of Sociotechnical Representations: Concept and Application.

[2] Weerasinghe, K., Pauleen, D., Taskin, N., & Scahill, S., Alignment of Big Data Perceptions in New Zealand Healthcare.

Glossary

Business-IT alignment	Refers to the fit between business (strategy or approach) and information technology. In this context it is defined as the fit between perceptions of big data and healthcare sector needs.
Macro	Government bodies involved in making policies that may affect the implementation and use of big data technologies
Meso	The planning and funding organisations that follow the guidelines of the macro bodies and plan to initiate (or have initiated) big data projects.
Methodological Lens	Use of theory to provide methodological guidance in a study
Micro	Individuals in the frontline care delivery, who will be generating big data and may at some point use big data tools (e.g., general practitioners)
Social dimension of alignment	Mutual understanding about the role of technology by different players
Social Representations Theory	A theory from social psychology looking into how people perceive a phenomenon
Sociotechnical Systems Theory	Well known Information Systems theory that explains the dependencies between people and technology
Subsector levels	Macro, meso and micro levels
Theoretical Framework	A framework developed based on literature and guided theory
Theory of Sociotechnical Representations (TSR)	A new theory developed as an output of this thesis, by merging Sociotechnical Systems Theory and Social Representations Theory

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Chapter 1: Introduction

The purpose of this chapter is to outline work carried out for this thesis by explaining the rationale behind this research, presenting the research question, and highlighting the significance of this thesis. Set out as a Thesis by Publication[1], the thesis consists of three journal papers and one conference paper - two published, two under review. The thesis comprises ten chapters: this chapter provides an overview of each of these chapters, also highlighting links to the research papers presented.

1.1. Rationale

In the recent past, with the advent of ever more sophisticated information technologies, healthcare sectors around the world have undergone major changes targeting improved patient care (Paré, Sicotte, Jaana, & Girouard, 2008; Sicotte, Paré, Moreault, & Paccioni, 2006). A wide range of clinical and operational information systems, which mainly transform manual tasks to software solutions, have been introduced and effectively used in developed countries such as the USA, New Zealand, and Canada. This growing use of information systems in the healthcare sector, on top of the increasing patient population, diseases and sophisticated medications, has been reported to generate unstructured and complex data that have the characteristics of 'big data' (Burns, 2014; Ward, Marsolo, & Froehle, 2014; Wyber et al., 2015).

Big data is distinguished from typical or standard data due to its three main characteristics, often referred to as the 3Vs: volume, variety and velocity. These three characteristics represent an enormous amount of data, from various sources, in many different forms and available in near real-time (McAfee & Brynjolfsson, 2012). Further, two additional Vs – veracity and value, meaning accuracy of the data and potential value to the business – are also commonly found in discussions of big data characteristics (Emani, Cullot, & Nicolle, 2015; Saporito, 2013). While traditional health data created

[1] Massey University guidelines for the thesis by publication state that the thesis is presented with research papers (two to six papers) that are published or ready to be submitted.

using modern health information systems show characteristics of big data, new types of data like genomics data and patient-generated data are also gaining momentum in the big data domain.

Until recent times taking data driven approaches in healthcare (for both clinical and administrative purposes) was considered difficult, if not impossible, because the technology available was not sophisticated enough to handle such data (Wyber et al., 2015). However, recent developments of technology around big data have opened promising avenues for healthcare to make use of big-healthcare-data for improved healthcare management and service delivery (Herland, Khoshgoftaar, & Wald, 2014; Mace, 2014; Nash, 2014; Tormay, 2015; Wyber et al., 2015). Some applications of big data technologies in healthcare include personalised medicine, detecting gaps in care delivery, identifying patterns related to medication side effects and hospital readmissions, fraud detection, and facilitating clinical decisions (Roski, Bo-Linn, & Andrews, 2014).

As there is no universally agreed definition for big data, the term big data is perceived in various ways. The perceptions around big data such as understanding, commitment, value and perceived challenges are identified as the social dynamics of big data (Shin & Choi, 2015). These social dynamics are often given less attention in big data research because big data itself is a technical phenomenon. Big data is typically researched for its technical dynamics such as analytic capabilities, security measures, infrastructure requirements and so on (e.g., Chen, Mao, & Liu, 2014; Davenport, 2013; Dhawan, Singh, & Tuteja, 2014; Jagadish et al., 2014). However, because social dynamics concern the subjective understanding of the technological phenomenon it often reflects and affects the use of technology (Dulipovici & Robey, 2013). Therefore, the social dynamics around big data are crucial for the success of big data implementations. As there is minimal literature examining the social dynamics of big data (e.g., Eynon, 2013; Shin & Choi, 2015), more research is called for (Shin, 2015).

Political, organisational and managerial decisions around the implementation of big data technologies are greatly influenced by the social dynamics around big data (Shin, 2015). The implementation of big data technologies spans across the healthcare sector and requires the support of multiple stakeholders (e.g., policy makers, implementer, funders, and users) (Weerasinghe, Pauleen, Scahill, & Taskin, 2018). It is important to note that perceptions about big data by stakeholders at different levels may, however, be different due to the diverse roles they play, their experience and many other factors (Moscovici, 1984b). Such differences in perceptions may create business-IT alignment issues across the sector (Dulipovici & Robey, 2013).

Business-IT alignment is generally defined as the fit between business and technology and is often investigated through understandings around strategy and structure of either business or technology (Henderson & Venkatraman, 1993). However, as highlighted in Chapter 2 (section 2.3) and Chapter 3, this research applies a social dimension lens to alignment which investigates people's understanding about technology and how it affects their current or future work (Chan & Reich, 2007). Business-IT alignment scholars highlight the social dimension lens as the least researched dimension, and more research is, therefore, desirable (Chan & Reich, 2007; Dulipovici & Robey, 2013). The social dimension lens fits well to an investigation of the social dynamics of technology.

A study by NewVantage Partners found that senior managers of Fortune 500 companies and US Federal Agencies see the alignment of business with big data technologies as the key to successful implementation of big data technologies (Bean & Kiron, 2013). Watson (2014) also acknowledged the importance of business-IT alignment when implementing big data analytics and related technologies. Considering such past literature that highlights the importance of aligning big data to business needs, this thesis takes a social dimension lens to alignment, defining alignment as 'the fit between perceptions of big data and healthcare sector needs at each level'. Additionally, there is scarcely any literature in the healthcare context around the notion of business-IT alignment of big data.

Internationally the healthcare sectors have not been early adopters of big data analytics (Groves, Kayyali, Knott, & Van Kuiken, 2013; Ward et al., 2014). However, developed countries like New Zealand have demonstrated a great interest in the potential to improve healthcare planning and service delivery through the use of analytics (Orion Health, 2016). The New Zealand healthcare sector is a complex system, which comprises three subsector levels: macro (policy makers), meso (funders and planners) and micro (frontline clinicians) (Cumming, 2011; Scahill, 2012b). These subsector levels are different groups which have dissimilar tasks and responsibilities within the healthcare sector and accordingly their perceptions around the application of big data technologies may vary (Weerasinghe, Pauleen, et al., 2018).

On this basis, the researcher was motivated to look into perceptions of big data across the NZ healthcare sector to understand how they influence alignment. This motivation was further supported by the scarce literature around social dynamics of big data, big data alignment, and big data in health. Therefore, the thesis set out to explore the influence of the perceptions of big data on business-IT alignment in the New Zealand healthcare sector, to provide an understanding around its implications through improving policy, planning, implementation and use of big data technologies.

1.2. Research Question

With an aim to investigate perceptions of big data across the subsector levels of macro, meso and micro, and to understand the alignment of these perceptions, the research question answered is:

> *How do perceptions of big data influence alignment across macro, meso, and micro levels in the NZ healthcare sector?*

1.3. Research Significance

The significance of this research is threefold. First, this study contributes to the literature in the fields of big data, healthcare and business-IT alignment through an empirical study. Although there is a vast body of literature around these three areas separately, there is scant literature on the integration of these areas, which is addressed by this research. The thesis further contributes to the research gaps identified around social dynamics of big data, and business-IT alignment of big data, while also contributing to the contemporary discussions in academia around the application of big data technologies in healthcare.

Secondly, the research contributes to the academic literature by developing a novel theory called the Theory of Sociotechnical Representations (TSR) that can be used to investigate social dynamics around any technological phenomenon. TSR is developed through the merging of two well-known theories: Sociotechnical Systems Theory (SST) and Social Representation Theory (SRT). The research demonstrates that TSR is appropriate for explaining how perceptions of technology can play a critical role in the way technologies are understood and used. TSR is a new theory that focuses on the perceptions of technology by the people who not only use and are affected by it, but also those who make decisions about choosing and implementing it. By examining social representations of technology, TSR can give greater insights into the sociotechnical systems around people and technology; therefore TSR represents a significant contribution to information systems research delivered through this thesis.

Thirdly, the research has significant practical implications for policy and practice. In order to answer the research question, analysing data across the three subsector levels indicated areas of alignment and misalignment of big data in the NZ healthcare sector. Across the three levels, alignment was found in the shared understanding of the importance of data quality, the increasing challenges of privacy and security, and the importance of new types of data in measuring health outcomes. Aspects of misalignment included the differing definitions of big data, as well as perceptions around data ownership, data sharing, use of patient-generated data and interoperability. While participants identified measuring outcomes, clinical decision making, population health, and precision medicine as potential areas of application for big data technologies, the three groups expressed varying levels of interest, which could cause misalignment issues with implications for policy and practice. This understanding around alignment and misalignment provides enhanced knowledge about the current perceptions of big data across the sector, allowing policy makers and practitioners (business, technical and clinical) to identify areas that should be addressed in order to successfully utilise big data technologies in the NZ healthcare sector.

1.4. Research Process

In the literature and in industry the term big data is broadly defined. Some scholars define big data with clear characteristics (Davenport & Dyché, 2013; Emani et al., 2015) while others define big data in broader terms like “enormous amounts of data” or “large and complex data” (Chen et al., 2014; Eynon, 2013). Understanding the concept, therefore, was challenging for the researcher herself at the beginning. Accordingly, this promoted an interest in investigating how people in the industry perceive the term “big data” which in turn led to the selection of the topic. Great interest within healthcare sectors around the potential of big data, as well as a notion that worldwide, healthcare sectors are lagging behind in utilising big data technologies, prompted an interest in investigating the healthcare context. A highly cited article by McKinsey & Company claimed the United States alone would save 300 to 450 billion dollars annually by utilising big data technologies in health (Groves et al., 2013). In addition, some hype was also seen in the NZ healthcare context which further suggested the selection of this research topic (Tormay, 2015). This understanding of the background and the researcher’s personal motivations contributed to the development of the research question which guided the research and the thesis. The research process followed is depicted in Figure 1.1.

The research question guided the review of literature in areas of big data, business-IT alignment, and healthcare with an IS focus. It also allowed for review of the selected context, which is New Zealand healthcare. Due to the research question and its focus on exploring alignment through understanding perceptions, there was a clear need for a sound theoretical basis; therefore Social Representations Theory (SRT) (a theory from social psychology) was used initially. Prior to selecting SRT, Sociotechnical Systems Theory (SST) was looked at. However, SRT was selected as the most appropriate because it brings not only methodological direction but also conceptual richness (Gal & Berente, 2008). With understandings gained from the literature, context, and SRT, the theoretical framework was developed and data was collected.

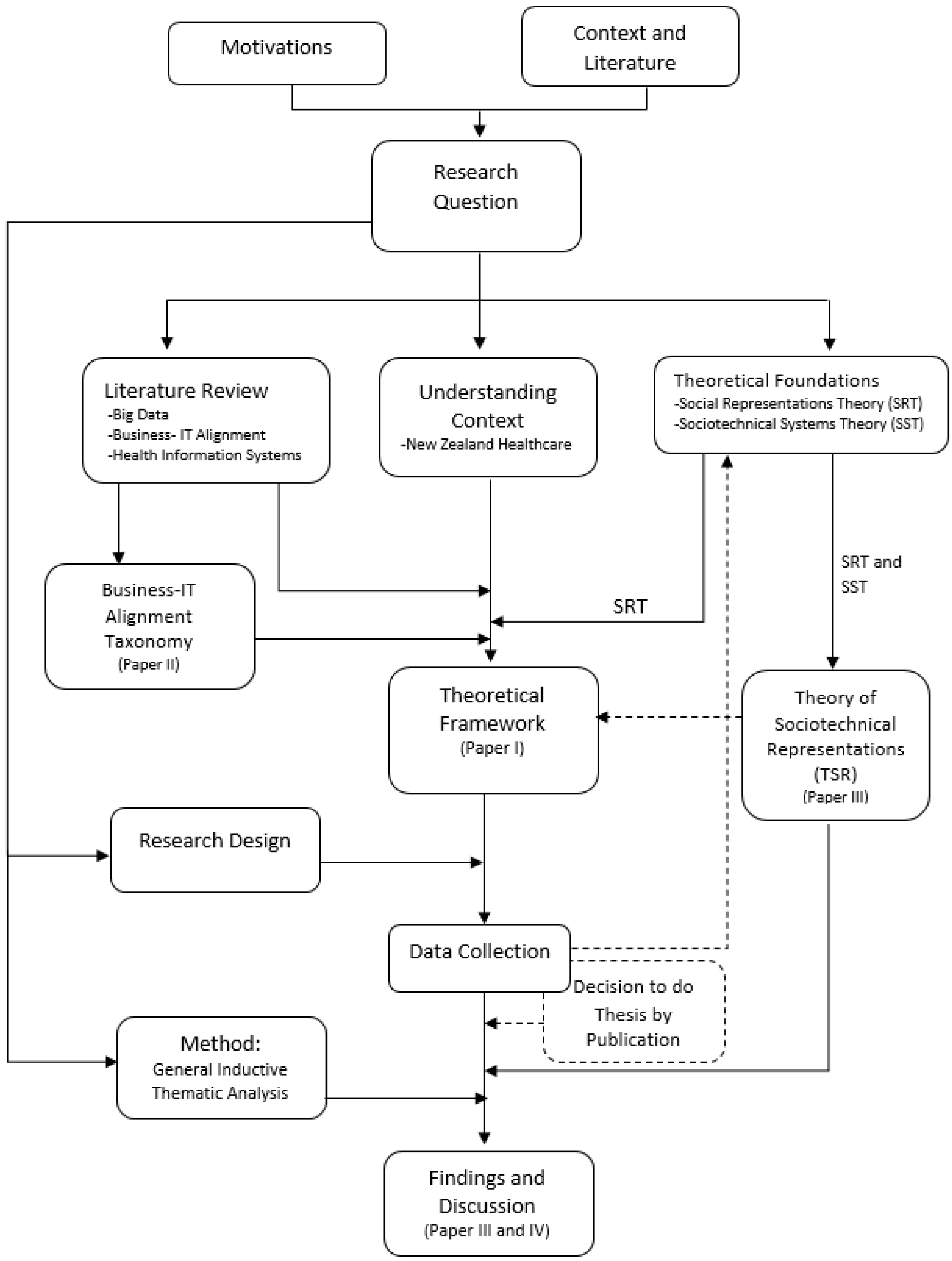

Figure 1.1: The Research Process

Once data had been collected the connections to SST became explicit. With this realisation, theoretical foundations were revisited. Through the understanding of collected data, the researcher identified that SST and SRT could be synthesised, thus the Theory of Sociotechnical Representations was created. The dashed arrow from Data Collection to Theoretical Foundations in Figure 1.1 shows this amendment conceptually. The applicability of TSR in developing the theoretical framework is acknowledged by the dashed arrow from TSR to Theoretical Framework. The research design and the selected method for data analysis were also guided by the research question. The theoretical framework and the selected research design influenced how data were collected. The method of analysis and the theoretical foundation influenced how data were analysed to explain the findings of this research.

1.5. Papers Presented

This work is set out as a thesis by publication in accordance with Massey University guidelines. Four research papers (three journal papers and one conference paper) were written and collectively they form the constituent parts of the whole thesis. Table 1.1 highlights the publications and information about them. The papers are numbered based on the order they are presented in the thesis. Papers I and II were written in the initial stage of data collection with some preliminary findings influenced by conceptualisations presented in these papers.

Table 1.1: Research Papers Included in the Thesis

Paper Number	**Title of the paper**	**Status**	**Journal/Conference**
Paper I	Development of a Taxonomy to be used by Business-IT Alignment Researchers	Published	22nd Pacific Asia Conference on Information Systems, 2018
Paper II	Development of a Theoretical Framework to Investigate Alignment of Big Data in Healthcare through a Social Representation Lens	Published	Australasian Journal of Information Systems (2018) Volume: 22
Paper III	Introducing a Theory of Sociotechnical Representations: Concept and Application	Awaiting Submission	
Paper IV	Alignment of Big Data in Healthcare: the case of New Zealand	Awaiting Submission	

1.6. Thesis Outline

This thesis is structured into ten chapters. Chapter 1 is the introduction to the thesis. It discusses the rationale of the thesis, identifies the research question and then explains the significance of the research, while also providing an outline of the thesis identifying the contributions of each chapter presented.

Chapter 2 is the background and literature chapter. It first highlights the New Zealand healthcare sector, describing its structure and key organisations. Secondly, it provides a review of literature under the topics of big data, healthcare and business-IT alignment. As a thesis by publication, some of the literature is presented in the papers written, and where this occurs it is highlighted in the respective sections.

Chapter 3 presents a Taxonomy of business-IT alignment conceptualisations presented through Paper I. Paper I examines different conceptualisations of business-IT alignment research that are found in the literature and develops a taxonomy that can be used for alignment studies when identifying their focus. It also highlights the areas of alignment for this research.

Chapter 4 is the theoretical foundation of this thesis. This chapter discusses both Social Representations Theory and Sociotechnical Systems Theory as the theoretical foundations. It also explains the basis of the Theory of Sociotechnical Representations (as explained in Section 1.4). Literature related to theoretical foundations in the papers is highlighted.

Chapter 5 highlights the theoretical framework, which is presented through Paper II. It shows how SRT is used to frame the research and develops a framework based on understanding the research question to explore big data in the NZ context. The developed theoretical framework facilitates understanding what, where and how to study perceptions around big data.

Chapter 6 is the Methodology chapter. This chapter explains the researcher's stance, the research design and the method used to conduct the research. This chapter highlights the work carried out for this research and the techniques used. While some of this information appears in Paper III and Paper IV, the methodology chapter is written as a complete chapter on its own.

Chapter 7 is the first part of the findings and discussion of this thesis. It is presented through Paper III discussing the development of the novel theory, TSR, and also its application in the NZ healthcare context. Due to the scope limitations of a journal paper and the vast amount of discussion needed when developing theory, the empirical data included in the paper are only around big data for clinical decision making, and not on the overall application of big data in health, which is presented in Chapter 8 and Paper IV.

Chapter 8 is the second part of the findings and discussion in this thesis. This chapter is presented through Paper IV. Presented as an alignment study, this paper identifies areas of alignment and misalignment in the concept of big data in the NZ healthcare sector. Some discussion around TSR is also present in this paper; however, it is not as in-depth as in Paper III.

Chapter 9 is the conclusion. This chapter highlights the contributions, implications and the limitations of this research. It draws on all four papers and their contributions to explain the thesis's contributions as a whole. This chapter also highlights future areas of research.

Chapter 10 is a postscript explaining the researcher's journey and reflections through the past four years of this study. It attempts to highlight challenges faced and changes made to the research along the way.

Table 1.2 outlines what has been done in this research and where that work appears in the Thesis. It also indicates the links to papers from Table 1.1.

Table 1.2: Mapping of Research Articles to Chapters

Topic	Focus	Presence in the Thesis
Introduction	Provides an overview of the thesis, highlighting the research question and the thesis structure	Chapter 1
Background: New Zealand Healthcare	Detailed discussion about the New Zealand Healthcare sector highlighting the structure, health strategy, and existing work around big data	Chapter 2*
Literature Review	Literature on big data, business-IT alignment and healthcare	Chapter 2*
Business-IT Alignment Taxonomy	Review of literature on business-IT conceptualisations to develop the business-IT alignment taxonomy; It identifies different conceptualisations of alignment and how to outline the focus for an alignment study.	Chapter 3 – Paper I
Theoretical Foundations	Sociotechnical Systems theory, a foundational IS theory, and Social representations theory, a theory from social psychology, are the theoretical foundations of this research.	Chapter 4* Chapter 4 provides literature about these theories. Paper III presented in Chapter 7 discusses development of a novel theory through merging SRT and SST.
Theoretical Framework	Development of the theoretical framework to conduct the empirical study	Chapter 5 – Paper II
Methodology	The adopted methodology, the research design, methods of data collection and analysis are discussed.	Chapter 6*
Theory of Sociotechnical Representations	Development of the theory by merging SRT and SST and explanation of findings through TSR are discussed.	Chapter 7 – Paper III
Influence of big data on business-IT alignment	Discussion of findings and key implications of the research with a focus on business-IT alignment	Chapter 8 – Paper IV
Conclusion	Conclusions, contributions, limitations and future work	Chapter 9*
Researcher Reflections	Reflects upon the work carried out for the thesis and highlights important changes along the way	Chapter 10

*Some parts of the literature are present in research papers and are highlighted in the chapter text.

1.7. Chapter Summary

This is the introductory chapter of the Thesis. Therefore, this chapter highlighted the background and motivations behind conducting this research, identified the research question and explained the significance of this Thesis. It also outlined the process followed when conducting the research. At the end of the Chapter, the papers presented were highlighted and other chapters in the thesis were outlined.

Chapter 2: Background and Literature

This section starts with the background of this research: the New Zealand (NZ) Healthcare sector, identifying the structure and the key organisations. It also highlights the use of technology in the NZ healthcare context. Next the chapter provides a review of literature on three distinct areas – big data, healthcare, and business-IT alignment – and also highlights the links and relationships identified among these three fields to build a foundation for the research. Some parts of the literature are found in papers generated as parts of this thesis and their respective sections highlight these parts of the literature.

2.1. The New Zealand Healthcare Sector

It is estimated that NZ spends about 10.3% of its GDP on healthcare, with 31% spent on in-patient care, 34% on out-patient care, 15% on long term care, 11% on medical goods and 10% on collective services[2] (OECD, 2013). These services are provided to New Zealanders through a complex, multifaceted system governed by the Ministry of Health (MoH). The health and disability system of NZ is funded nationally, planned regionally and delivered locally (Pollock, 2012). The MoH "provides whole-of-sector leadership" to the NZ healthcare system (Ministry of Health, 2014a, p. 1). Health policy development is undertaken by the Minister of Health with input from the Cabinet and the government, to set strategic direction for the healthcare sector. Although the MoH has a greater influence in healthcare policy development, the Health Workforce New Zealand, the Strategic Prioritisation Function, and other ministerial advisory committees also support and advise the Minister (Ministry of Health, 2017). The structure of the NZ healthcare system is depicted in Figure 2.1. This illustrates the complexity of the multi-layered health system of NZ highlighting the many relationships that influence interactions between the MoH and other healthcare units.

[2] Collective services include health education, training of health professionals, administration services and food, hygiene and water control.

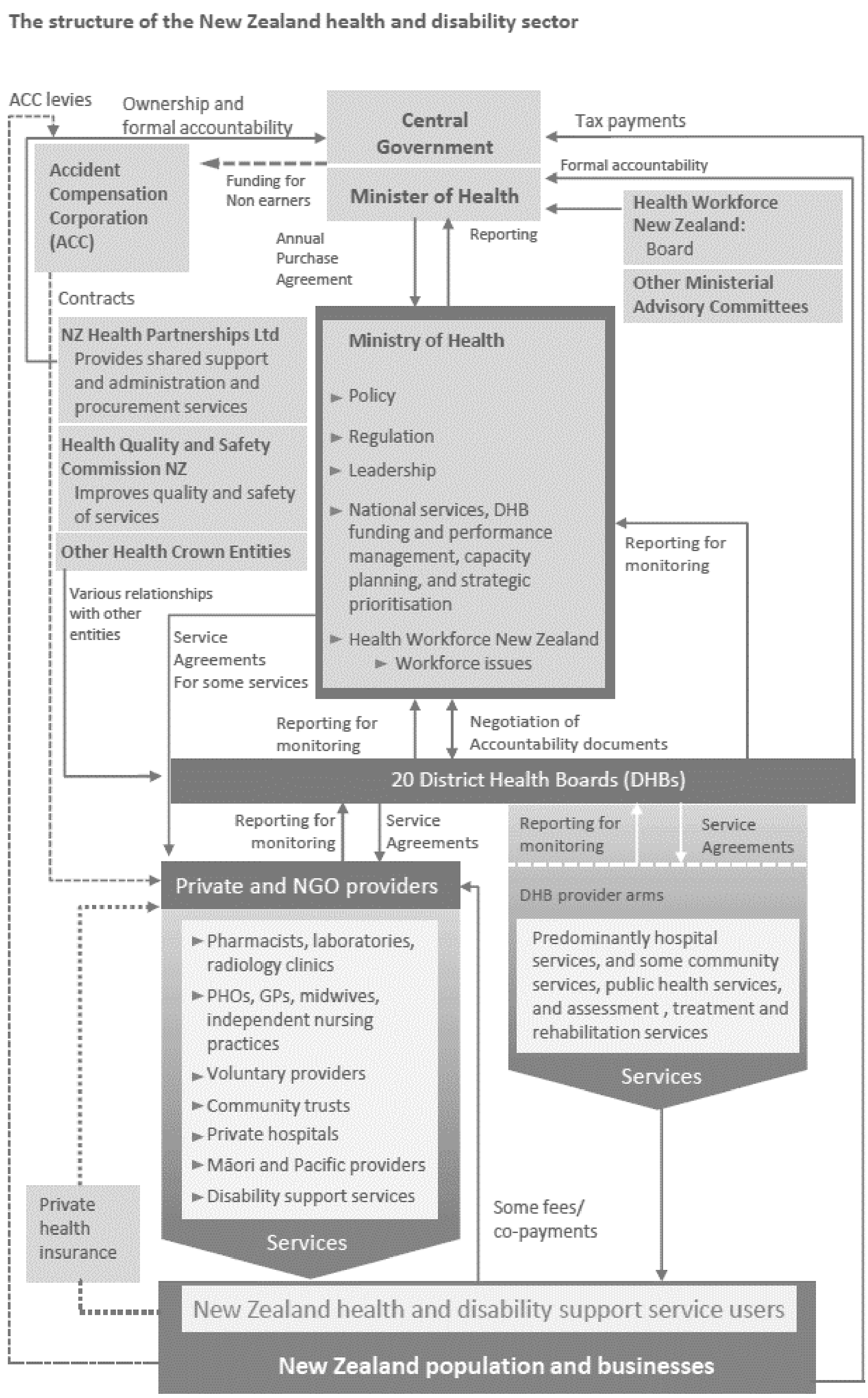

Figure 2.1: Structure of the NZ Healthcare System

(Ministry of Health, 2017)

2.1.1. Ministry directorates and Business units

The MoH is made up of directorates, which have their own areas of responsibilities. Table 2.1 provides information on these directorates and business units based on information from the website of the Ministry of Health (2019).

Table 2.1: Directorates and Business Units of the Ministry of Health
(based on Ministry of Health, 2019)

Directorate Name	**Description**
System Strategy and Policy	The responsibility of the System Strategy and Policy directorate is the Ministry's core policy function. This includes leadership and guidance on policy development as well as providing advice across the organisation.
Corporate Services	The Corporate Services directorate supervises the corporate functions of the Ministry.
Mental Health and Addiction	Supervision of activities and functions around mental health and addictions is the responsibility of the Mental Health and Addiction directorate.
Data and Digital	The Data and Digital directorate is responsible for making sure that the data collections of MoH and digital technology support the health system to deliver better services and health outcomes. Current data and digital functions and the national collections are also a responsibility of this directorate.
DHB Performance, Support and Infrastructure	Ensuring a strong working relationship with DHBs is the responsibility of the DHB Performance Support and Infrastructure Directorate. The directorate also has the responsibility for ensuring: (i) strategic leadership and support for DHB planning and funding, (ii) accountability for DHB operational performance, and (iii) oversight of DHB infrastructure and capital projects.
Population Health and Prevention	The Population Health and Prevention directorate leads the Ministry’s population health programmes (e.g. the National Screening Unit), leads services and programmes for specific population groups, non-communicable disease prevention and control, emergency management and key public health functions.
Office of the Director General	Government and Ministerial services, internal and external communications, global health and supporting the Director-General of

	Health, Ministers and the Executive Leadership Team are the key responsibilities of the Office of the Director-General of Health.
Māori Health	The Māori Health directorate has a focus on protecting and improving Māori health outcomes, by providing strategic advice and guidance on Māori health improvement across the Ministry and the sector.
Clinical Cluster	The Chief Medical Officer, Chief Nursing Officer and Chief Allied Health Professions Officer lead the Clinical Cluster, which is responsible for understanding how services can be better planned and delivered. Their responsibilities include: promoting innovations at a national level, providing oversight and direction on clinical and professional issues across the sector, and supporting the response to current and future workforce demand.
Health System Improvement and Innovation	The Health System Improvement and Innovation directorate is responsible for ensuring strategic leadership and support for the Ministry and wider health sector to continuously improve service quality and outcomes.
Disability	The Disability directorate is responsible for providing the oversight of 'end-to-end' activities and functions for the disability community.
Health Workforce	This directorate is responsible for developing and enabling a clear strategy and future pathway for the health workforce including: policy, planning, training, and developing and implementing innovative workforce initiatives across the sector.

It is important to note that these directorates were introduced recently and by the time of data collection[3], the structure was slightly different. As highlighted in Paper II, during the early stages of conducting the research there were business units which had similar responsibilities around healthcare management. The National Health Board was one such unit that was under the MoH, but was disbanded following the Health Strategy revamp in late 2016.

2.1.2. Key organisations that support healthcare delivery

The key organisations for healthcare delivery include the District Health Boards (DHBs), Primary Health Organisations (PHOs), Crown Entities and Agencies, National Ambulance Sector Office, Non-governmental Organisations, Public Health Units, and Professional and regulatory bodies (see Table

[3] Macro level interviews were conducted in 2016.

2.2). Healthcare services are provided by these organisations to the NZ population and are directed by the MoH (as shown in Figure 2.1).

Table 2.2: Organisations of Healthcare Delivery

District Health Boards (DHBs)	The daily healthcare services and majority of funding are governed by the District Health Boards (DHBs). A DHB is responsible for ensuring efficient and effective healthcare services to the population of their district by planning, managing, providing and purchasing suitable healthcare services (Ministry of Health, 2011b). NZ has 20 DHBs; boards of 11 members administer each of these 20 DHBs (Ministry of Health, 2014c).
Primary Health Organisations (PHOs)	PHOs are funded by the DHBs. These are established to provide essential health services to local communities through general practices (GP). Services provided by PHOs are either directly provided or through provider members. Improving and maintaining the health of the enrolled community by ensuring that GP services are properly linked with the other services is the main objective of a PHO (Ministry of Health, 2011c).
Crown Entities and Agencies	These are formed as a part of New Zealand's state sector and report to the Minister of Health. Examples of Crown entities and agencies include the Health Quality and Safety Commission (HQSC), Health Benefits Limited (HBL), Health and Disability Commissioner (HDC), Health Promotion Agency (HPA), Health Research Council of NZ (HRC), NZ Blood Service (NZBS), and PHARMAC (the government agency that decides which medicines and related products are publicly funded in New Zealand and to what level) (Ministry of Health, 2014b).
Capital Investment Committee	The Capital Investments Committee advises Ministers of Health and Finance about the prioritisation and allocation of funding for capital investment and health infrastructure in New Zealand (Ministry of Health, 2016a).
Mental Health Tribunal	The Mental Health Review Tribunal is an independent body that looks after mental health matters in New Zealand. Their tasks include: deciding whether patients are fit to be released, making recommendations about patients' status, investigating complaints, and appointing psychiatrists for second opinions on patients (Ministry of Health, 2018a).
National Ambulance Sector Office (NASO)	NASO is jointly funded by the Ministry and the Accident Compensation Corporation (ACC) and reports on strategic and operational matters regarding emergency ambulance services (Ministry of Health, 2015a).
Non-governmental Organisations (NGOs)	The health and disability NGOs provide numerous services in primary care, mental health, personal health and disability support services. NGOs have long been contributing to NZ healthcare service delivery (Ministry of Health, 2014d).
Public Health Units (PHU's)	The main focus of PHUs is on services such as environmental health, communicable disease control, tobacco control and health promotion programmes. PHUs are owned by

	DHBs and there are 12 PHUs providing the above mentioned services (Ministry of Health, 2015b).
Health Alliances	Health alliances are nine networks of primary healthcare providers and district health boards who are working to implement the Ministry's 'Better, Sooner, More Convenient' care initiatives. These initiatives are planned to provide services closer to home, make New Zealanders healthier and reduce pressure on hospitals (Ministry of Health, 2011a).
Professional and regulatory bodies	There are professional and regulatory bodies which are responsible for registration and supervision of healthcare practitioners in specific healthcare professions. These are established under the Health Practitioners Competence Assurance Act 2003. Examples of such bodies include Nursing, Pharmacy and Medical Councils.

Apart from the key organisations that are listed in Table 2.2, there are Ministerial health committees, which provide the Minister of Health with advice while acting as a forum for representatives of the sector to have a role in decision-making. Some examples of these committees are the National Ethics Advisory Committee, Mortality Review committees, and Advisory Committee on Assisted Reproductive Technology (Ministry of Health, 2018b).

2.1.3. Subsector Levels of the NZ Healthcare Sector

Due to the association of many different organisations, actors, and structural divisions of the NZ healthcare system (as shown in Figure 2.1) it can be identified as a complex system. Biological, socio-natural or socio-technical systems with more than three coupled components are likely to demonstrate chaotic behaviour under certain circumstances, and are thus identified as complex systems (Liljenström & Svedin, 2005). When studying such complex systems it is best to take an approach through the macro-meso-micro perspective of the system to obtain a holistic understanding (Dopfer, Foster, & Potts, 2004). Macro-meso-micro (MMM) can be conceptualised in a variety of ways dependent on the purpose of the study.

Within the NZ healthcare sector several authors propose MMM with slightly different but related conceptualisations. Cumming (2011) conceptualises macro as a single organisation, or a body that oversees organisation to organisation collaboration, meso as activities that promote work between organisations (e.g. clinical partnerships (Mays, 2013)), and micro as individual practitioners. Taking a slightly different view, Scahill (2012b) conceptualises policy setting organisations as macro, funders and planners as meso, and service provider organisations and the individuals within them as micro. Based on this understanding, in this study and as highlighted in Paper II, MMM levels are conceptualised in the context of big data in NZ healthcare as follows:

- Macro – Government bodies who set the policies that govern IT implementations, particularly around big data technologies, fall under the macro level. The MoH and its directorates (as well as Business Units that were there before the strategic revamp) can be identified as macro level bodies.
- Meso – Meso level incorporates organisations that follow the guidelines of the macro bodies and plan to initiate (or have initiated) big data analytics. The organisations that support healthcare delivery (as described in Section 2.1.2) can be mapped to the meso level (e.g. DHBs, PHOs, PHUs etc.).
- Micro – Individuals in frontline care delivery, who will be generating big data and may at some point use big data tools, are categorised under the micro level. These could be hospital doctors, general practitioners, nurses, and pharmacists.

Figure 2.2 illustrates the MMM levels in NZ healthcare and how the notion of big data may fit within each level. In the research, these levels were used as levels of analysis to gain a level by level as well as an integrated understanding of big data implementations in the NZ healthcare sector.

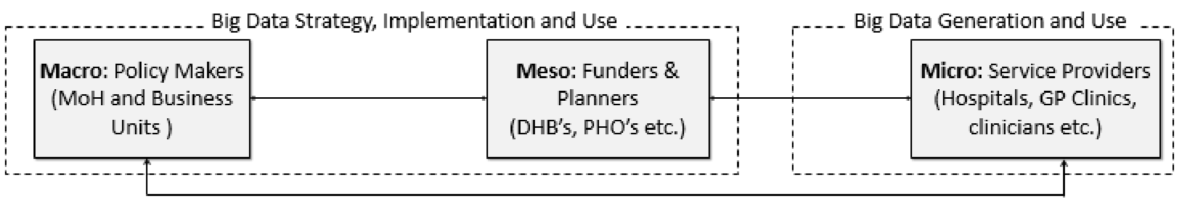

Figure 2.2: Conceptualisation of MMM in NZ Healthcare

(adopted from Weerasinghe, Pauleen, et al., 2018)

2.1.4. New Zealand Health Strategy

The Health Strategy sets the direction of the healthcare system and seeks to improve the health of people and communities. The Health Minister's foreword on Health Strategy states:

> "This strategy is the result of extensive consultation throughout New Zealand. It is designed to address our changing health priorities and fiscal targets. It encourages innovation and creating and using opportunities, including the exciting potential of medical and information and communications technologies" (Minister of Health, 2016, p. ii).

The NZ Health Strategy released in 2016 comprises two detailed documents: (i) the NZ Health Strategy: Future Direction, and (ii) the NZ Health Strategy: Roadmap of actions 2016. NZ Health Strategy: Future Direction identifies high-level direction for the NZ health system from 2016 to 2026. From an information and people's perspective, the strategy acknowledges that "[a]ll New Zealanders live well, stay well, get well, in a system that is people-powered, provides services closer to home, is designed for value and high performance, and works as one team in a smart system" (Minister of Health, 2016, p. 13), identifying five key themes as: (i) people powered, (ii) closer to home, (iii) value and high performance, (iv) one team, and (v) smart system. These themes are identified to provide the needed direction for the desired future. More information about these five areas is given in Table 2.3. The NZ Health Strategy: Roadmap of Actions 2016 on the other hand, documents areas of action for the first five years to achieve the strategy, and is intended to be updated as needed.

Table 2.3: Key areas of focus identified by New Zealand's Health Strategy

(based on Minister of Health, 2016)

Theme	**Description**
People-powered	Enabling patients to be involved and to understand and manage their own care (health literacy), while taking control over choices of care and support. To help make a patient health literate, the service providers need to work together with the patients, supporting and helping them as needed. As a part of being people powered, the strategy states that by 2026, people are likely to be able to "take greater control over their own health by

	making informed choices and accessing relevant information" (Minister of Health, 2016, p. 18).
Closer to home	This theme is about facilitating care closer to where people live. Through strategy, it is planned to provide preventative services that will keep people well, and also facilitate treatment services that can be accessed easily. For example while specialist care is available in hospitals, minor surgery and intravenous antibiotics will be available in the primary care setting, making it more accessible in a timely manner.
Value and high performance	This theme is about gaining better outcomes around patients' care experience, health status and acquiring best value from the used resources. This theme in the strategy identifies the need to measure performance as well as use information in a manner that facilitates decision making to drive better performance.
One Team	This theme is about creating the health system as a truly integrated system, while also starting integrations with other organisations outside of health that will facilitate health and wellbeing of people. This theme will enable flexibility across the health system, and will link healthcare providers to work as one team.
Smart System	This theme identified in the health strategy is about taking advantage of modern and emerging technologies to discover and develop effective innovations across the health system. With the "smart system" theme, the strategy highlights the need for the health system to become a learning system, enabled by data and technology. It acknowledges that "[t]echnology involves more than just digital technologies. Other technologies are revolutionising health systems: robots and other automated systems are carrying out repetitive and predictable processes, advanced analytics are providing new insights into complex health problems, and research breakthroughs in human and life sciences are making 'personalised medicine' a reality for more and more people" (Minister of Health, 2016, p. 34).

While the theme Smart Systems clearly acknowledges the importance of data and modern technology for the betterment and future of NZ health, other themes also implicitly show connections with better use of technology and data (e.g. value and high performance through better data analytics). Technology and information systems use in the NZ healthcare context is discussed in Section 2.4.

2.2. Big Data

'Big data' is a popular topic both in industry (Bennett, 2015; Burton, 2013) and academia (Davenport, 2013; Davenport & Dyché, 2013; McAfee & Brynjolfsson, 2012; Oussous, Benjelloun, Ait Lahcen, & Belfkih, 2018; Pentland & Berinato, 2014). Articles in the popular press like the New York Times (Lohr, 2012, 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). This section reviews the available definitions of big data, identifying its characteristics and how big data technologies bring organisational transformation.

2.2.1. The Rise of Big Data

Halevi and Moed (2012) in a review of 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 & Moed, 2012). However, an explosion of publications on big data was noted from 2008 onwards (Halevi & 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 & 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.

2.2.2. Defining Big Data

In simple terms big data refers to enormous amounts of unstructured and complex data produced by a wide range of computer applications (Blazquez & Domenech, 2018; Emani et al., 2015; Shin, 2015; X. Wang & 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; Eynon, 2013; Shin, 2015; Shin & Choi, 2015). Some examples of big data includes (but not limited to) business/industry operational data, mobile data, social media data, public data, commercial data, streaming data and sensor data (data from Internet of Things) (Mills, 2018).

Three characteristics, known as the 3Vs – volume, variety and velocity – are generally used to define big data and distinguish it from standard data (McAfee & Brynjolfsson, 2012; Oussous et al., 2018; Russom, 2011). According to Gartner big data is “high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation” (Gartner, 2013 para. 1). Oussous et al. (2018), Watson (2014), McAfee and Brynjolfsson (2012), and Russom (2011) also characterise big data using the 3Vs.

Two additional Vs – value and veracity – are also commonly seen extending the characteristics of big data to 5Vs (Baesens, Bapna, Marsden, Vanthienen, & Zhao, 2014; Emani et al., 2015; Saporito, 2013; Sathi, 2012). For detailed explanations of the 5V characteristics see Table 2.4. 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). Even though big data has various different definitions these all seem to share somewhat similar features.

Table 2.4: 5Vs of Big Data

Volume	Volume is the key attribute of big data definition. Volume of data created across the globe is anticipated to reach 40 Zeta bytes by 2020 (Oussous et al., 2018). For many decades the rapid growth of the size of data has been a challenging issue (Jagadish et al., 2014). Although it directly relates to the ‘size of data’ in terabytes or petabytes (Emani et al., 2015; McAfee & Brynjolfsson, 2012; Watson, 2014), organisations are also concerned about accumulating numbers of records and transactions, and expanding tables and files due to difficulties around managing such data (Russom, 2011).
Variety	Variety indicates heterogeneity of data types (Jagadish et al., 2014). It refers to data from different sources resulting in various types of data such as text, images, audio, video and so forth (Chen et al., 2014; McAfee & Brynjolfsson, 2012; Watson, 2014). As a result, this data could be structured, semi structured or unstructured (Emani et al., 2015; Russom, 2011).

	Although volume is the key attribute of defining big data, organisations seem to be more concerned about managing the variety (Bean & Kiron, 2013; Davenport & Dyché, 2013).
Velocity	Velocity denotes the frequency of data creation and delivery, real-time or near real time (Emani et al., 2015; McAfee & Brynjolfsson, 2012; Russom, 2011). It refers to "both the rate at which data arrive and the time frame in which it must be acted upon" (Jagadish et al., 2014, para. 6). Therefore, big data is generated in near-real time and requires techniques to summarise, sort, filter or interpret this data in a timely manner (Jagadish et al., 2014; Oussous et al., 2018).
Veracity	Veracity relates to uncertainty of data that necessitates accuracy measures (IBM, n.d.). According to X. Wang and Huang (2015), "modelling and measure of uncertainty for big data is significantly different from that of small data" (p. 1). This characteristic is therefore concerned with credibility and reliability of data sources (Abbasi, Sarker, & Chiang, 2016; Sathi, 2012). As a result, managing veracity enhances data quality and improves understandability (Saporito, 2013). However, in the big data domain while there are increasing demands for data quality measures, the potential for mishaps is well known (Song, Fisher, Wang, & Cui, 2018).
Value	Emani et al. (2015) identify value as the "purpose of big data technology" (p.3). Technologies that are created to handle big data are "economically designed to extract value" (Gantz & Reinsel, 2011, p. 6), and therefore, can be used to create business value through creation of new business models, products and services (Saporito, 2013) as well as analytical value (Emani et al., 2015). By performing analytics upon big data, such value can be created (Davenport, 2013). However, based on these reasons value can be seen more as a result of using big data than a characteristic of it.

These 5V characteristics show that "big" data means more than just the volume or the quantity of data. Therefore, making use of big data and technologies developed around big data is not just about dealing with large volumes. However, it is unclear whether data needs to have 3Vs or 5Vs to qualify as big data.

2.2.3. Big data and Analytics

Big data is 'data' which has 3V or 5V characteristics. Analytics means using tools to analyse data, not necessarily big data. Rather, analytics is an umbrella term for all data analysis applications (Watson, 2014, p. 1250). Analytics dates back to the early 1950s where businesses realised that machines could process data to help make decisions faster than the unassisted human mind (McAfee & Brynjolfsson, 2012). In the modern context analytics is about "the systematic use of data and analysis to drive decision-making and action" (Pauleen, 2017, p. 8). In the business context, big data and analytics are often discussed together; they are sometimes even confused with each other (McAfee & Brynjolfsson, 2012). Collecting and storing big data alone creates no value, unless analytics are performed to make sense of this data to improve decision making within business (Watson, 2014).

Traditional analytic capabilities are not sufficient to process big data. Much more advanced analytical techniques are needed to glean insight from data that is high in volume, high in variety and high in velocity (Emani et al., 2015). 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 & Wang, 2017). Such knowledge derived from big data analytics has the potential to transform business as business decisions based on 3V-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).

2.2.4. Organisational Transformation with Big Data

Big data "is not a single out-of-the-box product" (Loshin, 2013, p. 21). Making effective use of big data demands a specific combination of tools, techniques, and skills, and impacts organisations and industries to transform as it influences people, processes and technologies in use (Abbasi et al., 2016; Phillips-Wren, Iyer, Kulkarni, & Ariyachandra, 2015). Companies that were born in the internet era, such as Google, Facebook and eBay, were built around big data (Davenport & Dyché, 2013), and thus possess these capabilities. These companies have only had to deal with big data because they have been dealing with data with 3V characteristics from the beginning; big data analytics was already their main form of analytics. With technological advancements and the commercialisation of the internet, data has become a primary business asset for all businesses (Abbasi et al., 2016; Redman, 2008). Therefore, companies that existed before the internet era (traditional businesses) are also looking into opportunities to develop their business by using big data, as big data is known to deliver competitive advantage and increase productivity (Bholat, 2015; Chawla & Davis, 2013; Davenport & Dyché, 2013;

Dhawan et al., 2014; Phillips-Wren et al., 2015). It has been emphasized that “data with traditional roots and big data will equally play a more important role” in improving organisations into the future (Schermann et al., 2014, p. 265). However, for traditional businesses, big data is not the only data they deal with, and big data analytics is not the only form of analytics (Davenport & Dyché, 2013).

To integrate big data, traditional businesses need to consider making changes to their existing IT ecosystem. They will not only be working with big data but also with standard small datasets; they will have Hadoop[4] 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 & Dyché, 2013). Therefore, it is a 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 & Kiron, 2013; Davenport & 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, Coyne, & Walker, 2018). Technology architecture, IT infrastructure, security measures and analytics platforms can be identified as technical aspects affected by big data implementation (Davenport, 2013; Davenport & 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 & Kiron, 2013; Davenport & Dyché, 2013). By considering these forces, Figure 2.3 conceptualises the aspects of change that big data implementation brings to a traditional organisation. These aspects are discussed below.

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

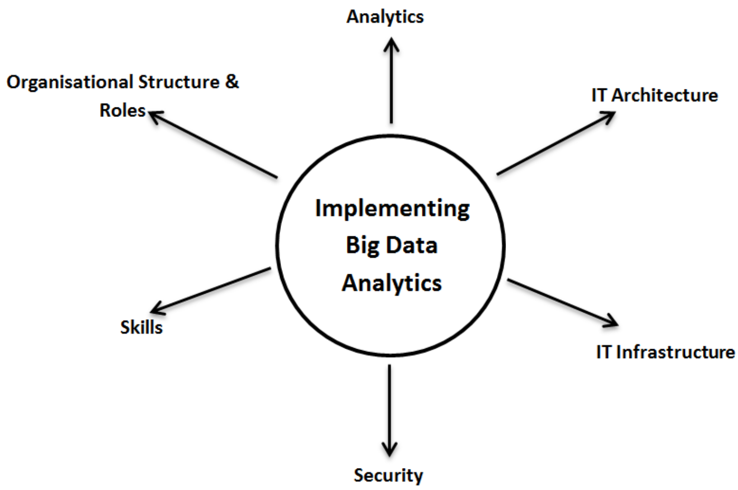

Figure 2.3: Aspects of Change with Big Data Technologies

Analytics is central to implementing big data technologies. It 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, high in variety and high in velocity (Emani et al., 2015; Yaqoob, Salah, Imran, Jayaraman, & Perera, 2019). Only with such advanced analytics techniques will companies be able to create value from big data by managing uncertainty (X. Wang & Huang, 2015). Traditional businesses should implement big data analytics in conjunction with the analytics of standard data (Davenport, 2013; Davenport & Dyché, 2013). There are four main variations of analytics that can be used with big data: (i) descriptive, (ii) diagnostic (ii) predictive, and (iii) 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).

IT architecture in Figure 2.3 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[5], in-memory analytics[6], and in-database processing[7] (Davenport & Dyché, 2013; X. Wang & 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.

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 & Dyché, 2013). Additionally, networking requirements and data warehouse requirements are significantly different for big data compared to traditional data (Demchenko, Zhao, Grosso, Wibisono, & De Laat, 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).

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

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

ensure security of big data is paramount to the success of big data implementations and use (Zhang, 2018).

Skills in Figure 2.3 refer to 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 for text mining, video image analytics, coding in scripting languages and so forth (Davenport & 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).

Organisational Structure and Roles refers to the groups of big data processing and roles of IT decision making 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 data revolution (Davenport & 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 & Kiron, 2013). Other executive roles like Chief Analytics Officer and Chief Science Officer are also emerging roles with big data technologies (Davenport & Dyché, 2013).

The above discussion shows that making use of big data goes beyond analytics or infrastructure when handling sheer 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.

2.2.5. Big Data and Business-IT Alignment

Organisations should not implement big data just to follow a trend, but rather should have clear goals which drive its use (Loshin, 2013). A study undertaken by NewVantage Partners with Fortune 500 companies' and Federal agency leaders identified that business-IT alignment is crucial for the success of big data implementations (NewVantage Partners, 2012). Business-IT alignment is achieved through business and technology (big data analytics) working together in harmony with proper understanding of business objectives and big data analytic capabilities (Bean & Kiron, 2013; Loshin, 2013). However, among the existing literature, although the importance of business-IT alignment has been highlighted, studies investigating the influence of big data on business-IT alignment could not be found (Weerasinghe, Pauleen, et al., 2018).

2.2.6. Big data in Information Systems Research

The phenomenon of big data has captured the interest of both academics and practitioners among many different domains including information systems (Abbasi et al., 2016; Baesens et al., 2014). It is evident that big data is an important field of study evidenced by the increasing discussions in Information Systems (IS) Journals and Conferences. Scholars investigating the phenomenon of big data in the field of IS have taken various approaches.

Abbasi et al. (2016) proposed a research agenda to investigate big data through the information value chain. They highlight the importance of IS researchers assessing economic and humanistic aspects of big data and explained the importance of rethinking behavioural, methodological, and ethical aspects as well as designing research that involves big data. Blazquez and Domenech (2018) elaborated on the socio-economic changes brought to organisations and sectors by implementations of big data technolohies. They proposed a lifecycle model that captures processes around the use of big data, and also proposed a framework to use big data, with an understanding of socio-economic changes. Maass, Parsons, Purao, Storey, and Woo (2018) talked about the importance of theory driven big data research and identified two perspectives for big data research in IS: theory driven research and data driven research. They identified a framework to link theory driven research to big data driven research in the big data era.

While highlighting the opportunities of big data for organisations, such as making faster and better decisions, gaining better knowledge about customers, providing customised and personalised outreach and gaining economic benefit, Phillips-Wren et al. (2015) developed a framework to use big data in the context of business intelligence. Their framework provides a view of the process of using big data from sourcing, preparation, storage, analysis, access, and usage. Schermann et al. (2014) highlighted the importance of: (i) education and training for responsible use of big data, (ii) development of modelling tools for consideration of big data, (iii) development of resilient models for responsible use of big data through research. Baesens et al. (2014) discussed technical and managerial issues in business transformation associated with big data.

Nonetheless, there is a common argument across IS research that more research is desiarable to understand the phenomenon of big data across different disciplines (Maass et al., 2018; Schermann et al., 2014).

2.2.7. Technical vs. Social Dynamics of Big Data

Technical forces (technology requirements of big data, challenges and opportunities around big data analytics, necessary security measures and so forth) towards big data implementations have been extensively researched (e.g., Chen et al., 2014; Davenport, 2013; Dhawan et al., 2014; Jagadish et al., 2014; Phillips-Wren et al., 2015). As a technological revolution itself, it is fair to say that big data research often leans towards technical aspects.

Social dynamics refer to the users' understanding, commitment, and perceived challenges and value of big data in a given context (more details on technical and social dynamics can be found in Paper II/Chapter 5 and Paper IV/Chapter 8). While, little empirical research could be found exploring these humanistic factors in relation to big data analytics implementations (Shin & Choi, 2015), scholars like Shim, French, Guo, and Jablonski (2015) argue the importance of social dynamics, claiming "perception is reality" in the big data era (p. 798). Furthermore, Someh, Davern, Breidbach, and Shanks (2019) highlighted that stakeholder perspectives of big data is important because big data "is a fast-evolving phenomenon shaped by interactions among individuals, organisations, and society" (p. 34).

Examining how big data is presented in popular press articles highlighting how it may influence people's views on big data, Pentzold, Brantner, and Fölsche (2019) reviewed images that representated big data in New York Times and the Washington Post. While this is an interesting approach to understand an aspect of the social dynamics of big data (investigation of how popular press articles impacts perceptions), it is different from investigating people's perceptions of the concept of big data itself.

Recently scholars have shown an interest in investigating perceptions of people around the use and application of big data analytics (e.g. Egan & Haynes, 2019; Fleming, Jakku, Lim-Camacho, Taylor, & Thorburn, 2018; Grishikashvili & Bechter, 2019). Fleming et al. (2018) examined farmers and farming stakeholders in Australia to understand their perceptions of big data using discourse analysis. Their findings showed that within the Australian agriculture industry, trust, equity, distribution of benefits and access were understood to be challenging issues around big data implementations.

Grishikashvili and Bechter (2019) examined perceptions of financial advisors in the United Kingdom to understand perceptions about using big data analytic for decision making. Similarly Egan and Haynes (2019) evaluated managers perceptions about the use of big data analytics for pricing decision making in the hospitality contex. They specifically examined perceptions around value and reliability of big data. These scholars highlight the importance of understanding people's perceptions of big data.

Shin (2015) examined perceptions of big data in private and public sectors as well as policy makers to understand normalization of big data in the Korean society. In his paper Shin (2015) uses Unified Technology Acceptance and Usage of Technology (UTAUT) model to understand user intentions of using technology. By highlighting the importance of understanding social dynamics of big data Someh et al. (2019) investigated stakeholder perceptions around ethics in the context of big data. The claims of scholars like Shin (2015) as well as Someh et al. (2019), on the importance of understanding perceptions across different stakeholders of big data as impacting adoption, has been used as a foundation for this thesis.

2.3. Healthcare

Healthcare management and service delivery have rapidly transformed over the past decades with the advancement of IT. This section will examine this transformation of healthcare and also its use of Information Systems (IS).

2.3.1. Defining Healthcare

According to the World Health Organization (WHO), "Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (WHO, 1946). Good health is desired by each and every person. A healthy population positively contributes towards a country's economy.

The term "healthcare" refers to the diagnosis and treatment of illness or injury in human beings. An effective healthcare system is essential to maintain a healthy population. The Constitution of the World Health Organization declares that governments have a responsibility towards the health of their people and should take adequate measures for healthcare provision (WHO, 1946). Healthcare is generally divided based on point of delivery into (i) primary, (ii) secondary, and (iii) tertiary care (see

Table 2.5) and is delivered by healthcare professionals such as doctors, nurses, dentists, pharmacists, and so forth.

Table 2.5: Points of Healthcare Delivery

(based on Dawson et al., 1920; IOM, 1978; Johns Hopkins Medicine, n.d.; Starfield, Shi, & Macinko, 2005)

Primary Care	**Secondary Care**	**Tertiary Care**
Primary care refers to the first point of consultation given to a patient. Access to primary care varies from appointment based clinics, walk in clinics to emergency units. The consultation is usually provided by a doctor, nurse and/or a pharmacist.	Secondary care refers to medical care or a facility provided to a patient upon referral by a primary care physician. The secondary care services are provided by medical specialists such as cardiologists, dermatologists, etc. The treatments at this point of care are usually provided for a short period of time.	Tertiary care refers to highly specialised medical care for advanced investigation and treatment. This includes in-patient care and referrals from primary and secondary health professionals. The tertiary care treatments typically take place at hospitals and may be of longer duration.

Apart from these, healthcare is also delivered via home care, rehabilitation services, community services, and hospital and community pharmacies in NZ.

Modern-day healthcare is a massive industry spanning various government bodies, public and private organisations and a variety of professions. This has resulted in utilising a substantial portion of a countries' GDP to fund it[8]. The Organisation for Economic Co-operation (OECD) declares that in 2012 overall health spending has averaged 9.3% of GDP across OECD countries (OECD, 2014).

2.3.2. Transformation of Healthcare with Information Technology

With the growth of human population, the complexity of healthcare delivery grows along with thousands of diseases and medications (Wyber et al., 2015). Until recent times healthcare has been dependent on the intelligence of practitioners. It has been successful because "they are bright, hard-

[8] Gross Domestic Product (GDP) = final consumption + gross capital formation + net exports. Final consumption of households includes goods and services used by households or the community to satisfy their individual needs. It includes final consumption expenditure of households, general government and non-profit institutions serving households.

working and well-intentioned – not because of good system designs or systematic use of data" (Celi, Mark, Stone, & Montgomery, 2013, p. 1157). However, recent research shows that there is a growing interest in using data to aid practitioners in healthcare (Mace, 2014; Patil, Raul, Shroff, & Maurya, 2014; Tormay, 2015).

The global healthcare industry has undergone major changes in the past few decades targeting enhanced patient care (Anderson, 2007; Bush, Lederer, Li, Palmisano, & Rao, 2009; Paré et al., 2008; Patil et al., 2014; Sicotte et al., 2006). IT and deployment of information systems (IS) can be identified as central to this transformation (Bush et al., 2009). These information systems focus on improving patient care, service quality, operational efficiency and patient satisfaction (Peng, Dey, & Lahiri, 2014) by reducing medical errors, streamlining clinical processes, increasing productivity and controlling healthcare costs (Anderson, 2007; Kannry, 2011) and are the key to creating information. Blumenthal (2010) refers to information as the "lifeblood" of modern medicine. In his article 'Launching HITECH', Professor of Medicine at Harvard Medical School David Blumenthal states that without an information system neither a physician nor a healthcare institute can perform at their best to deliver highest quality care, and compares healthcare without information systems to an Olympic athlete with a failing heart (Blumenthal, 2010, p. 382).

Many types of information systems are used across healthcare sectors ranging from simple applications like appointment schedulers to complex systems that provide diagnostics for images generated by MRI (Magnetic Resonance Imaging) scanners (J. Williams & Weber-Jahnke, 2010). A wide range of such information systems have been introduced and widely used by developed countries (e.g., USA, Canada, Australia, and NZ) for both clinical and operational tasks across healthcare sectors (Ward et al., 2014). Based on their use, these information systems are classified into two types: (i) Clinical IS, and (ii) Administrative IS (Menon, Yaylacicegi, & Cezar, 2009).

In their classification Menon et al. (2009) identify IS assisting primary value chain activities of healthcare as clinical IS; thus, these can be identified as information systems used in healthcare delivery. These capture, store and manipulate clinical data to provide an improved service in healthcare delivery (Paré et al., 2008). In addition to aiding professionals in clinical practice, CIS also provide information for strategic planning (Glandon, Austin, Boxerman, Smaltz, & Slovensky, 2008). Table 2.6 describes types of CIS seen in healthcare.

Table 2.6: Types of CIS in Healthcare

Type of Clinical Information System	**Description**
Electronic Medical Records (EMR)	EMR is an electronic version of a patient's medical history. It is used to capture family, social, surgical and medical history; allergies and immunisation details; laboratory results; clinical findings and clinical orders (McAlearney, Hefner, Sieck, & Huerta, 2015; Ward et al., 2014; Yuan, Bradley, & Nembhard, 2015). EMRs are used by care providers to manage and process medical information which is used for clinical care. EMRs may have built in features to enable alerts and reminders, and may provide best practice guidelines around care delivery (J. Williams & Weber-Jahnke, 2010).
Electronic Health Record (EHR)	An EHR is identified as a "'multi-tenant' EMR" that allows multiple care providers access to medical records of a patient to provide shared care (J. Williams & Weber-Jahnke, 2010, p. 76). EHR systems provide secure storage and share complete information about a patient entered by all healthcare providers, which is accessible through various geographical areas (J. Williams & Weber-Jahnke, 2010).
Picture Archiving and Communication systems (PACS)	PACS was introduced to clinical practice in the late 1990s (Zacharia, Sumner, & Saini, 2004). It is an imaging diagnostic tool that allows immediate access to medical images in digital format. The basic components of a PACS include an image acquisition device like film cassettes, video frame grabbers, digital imaging modalities like ultrasound, CT[9] or MRI; an image display station; and database management and image storage devices (Nunes et al., 2015; Zacharia et al., 2004). The images captured are interpreted by the PACS workstation and the results are made available within the hospital network (Nunes et al., 2015).
Laboratory Information Management Systems (LIMS)	The LIMS are used for processing and storing the results of laboratory tests. It is the foundation for appropriate acquisition of samples, supply of analytical results from measurement systems, medical reporting and billing for laboratory tests (Kammergruber, Robold, Karliç, & Durner, 2014; Ward et al., 2014).

[9] CT – Computed Tomography

Telehealth and telemedicine Systems	Telemedicine, also referred to as Telehealth, is the use of telecommunication facilities to deliver medical services remotely over distance (Goozner, 2015). It uses a range of telecommunication equipment from simple telephone or fax machines to complex communications using personal computers or full-motion interactive multimedia (Goozner, 2015; Huston & Huston, 2000).
Electronic Prescription systems (e-Prescribing)	Electronic prescribing systems allow prescriptions to be transmitted to pharmacies from the provider's office electronically (Kannry, 2011; Ward et al., 2014). The earliest forms of e-Prescribing systems were merely capable of sending the prescriptions electronically but the modern e-prescribing systems are equipped with medication decision support to avoid prescribing errors by drug-drug, drug-allergy, drug-disease, drug-laboratory, cost and dose checking (Kannry, 2011).
Health information exchange (HIE)	HIE is used to transfer electronic health information among healthcare organisations according to nationally recognised standards (Rahurkar, Vest, & Menachemi, 2015). The health information transferred via HIE includes laboratory results, clinical summaries and medication lists (Blumenthal, 2010; Yaraghi, Ye Du, Sharman, Gopal, & Ramesh, 2015).
Mobile Health (m-Health)	mHealth, short for mobile health, lets patients check symptoms, find doctors, make appointments, and do medical shopping online. These mHealth systems supply current and personalised data on claims, and enable members to compare services and treatments based on quality and cost (Nash, 2014).

Also identified as operational management systems by Glandon et al. (2008), administrative IS are used for healthcare administration and service management. These information systems are used to facilitate the secondary value chain activities (support activities) of healthcare (Menon et al., 2009). Thus, they support the non-patient care activities of healthcare organisations (Glandon et al., 2008). Some examples of these information systems include: Human Resource Management systems, Supply Chain Management Systems, Payroll Systems and Outpatient Clinic Scheduling Systems.

Apart from the above classification of information systems (as CIS and AIS), in healthcare there are complex integrated information systems that combine a variety of clinical IS as well as administrative IS. Some examples of these integrated information systems are Hospital Information Systems (HIS) (Ahmadian, Khajouei, Nejad, Ebrahimzadeh, & Nikkar, 2014) and Practice Management Systems (PMS) (Amar, Stone, Park, & Park, 2009; Yusof, Kuljis, Papazafeiropoulou, & Stergioulas, 2008). A PMS is used to manage a general practice providing primary care to a population (Amar et al., 2009). HIS and PMS systems integrate both clinical IS such as EMR, HER, PACS, e-Prescribing as well as administrative IS such as finance and accounting systems, and billing systems.

Nonetheless, the developments in health IS show notable trends in the global healthcare sector such as: (i) a shift from paper-based to completely computer based processing and storage, (ii) a shift from local (hospital or practice centred) to global HIS (patient centred), (iii) inclusion of patients in health IS, and (iv) use of health IS not only for patient care but also administrative purposes (Haux, 2006). The convergence of computational capabilities, the technological developments around the internet, as well as the abilities around capturing and leveraging data are the key drivers of this revolution around health IS (Carvalho, Rocha, van de Wetering, & Abreu, 2019).

2.3.3. Big Data in Healthcare

Increasing use of EHR and PMS and other IT deployments in healthcare are contributing to rapid growth of healthcare data (Bates, Saria, Ohno-Machado, Shah, & Escobar, 2014; Patil et al., 2014). Given the growing size of the human population and rising numbers of diseases and medications, large amounts of complex data is not new for the healthcare sector; thus traditionally healthcare data shows characteristics of big data (Wyber et al., 2015). Nonetheless, new types of data are emerging through developments of technology such as genomics data and patient-generated data originating outside of the healthcare systems (Roski et al., 2014; Sahay, 2016).

Y. Wang, Kung, Wang, and Cegielski (2018) highlighted that similar to other businesses, big data technologies act as a powerful tool bringing transformation to healthcare sectors around the world. Application of big data technologies bring opportunities to improve clinical care by facilitating evidence based medicine (Bates et al., 2014), and improving clinical decisions by utilising new data types such as genomics data (Sahay, 2016). Big data analytics are also known to bring opportunities to improve the quality and efficiency of healthcare management and service delivery by making use of traditional healthcare data along with new types of data effectively (Murdoch & Detsky, 2013).

Figure 2.4 shows the types of big health data and areas of application. More information and discussion on this topic can be found in Paper IV – Section 8.3.

As shown in Figure 2.4, the potential areas of application of big data technologies include, but are not limited to: (i) clinical decision making, (ii) precision medicine, (iii) measuring outcomes, (iv) population health analysis, (v) fraud detection, and (vi) research and development (Groves et al., 2013; Roski et al., 2014; Sahay, 2016). However, healthcare sectors are yet to grasp the full potential of big data analytics. Thus, it is important to investigate further into the notion of big data and its use in healthcare at multiple levels (Y. Wang, Kung, & Byrd, 2018). Paper III also discusses the literature around big data applications in health with a focus on clinical decision making (See section 7.7).

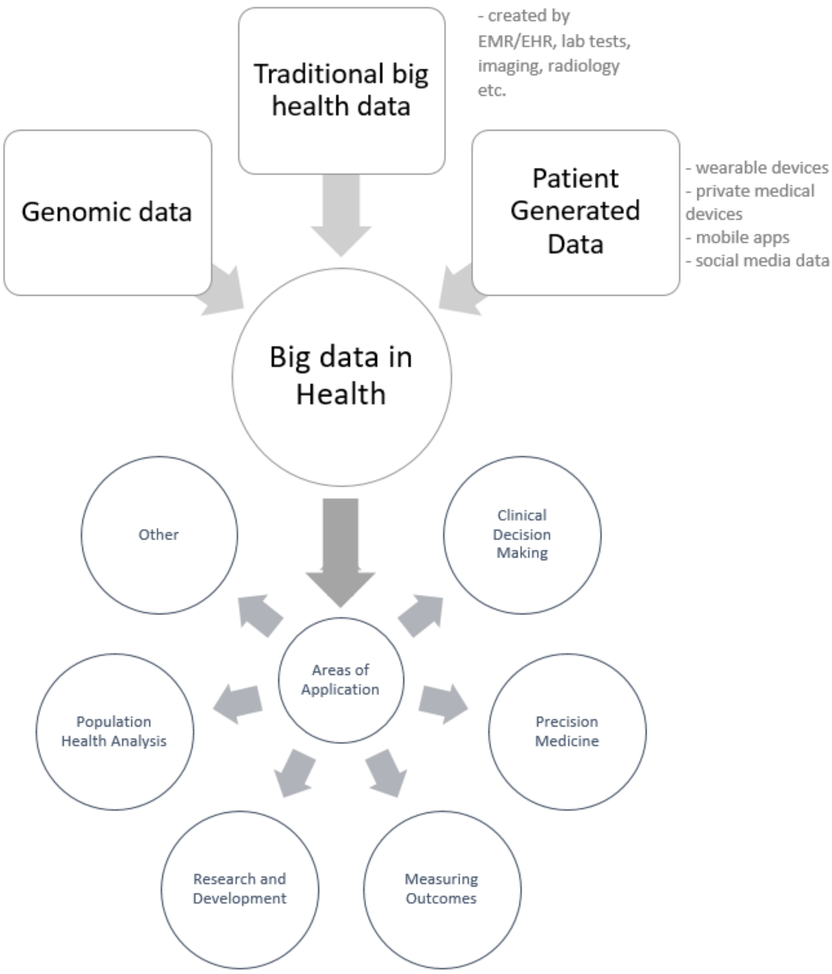

Figure 2.4: Types of Big data in Health and their Applications

2.4. Information Systems in New Zealand Healthcare

New Zealand's use of IT in healthcare is among the highest in the developed world (Bowden & Coiera, 2013). Pollock (2012) declared this as a result of the 'bottom-up' approach used in deploying IT in the NZ healthcare sector. This approach has an intense focus on deploying suitable IT solutions at point of care (Bowden & Coiera, 2013; Pollock, 2012). Extensive use of information systems is demonstrated, especially in the primary healthcare sector (Atalag, Gu, & Pollock, 2013). These information systems aid the clinicians in many tasks ranging from administration to management of patient care delivery as well as the associated clinical activity required to achieve this. Administrative IS are used for appointment scheduling, billing and financial administration. Clinical IS such as EHRs, ePrescriptions, eReferrals, and LIMS are used by clinicians to monitor patient histories, obtain the latest drug updates, refer patients to specialists, receive test results and so forth (Atalag et al., 2013; Pollock, 2012).

Similarly information systems are used in hospitals to aid clinicians in healthcare delivery and hospital management. The IS applications that are used in NZ hospitals include clinician portals, patient management systems, systems for admission management, systems for management of transfers and discharges, bed management, outpatient management, eReferrals, ePrescribing, laboratory ordering and result reporting systems (which are similar to LIMS), digital radiology reporting systems (which are similar to PACS) and systems to manage specific departments such as the intensive care unit, emergency department and operating theatres (Pollock, 2012). The use of such information systems rapidly generates different types of complex healthcare data in large volumes, which are therefore likely to have the characteristics of big data.

As a result of demand for health system automation the Health Information Exchange (HIE) was developed and has been used for many years in NZ (Bowden & Coiera, 2013). HIE is used to link general practitioners to share health data. The Ministry of Health collects health data and holds large scale datasets (e.g. the National Minimum Dataset) that can be used by people across the health system, as well as researchers, for the betterment of the healthcare system. This national health data can be linked through the National Health Index (NHI) and can be combined for large-scale data analysis (Atalag et al., 2013).

There is also information available about a precision medicine initiative, promoted by the Ministry of Health in partnership with Waitemata DHB, the University of Auckland and Orion Health (a technology vendor). While precision medicine is about understanding a person's genomic structure to provide individualised healthcare, currently it is more of a research initiative committed to driving NZ towards precision medicine in the future (Ross, 2017). The current precision health partnership brings together academics, healthcare professionals and a commercial company to build products that enable precision driven medicine to occur (Ross, 2017).

2.5. Business-IT Alignment

This section will review past literature related to business-IT alignment. A taxonomy of conceptualisations of alignment was developed and can be found in Paper I while the potential focus of alignment for this research is explained through Paper I (in Chapter 3).

2.5.1. Outlining Alignment

For the past 30 years Alignment has been a major concern for IT practitioners and company executives (Gerow, Thatcher, & Grover, 2014; Kappelman, McLeon, Luftman, & Johnson, 2013). Similarly, during the past decades many studies have explored the importance of business-IT alignment (e.g., Drazin & Van De Ven, 1985; Dulipovici & Robey, 2013; Henderson & Venkatraman, 1992; Luftman, 1996; Sabherwal & Chan, 2001) in various business domains. Thus, alignment has remained one of the dominant fields of IS research over time (Chan & Reich, 2007; Sousa & Machado, 2014).

"Alignment" is also recognised in numerous different terms such as fit (Chang, Wang, & Chiu, 2008), coherence (Venkatraman, Henderson, & Oldach, 1993), harmony (Luftman & Brier, 1999), integration (Van Der Zee & De Jong, 1999), congruence (Reich & Benbasat, 2000), relationship (Peppard & Ward, 1999), gestalt (Bergeron, Raymond, & Rivard, 2004), synergy (Lu & Ramamurthy, 2011) and linkage

(Reich & Benbasat, 1996) throughout the literature. It refers to the degree of fit between the domains of business strategy, organisational structure, IT strategy and IT infrastructure (Chan & Reich, 2007; El-Mekawy, Rusu, & Perjons, 2015; Grant, 2010; Henderson & Venkatraman, 1993; Jenkin & Chan, 2010; Luftman, 1996). Researchers who study alignment have typically studied the fit between two or more of these four domains (Henderson & Venkatraman, 1992). The following sections will look further into these four domains, which are central to business-IT alignment research.

2.5.1.1. Business strategy, goals and objectives

Business strategy, business goals and business objectives are central to investigating business-IT alignment. Business strategy typically refers to the business plan/approach followed by the organisation. It is the method of achieving a specific business goal or an objective. According to Michael Porter, “strategy is the creation of a unique and valuable position, involving a different set of activities” (Porter, 1996, p. 18). The three key areas a business strategy addresses are: (i) business scope, (ii) distinctive competencies, and (iii) business governance (Henderson & Venkatraman, 1992).

R. E. Miles and Snow (1978) identified four types of business strategies: defender, prospector, analyser, and reactor. However, over the years defender, analyser and prospector strategies have been further studied and validated while reactor has been identified as invalid (Sabherwal & Chan, 2001). A detailed review is provided in Table 2.7 on defender, prospector, analyser, and reactor strategies.

Table 2.7: The Miles and Snow Typology of Business Strategies

(Gnjidić, 2014; R. E. Miles & Snow, 1978; R. E. Miles, Snow, Meyer, & Coleman, 1978; Sabherwal & Chan, 2001)

Defender	A Defender strategy aims to capture a specific portion of a potential target market. This type of strategy allows businesses to achieve competitive advantage by becoming more successful in catering to existing markets with existing products. Defenders enforce high entry barriers to competitors by producing standard high quality products or services at low prices. Defender strategies do not cope well with change. While they have greater fixed asset intensity than others, they tend to use a highly cost efficient single core technology. Defenders follow a mechanistic organisational structure.

Prospector	As opposed to defenders, prospectors constantly look for new product and market opportunities. A prospector strategy creates change and innovation, and invests heavily in research and development as well as environmental scanning. As change is embraced by businesses with prospector strategies, a higher level of flexibility in technology is required. However prospectors have a primary risk of low profitability and overextension of resources due to their continuous pursuit of change. This kind of business follows an organic organisational structure.
Analyser	Analyser lies between the two extremes of defender and prospector, and is a combination of both. Analyser strategies seek to minimise risk while maximising opportunities for growth. Although a constant domain of core products is maintained by analysers, this type of business continuously scans for new products and markets. Typically analysers follow a prospector. Thus analyser strategies accept change, but do not create change. With this moderate nature analysers try to address the conflicting demands of efficiency and innovation. Analysers typically use a dual technological core having both stable and flexible components. They follow a matrix organisational structure.
Reactors	R. E. Miles et al. (1978) defined the reactor type of strategy as a residual strategy which appears when other strategy types are not properly followed or when in transition from one type of strategy to another. Therefore, later the reactor type was identified as not following a conscious strategy. Consequently the reactor was considered an invalid type and therefore is not included in new versions of the Miles and Snow typology.

2.5.1.2. Organisational Structure

Henderson and Venkatraman (1992) define administrative structure, processes and skills as the three measures of organisational structure. Organisation structures are established in three forms: mechanistic, organic and matrix. A mechanistic structure is formal, rigid in administrative relations, and strictly adheres to bureaucratic values. In contrast an organic structure is more flexible and informal, and authority is conferred by situational expertise (Covin & Slevin, 1988). A matrix structure has a dual authority relationship: it balances the power between managerial linking roles and normal line organisational roles (Galbraith, 1974).

2.5.1.3. IT Strategy

IT strategy reflects how IT is planned in an organisation (Kanungo, Sadavarti, & Srinivas, 2001). It is typically considered as a functional strategy that focuses on IT capabilities that leverage competitive success (Henderson & Venkatraman, 1992). Earl (1989) outlines three categories of IT strategies based on focus: (i) IS strategy, (ii) IT strategy and (iii) Information Management (IM) strategy (see Table 2.8).

Table 2.8: Categories of IT strategies

(Earl, 1989)

IS Strategy	**IT Strategy**	**IM Strategy**
The focus of IS Strategy is on the systems or business applications of IT, integrating them with the needs of the business and using them to achieve strategic benefits.	IT Strategy mainly targets the technology and policies. It may include the architecture, technical standards, security levels and risk attitudes.	IM Strategy relates to the structures and roles for management of IS and IT. Attention is given to issues like relationships between specialists and users, management responsibilities, performance measurement processes and management controls.

Moreover, IT strategy can be viewed from two perspectives: *intended use* and *situated use* (Dulipovici & Robey, 2013) (see Table 2.9). The level of alignment could be affected if the intended use of IS strategy is not congruent with situated use.

Table 2.9: Intended use vs. Situated use

(Dulipovici & Robey, 2013)

Intended use	Intended use refers to the planned purpose of the IT implementation. Intended use could be what is documented; it is the intention of implementing the IT.
Situated use	The situated use is the subjective understanding of knowledge, strategy and the system itself. This refers to how users of implemented IT understand the system and the purpose of the system.

2.5.1.4. IT Infrastructure

IT infrastructure is the configuration of the organisation's technical elements. It comprises the hardware, software, networks, telecommunications, and databases (Duncan, 1995; Roberts & Grover, 2012). It is believed that having a suitable IT infrastructure may provide greater agility to an organisation's performance (Roberts & Grover, 2012; Weill, Subramani, & Broadbent, 2002). In their model Henderson and Venkatraman (1992) address IT infrastructure as based on architecture, processes and skills.

2.5.2. Conceptualisations of Alignment

During the past 30 years researchers have conceptualised alignment in numerous ways. Henderson and Venkatraman (1992) proposed a conceptual model (the Strategic Alignment Model) to study alignment which identifies three types of alignment: bivariate fit, cross-domain alignment and strategic alignment. Reich and Benbasat (1996) conceptualise studying business-IT alignment through two dimensions: social and intellectual. Chan and Reich (2007), who grounded their study in previous alignment literature, identify different dimensions – strategic/intellectual, structural (formal and informal), social and cultural – and levels (organisational, operational, project, and individual) of business-IT alignment. A recent paper by Gerow et al. (2014) characterises six types of alignments as intellectual, operational, and four types of cross domain alignment (strategy execution, technology transformation, competitive potential and service level). Although different, these conceptualisations seem to share similar characteristics (e.g. the social dimension has strong ties with the individual level (Chan & Reich, 2007)). Additionally researchers emphasise alignment could be studied as an end state as well as a process (Chan & Reich, 2007; Dulipovici & Robey, 2013; Sabherwal & Chan, 2001).

The following Chapter, Chapter 3, presents Paper I (titled Taxonomy of Business-IT Alignment Conceptualisations, presented in the 22nd Pacific Asia Conference on Information Systems at Yokohama, Japan) which describes these different conceptualisations of alignment in detail and presents a taxonomy of business-IT alignment conceptualisations.

2.6. Chapter Summary

This chapter summarised the literature around big data, health IS and business-IT alignment, highlighting definitions and significant areas in relation to the research question. Reviewing past literature around big data provided understanding of the characteristics of big data as well as identifying gaps in big data research. The big data literature highlighted two gaps that need addressing: (i) the need for an investigation around social dynamics of big data, and (ii) the importance of examining business-IT alignment in big data implementations. Health IS literature allowed to understand the current work in health IS, but more specifically allowed the researcher to understand health-related IS in the context of big data (types of big health data and their applications). Examining a vast amount of business-IT alignment literature led to identifying an important need to develop a taxonomy that could be used for business-IT alignment research and is presented in Paper I (Chapter 3).

Chapter 3: Taxonomy of Business – IT Alignment (Paper I)

3.1. Overview of the Paper

This chapter is presented through Paper I, discussing the development of a taxonomy that can be applied to business-IT alignment studies. The taxonomy of business-IT alignment literature is a much-needed contribution to business-IT alignment research as it provides a robust lens to investigate alignment for any alignment study.

This is a conceptual paper, published and presented at the 22nd Pacific Asia Conference on Information Systems, 26th to 30th June 2018 in Yokohama, Japan. The paper is available through the Association for Information Systems (AIS) Library and confirmation has been received to approve inclusion of the paper in the thesis.

DRC 16

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of the candidate:	Kasuni Weerasinghe
Name/title of Primary Supervisor	Professor David J Pauleen
Name of Research Output and full reference:	
Weerasinghe, K., Scahill, S. L., Taskin, N., and Pauleen, D. J. (2018). Development of a Taxonomy to be used by Business-IT Alignment Researchers. Paper presented at the Twenty Second Pacific Asia Conference on Information Systems, Yokohama, Japan.	
In which Chapter is the Manuscript/Published work:	Chapter 3
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	90%
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
The paper was developed as a result of a gap identified during the literature review of Business-IT alignment. The initial development of the paper was done by the candidate and was refined after comments of the three supervisors. The paper was accepted after peer review at 22nd Pacific Asia Conference on Information Systems with comments from two reviewers for revision. Revisions were made after discussions with the supervisors. A draft of the final version was sent to supervisors before submission for publication.	
For manuscripts intended for publication please indicate target journal:	
22nd Pacific Asia Conference on Information Systems	
Candidate's Signature:	
Date:	20 May 2019
Primary Supervisor's Signature:	
Date:	20 May 2019

Paper I: Development of a Taxonomy to be used by Business-IT Alignment Researchers

3.2. Abstract

The nexus between Business and IT research is complex. Due to extended research over time, the context of business-IT alignment has resulted in many different conceptualisations that can be applied to ongoing research. It is challenging to select and adopt a suitable approach to study business-IT alignment across any given field due to the variability of the existing conceptualisations. This study reviews the existing literature to identify alignment conceptualisations and contributes to both theory and practice. Theoretically, through the uncovering of gaps in the literature a taxonomy has been developed which can be used as a guide to select an appropriate alignment lens for business-IT alignment studies. In practice, it is expected that this taxonomy will be beneficial for conceptualising the structure and philosophies underpinning future alignment studies. To validate the taxonomy, the paper presents a case study in healthcare applying the developed taxonomy to investigate alignment of big data in health.

Keywords: *Business-IT alignment, Taxonomy, Conceptualisation*

3.3. Introduction

For the past 30 years, “Alignment” has been a major concern to information technology (IT) practitioners and company executives (Kappelman et al., 2013). Similarly, during the past decades many studies have explored the importance of business-IT alignment in various business domains (e.g., Drazin & Van De Ven, 1985; Dulipovici & Robey, 2013). Thus, alignment has remained one of the dominant fields of information systems research over the years (Chan & Reich, 2007; Li & Palvia, 2017). Throughout the literature, “Alignment” is also addressed through different terms such as fit, coherence, harmony, integration, congruence, relationship, gestalt, synergy and linkage. Alignment refers to the degree of “fit” between different domains of business and information technology (Henderson & Venkatraman, 1993; Jenkin & Chan, 2010; Luftman, 1996).

Modern businesses are increasingly relying on IT to improve firm performance, investing millions of dollars in IT developments. Traditionally IT investments are undertaken to support organisations to achieve their business goals (Kahre, Hoffmann, & Ahlemann, 2017). However, IT expenditure does not automatically guarantee improvements in firm performance. Business-IT alignment is an important and much needed field of study as it allows an understanding of the degree of business and IT congruence, and how improvements in alignment can lead to better performing organisations (Chan & Reich, 2007; Kahre et al., 2017).

This paper presents a comprehensive literature review on existing business-IT alignment to present how and what aspects of business-IT alignment researchers have focused on. This paper strongly supports the work of Chan and Reich (2007) on business-IT alignment and compliments their thinking through the development of a taxonomy for researchers in this field to build their alignment studies on. The paper then presents a case that used this taxonomy to investigate alignment of big data in the context of healthcare. The case demonstrates that the use of this taxonomy was beneficial and strengthened (in a conceptual way) our ongoing alignment research. It is expected that this taxonomy will also be relevant to other alignment scholars working in this space through providing a conceptual platform which they can use dependent on their own needs.

The sections that follow include theoretical foundations of alignment, which discusses the pertinent literature that provides the basis for the taxonomy. This is followed by a discussion on the development of the taxonomy and its potential use. The discussion also presents a case on alignment featuring the application of the taxonomy. Finally, the conclusion section draws the paper together by giving recommendations and discussing implications.

3.4. Theoretical Foundations

Being one of the dominant fields in information systems (IS) research for the past three decades, alignment has been conceptualised in many different ways throughout the literature. Most typically, alignment refers to the "fit" between business and IT (Henderson & Venkatraman, 1992). Business strategy, business goals and business objectives are central to investigating business-IT alignment. Business strategy typically refers to the business plan/ approach that is followed by the organisation. It is the method of achieving a specific business goal or an objective. According to Michael Porter "strategy is the creation of a unique and valuable position, involving a different set of activities" Porter (1996, p. 18). The three key areas a business strategy addresses are: (i) business scope, (ii) distinctive competencies, and (iii) business governance (Henderson & Venkatraman, 1992). Business scope is the choices that the business makes relating to its products, services and the market. Distinctive competencies are the attributes of the strategy such as quality, pricing and channels, which aims to bring competitive advantage. Business governance include procedures around business administration such as joint ventures and strategic alliances (Henderson & Venkatraman, 1992).

R. E. Miles and Snow (1978) outline a typological classification which identifies four types of business strategies: (i) defender, (ii) prospector, (iii) analyser, and (iv) reactor. A Defender strategy aims to capture a specific portion of a potential target market. This type of strategy allows businesses to achieve competitive advantage by becoming more successful in catering to existing markets with existing products. Defenders enforce high entry barriers to competitors by producing standard high quality products or services at low prices. As opposed to defenders, prospectors constantly look for new product and market opportunities. A prospector strategy is a creator of change and innovation, and invests heavily on research and development as well as environmental scanning. As change is embraced by businesses with prospector strategies, a higher level of flexibility in technology is required. Analyser lies between the two extremes of defender and prospector, and is a combination of both. Analyser strategies seek to minimise risk while maximising opportunities for growth. Although a constant domain of core products is maintained by analysers, this type of business continuously scans for new products and markets. Typically, analysers follow a prospector. A reactor type strategy is defined as a residual strategy, which appears when other strategy types are not properly followed or when in transition from one type of strategy to another. Therefore, later it was indicated that reactor type is identified as not following a conscious strategy. Consequently, reactor was claimed as an invalid type therefore is not included in new versions of Miles and Snow typology. Similar to business strategies, businesses also develop IT strategy that reflects how IT is planned in an organisation (Kanungo et al., 2001). It is typically considered as a functional strategy that focuses on IT capabilities that leverage competitive success (Henderson & Venkatraman, 1992). Earl (1989) outlines three categories of IT strategy focus: (i) IS strategy (focuses the business applications of the information systems), (ii) IT strategy (focuses on technology and related policies) and (iii) Information Management (IM) strategy (focuses on roles for management of IS).

In order to investigate alignment of business and IT strategies, researchers have conceptualised alignment in numerous ways. Henderson and Venkatraman (1992) proposed a conceptual model – the Strategic Alignment Model, which identifies three types of alignment: bivariate fit, cross-domain alignment and strategic alignment. Reich and Benbasat (1996) conceptualise studying business-IT alignment through two dimensions: social and intellectual. Chan and Reich (2007) grounded in past business-IT alignment literature identify different dimensions: strategic/intellectual, structural (formal and informal), social and cultural; and levels: organisational, operational, project, and individual. A paper by Gerow et al. (2014) characterize six types of alignment as intellectual, operational, plus four types of cross domain alignment (strategy execution, technology transformation, competitive potential and service level). Additionally, researchers have emphasised that alignment can be studied as an end state as well as a process (Chan & Reich, 2007; Dulipovici & Robey, 2013; Sabherwal & Chan, 2001). Following is a detailed discussion of these different conceptualisations.

3.4.1. Strategic Alignment Model (Types of Business-IT Alignment)

As mentioned, Henderson and Venkatraman (1992) proposed the Strategic Alignment Model (SAM), which identifies three types of alignment: bivariate fit, cross-domain alignment and strategic alignment. The model explores the degree of fit between the domains of business strategy, organisational structure (refers to measures of administrative structure, processes and skills), IT strategy and IT infrastructure (the configuration of the organisation's technical elements) (Henderson & Venkatraman, 1992).

Bivariate fit in the SAM model refers to the simplest form of alignment; it represents alignment at any two domains in the model either horizontally or vertically (e.g., alignment of business strategy and IT strategy, alignment of business strategy and organisational infrastructure, etc.) (Henderson & Venkatraman, 1992). Cross-dimensional alignment takes a multi-domain approach to alignment linking any three domains sequentially. Technology exploitation, technology leverage, strategy implementation and technology implementation are identified as the four main perspectives of cross-domain alignment in the SAM model (Henderson & Venkatraman, 1992). Strategic alignment according to SAM is much more complex; it takes a more holistic approach giving "simultaneous or concurrent attention to all four domains" (Henderson & Venkatraman, 1992, p. 20). However, scholars referring to business-IT alignment in general too have used the term 'strategic alignment' (Dulipovici & Robey, 2013).

3.4.2. Levels of Alignment

Alignment can be studied across different structural levels of an organisation, such as organisational, operational, project, and individual levels (Chan & Reich, 2007; Dulipovici & Robey, 2013). In addition to this, the sector type can also be identified as a level where alignment is an important consideration and can be studied (Weerasinghe, Pauleen, et al., 2018). Ideally, business-IT alignment should be present at all levels but researching all levels at once can be difficult in the scope of a single research project that has limiting parameters. Therefore, researchers are encouraged to focus their work upon the most suitable level for their research question and the context. Figure 3.1 provides a conceptualisation of how levels of a sector may operate and how alignment could be studied.

Individual alignment represents the most micro level for studying alignment (Chan & Reich, 2007). Studies that explore individual alignment (e.g., Tan & Gallupe, 2006) investigate shared cognition of individuals and how this contributes to business-IT alignment within a business context. Such research investigates individuals' work aligning with their user goals. The next level of alignment that can be studied is the **project** level. Jenkin and Chan (2010) define project alignment as "the degree to which the IS project deliverables are consistent with the project's objectives, which are shaped by the organisation's IS strategy" (p37). Inability of a project to face internal and external change triggers may lead to project misalignment which could result in overall business-IT misalignment (Chan & Reich, 2007). Misalignment refers to the inefficiencies between business and IT and often promotes changes to the existing IT eco-system (Dulipovici & Robey, 2013).

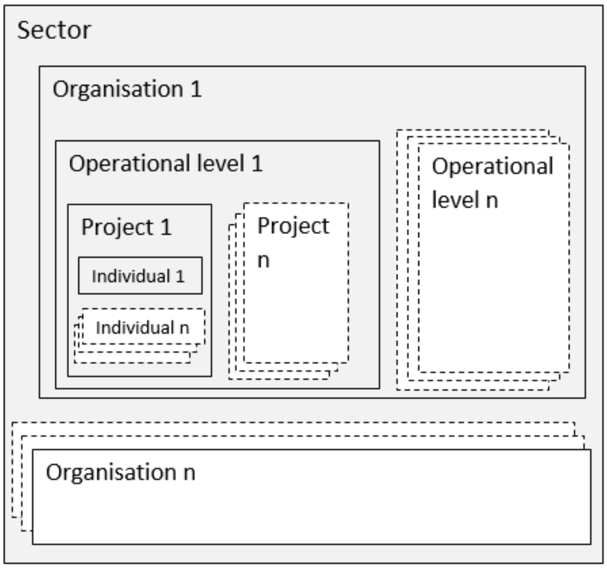

Figure 3.1: Levels of Alignment

Organisational strategies are often developed at the higher levels of the organisation (i.e., strategic level), while they are executed at a lower level (i.e., operational level). When studying **operational** level alignment, the aim is to understand the alignment of these strategic business goals as they are put into practice at lower levels of the organisation (Chan & Reich, 2007). For example, human resource management (HRM) is a key business operation. The higher level goals for HRM may include training goals supported by IS. The goals are realised at the operational level (human resource department). Investigating alignment of the goals that can only be realised with the support of IS used can be identified as an operational level alignment study. **Organisational** level on the other hand identifies broader organisational goals (e.g., a three-year sales goal). Alignment studied at the organisational level refers to the level of integration of organisational goals and strategies with IT. Researchers looking at organisational level alignment, explore the organisation as a whole and investigate different players across the organisation (Chan & Reich, 2007).

Apart from the above levels identified by Chan and Reich (2007), few alignment studies in literature have investigated alignment across a sector (e.g., Alghazi, Li, Shen, & Fosso Wamba, 2017; Yusof et al., 2008). Sector refers to an identified industry (e.g., healthcare, banking and so forth), and researchers studying sector level alignment should explicitly state the boundaries. **Sector** level alignment is the most complex, as it requires investigating different categories of players across the sector to provide a complete picture (Weerasinghe, Pauleen, et al., 2018).

3.4.3. Dimensions of Alignment

Reich and Benbasat (1996) conceptualise studying business-IT alignment through two dimensions: social and intellectual. Chan and Reich (2007) grounded in past alignment literature and complimenting dimensions conceptualised by Reich and Benbasat (1996) identify four different dimensions: strategic/intellectual, structural (formal and informal), social and cultural. This section will discuss those four dimensions of business-IT alignment.

3.4.3.1. Strategic/intellectual Dimension

The strategic dimension of alignment is conceptualised as the degree of fit between business strategy and IS/IT strategy and plan (Chan & Reich, 2007; Jenkin & Chan, 2010). Similarly, the intellectual dimension of alignment discussed by Reich and Benbasat (1996) refers to having a higher level of agreement between business and IT plans. Therefore, the strategic/intellectual dimension of alignment could be conceptualised as the alignment between the organisations' business strategy and the intended use of its IT plan. Research that looks at business-IT alignment through this dimension often maps the business strategy attributes with IT strategy attributes to assess alignment (e.g., Sabherwal & Chan, 2001).

3.4.3.2. Structural Dimension

The structural dimension refers to the congruence between the organisation's structure and IT. According to Chan (2002), structural alignment observes IS skills/business skills, centralised/ decentralised reporting relationships, career paths, cross-functional linkage, incentives, rewards and performance measures. Chan and Reich (2007) noted that although typical investigation of structural dimension focuses on formal structural division of the organisation, adapting an informal structural lens to examine alignment is also beneficial. Informal structure is defined as "relationship-based structures that transcend the formal division of labour and coordination of tasks" (Chan & Reich, 2007, p. 301).

3.4.3.3. Cultural Dimension

The cultural dimension denotes the degree of agreement between the approach taken to implement the IT strategy and organisational culture of the firm. The IT planning should be consistent with the cultural elements such as employee mind-set, top management communication style and business planning style. As stated by Chan and Reich (2007), studies show that it is important to align IT with the company culture (Pyburn, 1983).

3.4.3.4. Social Dimension

IT implementation involves utilisation of a set of technological, social and organisational interactions. It could mean having to deal with groups of stakeholders with different interests, interpretations and perceptions of IT and its purpose (Gal & Berente, 2008). Thus, the social dimension of alignment explores how IT is perceived by different players at different levels of the organisation. Further, the social dimension has strong ties with individual level alignment (Chan & Reich, 2007). According to Reich and Benbasat (1996) the social dimension can be defined as "the level of mutual understanding of commitment to the business and IT mission, objectives and plans" (p.58). Unpredictable social aspects influence the business-IT alignment of an organisation; accordingly, the social dimension of alignment explores the situated use of IS to determine how users perceive and understand IT implementation and how it is actually used (Dulipovici & Robey, 2013). Compared to strategic/ intellectual and structural dimensions of alignment, fewer studies have been carried out to investigate the social dimension of alignment. Tan and Gallupe (2006) and Dulipovici and Robey (2013) are two studies found in the literature investigating business-IT alignment through a social dimension lens.

3.4.4. States of Alignment

Jenkin and Chan (2010) conceptualise alignment through two components: (i) the process of aligning, and (ii) the outcome. This promotes the idea that alignment studies can be framed through two states: as a process and as a (end) result (Chan & Reich, 2007). Alignment is considered as a process where it will be ongoing and parallel to the changes in internal and external factors influencing an organisation. A process approach looks at a sequence of events where as the result approach is typically an identified outcome (Jenkin & Chan, 2010). The result (outcome/ end state) approach investigates a point of failing or achieving alignment with core business objectives (Tallon, 2007).

3.3.5. Environments to Study Business-IT Alignment

Chan and Reich (2007) in their review of the alignment literature identify that while organisations must be aligned internally in different aspects (i.e., levels, dimensions) they must also be aligned externally with industry and technology forces positioning business in the external product-market space (Chan & Reich, 2007; Henderson & Venkatraman, 1993). This provides the rationale for studying alignment with its environment conceptualised as internal and external.

3.5. Discussion

Drawing on the literature outlined in the previous section, this discussion section focusses on the development of a taxonomy of business-IT alignment conceptualisations. The paper then goes on to present an application of the taxonomy using a case study to illustrate the taxonomy's applicability and effectiveness.

3.5.1. Development of a Taxonomy for Alignment

All conceptualisations of alignment present ways in which business-IT alignment can be studied. The literature provides researchers with different conceptualisations to look at business-IT alignment, but what seems to be missing is a taxonomy of these different conceptualisations, which can be used to guide future alignment studies (see Table 3.1). Use of this taxonomy will aid business-IT alignment researchers in establishing a robust framework for their alignment study by identifying an appropriate lens to study alignment through the identification of type, level, dimension, state and environment. This taxonomy represents different types of conceptualisations as classes and identifies characteristics/aspects of each class as properties.

Table 3.1: Taxonomy of Alignment Conceptualisations

<table>
<tr><th>Classes</th><th colspan="6">Properties of Each Class</th></tr>
<tr><td>Types</td><td colspan="2">Bivariate fit</td><td colspan="2">Cross-domain alignment</td><td colspan="2">Strategic fit</td></tr>
<tr><td>Levels</td><td>Organisational</td><td>Operational</td><td>System</td><td>Project</td><td>Individual</td><td>Sector</td></tr>
<tr><td>Dimensions</td><td colspan="2">Strategic/Intellectual</td><td colspan="2">Structural (Formal/Informal)</td><td>Social</td><td>Cultural</td></tr>
<tr><td>States</td><td colspan="3">End (Result)</td><td colspan="3">Process</td></tr>
<tr><td>Environment</td><td colspan="3">Internal</td><td colspan="3">External</td></tr>
</table>

The idea of this taxonomy is that, when studying business-IT alignment one property of each class can be identified to frame the study. For example, a type of alignment (e.g., bivariate fit) would be studied at an identified level (e.g., project) within an identified environment (e.g., internal). The researcher should distinguish the most suitable dimension (e.g., cultural) for investigating alignment; dimensions are typically used as lenses to observe business-IT alignment. Based on the purpose of the research, the state of alignment (e.g., process) to be examined should also be determined. Having selected properties for each alignment class in the taxonomy researchers will be able to build a conceptual framework to carry out their own alignment study.

Some studies in the existing alignment literature tend to conceptualise alignment with one property from all of the classes in the taxonomy; although they do not clearly acknowledge such conceptualisations (e.g., Dulipovici & Robey, 2013). Dulipovici and Robey (2013) studied bivariate fit of a knowledge management system (project alignment) by investigating perceptions on individuals (social dimension) within the organisation (internal environment). Because their investigation was focussing on the process of the system being developed they have studied alignment as a process. It is also noted that, some studies only pay attention to features from one or two classes of the identified conceptualisations of alignment (e.g., Bush et al., 2009). As such, the validity could be further improved. Indeed, in some scenarios discussing alignment through all classes may not be possible.

3.5.2. The Case: Alignment of Big Data in Health

This section discusses application of the proposed taxonomy in a case to investigate alignment of big data across the New Zealand (NZ) healthcare sector. This is an important area with the requirement for IT alignment with business strategy so that the health sector gains optimal performance. NZ health system is a forward-thinking system that shows significant developments despite the challenges (Ministry of Health, 2014a). Being an early adapter of technology for healthcare delivery, NZ health system demonstrates possible positive avenues for big data applications (Weerasinghe, Pauleen, et al., 2018). Therefore, it is identified as an ideal context to study business-IT alignment and is taken as the case context to report application of the developed taxonomy.

The increasing use of information systems in healthcare, together with rising patient populations, diseases and medication, generates enormous amounts of unstructured and complex data (Ward et al., 2014). This data depicts characteristics of big data, which is commonly known as 3V's: volume (large in size), variety (many different types of data), and velocity (availability of data in near real-time) (McAfee & Brynjolfsson, 2012). Performing advanced analytics to analyse big data has resulted in identifying two additional Vs': veracity (accuracy of data) and value (potential value that can be created) (Emani et al., 2015). Technological developments around big data analytics to create value from big data have opened promising avenues for healthcare to make use of big-healthcare-data for more effective healthcare management and delivery (Mace, 2014).

Implementing big data capabilities in traditional businesses like healthcare requires the management of change in the socio-technical aspects of an organisation such as analytics platforms, IT architecture, IT infrastructure, security measures, required expertise and organisational structure (Weerasinghe, Pauleen, et al., 2018). Such change may influence business-IT alignment and therefore is important to be investigated (Bush et al., 2009). However, alignment studies are often complex and challenging (Chan & Reich, 2007). The complicated nature of the NZ healthcare sector along with big data has increased this complexity making it difficult for the researchers to frame the study to investigate alignment of big data. The use of the taxonomy to identify aspects to study has not only simplified the study but also informed the development of a conceptual framework to guide the research. The aspects of alignment identified as important to study are highlighted in Table 3.2 and the rationale for selection is discussed.

Table 3.2: Application of Taxonomy for the case of NZ healthcare

<table>
<tr><th>Classes</th><th colspan="6">Properties of Each Class</th></tr>
<tr><td>Types</td><td colspan="2">Bivariate fit</td><td colspan="2">Cross-domain alignment</td><td colspan="2">Strategic fit</td></tr>
<tr><td>Levels</td><td>Organisational</td><td>Operational</td><td>System</td><td>Project</td><td>Individual</td><td>Sector</td></tr>
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<tr><td>States</td><td colspan="3">End (Result)</td><td colspan="3">Process</td></tr>
<tr><td>Environment</td><td colspan="3">Internal</td><td colspan="3">External</td></tr>
</table>

Because of the complex nature of big data and its potential to transform business activity, researchers investigating alignment of big data need to pay attention to business strategies, structures, big data strategy and infrastructure. Based on this requirement for understanding, the case study presented investigates strategic fit of big data. In the NZ healthcare context, big data projects have their roots across the sector. Such projects may be strategized by the policy makers, but planned by different organisations and used by other organisations making them sector wide projects as opposed to single organisational projects (Weerasinghe, Pauleen, et al., 2018). This suggests a high degree of complexity and there is little understanding of the degree to which alignment occurs. As such, alignment across the sector is being investigated. Due to the complexity of the NZ health sector, three sub sector levels were identified to be investigated: macro (policy makers), meso (planners, funders and vendors) and micro (healthcare providers) (Scahill, 2012b; Weerasinghe, Pauleen, et al., 2018).

Because big data is a technological phenomenon, technical dynamics of big data (challenges, opportunities, security measures, etc.) have been extensively researched but little emphasis has been placed on understanding social dynamics (perceived value, usability, etc.) (Shin, 2015). In order to study the social dynamics our work uses the social dimension of alignment as a lens. This study focuses on internal alignment by capturing data from the three subsector levels, which includes policy makers, planners and funders, IT vendors and healthcare providers regarding their perceptions of big data in the New Zealand health system. Had the study investigated alignment across the sector by looking into how other related bodies (i.e., education providers, connected government bodies) align with the healthcare sectors' current state of big data this study would have been investigating the external environment. However, healthcare software vendors do not fall into the external environment, as they form part of the health system itself. Understanding alignment as a process as opposed to an end state addresses the potential of having various degrees of alignment across the sector. Therefore, it is anticipated that some organisations across the healthcare sector may have different levels of alignment with big data than others.

This identification of alignment conceptualisations has informed the development of a conceptual framework to underpin the case investigation (see Figure 3.2).

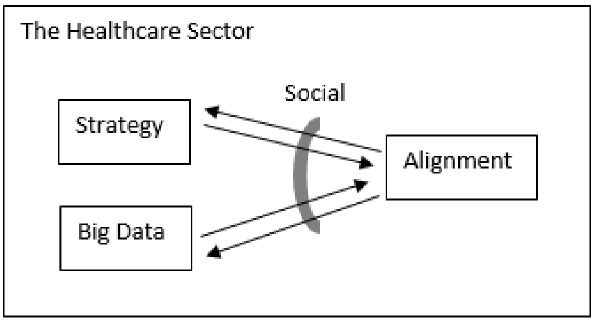

Figure 3.2: Conceptual Framework based on taxonomy

As shown in the Figure 3.2 big data and healthcare strategy is studied for its strategic fit, exploring the internal environment of the healthcare sector through a social dimension lens. The two way arrows in the conceptual framework represent the idea that the state of alignment studied is a process with the assumption being made that big data and strategy will be continuously changing to align with each other. Use of the above taxonomy has strongly shaped the case study and helped the researchers to understand what is important to study in such a vast and complex context. Alignment is investigated within the identified subsector levels and then across them to gain a sector wide perspective.

3.6. Conclusion

Business-IT alignment has been in existence for over 30 years resulting in large amounts of literature and many valid yet disparate ways of investigating it. Researchers often find alignment studies cumber-some and complex due to this diversity (Chan & Reich, 2007). This paper contributes to both theory and practice of business-IT alignment. A gap in literature was identified with a need to bring together all existing work into a robust framework to underpin our ongoing alignment work and to provide a sound platform for other alignment researchers to use. Thus, a taxonomy was developed grounded on literature. Theoretically, the taxonomy is a much needed development for the alignment literature. It brings together different conceptualisations of alignment under one frame, which has been fragmented. The paper presents a case study applying the developed taxonomy demonstrating the validity and applicability. The case study, which investigates alignment of big data in the healthcare context, demonstrates a solid foundation to the work by applying the developed taxonomy. The developed conceptual framework based on the direction provided by the taxonomy provides the researchers with a robust foundation upon which to understand the concept of business – IT alignment.

Practically, the developed taxonomy provides a sound platform for business-IT alignment research for both novice and experienced alignment researchers. This foundation has reduced the complexity of our research by providing a platform, which reduces complexity when moving forward with our alignment studies. It is expected to offer the same for other alignment researchers whilst bringing a degree of rigor into alignment studies and helping to streamline the pathway for ongoing alignment research. Therefore, we recommend that alignment researchers use this taxonomy to frame their business-IT alignment research in any context.

Proposed future work includes carrying out an empirical study based on the conceptual framework to investigate business-IT alignment to validate the use of the taxonomy in practice. In addition, further validation of the taxonomy in different contexts both conceptually and practically is required.

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Chapter 4: Theoretical Foundations

The theoretical foundations of this thesis are twofold. One the one hand it uses Social Representations Theory (SRT) as an underlying theory in the development of the theoretical framework to guide the research. On the other, the thesis presents a novel theory from the research; the Theory of Sociotechnical Representations (TSR) (presented in Chapter 7) which was created through the amalgam of SRT with Sociotechnical Systems Theory (SST). In the research design stage, many theories from information systems (IS) and other disciplines were examined before selecting SRT. Among the theories investigated as a possible theoretical basis for this research was SST, a well-known IS theory (Mumford, 2006). However, due to SST's perspective on understanding interrelationships between people and technology and its lack of emphasis on understanding perceptions of technology, which was the interest of the researcher, SST was not selected as the foundational theory for the research.

SRT, originating from social psychology, was found to be more relevant and useful in understanding perceptions around technology. SRT guided the development of the theoretical framework which is discussed in Chapter 5. As the study progressed, through data collection and preliminary analysis, findings through SRT were showing connections to SST perspectives around interdependencies between people and technology. Further investigations into the findings fostered the development of the Theory of Sociotechnical Representations, which is presented in Chapter 7. Most of the literature and related discussion around the theoretical foundations of this research is found within the publication outputs from this thesis, hence these links are highlighted below in the relevant sections.

4.1. Social Representations Theory

SRT is a theory "used to study the social production of common-sense knowledge" (Gal & Berente, 2008, p. 134). SRT investigates how individuals co-construct perceptions (identified as representations in SRT) based on the common understanding of an object, idea or a concept within a social group when *new* situations emerge (Andersén & Andersén, 2014). This approach is therefore applicable to understanding the social dynamics around implementing big data analytics in the NZ healthcare sector in order to investigate how it may influence business-IT alignment. SRT has been used to investigate the social dimension of alignment in past research, ensuring its applicability in business-IT alignment studies (Dulipovici & Robey, 2013). It is important to highlight that this thesis presents two distinct uses of SRT: (i) SRT as a methodological lens in developing the theoretical framework (presented in Paper II, Chapter 5), and (ii) SRT as a foundational theory for TSR (presented in Paper III, Chapter 7).

4.1.1. History of SRT

SRT is a theory from social psychology developed by Serge Moscovici in 1961 which provides a holistic stance from which to understand "meaning making" within social groups. The initial description of social representations was published in a thesis written in French, which was later translated[10] to English in 2008 (Moscovici, 2008). Moscovici had published on SRT in English prior to that (e.g., Moscovici, 1963, 1984a, 1984b, 1985, 1988, 2001). In the early years, there had been some criticisms of SRT concerning consensus of group selection, role of language in a representation, resistance to the notion of self-identity and context specificity (Parker, 1987; Potter & Litton, 1985). Such criticisms were addressed by Moscovici himself or his followers which resulted in further improvement and explanation of SRT (Moscovici, 1985, 1988; Räty & Snellman, 1992). Over the past 50 years, SRT has been extensively used in many different fields, including: social sciences, media research, organisational change, IT implementation, and information security (e.g., Andersén & Andersén, 2014; Breakwell, 1993; Dulipovici & Robey, 2013; Gal & Berente, 2008; Nichols, 1981; Vaast, 2007; Wagner et al., 1999).

4.1.2. Social Representations

Representation of a phenomenon (a concept, object or situation) is the central idea of SRT. As Moscovici defines it, social representation is "the elaborating of a social object by the community for

[10] This translation is of the 2nd Edition which was a book published in 1976 and has substantial revision of the original edition of the thesis (Moscovici, 2008).

the purpose of behaving and communicating" (Moscovici, 1963, p. 251). This definition was later refined to mean that objects or concepts are constituted within a social group upon thoughts, feelings and behaviours of the actors (Wagner et al., 1999). Therefore, a representation can be characterised using three elements: (i) the object, (ii) the individual, and (iii) the group (Dulipovici & Robey, 2013). More detail about the notion of 'representation' and these three elements is provided in Paper II, presented in Chapter 5 (Section 5.5).

According to Moscovici (1984b) a social representation is formed through two component processes: (i) anchoring, and (ii) objectification. Objectification is the individual mapping of the phenomenon while anchoring refers to how the people around it (the group) influence the perception (Moscovici, 1988). Explanations about anchoring and objectification are provided in more depth in Paper II (Section 5.5) and Paper III (Section 7.5). Paper II also identifies big data as an emancipated representation (explained in Paper II, Section 5.5), and acknowledges the possibility of differences in perceptions about big data across the healthcare sector created by subsector levels (macro, meso and micro). Through this understanding Paper II presents the theoretical framework guiding this study, created using SRT as a methodological lens. The notion of SRT as a methodological lens to develop the theoretical framework is also presented in Paper II (Chapter 5). Additionally SRT is one of the foundational theories for TSR, developed as a result of the study (explained below in Section 4.3).

4.1.3. Use of SRT in Information Systems Research

Scholars have demonstrated an interest to bring SRT into IS research (Dulipovici & Robey, 2013; Gal & Berente, 2008). Reviewing studies in past IS research, Gal and Berente (2008) illustrated how such studies could make a more significant contribution if studied through SRT. Studying social representations brings not only methodological direction but also conceptual richness; therefore, it is favourable to be used for IS/IT research (Dulipovici & Robey, 2013; Gal & Berente, 2008).

Dulipovici and Robey (2013) applied social representation theory to explore how a Knowledge Management System (KMS) is perceived and embraced by different groups of people within an organisation. They discussed how the KMS implementations influenced business-IT alignment of the organisation through a social dimension lens. This notion of using SRT to investigate social dynamics of technology phenomena has been adopted within this thesis. Dulipovici and Robey (2013) investigated stakeholders' representations of KMS, and their findings were around groups within a selected organisational context. This thesis goes beyond organisational boundaries and explains representations and anchoring and objectification processes within broader groups of the healthcare sector.

4.2. Sociotechnical Systems Theory

In simple terms, Sociotechnical Systems Theory (SST) identifies social and technical subsystems as two interdependent subsystems that interact and influence each other (Bostrom & Heinen, 1977). While the technical subsystem includes the technological system, machinery, and business processes, the social subsystem is about roles and responsibilities of people involved in making use of the technical subsystem (Bostrom, Gupta, & Thomas, 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. More information on SST including identifying characteristics of the social and technical subsystems and highlighting the potential connections between SRT and SST is highlighted in Paper III (see Section 7.6).

4.3. Theory of Sociotechnical Representations

The Theory of Sociotechnical Representations is a novel theory developed as part of this thesis, through the integration of SST and SRT. The development of TSR was a rigorous and emergent process that was influenced by the researcher's understandings of the research, theoretical foundations, analysis of data, process of data analysis and reflections on the data analysis (Mintzberg, 2017). It was further shaped by journal paper reviewer comments for the first version of Paper III and countless discussions with the supervisors throughout the process of theory development.

TSR combines perspectives from IS literature about technology (through SST) with understandings of social psychology (through SRT) to explain the importance of understanding people's perspectives on technology for its successful implementation and use. TSR explains that any given technological phenomenon is interdependent with the people involved with it (policy makers, planners, implementers and users), and not just in what people do with it (roles, responsibilities and the like) but also in terms of how people perceive it (commitment, value and the like).

As explained in SST by Emery and Trist (1965) the social subsystem (people) and the technical subsystem (technology) interact with each other and are interdependent. Therefore, the roles and responsibilities of people depend on the capabilities of the technology in use. Nonetheless, because TSR merges SRT with SST perspectives, this interdependence of technology and people goes further than concrete properties like roles and responsibilities. TSR explains that the perception of technology (identified as sociotechnical representations) is vital in the success of a technological phenomenon. Paper III (presented in Chapter 7) further discusses the development and application of TSR in detail as a finding of this research. A comparison of TSR with existing IS theories that describe relationships between people and technology can be found in Appendix 10.

4.4. Chapter Summary

Presented as a summary, this chapter outlines SRT, SST, and TSR as the theoretical foundations of this thesis and links the foundations back to the appropriate papers within the thesis. More exhaustive descriptions of these theories appear in Paper II (Chapter 5) and Paper III (Chapter 7). Appendix 13 highlights the researchers interpretations of theory, framework and taxonomy.

Chapter 5: The Theoretical Framework (Paper II)

5.1. Overview of the Paper

This chapter presents Paper II, discussing the development of a theoretical framework which was used as the basis for data collection and analysis. As presented in Paper II, the development of the theoretical framework is methodologically guided by Social Representation Theory (SRT). The paper explains the novel approach of using SRT as the methodological lens in the development of a theoretical framework that can be used to conduct SRT based research.

As explained in Chapter 4, SRT is a foundational theory for the Theory of Sociotechnical Representations (TSR), which was developed as a result of data analysis and reflecting upon the research process. TSR was not conceptualised at the time of publishing Paper II. As presented in Paper III (Chapter 7), TSR can also be used in a similar manner to develop a theoretical framework to investigate alignment.

This paper was published in the Australasian Journal of Information Systems (AJIS) which is an open source journal[11]. The Editor-in-chief was contacted and confirmation was obtained to include the paper in the thesis.

[11] AJIS copyright information: https://journal.acs.org.au/index.php/ajis/about/submissions#copyrightNotice

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of the candidate:	Kasuni Weerasinghe
Name/title of Primary Supervisor	Professor David J Pauleen
Name of Research Output and full reference:	
Weerasinghe, K., Pauleen, D., Scahill, S., and Taskin, N. (2018). Development of a Theoretical Framework to Investigate Alignment of Big Data in Healthcare through a Social Representation Lens. Australasian Journal of Information Systems, 22.	
In which Chapter is the Manuscript/Published work:	Chapter 5
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	90%
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
This paper presents the theoretical framework of this thesis. The initial theoretical framework was presented by the candidate at a New Zealand Doctoral consortium as a poster presentation in mid-2015. Based on the comments received, an initial version of this paper was drafted for the Health Informatics New Zealand Conference in 2015 (HiNZ2015). The comments from the paper reviewers of HiNZ and well as the comments received after the candidate presented the paper were incorporated when developing the theoretical framework further. The first draft of the journal paper was shared with supervisors for comments and was refined based on their feedback. It was then submitted to the Australasian Journal of Information Systems; with comments from two blind reviewers the paper and the theoretical framework were further developed before publication.	
For manuscripts intended for publication please indicate target journal:	
Candidate's Signature:	
Date:	20 May 2019
Primary Supervisor's Signature:	
Date:	20 May 2019

Paper II: Development of a Theoretical Framework to Investigate Alignment of Big Data in Healthcare through a Social Representation Lens

5.2. Abstract

The aim of this paper is to develop a theoretical framework grounded in the literature, which can be used to explore the influence of big data on business-IT alignment in the healthcare context. Increasingly the availability of information systems in healthcare delivery and service management results in massive amounts of complex data that have the 3V characteristics of big data (i.e. volume, variety, velocity). Use of big-healthcare-data has been identified as bringing significant benefits to the healthcare sector from improved decision making through to population health analysis. Although the technical dynamics around big data such as analytics and infrastructure requirements are extensively researched, less attention has been given to social dynamics such as peoples' experience, understanding and perceived usefulness of this data. To address this gap, the paper uses social representation theory as a methodological lens to develop a theoretical framework to study the social dynamics around big data and its use in the healthcare context. The selected case for this development is the New Zealand healthcare sector and an approach using multi-level macro, meso, and micro analysis is taken. Use of social representation theory as a methodological lens to develop a theoretical framework is a novel approach. Such a theoretical framework will be useful as a foundation for carrying out on-going empirical research on big data to understand its influence on business-IT alignment in the healthcare context.

Key words: big data, healthcare, business-IT alignment, social representation theory, New Zealand healthcare, healthcare information systems.

5.3. Introduction

The growing use of information systems (IS) in the healthcare sector, alongside increasing patient populations, diseases and medication, is generating enormous amounts of unstructured and complex data that have the characteristics of ‘big data’ (Ward et al., 2014; Wyber et al., 2015). Big data is commonly known for its ‘3V’ characteristics: volume (large in size), variety (many different types of data), and velocity (availability of data in near real-time) (McAfee & Brynjolfsson, 2012). The analysis of big data, also known as ‘big data analytics’ is central to a revolutionary change in the business world (Davenport, 2013). Until recent times data driven approaches in healthcare to make use of large volumes of complex data were considered difficult, if not impossible, because available technology was not mature enough to handle such data (Wyber et al., 2015). However, recent technological developments have opened promising avenues for healthcare to make use of big-healthcare-data for more effective healthcare management and delivery (Mace, 2014).

As opposed to companies born in the digital era, traditional businesses face a greater challenge in integrating big data into their existing information technology (IT) ecosystems (Davenport & Dyché, 2013). Implementing big data capabilities in traditional businesses like healthcare requires the management of change in the socio-technical aspects of an organisation such as: analytics platforms, IT architecture, IT infrastructure, security measures, required expertise and organisational structure. Within the healthcare sector, change is identified as a key factor that influences business-IT alignment (Bush et al., 2009). The importance of aligning uses of big data with clear business objectives has been acknowledged (Bean & Kiron, 2013; Watson, 2014). However, no alignment studies could be found in the literature which investigate the influence of big data analytics on business-IT alignment in either the business or wider healthcare literatures.

Furthermore, as a recent IT phenomenon, big data research shows a bias towards understanding technical dynamics and as such social dynamics around big data use have been largely ignored, and are not adequately researched (Shin, 2015). Business-IT alignment can be examined through four dimensions: (i) strategic, (ii) structural (formal and informal), (iii) social, and (iv) cultural (Chan & Reich, 2007). As the least studied and most suitable to investigate, social dynamics – the social dimension of alignment – is posited in this paper to be the ideal platform to support the investigation of the social dynamics associated with the big data construct.

Healthcare systems differ from country to country; the selected case context for the development of the framework discussed in this paper is the New Zealand healthcare system. When studying complex systems such as healthcare, which are composed of different components, structural divisions, organisations, and actors it is useful to categorise the system into macro, meso and micro (MMM) levels (Dopfer et al., 2004). For this study, we use the MMM conceptualisation discussed for the New Zealand healthcare system by Scahill (2012b): macro – policy setting organisations, meso – funders and planners, and micro – service providers. Based on the findings from the literature on big data, business-IT alignment and healthcare, this paper discusses development of a framework that can be used to investigate the influence of big data on business-IT alignment in this context.

Social Representation Theory (SRT) (Moscovici, 1963) is used as a methodological lens that guides the development of the theoretical framework (see Figure 5.1). SRT provides a holistic stance allowing us to understand how individuals co-construct representations within a social group when new situations emerge (Andersén & Andersén, 2014). Representations are influenced by the pressure, opinions, social negotiation and collective sense-making of a group (Dulipovici & Robey, 2013). Studying social representations brings methodological direction to a study and is therefore appropriate to be applied to IS/IT research (Gal & Berente, 2008). Based on SRT, MMM levels are identified as social groups, which could have different representations of big data and thus impact alignment in different ways. Sub-groups such as organisations, departments or project teams within these levels are anticipated.

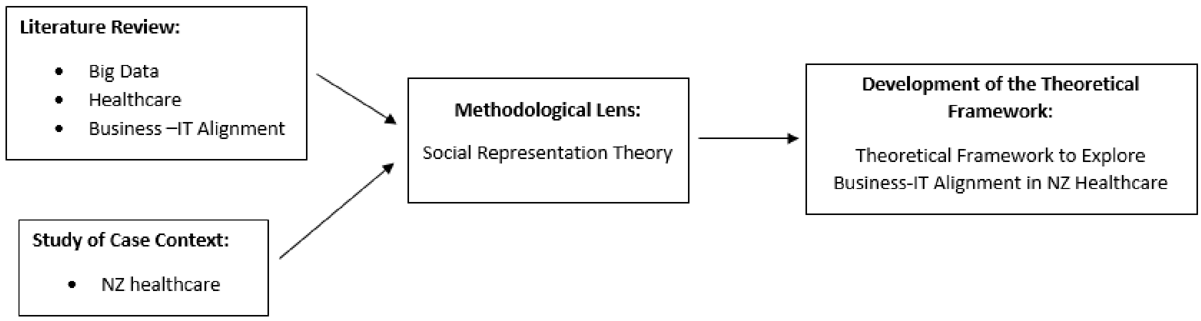

Figure 5.1: Use of methodological lens for the development of a theoretical framework

The term 'methodological lens' refers to the use of SRT as the methodology that guides the development of a theoretical framework (see Figure 5.1). The use of SRT allows not only the study of social dynamics but it also informs the structure of the theoretical framework in terms of what is to be explored and how this needs to be studied. In this manner SRT acts as a methodological lens as opposed to a theoretical lens. SRT has been used as a theoretical lens in past research (e.g., Dulipovici & Robey, 2013; Gal & Berente, 2008) but the authors are not aware of literature outlining the use of SRT as a methodological lens in developing a theoretical framework.

This paper discusses the development of a theoretical framework to study the influence of big data on business-IT alignment based on the New Zealand healthcare context. The process of developing such a framework could be applied to healthcare systems in other countries. Moreover, such frameworks can then be used as the basis for empirical studies which aim to develop theory.

In the following sections, we discuss the literature around big data, business-IT alignment and healthcare, highlighting the identified gaps, while SRT is discussed separately. A description of the NZ healthcare system is provided as the case under study. The aim of this paper is to posit a framework grounded in the appropriate literature, which will later be used to explore the influence of big data within the healthcare sector.

5.4. Literature Review

In this section we review the relevant literature on big data, the healthcare sector, and business-IT alignment to identify the gaps and build a foundation for the theoretical framework.

5.4.1. Big data

Based on past literature we define big data as enormous amounts of structured, unstructured and complex data produced by a wide range of computer applications (Emani et al., 2015; Groves et al., 2013; Shin, 2015; X. Wang & Huang, 2015). Phrases such as "massive amounts of data", "enormous growth of data" and "large data sets" are typically seen within the literature as defining big data (Chen et al., 2014; Eynon, 2013; Shin, 2015).

Three characteristics, known as the 3V's – volume, variety and velocity – are generally used to define big data and distinguish it from standard data (McAfee & Brynjolfsson, 2012; Russom, 2011). According to Gartner (2013) big data is "high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation" (para. 1). Watson (2014), McAfee and Brynjolfsson (2012), and Russom (2011) also characterise big data using these 3V's. Two additional V's – value and veracity – have also been identified, extending the characteristics of big data to 5V's (Emani et al., 2015; Saporito, 2013; Sathi, 2012). Based on the 5V characteristics Emani et al. (2015) state "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).

"Analytics" is an umbrella term for all data analysis applications (Watson, 2014, p. 1250) and refers to the use of tools to analyse data, not necessarily big data. In the business context, big data and analytics are often discussed together; they are sometimes even confused with each other with the terms being used interchangeably (McAfee & Brynjolfsson, 2012). Simply collecting and storing big data creates no value unless analytics is performed to make sense of this data to improve decision making within a business (Watson, 2014). However traditional analytic capabilities are not sufficient to process big data. Much more advanced infrastructure and analytical techniques are needed to glean insight from data that is high in volume, variety and velocity (Emani et al., 2015).

Big data or big data analytics "is not a single out-of-the-box product" (Loshin, 2013, p. 21). Making effective use of big data demands a specific combination of tools, techniques, and skills. Companies that were born in the internet era, such as Google, Facebook and eBay were built around big data (Davenport & Dyché, 2013), thus these companies possess the capabilities to manage and make use of it. With technological advancements and the commercialisation of the internet, companies that existed before the internet era (deemed traditional businesses) are also looking into opportunities to develop their businesses by effectively using big data (Bholat, 2015; Chawla & Davis, 2013; Davenport & Dyché, 2013; Dhawan et al., 2014).

To integrate big data, traditional businesses will need to consider making changes to their existing IT ecosystem. They will not only be working with big data but also with standard small datasets. Their Hadoop[12] clusters may run along with their IBM mainframes; big data analytics will be used to complement traditional analytics; their data scientists will be working together with quantitative analysts (Davenport & Dyché, 2013). Therefore, it is likely to be a challenge for traditional businesses to integrate the new (implementation of big data analytics) with the known (traditional data technologies in the IT ecosystem) (Bean & Kiron, 2013; Davenport & Dyché, 2013). In a traditional business it is expected that the use of big data would be associated with a wide range of social and technical aspects.

Technical dynamics (technology requirements of big data, challenges and opportunities of big data analytics and so forth) towards big data implementations have been extensively researched (e.g., Chen et al., 2014; Davenport, 2013; Dhawan et al., 2014; Jagadish et al., 2014). As a technology revolution itself, it is fair to say that big data research often shows a bias toward technical dynamics. Due to this

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

bias adequate research has not yet investigated the associated social dynamics surrounding big data and its use (Shin, 2015; Shin & Choi, 2015). In this paper, social dynamics refer to the users' understanding, commitment, and perceived value of big data, within a given context.

Among the scarce research that has been found exploring these humanistic factors in relation to big data analytics implementations, Shin (2015) extended the Unified Technology Acceptance and Usage Theory (UTAUT) with characteristics such as perceived usefulness and perceived ease of use extracted from the Technology Acceptance Model (TAM). Shin used this model to test the normalisation process of big data in Korean society. In his research, Shin (2015) discovered that big data implementations should be user centric and driven by the requirements of end-users. However, more research is needed to investigate the influence of social dynamics when implementing big data analytics in the traditional business context, because utilisation and management of big data is equally complex.

Traditional businesses should not implement big data just to be "trendy", but rather clear goals must drive the strategy and process (Loshin, 2013). A study undertaken by NewVantage Partners (2012) with Fortune 500 companies and federal agency leaders identified that business-IT alignment is crucial for the success of big data implementation. Business-IT alignment is achieved through business and technology (big data analytics) working together in harmony with proper understanding of business objectives and big data capabilities (Bean & Kiron, 2013; Loshin, 2013). Although the existing literature highlights the importance of business-IT alignment, studies investigating the influence of big data on business-IT alignment have not been found.

5.4.2. Business-IT alignment

For the past 30 years, alignment has been a major concern for IT practitioners and company executives (Kappelman et al., 2013). Similarly, for the past few decades many researchers have explored the importance of business-IT alignment in various business domains (e.g., Drazin & Van De Ven, 1985; Dulipovici & Robey, 2013; Henderson & Venkatraman, 1992; Luftman, 1996; Sabherwal & Chan, 2001).

And therefore, alignment has remained one of the dominant fields of IS research through the years (Chan & Reich, 2007; Sousa & Machado, 2014).

Cognates for “alignment” include terms such as fit, coherence, harmony, match, integration, congruence, relationship, gestalt, synergy and linkage. These all refer to the degree of fit between business strategy, organisational structure, IT strategy and IT infrastructure (Chan & Reich, 2007; Henderson & Venkatraman, 1993; Luftman, 1996). Researchers who study alignment typically study the fit between two or more of these four domains (Henderson & Venkatraman, 1992). Grounded in the literature, our definition of alignment refers to how well technology is utilised to bring value to a business. In the context of big data, this definition can be extended to describe how well technology is realised to make sense out of big data to create value. Creating value in the business context signifies achievement of business goals and objectives.

Over 30 years of research on alignment has led to conceptualising it in numerous ways. As such, Henderson and Venkatraman (1992) proposed the Strategic Alignment Model (SAM) to study this phenomenon. Their paper explores alignment between the domains of business strategy, business structure, IT strategy and IT structure. They identify three types of alignment: bivariate fit, cross-domain alignment and strategic alignment. Bivariate fit in the SAM model refers to investigation of alignment at any two domains of the model. Cross-domain alignment explains alignment across three of these domains. The third and most complex type of alignment defined in the SAM model is strategic alignment, which refers to giving “simultaneous or concurrent attention to all four domains” (Henderson & Venkatraman, 1992, p. 20). Reich and Benbasat (1996) conceptualise studying business-IT alignment through two dimensions: social and intellectual. Chan and Reich (2007), grounded in past alignment literature, identify a number of different dimensions of business-IT alignment including: strategic/intellectual, structural (formal/informal), social and cultural. Strategic/ intellectual dimension of alignment looks at fit between business strategy and IT strategy. Structural dimension investigates the relationship between an organisation’s structure and its IT. The social dimension is applied to understand how IT is perceived by different players within the organisation or the unit under study. The cultural dimension is the degree of agreement between the IT approach and the organisational culture. Chan and Reich (2007) also identified different levels of alignment as: organisational, operational, project, and individual. Although different, these conceptualisations seem to share similar characteristics, i.e. the social dimension has strong ties with the individual level (Chan & Reich, 2007).

As discussed above, research on big data shows a lack of empirical studies on the social dynamics associated with big data implementations. The ideal dimension to study social dynamics to understand alignment is the social dimension of alignment as it explores how the IT is perceived by different players at different levels of an organisation. According to Reich and Benbasat (1996, p. 58) the social dimension can be defined as "the level of mutual understanding of commitment to the business and IT mission, objectives and plans". Unpredictable social aspects may influence the business-IT alignment. The social dimension of alignment explores how users perceive and understand the IT implementation and how the technology is actually used (Dulipovici & Robey, 2013).

Compared to the strategic/intellectual and structural dimensions of alignment, fewer studies have been carried out to investigate the social dimension of alignment. Tan and Gallupe (2006) used a cognitive approach to examine the shared understanding between business and IT executives. They studied both the commonalities[13] and individualities[14] among people that contributed to shared cognition in an organisation. Dulipovici and Robey (2013) applied social representation theory to explore how a Knowledge Management System (KMS) is perceived and embraced by different groups of people within an organisation and discussed how the KMS influenced business-IT alignment of the organisation.

[13] Commonalities: Similarities in individuals' cognition.

[14] Individualities: Differences in individuals' cognition. This reflects the diversity in values and beliefs of individuals in a team.

To address the identified gaps in the literature, this paper incorporates the social dimension of alignment and examines how social dynamics may influence the alignment of big data within the traditional business setting. Healthcare is selected as the context to carry out the research as it fits well with the notion of traditional business and it is also one of the fields in which big data has been identified as being beneficial (Groves et al., 2013). This provides the basis to investigate alignment in terms of how implementation and technologies around big data are perceived to be creating value and how knowledgeable actors are of the business objectives of such implementations, across a country's healthcare sector.

5.4.3. Transformation of healthcare with Information Technology

Until recently the quality of healthcare delivery has been largely dependent on the intuition and intelligence of clinical practitioners. Healthcare services have been successfully delivered because the clinical practitioners within these systems "are bright, hard-working and well-intentioned – not because of good system designs or systematic use of data" (Celi et al., 2013, p. 1157). However, recent research shows that there is a growing interest in using data to aid clinical practitioners in healthcare delivery and service management (Mace, 2014; Patil et al., 2014; Tormay, 2015).

The global healthcare industry faces significant challenges as populations grow and age – with more chronic disease, resources are constrained and systems are under significant pressure to perform (Gauld, 2009). As a result, internationally health systems have undergone major changes in the past few decades to address the call for enhanced patient care and improved outcomes (Anderson (Anderson, 2007; Bush et al., 2009; Paré et al., 2008; Patil et al., 2014; Sicotte et al., 2006). IT and deployment of information systems (IS) is identified as central to this transformation of healthcare systems (Bush et al., 2009). These information systems focus on improving patient care, service quality, operational efficiency and patient satisfaction (Peng et al., 2014). Such targets are achieved by reducing medical errors, streamlining clinical processes, increasing productivity and controlling healthcare costs (Anderson, 2007; Kannry, 2011). The information systems used across health are key in creating healthcare data.

A wide range of clinical and operational information systems have been introduced (Ward et al., 2014) and used effectively within healthcare in many developed countries (e.g. USA, New Zealand, and Canada). Based on their use, these information systems are classified into two types: (i) Clinical IS (CIS), and (ii) Administrative IS (AIS) (Menon et al., 2009).

In their classification Menon et al. (2009) identify IS assisting primary value chain activities of healthcare as clinical IS; thus, these can be identified as information systems used in healthcare delivery. These systems capture, store and analyse clinical data to provide improved services in healthcare delivery (Paré et al., 2008). Electronic health records (EHR), laboratory information management systems, picture archiving and communication systems are some examples of clinical IS (Menon et al., 2009; Ward et al., 2014). In addition to aiding professionals in clinical practice, CIS also provide information for strategic planning (Glandon et al., 2008).

Also identified as operational management systems by Glandon et al. (2008), administrative IS are used for healthcare administration and service management. These information systems are used to facilitate the secondary value chain activities (support activities) of healthcare (Menon et al., 2009). Thus, they support non-patient care activities of healthcare organisations (Glandon et al., 2008). Some examples of these information systems are human resource management systems, supply chain management systems and payroll systems, similar to those in any other organisation (Glandon et al., 2008; Menon et al., 2009; Ward et al., 2014).

In addition to these stand-alone discrete information systems, complex integrated systems that combine a variety of CIS and AIS can be found across healthcare sectors. Some examples of these integrated information systems are Hospital Information Systems (HIS) (Ahmadian et al., 2014) and General Practice Information Systems (GPIS) (Yusof et al., 2008).

5.4.4. Big data in healthcare

The increasing use of EHR and other IT deployments in healthcare is contributing to the rapid growth of healthcare data (Bates et al., 2014; Patil et al., 2014). Given population growth and the rising numbers of diseases and medications, large amounts of complex data are being generated in the healthcare sector (Wyber et al., 2015). Due to the complex nature of this sector, data generated by information systems typically have characteristics (i.e. the 3V's) of big data. Although data with the 3V characteristics of big data have been generated within the healthcare sector for some time, making use of this data in healthcare has been considered complex, if not impossible, because the available technology was not mature enough to handle such data (Wyber et al., 2015).

Recent developments of technology around big data analytics are opening up promising avenues for the healthcare sector to make use of big-healthcare-data for improved healthcare delivery (Mace, 2014; Nash, 2014; Tormay, 2015; Wyber et al., 2015). For example, Hadoop clusters introduced as a result of the big data phenomenon can be used to store massive amounts of data in an economic fashion which was not previously possible. Additionally, the development of data science skills has produced people who are capable of making sense of large and complex datasets generated in near real time. Hence, with the recent improvements to technology, the healthcare sector is now capable of deriving accurate data (veracity) to create value through big data analytics for improved healthcare delivery (Wyber et al., 2015). Consequently, although big data is not new for healthcare, making use of big data and creating value (through big data analytics) for improved healthcare delivery and management is an innovation that healthcare sectors globally are grappling with.

Nonetheless, compared to other industries such as retail merchandising and banking, the uptake of big data in the healthcare sector has been slow and limited (Bates et al., 2014; Groves et al., 2013). On top of the complex nature of the healthcare system, resistance to change by healthcare practitioners, uncertainty of returns on capital investment, and privacy concerns are identified as possible reasons for this lag (Groves et al., 2013). However, due to increasing IT expenditure and the enormous amounts of under-utilised and complex data, the healthcare sector needs more efficient practices, research and tools to analyse big data and optimise its use (Chawla & Davis, 2013; Groves et al., 2013).

Recently, developed countries have recognised the importance of big data analytics for healthcare (Prewitt, 2014). An estimate by McKinsey & Company reports that with the use of big data analytic tools and technologies for healthcare, the United States can save an extraordinary $300 billion to $450 billion per year (Groves et al., 2013). According to experts, harnessing big data for knowledge could have significant implications for the healthcare sector. Predicting disease outbreaks, detecting gaps in care delivery, discovering the most effective treatments, identifying patterns related to medication side effects and hospital readmissions, improving pharmaceutical research, and personalised medicine are some of the identified benefits of big data analytics for healthcare (Groves et al., 2013; Nash, 2014; Tormay, 2015).

Because the healthcare system falls under the category of traditional business, implementing big data analytics could transform the existing IT ecosystem of the healthcare sector. As discussed previously, research outside of the healthcare sector has recognised that big data initiatives to succeed they need to be aligned with business objectives. Thus, although the healthcare sector is interested in using big data, for such initiatives to succeed, the basis for big data implementation should be driven by clinical and/or administrative healthcare goals and objectives.

5.5. Social Representation Theory as a Methodological Lens

Social representation theory (SRT) is used as a methodological lens for guiding and structuring the proposed theoretical framework of this paper. By methodological lens, we mean a lens that methodologically guides development of a framework. Dulipovici and Robey (2013) applied SRT to frame the investigation of how social representation of a new Knowledge Management System (KMS) in a government agency influenced business-IT alignment. Our paper adopts their approach but extends it with the aim to develop a theoretical framework using SRT to frame the study of social dynamics associated with implementing big data analytics in the healthcare sector, in order to investigate how it may influence business-IT alignment. Use of SRT in this manner forces structure and direction upon the theoretical framework, hence acting as a methodological lens. Adopting SRT as a methodological lens allows the humanistic aspects of business-IT alignment to be considered in depth.

SRT is a theory from social psychology developed by Serge Moscovici in 1961, which provides a holistic stance to understand meaning making within social groups. Over the past 50 years, SRT has been extensively used in many different fields including social sciences, media research, organisational change, healthcare, IT implementation, and information security (e.g., Andersén & Andersén, 2014; Breakwell, 1993; Dulipovici & Robey, 2013; Gal & Berente, 2008; Nichols, 1981; Vaast, 2007; Wagner et al., 1999).

Representation of a phenomenon (concept, object or a situation) is the central idea of the SRT. As Moscovici (1963, p. 251) defines it, social representation is “the elaborating of a social object by the community for the purpose of behaving and communicating”. This definition was later refined to mean that objects or concepts are constituted within a social group upon thoughts, feelings and behaviours of the actors (Wagner et al., 1999). Therefore, a representation can be characterised using three elements: (i) the object which is represented; (ii) the individual who builds the understanding; and (iii) the group to which the individual belongs (Dulipovici & Robey, 2013).

Gal and Berente (2008, p. 134) outline SRT “as a socio-cognitive framework used to study the social production of common-sense knowledge. It offers a set of concrete conceptual tools for addressing the social context from which shared meanings emerge, and for capturing the temporal nature of socio-cognitive activity”. Fundamentally, SRT denotes how individuals co-construct representations based on common understanding of an object, idea or a concept within a social group when new situations emerge (Andersén & Andersén, 2014). The representation is therefore influenced by the pressure, opinions, social negotiation and collective sense-making of the group (Dulipovici & Robey, 2013). Due to these continuous social interactions, representation of the object is constantly developing.

As it provides methodological direction (Dulipovici & Robey, 2013) SRT is ideal for use as a methodological lens. Reviewing studies in past IS research, Gal and Berente (2008) illustrated how such studies could make a more significant contribution if studied through SRT. Studying social representations brings not only methodological direction but also conceptual richness; therefore, it is favourable to be used for IS/IT research (Dulipovici & Robey, 2013; Gal & Berente, 2008). Additionally Andersén and Andersén (2014) point out that SRT is much more useful when examining situations concerning organisational change. As explained, big data has the potential to change many aspects of a traditional business. Hence, SRT is identified as an appropriate methodology to guide an alignment study of big data around social dynamics.

According to Moscovici (1984b) the social representation process emerges through two component processes: (i) anchoring, and (ii) objectification (as cited in Dulipovici & Robey, 2013). Anchoring is the symbolic classification of a new phenomenon based on past experience, common background and aspirations (Gal & Berente, 2008). Anchoring will develop a common understanding of the phenomenon within the group. Through anchoring the group classifies the unfamiliar and represents it in a known arrangement (Wagner et al., 1999). Objectification supports the classification (anchoring) by mapping it with examples, images, models, methods or metaphors. It is the individual interpretation of the novel concept by each individual member of the group (Dulipovici & Robey, 2013; Gal & Berente, 2008). Therefore these two processes complement each other, as anchoring being a social process promotes stability, and objectification being a cognitive process prompts change (Dulipovici & Robey, 2013). Consequently, social representations are continuously shaped within the social group. Figure 5.2 illustrates how we conceptualise this understanding of anchoring, objectification and the formation of a representation within a social group.

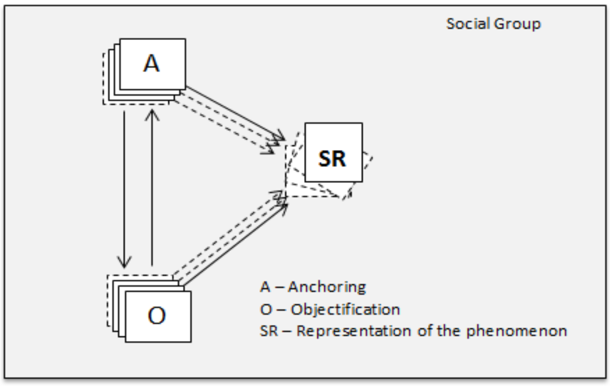

Figure 5.2: Conceptual illustration of SRT

Based on this, it is understood that the concept of big data and its use may be perceived within a socially constructed group through anchoring and objectification. Objectification of the notion of big data and its potential by an individual will be influenced by the individual's background, knowledge, past experience and understanding. Objectification will then influence anchoring of big data analytics within the group and result in constructing a representation.

The boundaries of a social group were broadly explained in the early definitions of SRT (Moscovici, 1963). For example, society, the community or the public was seen as the social setting that influences a social representation (Andersén & Andersén, 2014). But the most recent uses of SRT divide the population into much smaller entities such as organisations (Gal & Berente, 2008), and departments within organisations (Dulipovici & Robey, 2013). A group may consist of two or up to an infinite number of members (Wagner et al., 1999). Moscovici (1988) defines three types of representations based on formation of social groups: (i) hegemonic, (ii) emancipated, and (iii) polemic (see Table 5.1). Thus as a theoretical underpinning to an empirical study of social groups, the representation to be studied can guide the selection of the group.

Table 5.1: Types of representations based on formation of social groups

(based on Moscovici, 1988, p. 221)

Hegemonic Representation	A straightforward representation shared usually by a highly structured group (e.g. city). This type of representation is already established and is not produced by the group.
Emancipated Representation	A representation formed within a group. It could be influenced by several representations of sub-groups within the group; collectively the representations of sub-groups influence the representation of the phenomenon within the group.
Polemic Representation	Mutually exclusive representations within a group due to conflict and social controversy. For example Marxism is a polemic representation that requires studying groups with contrasting perceptions of it.

The phenomenon of big data analytics is not a known representation in the healthcare context; therefore, it is not a hegemonic representation. Nor is it known to have a conflicting identity with a polemic representation. Thus, based on Moscovici's definition of types of representations, we suggest that implementing big data analytics falls under the classification of an emancipated representation. It is anticipated that big data analytics could be socially constructed within a group, which may have sub-groups that contribute to the representation.

5.6. The Case: New Zealand Healthcare Sector

The healthcare systems of countries across the world operate in different ways. We have selected New Zealand as a case to develop the theoretical framework. It is our expectation that the process of analysis of the influence of big data on alignment developed here will be applicable to other countries with similar health systems.

It is estimated that NZ spends about 10.3% of its GDP on healthcare, with 31% of this spent on acute in-patient care, 34% on out-patient care, 15% on long term care, 11% on medical goods and 10% on collective services[15] (OECD, 2013). These services are provided to New Zealanders through a multifaceted system governed by the Ministry of Health (MoH). The health and disability system of NZ

[15] Collective services include health education, training of health professionals, administration services and food, hygiene and water control

is funded nationally, planned regionally and delivered locally (Pollock, 2012). The MoH "provides whole-of-sector leadership" to the NZ healthcare system (Ministry of Health, 2014a, p. 1). High level health policy development is undertaken by the office of the Minister of Health with input from Cabinet and the government, to set strategic direction for the healthcare sector. Although the MoH has a greater influence in healthcare policy development, the National Health Board, Health Workforce New Zealand, the National Health Committee, and other ministerial advisory committees also support and advise the Minister (Ministry of Health, 2011b, 2014a).

Organisations under the MoH are divided into 2 categories: (i) organisations that support healthcare delivery, and (ii) business units. The key organisations for healthcare delivery include the District Health Boards (DHBs), Primary Health Organisations (PHOs), Crown Entities and Agencies, National Ambulance Sector Office, Non-governmental Organisations (NGOs), Public Health Units, and professional and regulatory bodies. Apart from the organisations supporting healthcare delivery, several business units also support the MoH focusing on a variety of functions and areas. These business units are composed of: (i) client insights and analytics, (ii) strategy and policy, (iii) service commissioning, (iv) protection, regulation and assurance, (v) technology and digital services, (vi) finance and performance, (vii) people and transformation, (viii) office of the Director-General, (ix) Maori leadership, (x) chief nursing officer, (xi) chief medical officer and chief pharmacy advisor as well as (xii) critical projects (Ministry of Health, 2016b).

Due to the inter-relationships between many different organisations, actors, and structural divisions of the NZ healthcare system this can be identified as a complex health system. Biological, socio-natural or socio-technical systems with more than three coupled components are likely to demonstrate chaotic behaviour under certain circumstances and are then identified as complex systems (Liljenström & Svedin, 2005). When studying such complex systems, it is best to take an approach through the macro-meso-micro perspective of the system to compartmentalise, reduce complexity and obtain a holistic understanding (Dopfer et al., 2004). The macro-meso-micro (MMM) model can be used to conceptualise in a variety of ways dependent on the purpose of the study. Additionally, MMM levels will provide an ideal basis upon which groups can be segmented in order to study social representations.

Within the NZ healthcare sector several authors propose MMM models with slightly different but related conceptualisations. Cumming (2011) conceptualises macro as a single organisation, or a body that oversees organisation to organisation collaboration, meso as activities that promote work between organisations – e.g. clinical partnerships (Mays, 2013), and micro as individual practitioners. From a slightly different view Scahill (2012b) conceptualises policy setting organisations as macro, funders and planners as meso, and service provider organisations and the individuals within them as micro. Following Scahill (2012b) we define MMM around the use of big data as:

- Macro – Government bodies who set the strategy direction and policies that govern IT implementation, particularly implementations utilising big data fall under the macro level. Therefore, the business units as well as the MoH are conceptualised as the macro level bodies. In the NZ context apart from providing strategy direction the MoH and its business units are currently interested in initiating implementations around big data[16]
- Meso – The planners and funders meso level symbolises organisations that follow the guidelines of the macro bodies and plan to initiate (or have initiated) big data analytics. The organisations that support healthcare delivery can be mapped to the meso level (e.g. DHBs, PHOs). In the NZ context these organisations are likely to work with the government (e.g. DHBs) or have their own plans and initiate projects around big data (e.g. PHOs).[5]

[16] Based on preliminary interviews

- Micro – Service provider organisations (e.g. hospitals, general practices) and individuals (e.g. general physicians, clinicians) within those organisations are identified as the micro level. Big data is typically generated at this level and has considerable potential to be utilised in this environment. However, it is observed that the use of big data does not solely lie with service provider organisations and their individual members. Organisations that fall under the macro and meso umbrellas are keen to make use of big-healthcare-data generated at the micro level for better planning and service delivery within the NZ health system.[5]

Figure 5.3 provides a conceptualisation of the MMM levels in NZ healthcare and how the notion of big data fits within each level.

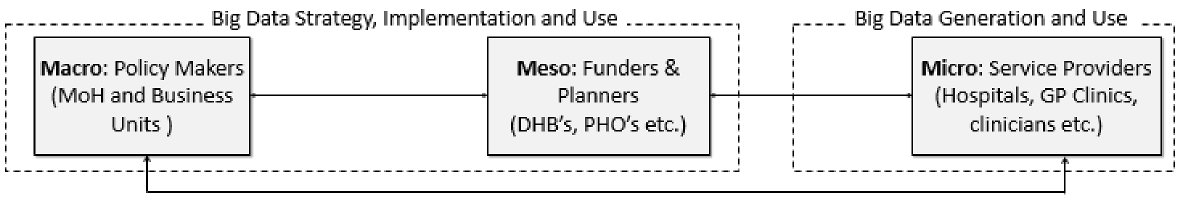

Figure 5.3: Conceptualisation of MMM in NZ Healthcare

Table 5.2 presents the elements of SRT mapped to the NZ setting. Big data is the construct of interest for the study, however depending on the group (MMM level) that is being studied at that instance, big data analytics sit within planning, implementation or use stages. The groups are mapped to the identified levels of healthcare (MMM). Individuals vary depending on the level (group) under study.

Table 5.2: Elements of social representation theory for proposed research

Object	Big data
Group	Macro, meso, micro levels (each level is considered as one social group)
Individual	Macro – Directors, strategy level roles of MoH and business units; Meso – Managers of healthcare planning and funding bodies; Micro – The users of systems that generate data and analytics outcomes

Although based on SRT MMM are identified as social groups to study, it may be that there are unseen sub-groups within them. These sub-groups could be influencing representation of big data within each level (group) which can only be identified through investigation. However, within each of these socially constructed groups (MMM), a social representation of big data will be uniquely constructed with or without the influence of sub-groups.

New Zealand's application of IT within the healthcare sector is among the highest in the developed world (Protti & Bowden, 2010). In particular, the primary healthcare sector makes extensive use of information systems (Atalag et al., 2013). These information systems aid the clinicians in many tasks varying from administrative to management of patient care delivery as well as the associated clinical activity required to achieve this. Administrative IS are used for appointment scheduling, billing and financial administration. Clinical IS such as EHRs, ePrescriptions, eReferrals, and LIMS are used by clinicians to monitor patient history, obtain the latest medicine updates, refer patients to specialists, receive test results and so forth (Atalag et al., 2013; Pollock, 2012). Therefore, CIS and AIS are effectively used across meso and micro levels of the NZ health sector.

Additionally, information systems are used in hospitals to aid clinicians in healthcare delivery and hospital management. The IS applications that are used in NZ hospitals include clinician portals, patient management systems, systems for admission management, systems for management of transfers and discharges, bed management, outpatient management, laboratory ordering and result reporting systems, digital radiology reporting systems and systems to manage specific departments such as the intensive care unit, emergency department and operating theatres (Pollock, 2012). Use of such information systems rapidly generates different types of healthcare data in large volumes; therefore, it is likely to have the characteristics of big data (Andreu-Perez, Poon, Merrifield, Wong, & Yang, 2015). A recent study undertaken by the National Institute for Health Innovation (NIHI) found that most datasets generated by information systems across the NZ healthcare sector are able to be linked through the National Health Index (NHI) and thus can be used together for large-scale data analysis (Atalag et al., 2013). This provides some evidence that NZ has taken a step towards implementing big data analytics and there is significant opportunity to further perform analyses within and across these multiple large data sets.

In addition to this, the recently revised NZ Health Strategy (Minister of Health, 2016) identifies the "Smart system" as a key action area. The concept of a smart system is to collect well-organised data from across the healthcare system as well as from other sources, to be able to achieve better health outcomes as well as to share information with other government bodies in order to achieve inter-sectorial government-wide goals (Minister of Health, 2016).

Although some work around the use of big data analytics is available within the global healthcare sector, published research is very limited in the NZ context. At the time of writing Tormay (2015) and Atalag et al. (2013) are the only publications that could be found in the NZ setting which directly discuss big data in the NZ healthcare context. Neither of these two publications addresses social dynamics nor investigates business-IT alignment.

5.7. Discussion: The Theoretical Framework

5.7.1. The Framework

This section describes the theoretical framework, Big Data Alignment using SRT (BA-SRT) (see Figure 5.4), that has been developed from the findings in the literature on business-IT alignment, big data and the healthcare sector. SRT as the methodological lens guided the development of this framework[17]. As the framework was developed by considering the structure of the NZ healthcare sector it is ideal for use in that setting. The theoretical framework guides investigation of internal alignment by looking at government/business objectives and big data using the social dimension as a lens at each sector level (macro, meso and micro). SRT enforces studying social representations of big data at each level to understand alignment through a social dimension lens. Using the developed

[17] Formation of groups and their functions are informed by the preliminary interviews conducted.

framework in a different country context may require the framework to be adapted dependent on whether it is a similar health system.

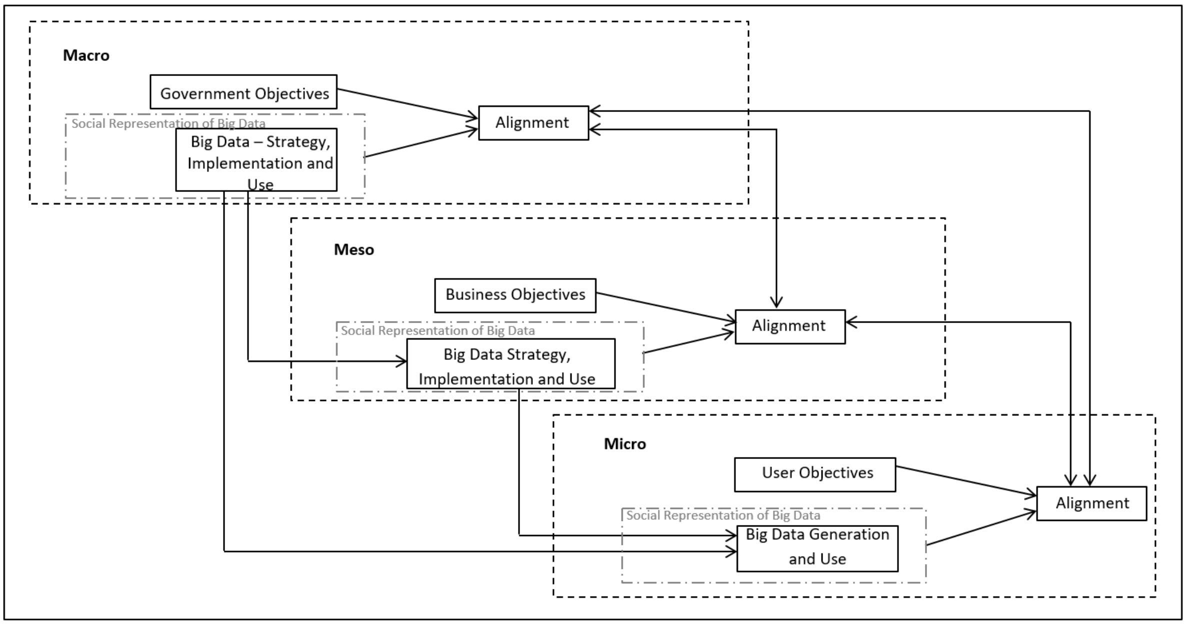

Figure 5.4: Big Data Alignment using SRT (BA-SRT)

As shown in the framework above (see Figure 5.4), although big data is generated at the micro level by the clinical interface, big data can be used across the healthcare sector for strategy and policy making, planning and funding, as well as for clinical decision making. Both macro and meso level organisations can be identified for implementing strategies and plans for successful use of big data, along with their involvement in the implementation of big data-related tools. Big data can be used for strategy and planning decisions at both macro and meso levels (e.g. population health). Therefore, the framework can be used to guide researchers looking into alignment, strategy, implementation and use of big data at the macro and meso levels. Big data generation and use can also be studied simultaneously at the micro level using this framework.

5.7.2. Advantages of applying this framework

This framework can be used as a guide to explore the influence of big data on business-IT alignment using the social dimension of alignment. As Shin (2015) suggests, the use of big data involves social practices and so there needs to be more focus on integration with the social setting. Moreover, investigating the social dimension will facilitate understanding of how big data is integrated amongst the social elements of healthcare planning and delivery. The framework that has been formulated in this synthesis provides clear guidance through understanding: (i) what to study (big data strategy, implementation, generation and use at respective levels), (ii) where to study (MMM levels), and (iii) whom (Policy makers, planners and funders and clinicians) to study when researching big data in the NZ context.

Achieving and sustaining alignment is not as simple as ensuring effective formulation of big data plans and strategies and maintaining consistency with documentation, but rather the execution of IS strategies, which includes user interactions (Dulipovici & Robey, 2013). Using a social dimension lens to explore business-IT alignment, we can study how strategies, plans, projects and implementations around big data are perceived by different players at different levels within the sector. This brings a focus to the human interaction with technology from a sector perspective. It is important to know how plans around big data are interpreted by different players in organisations and bodies throughout the sector. Although documented IS strategy (big data plans) could be properly aligned with the documented business strategies, the situated use could influence alignment differently. The situated use of IS involves the subjective understanding of a technological concept (i.e. big data analytics) (Dulipovici & Robey, 2013). Thus it is important to look at the level of understanding and commitment to big data across healthcare organisations by key stakeholders. In order to do so, we propose that it is appropriate to look at alignment through a social dimension lens, to gain the greatest insights on the influence of big data on business-IT alignment. Our theoretical framework recommends studying social representations of big data analytics, allowing a more humanistic approach.

The developed framework will enable researchers studying business-IT alignment to engage with all levels of the healthcare sector, from policy makers, planners, funders to practitioners. The framework therefore specifically encourages sector wide alignment, ensuring a holistic understanding of the situation of big data within the NZ healthcare sector. It is also important that alignment is present internally (within the healthcare organisations) as well as externally aligning to the government (e.g. NZ health strategy) and other funders' plans. As such we propose alignment should be studied internally within healthcare organisations as well as externally across the sector. Given the strategic refocus of the NZ Health Strategy (Minister of Health, 2016) on refining the health strategy to set new directions for the next 10 years, it will be beneficial to understand how the NZ healthcare sector is reacting to the notion of big data analytics and its developments.

As our framework takes a holistic view of alignment we believe it provides a sound platform for studying business-IT alignment. Given that big data is a high profile phenomenon within the healthcare context in NZ and internationally, it is important to examine the perceived effect of these big data initiatives on business-IT alignment.

5.7.3. Limitations of the Framework

An identified limitation of our theoretical framework is that it has been formulated to meet the needs of a big data study in the New Zealand healthcare context. Based on the interpretative nature of the study and the fact that social constructions will inform the findings, it is expected that this framework is not generalizable to other healthcare contexts in its current form, and this is identified as a pitfall. Countries with similar healthcare settings may wish to adopt this framework with minimal change, but for the large majority of nations this framework will require modification based on the structure of the system and how much their system differs from the New Zealand context. However, it is expected that within most developed countries where there is a structured health system in place the macro, meso and micro levels should be able to be identified.

Another identified pitfall of the developed theoretical framework is that although it encourages studying health sector wide alignment, it has not engaged the technology vendors that work within the system and alignment with these groups must be investigated in future research. In such cases, researcher will need to analyse the similarity of the external party (such as IT vendor) with an identified level (i.e. meso) and amend the framework as required.

5.8. Conclusion: Implications, Recommendations and Reflections

There is much interest in the phenomenon of big data analytics in the modern business world. The big data construct has been discussed and researched largely through technical dynamics such as analytics, security and technological infrastructure requirements. Much less research has been reported in the area of social dynamics and the influence of these dynamics on big data strategies and use: i.e. the human side of IS implementation. Therefore, research on social dynamics such as experience, perceived value and usefulness is an important contribution for contemporary big data literature and especially in the inherently complex healthcare sector. In addition to the context, the study of social dynamics is complex, particularly in the case of a construct such as big data. As such, sound planning and a theoretical foundation is required before entering the field in order to carry out an empirical study.

In addition, in this paper we discuss the development of a theoretical framework that is founded on and grounded in the literature, which will be used to guide this research on social dynamics associated with the big data construct. SRT was used as a methodological lens to guide the development of a theoretical framework. Big data research suggests that alignment of big data to business goals and objectives is key to the success of big data initiatives. Using SRT as the methodological lens to study social dynamics, the developed framework identifies the groups to be studied and sub-groups within the groups to study. This will act as a guide to an empirical study which aims to investigate the complex nature of business-IT alignment around big data use in the NZ healthcare context.

The development of a theoretical framework to study the influence of big data on business-IT alignment through social representations has two implications: on the one hand, it forces structure and direction to study the identified gaps in the literature. On the other, it aims to investigate how social dynamics around on-going and planned big data projects influence alignment between business and IT in the healthcare context. To date, such a framework is not available and such studies have not been conducted in the New Zealand or global context.

A study using the developed theoretical framework will capture a broader view of the NZ healthcare sector and its players' understandings and perceptions that will lead to actions around big data use. Therefore, this framework and subsequent study findings has the potential to influence policy and practice. Additionally, understanding social dynamics around big data at each level outlined in the framework (Macro, meso, micro) will facilitate investigation of alignment of these social dynamics across the sector levels. Because big data is a phenomenon that runs through all the sector levels (i.e. generated at the clinical interface but can be used by policy makers, planners and funders) it is important that optimal inter-sector alignment is achieved across the health sector. Research studies using this theoretical framework will identify the current level of inter-sector alignment between levels (macro, meso, micro) that will better inform policy makers, planners, funders as well as the practitioners of the current status of big data and its possible implications.

The use of SRT as a methodological lens is a contribution of this paper. Using theory to explain and simplify phenomena is common practice (Mintzberg 2005). In this paper, we have used theory to focus and simplify the literature into a theoretical framework, which can then be used to explain phenomena. We believe this is the first time SRT has been used in this fashion. We recommend that theories like SRT can provide methodological guidance to studies and are capable of providing a basis for the development of theoretical frameworks, which can then be used in empirical studies.

This review of the literature provides an understanding of the gaps to be filled and the direction our future study will take. However, to go a step beyond, having a methodological lens to pull literature and context together to provide a solid foundation in the form of a preliminary theoretical framework is desirable for this research.

Our theoretical framework was developed in the context of the NZ healthcare sector and generalisability will be limited. Varying degrees of modification may be required if applying this framework to other countries' healthcare contexts, dependent on how similar the systems are. Despite this, the applicability of SRT as a methodological lens to investigate social dynamics around big data in a healthcare context is a novel approach which any healthcare sector should be able to benefit from. We recommend the use of SRT to study social dynamics around big data, beyond the healthcare sector. Other government sectors, such as education and transportation, may be able to adopt our framework, however considering sectorial differences there may be a need for amendments. Additionally, the healthcare sector can use the developed framework to investigate the introduction of novel technological concepts with minimal change to the developed theoretical framework.

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Chapter 6: Methodology

This chapter begins by introducing the ontological and epistemological stance of the researcher. It explains the research design and the research approach in conducting the qualitative exploratory study framed by the identified research question. The methods used for data collection and data analysis technique are also discussed in this chapter. Issues and challenges faced throughout the process are highlighted where necessary.

6.1. Research Philosophy

Research is an activity carried out by a researcher to understand a phenomenon (Vaishnavi & Kuechler, 2004). Considering the researcher's ontological and epistemological assumptions about the world is important to understand how research is carried out (Hudson & Ozanne, 1988) and why things are done in a certain way (Hussey & Hussey, 1997). These philosophical assumptions are the basis for the researcher's choice of theories, methodology and methods of data collection and analysis of the research (Creswell, 2013). Therefore, it is important to understand the researcher's epistemological and ontological stance to determine the methodology (Hussey & Hussey, 1997).

Ontology refers to the nature of reality as understood by the researcher, and therefore makes assumptions about the reality of the phenomenon being studied (Hudson & Ozanne, 1988). Depending on how a researcher interprets reality, they are seen as subjectivist or objectivist. Subjectivism and objectivism are the two extremes of ontological assumptions (see Figure 6.1). Subjectivists see the world as a projection of a person's consciousness, while objectivists see the world as a concrete structure independent of their actions (Morgan & Smircich, 1980). Objectivists believe social reality is external to the researcher and therefore there is only one reality (Collis & Hussey, 2014). This notion of a single reality does not align with this researcher's understanding of reality, and thus is not the basis of ontological assumptions for this thesis. The researcher believes that reality is constructed by individuals as opposed to being external to an individual.

While subjectivism and objectivism are two extremes of ontological assumptions, social constructionism falls in between, closer to subjectivism (as shown in Figure 6.1). Bryman and Bell (2015) further highlight that in social science research, social constructionism is the opposite of objectivism. Social constructionism (a subjective view of reality) understands the world as being constructed through interactions and interpretations of everyday life (Morgan & Smircich, 1980). Based on a social constructionist perspective, social actors influence the shaping of social phenomena and their meanings (Bryman & Bell, 2015).

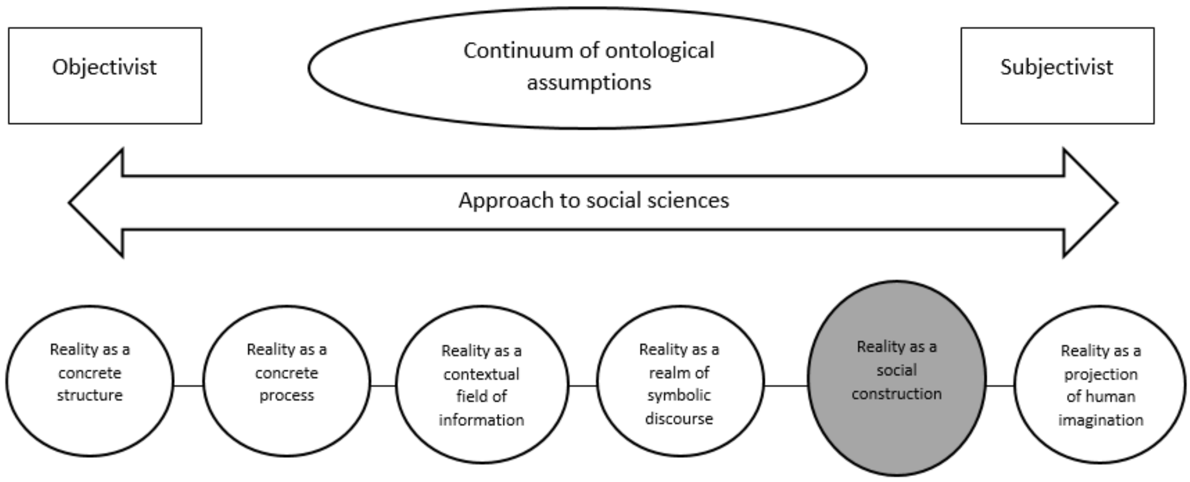

Figure 6.1: Ontological assumptions

(adopted with permission from Scahill, 2012a)

Understandings of social constructionism align well with the researcher's ontological assumptions, and therefore act as the ontological basis for this thesis. Employing social constructionism suggests the need for an interpretative investigation to explore alignment of big data. The views of social constructionism therefore lay the foundation for the theoretical framework (presented in Chapter 5) created to investigate differences in perceptions about big data across the sector.

A researcher's ontological assumptions lay the ground for the epistemological perspective of their research (see Figure 6.2) (Bryman & Bell, 2015).

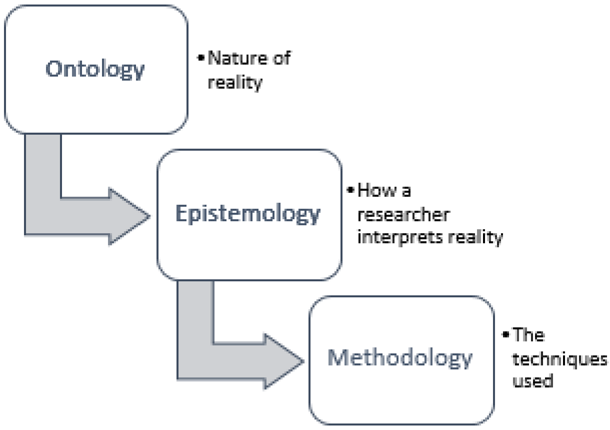

Figure 6.2: Relationship between Ontology, Epistemology and Methodology

On the other hand, epistemology is "a way of understanding and explaining how we know what we know" (Crotty, 1998, p. 3). Therefore, epistemological views relate to the nature of knowledge (Collis & Hussey, 2014). Two opposite epistemological views are positivism and interpretivism (Carson, Gilmore, Perry, & Gronhaug, 2001). Positivists see the world as external and objective (Carson et al., 2001), and believe that phenomena under investigation can be observed and should be measured to be considered as knowledge (Collis & Hussey, 2014). According to Orlikowski and Baroudi (1991), "positivist studies are premised on the existence of *a priori* fixed relationships within phenomena which are typically investigated with structured instrumentation" (p. 5). Thus positivists use a step-by-step approach to test a theory or a hypothesis (Vaishnavi & Kuechler, 2004). Because positivists consider the researcher to be a separate entity from the context they research, they follow a structured research design (Collis & Hussey, 2014).

In contrast, interpretivism considers that knowledge is shaped or constructed, and is underpinned by the belief that social reality is not objective (Collis & Hussey, 2014). While positivists seek out general and abstract laws around phenomena that are not bound by time or context, interpretivists study a specific phenomenon in a specific time and context (Hudson & Ozanne, 1988). Interpretivists investigate meaningful social action and the subjective perceptions of the people involved (Neuman, 2006). Thus, social constructionist ontological assumptions align with the adoption of interpretive methods of research (Walsham, 1995a). Describing perceived realities that cannot be seen prior to the research being undertaken is usually the aim of interpretivist research (Hudson & Ozanne, 1988). Interpretive research "assume[s] that people create and associate their own subjective and intersubjective meanings as they interact with the world around them" (Orlikowski & Baroudi, 1991, p. 5). Accordingly, positivism and interpretivism are at two extremes of the subjective-objective continuum (Morgan & Smircich, 1980). Postmodernism, critical studies and feminist perspectives are other less-known epistemological paradigms (Hatch & Cunliffe, 2013; Neuman, 2006; Orlikowski & Baroudi, 1991).

Understanding social issues by studying human interactions in the Information Systems (IS) context is important (Walsham, 1995b). Thus, interpretivist research is seen as a useful approach in IS as it allows researchers to understand human thoughts and actions in social settings and is able to produce valuable insights into technological phenomena (Klein & Myers, 1999). While positivist research dominated the early days of IS research, since the beginning of the 1990's, the interpretist approach has gained momentum (Walsham, 2006).

While positivism and interpretivism are at two extremes of the research continuum, in my view, both approaches have their place. Yet, for any given piece of research, alongside the researchers stance, the phenomenon under examination and the issues to be addressed will influence the approach to be taken. In addition, I believe that my ontological assumptions of reality as socially constructed (social constructionism) aligns more with interpretivism. While the STT and SRT theories that form TSR have been used in both positivist and interpretivist research, this research, given the complexity of the healthcare sector and the need to understand perceptions of big data within this setting, calls for an interpretivist approach.

A researcher's ontological and epistemological assumptions influence the methodology adopted (Bryman & Bell, 2015). Methodology refers to the approach taken to carry out the research and may consist of one or multiple methods which should align with the epistemological approach (Collis & Hussey, 2014). While quantitative research takes an objective ontological position and a positivist epistemological stance, qualitative research is based around subjectivism and interpretivism (Bryman & Bell, 2015). Quantitative research aims for generalisation and explanation (Stake, 2010), and thus analyses data statistically (Collis & Hussey, 2014). Qualitative research methods, on the other hand, explore in order to understand phenomena with an emphasis on understanding words rather than quantifying them (Bryman & Bell, 2015; Stake, 2010). The aim of the proposed research is to explore how big data is socially represented in the healthcare sector and how this representation influences business-IT alignment across multiple levels. Thus, an exploratory qualitative approach is proposed. Qualitative research provides a way to study naturally occurring social and cultural phenomena in their original setting, and is designed to understand people and the real life world they live in (Avison & Myers, 2005; M. B. Miles, Huberman, & Saldana, 2014). Therefore, taking a qualitative approach fits the research objectives well.

6.2. Research Approach

A qualitative research design nurtures "richness and holism" and is capable of uncovering complexities (M. B. Miles et al., 2014, p. 11). The very nature of the healthcare sector, and implementing big data analytics across this multi-level system, can raise unseen complexities. Considering social dynamics around big data adds a further level of complexity. Thus, in-depth investigation is needed to grasp the socially constructed representation of big data to examine how it influences business-IT alignment. Therefore, the research is not hypothesis-testing in nature, but rather is guided by the research question: *how do perceptions of big data influence alignment across macro, meso, and micro levels in the NZ healthcare sector?*

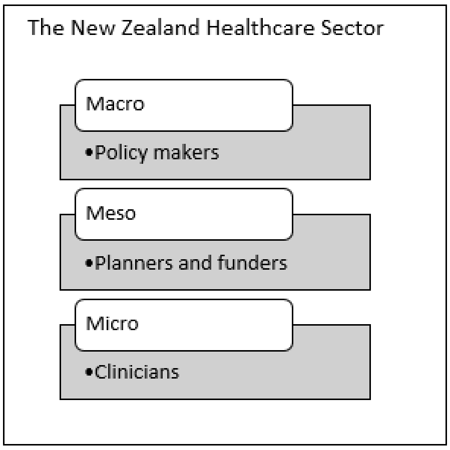

Figure 6.3: Research design

The research question recognises the three subsector levels at which data needs to be collected as macro-meso-micro (MMM) (Cumming, 2011; Scahill, 2012b). The use of TSR promotes (through SRT) collecting data from individuals and interpreting it at a group level (Dulipovici & Robey, 2013). Individual subsector levels (macro, meso and micro) were identified as the smallest unit of analysis. Therefore, the research was designed to collect data from these three subsector levels separately and, as the first step, to interpret data at each of the three sector levels to understand perceptions of big data at each level (as shown in Figure 6.3). The second step was to conduct a cross level analysis to understand the influence on alignment across the healthcare sector. Within the healthcare sector, the identified MMM levels have different tasks and responsibilities associated with big data initiatives, and therefore are likely to construct different sociotechnical representations of big data. Thus, analysing the groups separately minimises the abstract level of analysis, allowing for more fine-grained examination of operational details within the sector (Yin, 2014).

The research procedure undertaken is shown in Figure 6.4. The research question, literature and context along with the theoretical framework influenced the selected research methodology (to conduct the study as a qualitative exploratory study). As discussed in Chapter 5, Paper II discusses the theoretical framework developed by bringing together literature, context and understandings through

SRT[18]. Paper II further explains the use of SRT as a methodological lens in developing the theoretical framework. The term methodological lens describes SRT's influence in methodologically guiding the development of the framework (see Section 5.5 for further information). As explained in Section 6.1, ontological assumptions and epistemological views of the researcher also influenced the selected research methodology. Three interview schemas were developed to collect data from each of the MMM levels. A participant information sheet (attached in Appendix 1) highlighting the study conditions, a participant consent form (Appendix 2), and a demographics sheet (Appendix 3) to collect the demographic details of the participants were also drafted at this stage.

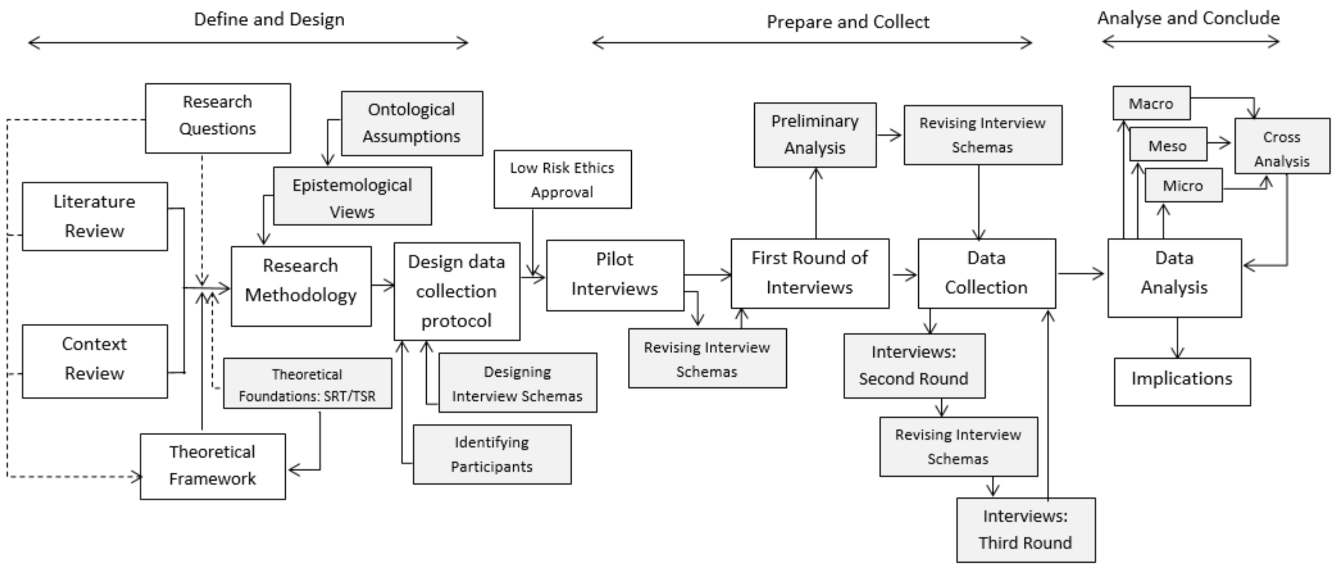

Figure 6.4: Research procedure

The drafted interview schemas (all three) were piloted with two fellow PhD students. A piloting strategy is important to refine interview schemas with respect to data to be collected as well as procedures to be followed for data collection (Yin, 2014). Therefore, three pilot interviews were conducted with one participant who was able to answer all three interview schemas (an academic who had worked in different roles across the healthcare sector). Feedback from the pilot interviews resulted in some interview questions being altered, and a few prompts were added to questions for

[18] As explained in Chapter 4, although TSR would have been an ideal theoretical foundation to develop the framework, by the time of writing Paper II the concept of TSR had not been developed.

purposes of clarity. Data collection and analysis is further explained in the Method section below (Section 6.3).

6.3. Method

6.3.1. Data Collection

This section of the thesis explains the data collection process. It provides detailed information on the unit of analysis, and outlines the data collection procedures.

6.3.1.1. Unit of Analysis

Social representation theory was used as a theory to design this study (Walsham, 2006). Such use of SRT as a theory to design, guided the plan and procedure of the data collection process. SRT allowed data to be collected at the individual level (unit of observation) yet analysed at a group level (Dulipovici & Robey, 2013). Thus, the individual subsector levels (MMM) of the NZ healthcare sector were identified as the unit of analysis. Individual interview data was analysed and interpreted at each of the three sector levels (unit of analysis) to understand perceptions of big data in New Zealand Healthcare context.

6.3.1.2. Data Collection Procedure

The data collection process started after obtaining the low risk ethics notification from Massey University Human Ethics Committee (attached in Appendix 4). In-depth interviews were conducted to gather rich data from participants at each subsector level (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). Three different interview schemas (interview schemas and their versions are given in Appendix 5) were used to conduct interviews with those at the three subsector levels. Due to the varying nature of work and their roles around current or potential big data technologies, the same schema could not be used for all three groups. However, there was some overlap of questions across the three schemas. Each interview schema consisted of 12 to 16 semi-structured questions as well as prompts to obtain further clarity. However, as data collection progressed, as explained later in this section, changes were made to the questions, due to better understanding of the context and data.

In order to investigate the social dimension of alignment, as explained in Section 3.4.3.4, stakeholders understanding of big data was investigated. Based on the developed taxonomy (Weerasinghe, Scahill, Taskin, & Pauleen, 2018), this thesis investigated the strategic fit across the sector, using a social dimension lens; alignment was considered a process, and the environment investigated was within the New Zealand healthcare sector (further details available in Section 3.5.2). This understanding through the taxonomy led to define alignment for this study as the 'fit between perceptions of big data and healthcare sector needs'. The interview protocals question participants' understandings, their views on applications, use, issues, and challenges around the phenomenon of big data within their level (MMM). While the participants were not specifically questioned on their views of other MMM levels, some participants voluntarity highlighted what they are seeing in other levels relating to big data. Some participants belonged to more than one MMM level (further explained below in pg 118), answered questions for both levels.

Purposive sampling techniques were used as the research required gathering data from informants who are involved in constructing policies about, planning and implementing, or using (current or future) big data technologies (M. B. Miles et al., 2014; Patton, 2015). A snowball sampling strategy was also used to ask informants to direct the researcher to other possible participants (M. B. Miles et al., 2014). Table 6.1 provides an overview of the types of organisations and participants that were involved in this research. As the snowball sampling technique could inherently result in participants referring to others with similar views as them (Biernacki & Waldorf, 1981), there was a concern that this technique could create an impression of alignment by creating similar representations. Therefore, within levels as well as across levels, snowball referrals were carefully monitored (data were carefully analysed) to ascertain whether snowballed samples were creating similar representations. Some similarity in representations for snowballed participants within the same level was apparent and expected (e.g. MAC1 and MAC3). Most snowballed participants across levels did not have identical representations; however, some associations could be found (e.g. MES1, referred by MAC1, was working in a big data project sponsored by MAC1's organisation, so both of them agreed it is an important application of big data in health). Basic information on all participants (anonymised) selected through the snowball technique and the participants they referred is given in Appendix 6.

Table 6.1: Types of participants and organisations

Subsector Level	Types of Organisations	Types of Participants	Number of Participants
Macro	Ministry of Health (MoH) Business units of MoH (see Section 2.1.2)	Policy makers in the NZ healthcare sector (e.g., the directors, senior executives)	6
Meso	District Health Boards (DHBs) Primary Health Organisations (PHOs) Universities Technology Vendor Organisations	Senior executives Managers (Health focus, IT focus) Academics	17
Micro	Hospitals GP clinics	GPs, nurses and managers of hospitals or other clinics who could be potential users of big data analytics tools	9

The macro level participants, being policy makers, were largely from the Ministry of Health or other business units closely related to the Ministry. Two initial participants were identified by looking at the Ministry's website and where confirmed after discussions with one of the supervisors who has a healthcare background. Both of them were approached via email, and one of them was interviewed. Seven other invitations were sent: five to participants gained through snowballing techniques and two identified through the Ministry website. Four out of the other five macro level participants were recruited through the snowballing technique. The data was collected between March 2016 and June 2018. During this period the government of NZ changed, and the Ministry of Health went through a restructure; thus NZ health strategy was revised. Therefore, some of the participants who were interviewed in 2016 provided information on things that are now no longer in use. Some of the business units that were thought to have a major role in the health system with regard to health-IT were disbanded (e.g. the National Health IT Board).

Organisations that support healthcare delivery through planning and funding were identified as meso level. DHBs and PHOs are primarily the organisations that fit into this definition. However, due to the nature of big data projects involving universities as well as technology vendor organisations as planners of these projects, the types of organisations included within the meso level were expanded to incorporate these, hence resulting in a larger number of participants. Participants who fall into this category were selected and approached via email and Linked In™. Over 25 invitations were sent to potential meso level participants (selected through purposive and snowball techniques).

Healthcare provider organisations that would be generating as well as using big data technologies for healthcare delivery, were identified as the micro level. Clinicians within these organisations were interviewed as the micro level participants. Micro level participants were the most challenging to recruit. Over 30 invitations were sent to recruit micro level participants including doctors and nurses, as planned. Due to receiving no response from nurses during the first stage of the recruitment process, it was decided to include doctors only in this study. It was still challenging to get doctors involved and some of the micro level interviews were rushed due to the busy schedules of doctors.

Data was collected in three rounds: (i) round 1 from March 2016 to May 2016 (eight interviews), (ii) round 2 from Aug 2016 to November 2016 (thirteen interviews), and (iii) round 3 from September 2017 to July 2018 (twelve interviews). After the first interview round there was a hiatus, in order to assess how well (or otherwise) the interview schemas were working. Preliminary analysis of the eight interviews was done in June and July 2016 and allowed data collection to then resume. These eight interviews included four macro, three meso and one micro level participant. Some minor changes were made to all three interview schemas. The second round of interviews came to an end in November 2016 due to the approaching holiday season (Christmas and New Year). Minor changes were made to the meso and micro interview schemas through researcher's experience and preliminary analysis of the interviews. Due to other life events (as explained in Chapter 10) the researcher could not resume data collection until September 2017. Interview schemas (two versions of macro, three versions of meso and two versions of the micro interview schema) are given in Appendix 5.

Overall 32 interviews were conducted: six at macro level, seventeen at meso and nine at the micro level. Sample size was determined upon reaching theoretical saturation. Theoretical saturation was reached when new information was not received as interviewing progressed (Mason, 2010). Often it was observed that participants had more than one role (e.g. clinical director as well as an academic). More interviews were conducted at the meso level as there were different sub groups within the meso level (DHBs, PHOs, academics and vendors), and more data were needed to get a clear picture, and to reach theoretical saturation. In cases where the participant had two different roles that spanned two different MMM levels, they were interviewed for both levels. For example, four participants at the meso level also had clinical duties and therefore also answered questions relating to the micro level. However, when the roles were within the same level, no action was taken other than noting the two roles (e.g. member of a government board as well as a senior executive at a policy level organisation). An overview of participant demographics is given in Table 6.2.

Table 6.2: Overview of participant demographics

Demographic	Macro		Meso		Micro	
Age	36-45 years 46-55 years 56-65 years	2 3 1	26-35 years 36-45 years 46-55 years 56-65 years >65 years	1 7 6 2 1	26-35 years 36-45 years 46-55 years 56-65 years >65 years	1 1 3 3 1
Gender	Male Female	4 2	Male Female	14 3	Male Female	8 1
Ethnicity	NZ European European	5 1	NZ European European	10 2	NZ European European	4 3

			American Chinese Other Asian African	1 1 2 1	Middle Eastern	2
	Total Participants	6	Total Participants	17	Total Participants	9

A detailed demographics table is available in Appendix 7. Ideally, in-depth interviews are best conducted between the researcher and one participant (Liamputtong, 2009). However, three participants invited one of their colleagues into the discussion, making the interview a two participant interview/discussion. Such two participant interviews typically took more time than other interviews as answers were taken from both participants for each question.

Interviews were audio recorded and transcribed verbatim. The researcher transcribed 15 interviews first-hand[19] using Express Scribe software. Transcribing was found to be challenging and very time consuming. Due to time constraints around completion (having significant personal and work commitments), after discussion with supervisors, the decision was made to utilise a professional transcription service (Myers, 2013). A confidentiality agreement was signed with the professional transcriber before audio files were sent to them. Once transcripts were received, the researcher checked all transcripts along with the recording before using them for the analysis. Apart from interviews with participants, health policy documents, other publications and publicly available documents and databases were used as secondary data where necessary (Yin, 2014).

6.3.2. Data Analysis

Data was analysed using general inductive thematic analysis (Thomas, 2006). An inductive approach was adopted as the research design because TSR was exploratory in nature and there was a need to see what ideas emerged from the data rather than from theory around big data (Bryman & Bell, 2015). The first step in the inductive analysis was to clean the raw data files and to bring all transcripts into a similar format using Microsoft Word (383 pages of transcripts in total, 1.5 line spaced, Calibri 11pt

[19] The researcher transcribed all interviews in the first round, five interviews in the second round, and three interviews in the third round by herself.

font). Then, the researcher read them several times, and wrote memos. Once familiar with the data, transcripts were coded and themes were identified for each MMM level separately (Braun & Clarke, 2006). NVivo 11 software was used for coding. All themes at each MMM level were analysed separately to identify categories (Thomas, 2006). Developed categories were re-analysed to remove any unnecessary categories and to merge similar ones. An example of themes and categories identified is given along with an interesting and relevant quote for each theme in Table 6.3. Three summary tables were created for each of the MMM levels for analysis.

Table 6.3: Example of Coding – Themes and Categories

Category	**Theme**	**Description of the Theme**	**Representative Quote**
		Macro	
Definition of Big Data	Ambiguous	No clear understanding about what big data is, or how to define big data	"I very infrequently use the term because I don't think it's got any definition that makes any sense." (MAC5)
	Characteristics: Volume*	Big health data is large in volume.	"Big data is about scale." (MAC2)
Issues	Privacy and Security	Privacy and security of health data is an issue in the big data era.	"I think someone will make a mess of this at some point and some data will end up in the wrong hands." (MAC1)
Health Policy and Strategy	Opportunity	Health strategy provides more opportunity to use big data.	"So the strategy is all about a person-centred view of every person in NZ which is the electronic health record, it's a summary view only. Keeping with that key information which is available universally across the system, that the details of that drill down through links into electronic medical records and clinical data repositories which are scattered across the entire health system." (MAC5)

Category	**Theme**	**Description of the Theme**	**Representative Quote**
		Meso	
Definition of big data	Buzzword	Big data is a buzzword.	“For me personally, it’s a terminology, like the Cloud. You know how some people coin the term Cloud, but it’s basically it's just the internet.” (MES8)
Challenges	Skills	Technologies around big data require new skills.	“We are constantly adapting and constantly upskilling and constantly looking for new skills and new tools and so forth.” (MES10)
Issues	Data Ownership	Data ownership is a complicated issue in the big data era.	“The problem is there's always the big question of ‘who owns the data?’ so if you ask this from a doctor, GP or a specialist or a DHB or a ministry of health I'm not sure they will answer you. They will say the patient owns the data. So can you share it?” (MES8)
	Interoperability	System linkage issues	“Another error occurs when you’ve got the configuration of the software where there’s data about a person in the background that’s relevant to what you’re doing now, but you can’t see it. So it’s invisible to you but it’s there and you write a decision in your system like prescribing medication but there’s data in the background would have influenced your decision.” (MES14)
Applications	Precision Medicine	Application of big data technologies around genomics	“What gets me excited about where we’re heading as an organisation is that we will be in a position to personalise somebody’s healthcare to a degree that we haven’t even been able to dream about really or have only been able to dream about.” (MES17)
Health Policy and Strategy	Issues: Ignorance	Some important areas around big data are not captured through health policy and strategy.	“…nobody is looking at it [patient-generated data] and saying we need to think about what we can do with that data to transform the health system so we can handle the silver tsunami.” (MES14)

Category	**Theme**	**Description of the Theme**	**Representative Quote**
		Micro	
Definition of Big data	Not new	Big data is not new, healthcare has been dealing with big data for some time.	"It [big data] is about all the big house data that maybe say the ministry collects or the DHB collects and it would be things like the data on preventable admissions or the whole New Zealand data on immunisation rates for children or that sort of stuff." (MIC9)
Concerns	Privacy and security	Privacy and security is a concern around healthcare data.	"People getting access to the information that shouldn't have had it, and that certainly happens nationally and there have been people looking up imaging that they didn't have direct clinical responsibility over." (MIC3)
	Interoperability	System linkage issues	"The GPs just did the test, but then the hospital goes and redoes all these tests! There must be hundreds of millions of dollars of duplicate tests done every month because the data isn't linked up." (MIC6)
Applications	Patient-generated data: Potential*	Understand that Patient-generated data has applicability in point of care	"I mean in the future they'll be bringing their averages and we are not even going to bother doing the readings, because they are meaningless." (MIC2)

* Subthemes (e.g. under the category Applications, Patient-generated data is one of the main themes. Potential is a subtheme under Patient-generated data).

Three summary tables were created with categories, and themes for each MMM level facilitated the cross level analysis. The concept of summary tables was adopted from Interpretative Phenomenological Analysis (IPA) (Smith, Flowers, & Larkin, 2009); however, the analysis conducted has no relationship to IPA methodology[20]. By doing the cross group analysis, five key categories were

[20] IPA is a phenomenological method of analysing data (Willig, 2013). In early stages of analysis of this research, IPA was considered as a possible methodology for this study, but because of the need to have MMM levels as the unit of analysis it was decided to proceed with general inductive thematic analysis instead of IPA. Nonetheless, the concept of summary tables in IPA was a useful technique adopted for this thesis to use for cross group analysis.

identified as influencing big data representations across the NZ healthcare sector. While other categories were also present, these five categories were chosen as those most crucial to analyse alignment based on their relevance and importance to the research question, rather than based on the quantity of data in that category (Braun & Clarke, 2006). The cross-level summary table with these key categories and respective themes and descriptions can be found below in Table 6.4.

Table 6.4: Summary of key findings through cross group analysis

MACRO		**MESO**		**MICRO**	
Theme	**Description**	**Theme**	**Description**	**Theme**	**Description**
Category: Perceived Definition					
Unclear	Not clear about what is defined as big data	Unclear	Not clear about what is defined as big data	Unaware	Unaware of the term big data or its definition
Not new	Big data is not new to health.	Not new	Big data is not new to health.	Not new	Big data is not new to health.
Buzzword	Big data is just a buzzword (or a catchall term).	Buzzword	Big data is just a buzzword (or a catchall term).	National data	Big data is large national databases held by the Ministry.
Evolving technology	Big data is a result of evolving technology.	Evolving technology	Big data is a result of evolving technology.	Characteristics *	Big data is data with 2V characteristics: volume** and variety**.
Characteristics*	Big data is data with 4V characteristics: volume**, variety**, velocity** and veracity**.	Characteristics*	Big data is data with 5V characteristics: volume**, variety**, velocity**, veracity and value**.		
Category: Challenges					

Skills	Big data requires people with new skills.	Skills	Big data requires people with new skills.	N/A	
IT architecture	Big data requires changes to how IT is designed and used.	IT architecture	Big data requires changes to how IT is designed and used.		
IT infrastructure	Big data promotes changes to IT infrastructure.	IT infrastructure	Big data promotes changes to IT infrastructure.		
		Organisationa l Structure	Organisational structures may change as a result of big data.		
Category: Concerns					
Accuracy	Importance and difficulties of achieving data quality	Accuracy	Importance and difficulties of achieving data quality	Accuracy	Importance and difficulties of achieving data quality
Data ownership	Undesirable practices around data ownership	Data ownership	Unclear definitions and practices around data ownership	Summarised data	Summarised data is important to make fast clinical decisions.
Data availability	Challenges of making data available	Data sharing	Concerns regarding sharing data with other organisations	Ethical use	Ethical use of data by PHOs and other organisations is important.
Misuse	Tackling misuse of data is a challenge.	Misuse	Organisations or people who you share data with have an ability to misuse data.	Privacy and security	Privacy and security around health data is important but sometimes could be blocking doctors from getting needed information.

Obtaining trust	Maintaining trust of patients is important.	Obtaining trust	Maintaining trust of patients is important.	Interoperability	Inability of the systems to connect with each other is a huge challenge causing many problems.
Privacy and security	Tacking privacy and security is a challenge.	Privacy and security	Tacking privacy and security is a challenge.		
Promoting data lakes	Organisations collecting data without a goal thinking it will be useful for the future is an issue.	Context dependency	Capturing the context is important but difficult.		
Interoperability	The nature of the NZ health system creates fragmentation.	Ethical use	Ethical use of data is a challenge when data is shared among organisations.		
		Interoperability	The nature of the NZ health system creates fragmentation and disconnected systems.		
Category: Applications					
Measuring outcomes	Use of big data and analytics for effective measurements of health outcomes	Measuring outcomes	Use of big data and analytics for effective measurements of health outcomes	Measuring outcomes	Use of data and analytics for effective measurements of health outcomes
Population health analysis	Analysing populations to understand health issues and delivery better	Population health analysis	Analysing populations to understand health issues and delivery better	Preventative care	Preventative care through population analysis

Linking data across government	Linking data across government sectors to understand how things are happening outside the health system	Linking data across government	Linking data across government sectors to understand how things are happening outside the health system	Clinical decision making	Tools based on data can aid in making effective clinical decisions.
Precision medicine	Use of genomics to provide personalised health care	Precision medicine	Use of genomics to provide personalised health care	Patient-generated data	Use of data generated by patients through wearable devices, other private medical devices or mobile apps
Clinical decision making	Making clinical decisions based on more and new sources of data	Clinical decision making	Making clinical decisions based on more and new sources of data	Precision medicine	Applicability of genomics in clinical care
		Patient-generated data	Applicability of data generated by patients through wearable devices, other private medical devices or mobile apps		
		Artificial intelligence	Artificial intelligence has potential in healthcare		
Category: Health Policy					
General terminology	The term 'big data' is not used in health policy as policy needs to be more general.	Terminology	The term 'big data' is not used in health policy but is captured using "smart system".	Interoperability issues	Systems that cannot talk to each other is a problem that policy needs to solve.

Strengths	Strengths of health policy are connected information, well defined NHI and ability to understand data collection settings.	Strengths*	Initial step** - Policy takes an initial step toward big data. Constantly updated** – Policy is constantly updated to capture new changes. Storing data** – policy around gathering and storing data is good.	Problematic funding scheme (GP)	Current funding system (model of care) inhibits using technology or new tools as it is based on time and not on service.
		Issues*	Hinders use of data** - health policy hinders the ability to use captured health data. Unfitting strategies**- some parts of policy are controversial and do not fit. Inability to capture important areas**- policy misses some important areas of big data. Non-involvement of health informaticians – health informaticians who are aware of technology are not involved in policy discussions. Too many policies** – unclear whether to follow DHB policy or government policy	Incorrect understanding of primary care	Policy does not acknowledge the importance of primary care or GP work in a correct way.

		Improvements needed*	Data ownership** – policy needs to facilitate discussions around clear definitions of data ownership. Ethical guidelines** – policy needs to provide a set of ethical guidelines around using data for protection and open up the ability of using data. Patient-generated data** - capture patient-generated data in policy	Ignored advice	Policy makers ignore advice given by doctors around health information systems.

* themes that have sub themes;
** subthemes within a theme (e.g. under the main category Health Policy, analysis of the meso level identified Strengths as a theme, within this theme, 'As an initial step', 'constantly updated', and 'storing data policy' were identified as subthemes, thus marked by **).

Paper III (presented in Chapter 7) takes a slightly different approach to analysing a selected cohort within the dataset. Paper III was written with a focus on articulating and carefully explaining the concept of TSR. In doing so, it proved extremely challenging to include data addressing the overarching research question, while remaining consistent within journal requirements for the length of the paper. Initially only data from one main category (e.g. perceived definition) was included. However, after further brainstorming and discussions with supervisors it was decided to focus on one particular application of big data: the application of big data in clinical decision making. This was done in order to build a comprehensive picture for the reader that spanned multiple issues relating to big data, as opposed to just one aspect such as its perceived definition. Following this decision, the research question to address in Paper III was changed to: *how is the role of big data perceived by policy makers, funders and planners, and clinicians in the context of clinical decision making?* This was only used for Paper III.

All themes relating to the clinical decision making context were extracted into a new NVivo file, and were analysed again to identify categories relating to clinical decision making. By doing so, as the data set was relatively small (restricted by the scope), it was possible extend the analysis around TSR to explain the findings in more depth through TSR. All themes were classified into TSR based subthemes: sociotechnical representations, anchoring, and objectification. All themes (classified under subthemes) at each MMM level were analysed separately to identify categories. Developed categories were re-analysed to remove any unnecessary categories and to merge similar ones. Table 6.5 presents example categories and themes identified in this analysis for Paper III.

Table 6.5: TSR Analysis of data in the context of clinical decision making

Categories	**Themes**	**Description of the Theme**	**Representative Quotes**
Macro: Use of big data for Clinical Decision Making	Sociotechnical Representation: Significant Potential	Big data has significant potential in clinical decision making.	"I think the biggest potential for me is in the clinical care side. In the public health side, I think we've actually being doing a lot of what we do anyway." (MAC2)
	Anchoring: Low Priority	Problems more serious than clinical decision making require immediate attention.	"There's not a lot of people who understand the potential of big data in a clinical environment. They are probably more interested in big data and the whole health system." (MAC1)
Macro: Guidance of Health Strategy	Sociotechnical Representation: Opportunity	Health strategy provides more opportunity to use big data.	"So the strategy is all about a person centred view of every person in NZ which is the electronic health record, it's a summary view only. Keeping with that key information which is available universally across the system, that the details of that drill down through links into electronic medical records and clinical data repositories which are scattered across the entire health system." (MAC5)

Meso: Importance of Patient-generated data	Anchoring: Policy	Policy makers are not thinking about the use of patient-generated data.	"…nobody is looking at it [patient-generated data] and saying we need to think about what we can do with that data to transform the health system so we can handle the silver tsunami." (MES14)
Micro: Current Point of care	Sociotechnical Representations: Fragmented systems	Systems in use do not talk to each other and it is difficult getting information needed.	"…everyone's got different systems and different platforms and different data management platforms which makes it very difficult if we want to compare say our data in Christchurch with say a group in Auckland. We're not using the same structures."
Micro: Clinical Profession	Objectification: Medical training	Medical training does not include information analysis.	"When you do medical training, you obviously you develop analytical thinking skills but in a different way. Not so much in terms of information analysis or operations management which are important for managing the hospital but not part of our training. So that's all new to all of us. " (MIC1)

It is important to highlight that the interview schemas had questions and probes relating to clinical care, which produced data about clinical decision making across the three MMM levels, thus allowing to present clinical decision making as a separate case from the main research. Nonetheless, the main analysis still included clinical decision making data. Alignment is discussed (in Paper IV, see Chapter 8) in relation to the main research question and includes findings around clinical decision making where necessary.

6.3.3. Research Rigour

A qualitative approach is often considered desirable to conduct rigorous and relevant research in the field of business management (Myers, 2013). The research design, method of data collection, interpretation, and communication ensure rigour in qualitative research (Mays & Pope, 1995).

Theoretical rigour was achieved by framing the research question using SRT and integrating it with the research design to develop the theoretical framework. SRT was used as a methodological lens in the development of the theoretical framework (this is further explained in Paper II). Peer reviewed academic papers presented in this thesis add a further level of rigour to this research (Myers, 2013).

Explicitly stating how the research was conducted is important for credibility and authenticity (Liamputtong, 2009). The stages of sample selection, data collection, analysis, and interpretation were all documented to assure rigour through credibility and authenticity. A Google doc was used to document the data collection process (including invited participants, comments and memos about interviews, issues, and memos during data analysis and the like) as it allowed the researcher to access the documents anytime, anywhere when it was necessary to take notes (a snippet of the Google doc used is given in Appendix 8). This form of documentation improved traceability of the findings by providing the ability to be traced back to the original source transcript.

Describing perceived realities that cannot be seen prior to the research is usually the aim of interpretivist research (Hudson and Ozanne, 1988). Based on the constructivist assumption of multiple realities, individuals construct their own interpretations (Berger and Luckmann, 1967; Crotty, 1998). Therefore, multiple interpretations of the use of big data were observed as anticipated even within the same MMM level. In such scenarios, data was carefully observed to identify commonalities in the representations. For example MAC1 was able to define big data with 3Vs, while MAC5 rejected the idea of big data because he was unclear about it. Although other participants at the macro level did not reject big data, they also displayed confusion around defining big data. Thus while 'Perceived Definition' was defined as a key category, within this key category the ambiguity as well as clarity was acknowledged as themes and later discussed through TSR (lack of anchoring, as explained in Paper IV). While researcher triangulation could not be obtained by having multiple coders (Tong, Sainsbury, & Craig, 2007), during the coding stage, emerging themes and categories were often discussed in formal research meetings with the supervisors to ensure their validity.

None of the participants asked to see their interview transcript, which was provided as an option in the study information sheet and also acknowledged verbally by the researcher. After completing the data analysis, it was found that while precision medicine and genomics was a key theme at the macro and meso levels, at the micro level there was no data about it from micro only participants. However, two participants who were interviewed for both meso and micro talked about precision medicine. Since this was an important topic with applicability to clinical care, as a credibility strategy (Krefting, 1991), the micro only participants were contacted through email with a question regarding genomics and precision medicine. Only one response was received.

Lincoln and Guba (1985) identified member checking as a method that enhances the rigour of qualitative research by improving credibility of findings. Member checking is important to ensure “the participants' own meanings and perspectives are represented and not curtailed by the researchers' own agenda and knowledge” (Tong et al., 2007, p. 356). Thus all participants were sent a summary of key findings (given in Appendix 9) via email and feedback was requested. Fourteen emails bounced back as the participants were no longer working at the same organisation. The report was sent to eight of them through Linked In. The report requested feedback through a short survey, and four responses were received verifying the findings of the research.

6.4. Chapter Summary

This section started by explaining and clarifying the researcher’s ontological and epistemological stance, and therefore justifying the chosen research methodology of qualitative exploratory research. The approach taken to conduct the research, including the data collection protocol, and the methods of data collection and analysis were explained in this section. While some of this information also appears in Paper III and Paper IV, to bring better clarity to the adapted methodology, it was decided to present it as a chapter in this thesis. Links to papers were highlighted where necessary.

Chapter 7: Findings and Discussion Part I (Paper III)

7.1. Overview of the Paper

This chapter presents Paper III, explaining the development of a novel theory – the Theory of Sociotechnical Representations (TSR) – developed through merging two well-known theories: Sociotechnical Systems Theory (SST) and Social Representations Theory (SRT). As explained in previous sections of this thesis, the development of TSR is a contribution of this research as it was developed through understanding and sense-making of findings that influenced the integration between SST and SRT. This paper was developed to articulate the concept of TSR and also to empirically present an application of TSR to sociotechnical research. However, as highlighted in Chapter 6 (Methodology), due to the constraints around paper length in peer review journals it was decided to contain the paper through selecting clinical decision making as the context for this paper.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of the candidate:	Kasuni Weerasinghe
Name/title of Primary Supervisor	Professor David J Pauleen
Name of Research Output and full reference:	
Weerasinghe, K., Pauleen, D. J., Scahill, S. L., and Taskin, N., Theory of Sociotechnical Representations: Concept and Application.	
In which Chapter is the Manuscript/Published work:	Chapter 7
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	85%
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
This paper presents a theory developed as a contribution of this thesis. The candidate drafted the initial version of this paper while data was being analysed. The initial paper did not present the novel theory, but the idea of connecting Social Representation Theory with Sociotechnical Systems Theory was present. The paper was submitted to a journal, and was rejected with comments from three reviewers. The comments of the reviewers and further discussions with the supervisors contributed to the development of the Theory of Sociotechnical Representations. The paper was drafted by the candidate, revised after feedback from three co-authors (supervisors) and submitted to the Information Systems Journal.	
For manuscripts intended for publication please indicate target journal:	
Information Systems Journal	
Candidate's Signature:	[signature]
Date:	20 May 2019
Primary Supervisor's Signature:	[signature]
Date:	20 May 2019

Theory of Sociotechnical Representations: Concept and Application

7.2. Abstract

The paper offers a new way to understand technological phenomena through the conceptualisation and testing of a theory called the Theory of Sociotechnical Representations (TSR). TSR is developed through the merging of two well-known theories: Sociotechnical Systems Theory (SST) and Social Representation Theory (SRT). SST identifies social and technical subsystems as interdependent subsystems that interact and influence each other, while SRT provides a holistic ground to understand meaning making within social groups in new situations. The paper explains why and how SRT can be used to investigate the technical subsystem of SST: first by establishing the theoretical links between the TSR developed from the two theories and identifying the importance of SRT in understanding people's perceptions of technology; and then by applying and evaluating the TSR framework through an empirical study. The research demonstrates that TSR is appropriate for explaining how social representations of technology can play a critical role in the way technologies are understood and used. The research case is on the use of big data in clinical decision making in New Zealand healthcare, and the findings show how key representations of big data influence policy and practice. TSR is a new theory that focuses attention on the representations of technology by the people who not only use and are affected by it, but also those who make decisions about choosing and implementing it. By examining social representations of technology, TSR can give greater insight into the sociotechnical dynamics of people and technology.

Keywords: Sociotechnical theory, social representation theory, theory of sociotechnical representations, big data, clinical decision making, New Zealand healthcare

7.3. Introduction

This paper aims to better understand technological phenomena, particularly emerging technologies through the conceptualisation and testing of a theory labelled the Theory of Sociotechnical Representations (TSR). It has been suggested that any technological phenomenon has two components: technical and social (Shin, 2015). The technical component includes technical requirements (such as infrastructure, architecture, tools and so forth) and related challenges (security, ethics and so forth) (Emery & Trist, 1965). The social component includes aspects such as technology users' roles, responsibilities and goals about technology. This understanding of the social and technical components of technology is central to Sociotechnical Systems Theory (SST) founded by Eric Trist and Fred Emery in the 1950s. SST is a foundational theory in the field of Information Systems (IS) that seeks to explain the interplay between social and technical components within a system. SST perspectives allow a better understanding of how human, social and organisational factors affect the ways that work is done and technical systems are used (Baxter & Sommerville, 2011).

In SST, the social subsystem includes the people and their tasks, roles and the like. It features eight dimensions identified by Emery (1959) as: (i) cooperative work roles, (ii) individual's responsibility (accountability) for tasks, (iii) joint responsibility for support services provided, (iv) distributed control (empower) over the tasks carried out, (v) simultaneous interdependencies among workers, (vi) understanding about dependencies, (vii) coordination of dependencies, and (viii) personal worker goals relating to the interdependencies.

The eight key features of the technical subsystem are identified by Emery (1959) as: (i) characteristics of input that may influence labour requirements, (ii) the physical setting of the technical subsystem (the actual environment), (iii) spatio-temporal dimensions of work and processes involved, (iv) the level of automation, (v) individual units of operations within the technical subsystem, (vi) identification of necessary and optional operations, (vii) most economical maintenance options, and (viii) supply operations for unplanned variations. It is important to highlight that these features are technical features themselves and are not about the value or the way people perceive the technical subsystem. While these technical features are important, this paper argues that the way people perceive these features and the value they see in them influences the success of the whole sociotechnical system.

While the pioneers of sociotechnical perspectives argue that it is important to pay attention to human needs through the social subsystem (Pasmore, 1995), this paper highlights the importance of also exploring the technical system's dynamics from the perspective of the people who are involved in the technical system's implementation and use. This will certainly involve the IS professionals and technologists who develop and apply the technology but may also include policy makers, financial decision makers, line managers, end users of the technology and other stakeholders involved in the selection, implementation and use of the technical system.

In this paper we suggest using Social Representation Theory (SRT) (Moscovici, 1984) as a methodological lens to investigate the technical subsystem. SRT is a theory originating from social psychology, which provides a rationale for meaning making within social groups when new situations emerge (Andersén & Andersén, 2014). Representation of a phenomenon (concept, object, or situation) is the central idea of SRT. Representation can be influenced by social pressure, opinions, social negotiation, and collective sense making of a group (Dulipovici & Robey, 2013). Because "[t]he technical and production requirements of work under an STS [SST] framework are jointly optimized with psychological and social aspects of the individual and group requirements" (Bostrom & Heinen, 1977, p. 14), SRT is appropriately aligned with a sociotechnical study. This paper takes a novel approach bringing SRT under the umbrella of SST, as a tool that can be used to investigate sociotechnical perspectives. In this study, the application of SRT will enable investigation into stakeholder representations of the technical subsystem, which we suggest are critically important in analysing and understanding a sociotechnical system.

It is important to note that the social representation of the technical subsystem is distinctly different to that of the social subsystem (as defined in SST), because the social subsystem itself is the people and their tasks, roles and the like. These features of the social subsystem are important, and highlight the interdependencies with the technical subsystem. However, we believe that extending analysis beyond the eight social system dimensions mentioned above by using a social representation view of the technical subsystem will enable a richer and a more practical understanding of the actual situation of the technical subsystem within the sociotechnical system under study. The following sections explain how SST and SRT are used to build an extended version of the SST. The paper then applies the extended theory to analyse a study of big data in the context of clinical decision making.

7.4. Sociotechnical Systems Theory

Eric Trist introduced sociotechnical systems theory (SST[21]), in his work at Tavistock Institute of Human Relations in London in the early 1950's. SST is also known as sociotechnical theory, sociotechnical systems, sociotechnical approach, and sociotechnical perspectives in the literature. Fred Emery is also a major contributor to the foundations of SST (Fox, 1995). Pasmore (1995, p. 1) claimed the SST perspective by Tavistock researchers transformed social science as it helped social scientists understand that their work has to be "driven by a combination of ideas and values in the face of strong and constant opposition to change". The original concept of sociotechnical perspectives founded by Trist is influenced by Lewin's Theory of Change, General Systems Theory and Open Systems Concept[22] (Emery & Trist, 1965; Pasmore, 1995). The open systems concept acknowledges that systems have "parts that have to be related to the whole" and "the wholes had to be related to their environments" (Emery & Trist, 1965, p. 21).

Simply, SST identifies social and technical subsystems as two interdependent subsystems that interact and influence each other (Bostrom & Heinen, 1977) (see Figure 7.1).

[21] To date different abbreviations like STS and STT are used to discuss sociotechnical systems. In this paper we use SST to capture the complete term "sociotechnical systems theory".

[22] Miner (2006) claims sociotechnical systems is the European version of Likert's System 4 Theory (Likert's Management Theory)

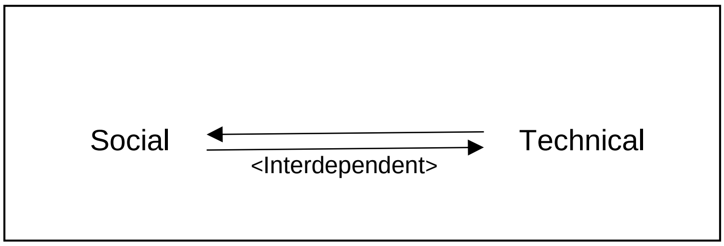

Figure 7.1: Conceptualisation of Sociotechnical Systems Theory

The technical subsystem consists of technological systems, machinery, business processes and technologies (Bostrom et al., 2009; Fox, 1995). While setting limits on what can be done, the components of the technical subsystem makes demands for certain things that the organisation must do (Fox, 1995). For example, if a decision support tool uses data to facilitate decisions, it requires good quality data in terms of validity, accuracy, timeliness and so forth. If the quality of data that goes into the system is not good, the expected outcome of improved decisions will not be achieved.

The *social subsystem,* although seen by researchers as less precise (Pasmore, 1995), consists of the occupational roles that are established and influenced by the work of the technical subsystem (Fox, 1995). Tasks and task interdependencies were identified as the main facets of occupational roles (Pasmore, 1995). Later Bostrom et al. (2009) claimed that such occupational roles recognise people's knowledge, skills, and needs. Authority structures as well as the reward schemes are also considered to influence the social subsystem (Bostrom et al., 2009). Considering the example given above to explain the technical subsystem, the social subsystem in that instance will consist of people who make decisions using the tool. Because the technical subsystem requires quality data, the users should have knowledge and skills and understanding to input valid (accurate and complete) data into the system. The authority structures such as rules and regulations may influence the quality of data entered into the system. Ultimately the users are accountable for the decisions made with the help of the system that uses such validated data. If the data was not validated the decisions made will be problematic. Thus, it is evident that the social subsystem and technical subsystems are interdependent.

Typically, SST has been used as an underlying perspective in IS research addressing the interdependencies of people and technology. SST perspectives understand that it is the interactions between the social and technical subsystems that result in successful or unsuccessful systems performance. As a result, SST can help facilitate optimization of either social or technical subsystems. Therefore, SST is "all about 'joint optimisation'" (Walker, Stanton, Salmon, & Jenkins, 2008, p. 4). While there is no single set of principles to be followed (Fox, 1995), SST states that the interdependencies of social and technical subsystems need to be identified and addressed in order to have better organisational or industrial performance (Bostrom et al., 2009).

Organisations have individuals using technology in day-to-day tasks to achieve specified business goals. Therefore, studying the technical subsystem in isolation of the social subsystem, or vice versa, is deemed insufficient (Bostrom et al., 2009; Trist, 1981). Work of the Tavistock Institute explains that work relationships between the two subsystems are what brings them together (Pasmore, 1995). According to Trist (1981) SST studies can be conducted at three levels based on the work relationships: (i) Primary work systems level – systems that carry out work for an identified subsystem (department) of an organisation, (ii) Whole organisation systems - self-standing workplaces, corporations or agencies, and (iii) Macrosocial systems level - institutions operating at a macro level such as industrial sectors or governing institutions. Trist (1981) in his review of SST claimed that these three levels of work systems are interrelated. Pasmore (1995) highlighted that work systems are identified in SST as a functioning-whole that includes a set of activities and is not just a collection of individual jobs, and therefore the work group is predominant in an investigation than the individual jobholder. However, SST acknowledges the importance of understanding human needs beyond what is required to do the job using technology (Emery, 1959).

7.5. Social Representation Theory

Social Representation Theory (SRT) is a theory from social psychology developed by Serge Moscovici in 1961. It provides a stance to understand meaning making within groups. Representation of a phenomenon (concept, object or situation) is the central idea of SRT, and is created within the social group for the purpose of understanding and communicating (Moscovici, 1963). Therefore, a representation has three elements: (i) the object/concept that is represented, (ii) the individual who builds the understanding, and (iii) the group to which the individual belongs (Dulipovici & Robey, 2013).

SRT identifies two sub processes that formulate social representations: anchoring and objectification (Moscovici, 1984b). Anchoring refers to identifying a phenomenon within a group based on the aspirations of the group, while objectification supports the anchoring process through an individual's interpretation (Gal & Berente, 2008). Anchoring is therefore influenced by the work type of the group, the common background, experience of the group as well as the goals. Objectification, being individual measures, are influenced by education background, past experience of the individual, and interests of the individual. Objectification is about linking the new phenomenon to known concepts (e.g., models, images, examples from the past). These two processes complement each other. Anchoring is the social process that promotes stability of a created social representation. Objectification is the cognitive process and it facilitates change (Dulipovici & Robey, 2013). As shown in Figure 7.2, these two processes continuously influence each other and social representations are continuously evolving within the social group. Figure 7.2 shows how we conceptualise this understanding of anchoring, objectification and the formation of a social representation of a new phenomenon within a social group.

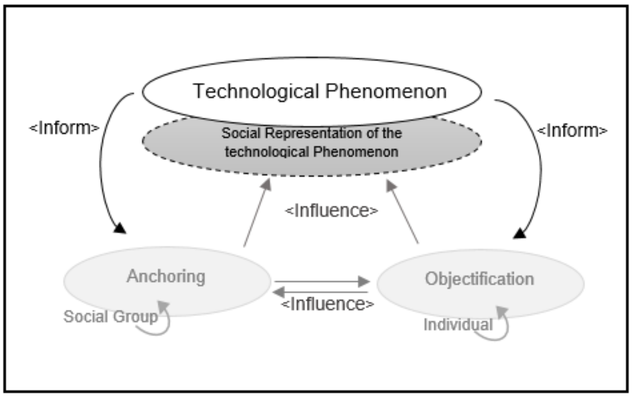

Figure 7.2: Conceptualisation of Social Representation Theory

Although boundaries of social groups were loosely defined in the early definitions of SRT (e.g., Moscovici, 1963), most recent use of SRT identifies smaller groups (Dulipovici & Robey, 2013). Moscovici (1988) identifies three types of representations that guide the formation of groups to study, which are: (i) hegemonic, (ii) emancipated, and (iii) polemic. A hegemonic representation is relatively straightforward, naturally known and not produced by the group. An emancipated representation is formed within a group but also may have sub-groups within the main group that have created the representation differently. A polemic representation has conflicting meanings and may require studying groups with contrasting perceptions (Moscovici, 1988).

7.6. Theory of Sociotechnical Representations

This section discusses the development of a novel theory, the Theory of Sociotechnical Representations (TSR) by extending SST using SRT.

SRT provides the necessary tools, and methodological direction to investigate humanistic aspects of technology and its use (Gal & Berente, 2008). While SST acknowledges the involvement and dependence of humans within a sociotechnical system, we suggest that it does not investigate the social interpretations of technology. Pasmore (1995) explains Emery's identification of psychological requirements for humanistic characteristics of the social subsystem, which includes more control to individuals, variety in tasks, opportunity for learning and tasks to be interesting. While these are all valid and important for the social subsystem, we do not see that social interpretation of the technical subsystem such as the perception of technology, the value and importance, awareness and the like, being discussed in SST literature.

What SST addresses through the social subsystem are the tasks and roles of people and their interdependence with the technical subsystem: thus social interpretations are not seen to be of interest. For example, consider a person using a computer system to type a report. The social subsystem (the person) has features like the person's ability to type, his or her requirements of the report structure that is to be facilitated by the computer system, and the level of authority to change the report and accountability. While SST accommodates these features of the social subsystem and its dependence on the features of the technical subsystem, what SST does not address is this person's perception of the computer system, which may be negative due to past experiences with a different system or due to lack of training for this type of work. For these reasons the person may suggest the system is difficult to use, which may just be his or her perception, and may or may not be shared by others. The use of SRT addresses these gaps by providing tools to understand how the computer system is perceived (represented) by the person. SRT also claims that the person's views may be influenced by the group he/she belongs to; e.g., if the person works for a team which uses outdated computer systems that are not user friendly the representation the group has about computer systems as a whole could be a negative one. In this paper, using SRT we highlight that understanding the representation of the technology phenomenon is paramount to the successful implementation of sociotechnical systems.

SST typically acts as a perspective that underlies the research influencing what to study. While the SST perspective acknowledges the interdependence of social and technical subsystems SRT can provide a better understanding of the representations of the technical subsystem, which is likely to influence this interdependence (see Figure 7.3). Therefore, we argue that the use of SRT as a tool to understand interdependencies between social and technical subsystems is appropriate for research founded on SST. This application of SRT in extending SST is a unique approach, developed by the authors as the Theory of Sociotechnical Representations (TSR). The authors are not aware of any prior research that explicitly uses SRT to extend SST. Researchers such as Gal and Berente (2008) and Dulipovici and Robey (2013) have demonstrated the value of using SRT in humanistic inquiry of IS, but did not associate the potential affinity with SST.

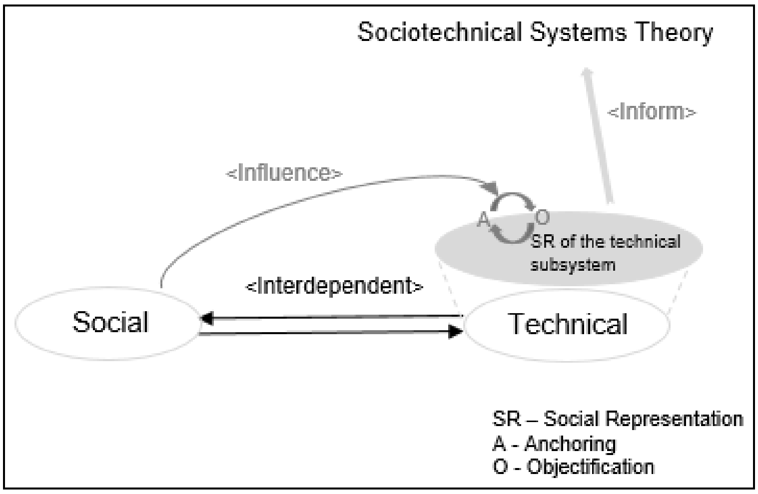

Figure 7.3: Theory of Sociotechnical Representations (TSR)

As seen in Figure 3, the TSR framework utilises SRT as a theoretical tool to examine the technical subsystem while also acknowledging the interdependencies between the social and technical sub systems. Because SRT is a tool to explore user perceptions of technology (the technical subsystem) and the potential social capabilities (social subsystem), Figure 7.3 conceptualises that SRT will inform SST. A SRT investigation of the technical subsystem does not stand alone as a single investigation of the technical component, because the social subsystem of SST will also influence the representation of the technical subsystem on both anchoring and objectification (discussed previously under SRT). Therefore, SRT supports a richer understanding of SST perspectives by helping to understand the sociotechnical representations created by the social subsystem about the technical subsystem.

It is important to emphasise that in the TSR framework, SRT is used to understand the technical subsystem, and not the social subsystem. The reason is that using an SST perspective already provides sufficient tools to understand the social subsystem as discussed earlier. Along with original work on SST, recent researchers including Mumford (2006) and Berg and van der Lei (2003) highlight what to focus on in the social subsystem when designing sociotechnical systems. We argue that it is the technical subsystem that lacks theoretical tools around social interpretations in an SST investigation. While the technical subsystem typically investigates technical dynamics (like the system itself, or related infrastructure), using a SRT lens to investigate sociotechnical interrelationships provides researchers with an understanding of the technical subsystem from the perspective of the social subsystem. Therefore, it contributes to understanding how the technical subsystem is understood and appreciated (or not) by the stakeholders themselves who are in fact the social subsystem. This understanding will help researchers to identify issues and derive understandings about social interpretations and reasons around the technical subsystem influencing sociotechnical interdependencies. We agree that the SST perspective explains that the social and technical subsystems are interdependent in the sense that peoples' skills, values and other humanistic characteristics are interrelated with the technological aspects, such as the systems, IT infrastructure and tools. However, we argue that the social representation of the technical subsystem by the stakeholders of this subsystem plays an important part in the success and acceptance of technical systems. Because a social representation of the technical subsystem is created, TSR uses the term "sociotechnical representation" as opposed to social representation.

Appendix 10 provides a discussion of other prominent IS theories and highlights similarities and differences with TSR. In this section the theoretical foundation has been laid out for by explaining the extension of SST through SRT. In the next section, we elaborate on the application of TSR through a case.

7.7. The Case of New Zealand Healthcare

7.7.1. The Case Context

The case concerns the New Zealand (NZ) healthcare sector and the phenomenon under study is *big data*. Within the healthcare sector there are many areas where big data can be utilised: the focus of this case is the application of big data for clinical decision making[23]. The research question addressed is: *how is the role of big data analytics perceived by policy makers, funders and planners, and clinicians in the context of clinical decision making?* Addressing the research question, this section explains the

[23] The case presented here (in clinical decision making) is a part of a larger study looking at social representations of big data within the broader healthcare context in New Zealand.

development of a theoretical framework based on TSR and discusses the findings from a TSR perspective.

Big data refers to enormous amounts of structured, unstructured and complex data produced by a wide range of computer applications (Davenport, 2013; Groves et al., 2013) and is typically explained through 3V characteristics (McAfee & Brynjolfsson, 2012) as shown in Table 7.1. Table 7.1 summarises generic definitions of the 3Vs as well as their specific manifestations in healthcare. Application and use of big data in healthcare can benefit many areas across the healthcare sector ranging from personalised medicine, population health analysis, measuring outcomes (clinical and financial), research and development among others (Groves et al., 2013).

Table 7.1: 3V Characteristics of big data

The V	Generic Definition of the Characteristic	Specifics in Healthcare
Volume	Volume is the key attribute of big data definition. For many decades rapid growth of the size of data have been a challenging issue (Jagadish et al., 2014). Although it directly relates to the 'size of data' in terabytes or petabytes (Emani et al., 2015; McAfee & Brynjolfsson, 2012; Watson, 2014), organisations are also concerned about accumulating numbers of records and transactions, and expanding tables and files (Russom, 2011).	Healthcare data are large in volume due to increasing population, diseases and medications and use of IT upon them (Bates et al., 2014; Wyber et al., 2015). Current technology is capable of completing a single organ scan in one second and a full body scan in 60 seconds. This generates 10 gigabytes of data each time for a single patient, illustrating the volume of healthcare data that is being generated and accumulated (Burns, 2014). Moreover, contemporary healthcare research, from drug developments to genetics and biotechnology, is growing exponentially (Frost & Sullivan, 2012). Therefore, the growth of data *volume* in healthcare is arguably very high.
Variety	Variety indicates heterogeneity of data types (Jagadish et al., 2014). It refers to data from different sources resulting in various types of data such as text, images, audio, video and so forth (Chen et al., 2014; McAfee & Brynjolfsson, 2012; Watson, 2014). As a result, this data could be structured, semi structured	Healthcare data is also varied as data comes from a variety of sources such as Electronic Medical Records (EMR), laboratory data research related data, insurance claims data, and patient behaviour data (Patil et al., 2014). Modern data sources such as social media, wearable devices

	or unstructured (Emani et al., 2015; Russom, 2011). Although volume is the key attribute of defining big data, organisations seem to be more concerned about managing the variety (Bean & Kiron, 2013; Davenport & Dyché, 2013).	and data from mobile apps adds more complexity to the *variety* of data (Roski et al., 2014).
Velocity	Velocity denotes the frequency of data creation and delivery, real-time or near real time (Emani et al., 2015; McAfee & Brynjolfsson, 2012; Russom, 2011). It refers to "both the rate at which data arrive and the time frame in which it must be acted upon" issue (Jagadish et al., 2014, para. 6). Therefore, big data is generated near-real time and demands for techniques to summarise, sort, filter or interpret this data in a timely manner issue (Jagadish et al., 2014).	Healthcare data is accumulating at an accelerating speed (Wyber et al., 2015). The use of sensor technology and increasing number of wireless medical devices are capable of monitoring patients continuously and communicating real-time clinical records to healthcare providers (Frost & Sullivan, 2012). Widespread uses of these technologies are the key contributors to the *velocity* of healthcare data. However, many of the traditional health IS are not able to handle data on speed- they fail to refresh and analyse differently formatted data in real time (Roski et al., 2014).

Classed as a forward-thinking system and showing important developments despite challenges (Ministry of Health, 2014a), the NZ healthcare sector was one of the early adopters of technology for healthcare delivery, introducing EMRs as early as the 1980s resulting in the accumulation of huge repositories of health data. Past research has identified three levels within the NZ healthcare sector in the context of big data as macro: policy makers – government organisations; meso: planners and funders - District Health Boards (DHBs) and Primary Health Organisations (PHOs); and micro: healthcare providers - clinicians (Cumming, 2011; Scahill, 2012b; Weerasinghe, Pauleen, et al., 2018). By conducting interviews across macro, meso and micro levels (MMM levels), this paper investigates sociotechnical representations (based on TSR) of big data in the context of clinical decision making. Understanding similarities and differences in sociotechnical representations across the levels could lead to improvements in the use of big data in clinical care for both policy and practice.

In clinical decision making, a clinician makes a diagnosis estimating the extent of the illness by making assumptions and determining a treatment plan or requesting further testing (Pauker & Kassirer 1980). Use of evidence-based medicine in modern healthcare practice has structured the decision making process (Dang & Mendon, 2015). Clinical decision making tools provide evidence-based decisions, patient-specific assessments, and/or recommendations (Kawamoto, Houlihan, Balas, & Lobach, 2005). Clinical decisions supported by data from health systems can assist decision makers to achieve gains in performance, reduce gaps between knowledge and practice, and improve patient safety (Bates et al., 2003). Basic computerised clinical decision support tools available include appointment reminders, patient-specific recommendations, and prescribing support, which can reduce medical and prescribing errors and ensure standards (Kawamoto et al., 2005) .

The use of analytics techniques on big healthcare data sets can provide better clinical decision support (Dang & Mendon, 2015). Big data provide opportunities for clinical care to go beyond the data recorded in the EMR and to find new data sources such as patient-generated data, data from wearable devices and genomics to improve clinical decision making. One potentially exciting way forward, based on big data and analytics, is precision medicine that uses genomics to create individual patient treatment strategies (Jameson & Longo, 2015). Other important improvements to clinical decision making through big data analytics include but are not limited to identifying clinically appropriate and effective treatments, and predictive analysis and risk calculations and modelling for better and improved healthcare delivery (Raghupathi & Raghupathi, 2014). However, it is important that the application of big data analytics and its potential for clinical care is understood by policy makers, funders and planers as well as practitioners to identify gaps or issues that might hinder the future use of big data for clinical decision making.

A qualitative approach based on TSR was used to answer the research. The use of SRT in TSR promotes collecting data from individuals and interpreting the data at a group level. Subsector levels (MMM) of the NZ healthcare sector were identified as the unit of analysis. Data was collected from individuals and was analysed and interpreted at each of the three sector levels to understand perceptions big data in the context of clinical decision making. While supporting the study of three levels, SRT also investigates the social representation of big data at each of the three levels irrespective of what is happening at the other levels (e.g., although big data related strategy and implementation are taking place at the macro level, SRT facilitates studying how big data as a concept is socially represented at all levels). Figure 7.4 is an illustration of how TSR is applied to the case context.

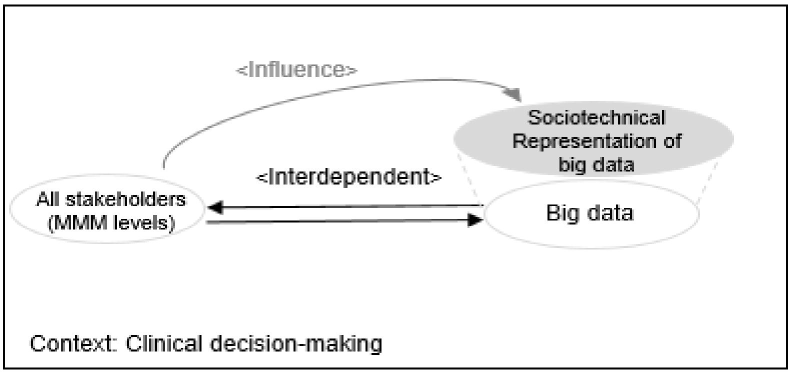

Figure 7.4: Theory of sociotechnical representations in the case context

Although any of the MMM levels could have been used separately to validate the use of the theory of sociotechnical representations, we have presented the case with findings from all three levels to emphasise that there may be different representations of the same technical phenomenon by different groups. Considering the theory of sociotechnical representations and the nature of the case (MMM levels) and big data, we have developed a theoretical framework (Figure 7.5) to guide us with the data collection and analysis.

As shown in Figure 7.5, at both macro and meso levels, due to the nature of their work as well as based on the preliminary interviews, it was identified that the main focus of big data and analytics in the context of clinical decision making is strategy and implementation. Therefore, the data collection and the interview questions focused the discussion around strategy and implementation of big data and analytics. At the micro level, discussion was around data generation and use. The theoretical framework anticipated that social representations at each of the three levels will influence the other levels.

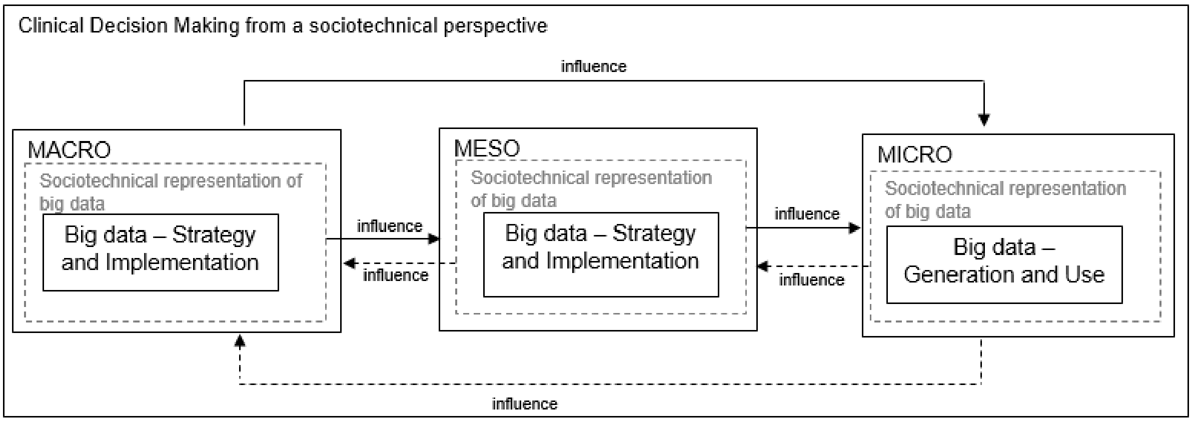

Figure 7.5: Theoretical framework

7.7.2. Method of Data Collection and Analysis

Based on the theoretical framework three interview schemas were specifically developed for each of the MMM levels[24]. Semi-structured interviews were conducted to gather rich data from participants (Merriam, 2009). At the macro level, the participants interviewed were from government bodies (i.e. Ministry of Health and its business units/advisor bodies). At the meso level, the participants interviewed were largely from DHBs and PHOs. A few academics and technology vendors were also interviewed under the meso level as the nature of their work is similar to that of meso (planners). General Practitioners (GPs) and Hospital doctors were interviewed under the micro level. Purposive sampling techniques were used as the research required gathering data from informants who were involved in constructing policies, planning, and implementing, or who use or have the potential to use clinical decision making tools with big data analytics (M. B. Miles et al., 2014; Patton, 2015). A snowball sampling strategy was used to ask informants to direct the researchers to other possible participants (Miles, Huberman, & Saldana, 2014). Thirty-two in-depth interviews were conducted ranging from 45-90 minutes long. A summary of demographics is given in Appendix 7. Four clinical leaders/directors

[24] There was an overlap in all three schemas in terms of general questions about big data.

interviewed at the meso level also answered the micro level questions thinking about their role as a doctor in a hospital. The number of interviews at each level was determined by data saturation (Fusch & Ness, 2015). General inductive thematic analysis (Thomas, 2006) was used to analyse the data. More information on the analysis approach and coding can be found in Section 6.3.2.

7.7.3. Case Analysis

Through a TSR lens this research investigates the social subsystem (people in MMM levels) and the technical subsystem (big data) and their interdependencies in the context of clinical decision making in NZ. This would be the general approach in a sociotechnical study. However, the TSR lens specifically allows us to understand big data (technical subsystem) from the perspective of people in MMM levels (social subsystem), and also allows us to understand the reasons behind such perceptions by evaluating anchoring and objectification processes (tools provided by SRT). This section first describes findings of the three levels (MMM) separately analysing how big data is socially represented in the context of clinical decision making at each level. Then, the paper provides an overall analysis of the sociotechnical representation (based on TSR) of big data in the clinical care context highlighting similarities and differences across the sector.

7.7.3.1. Macro Level: Policy Makers

From a sociotechnical point of view, the potential of big data for clinical decision making is well understood by the macro level participants. They understood the importance of technologies like precision medicine to improve clinical decision making in the future. However, they see a low priority for the implementation of big data for clinical decision making. One participant explained, “it is not our [ministry’s] role” (MAC2) to understand the applicability of big data for clinical decision making. To explain this, we draw on the theoretical tools from SRT.

The participants’ representation of big data does not have a high priority for clinical decision making, because they do not see it as the government’s role to get involved in clinical decision making related applications. They believe the government is looking at a more overarching approach to health and is interested in the use of big data in areas like measuring outcomes and population health analysis because of its role in directing the healthcare sector as a whole. They also believe that it is too soon to talk about clinical decision making because there are more important issues involving big data that need to be dealt with first.

Macro level participants believe that overall, required health system outcomes are most important, and this is where big data has great potential. Because of their role in setting policy direction, they feel it is more important to achieve national healthcare objectives, and the application of big data in measuring such objectives has the highest priority. SRT explains this role of the organisation/agency as being directly related to anchoring, which shapes a social representation (Andersén & Andersén, 2014).

In SRT, past experience influences social representation through objectification (Weerasinghe, Pauleen, et al., 2018). The macro level participants talked about their experience with problematic data quality across the healthcare sector with incomplete and inconsistent data followed by issues of accuracy that largely happen because of patient interactions with the health system. Because of such experience, these macro level participants see it as an issue that has greater priority than clinical decision making. While highlighting the importance of "right data as opposed to lots of data" (MAC1) they talked about the importance of dealing with quality issues to be sure that the healthcare sector is capturing complete and accurate data. At the moment the priority seems to be getting higher quality data than the actual application towards clinical care. There was an understanding that the modern technology has tools (like Internet of Things) that enable collecting data from source automatically eliminating the need for a person to enter data into the health system. It is identified as a huge step towards capturing good quality data, however, the level of this being done was unclear.

With big data, policy makers see their role as promoting its use through sustainable policy and strategy – so that data can be used across many different fields including clinical care and decision making. SST perspectives acknowledge the importance of setting strategy to guide the sociotechnical interdependencies (Craig & Kodate, 2018). The participants talked about the NZ health strategy[25] and how they saw the problems around big data being addressed in the strategy. They acknowledged that the health strategy provides opportunities for effective use of big health data through: (i) connected information, (ii) a well-defined National Health Index (NHI), and (iii) understanding of data collection settings. Therefore, NZ health strategy is expected to lead to improved accuracy and quality of big healthcare data that will later be used for big data analytics to undertake population health analytics, achieve and measure health outcomes, and make clinical decisions.

Big data in the macro level seem to have a sociotechnical representation of being a part of "evolving technology" (MAC6) and is not deemed new. While a clear representation was not yet present (some participants being unclear about the term, some claiming it is only a buzz word, and some very positive about it), there was clear agreement that big data is about developments in technology around data creation, sharing, storage, and management. Literature (e.g., Andersén & Andersén, 2014; Dulipovici & Robey, 2013) explains that representations are always evolving, and therefore at any given point in time, there may not be a clear representation, or a clear representation at one point of time may change. While they saw the role of big data as "continuing to grow" (MAC2), one specific area they were interested in was precision medicine. They saw that precision medicine "at some point in time will provide useful tools for clinical decision making" (MAC5). Precision medicine in NZ is still at the very early stages[26] with multiple research projects in place. However, taking these first steps towards the implementation of precision medicine is important and is expected to eventually enhance clinical care through evidence from genomics. The policy makers also acknowledged the need for infrastructure developments to facilitate precision driven medicine.

When talking about big data and clinical decision making, the policy makers commented on the semi-autonomous nature of the healthcare sector, and how not everything happens (or is required to

[25] NZ health strategy was being refreshed at the time of data collection
[26] At the time of data collection

happen) as directed by the government. On the positive side, policy makers are aware of several GPs who have already initiated collaborations among practices and shared patient information to provide better care to their patients. A good example of tech savvy doctors initiating interesting and advanced patient care is the use of a precision type approach by a GP practice to understanding stem cell use and basing treatments upon their structure as opposed to general treatments. Policy makers see these as very positive trends emerging due to the nature of the healthcare sector and available technologies. They place importance on these initiatives in frontline delivery for the betterment of patient care.

7.7.3.2. Meso Level: Funders and Planners

A clear, universal representation of big data was not seen within the meso level. Academics and vendors were able to clearly define big data while participants from DHBs and PHOs often voiced their confusion of how it differed from 'small' data[27]. Based on Moscovici (1988), SRT acknowledges the possibility of sub groups developing different representation of the same phenomenon. When asked about what influenced their understanding of big data academics spoke of their work (teaching or research) in a related field. Thus, as explained in SRT, their work has allowed them to clearly understand and articulate (objectification) the term big data in the healthcare context. Similarly, because of vendor participants' involvement in big data projects and their organisations constant promotion of big data related discussion (anchoring) they have a clear understanding of the term as used within their organisation.

The meso level participants identified that the current sociotechnical system of clinical decision making was at a "rudimentary stage" (MES2) mostly used as prompting or warning systems. There are tools like risk predictors (e.g., Predict) and population analysis tools (e.g., Atlas) that are used by GPs and hospital doctors across the country. These tools are not mandated but the meso level see that some clinicians use them as an aid in clinical care. Similar to the macro level, the meso level

[27] Small data is traditional data that is generated by information systems. Small data does not have the 3V characteristics of big data. However small data can eventually become big data.

participants also saw experienced clinicians building their own tools to facilitate care. Thus a sociotechnical representation of the current situation of clinical decision making at the meso level is that while there are many improvements needing to be made for clinical decision making, the application of big data can improve such tools.

While the meso level participants did not think big data is new to healthcare, they identified that areas like measuring outcomes, population health analysis and clinical care can be improved with the use of more data. They also identified new areas of potential for health, such as precision medicine and cross government analysis through Integrated Data Infrastructure (IDI). Although big data is not a novelty at the meso level, they did identify new types of data emerging within the healthcare sector such as genomics data and patient-generated data that has great potential to improve clinical care. However, it was noticed that meso level participants (especially PHOs and DHBs) showed little interest in the application of big data for clinical decision making, because their focus is more on measuring performance. The IT vendors and PHOs showed a great deal of interest in patient-generated data, but claimed that "it's a pipe dream" (MES9) to use such data in clinical care, specifically because there is lot more that needs to be improved before integrating patient-generated data. The meso level participants (all subgroups equally) understood that big data brings great opportunity to create better tools to improve clinical care and decision making, although it may not be a priority for some of the groups (e.g., DHBs).

Meso level participants talked about how current initiatives around big data will lead to better clinical decision making in the future. They emphasised the role of NHI, which will enable aggregating data across the healthcare sector for improved decision making, including clinical decision making. They commented that more patient data allow clinicians to be able to provide better care. They also talked about how accuracy is promoted by big data initiatives around quality which will eventually result in better data for decision making.

Based on the experience of the participants at the meso level, clinical decision making tools (not necessarily big data-related) can sometimes provide unwanted support, resulting in warning fatigue for clinicians if they get too many prompts or unwanted warnings. Therefore, the participants at this level explained that the application of big data in this context has to be very carefully done, with the involvement of the clinicians and an understanding of their needs for such tools.

When talking about clinicians, the planners and funders saw a lack of understanding by the clinicians about the use of big data for clinical care, as there is no professional discussion about the potential of big data across the sector. However, they explained that if clinicians were shown evidence of the potential benefits of big data then they would get on board. Participants emphasised that there are clinical level people who can influence their organisations to make better systems. On this basis, they highlighted that the government needs to promote a discussion of big data across the healthcare sector to enhance everyone's understanding about it.

From a sociotechnical view, the meso level participants claimed the effective use of big data on clinical decision making tools will eventually promote more effective use of the workforce because such tools will enable less qualified and less experienced clinicians to make decisions freeing up senior clinicians for more complicated tasks. However, they emphasised that "right now they [clinicians] are only really dealing with probably about 10% of the data that will be available to them in the next five years" (MES17). Thus big data will put a lot of pressure on the clinicians because it will be exponentially more data that they have been dealing with.

A majority of the participants at the meso level agreed that the government (macro level) is heading in the right direction with healthcare policy by identifying big data under 'smart system[28]'. Because data is a key part of a smart system, this understanding of big data as a part of smart systems can be explained as anchoring of big data through health policy. However, some participants pointed out that

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[28] NZ health policy identifies the health system as a smart system defining it to be a "learning system, by seeking for improvements and innovations, monitoring and evaluating what we [health system] are doing, and sharing and standardising better ways of doing things when this is appropriate" (Ministry of Health, 2016c, p. 1).

health policy is not catering enough (if at all) to capturing patient-generated data, which they identified as being an important aspect of big data in healthcare, saying "no policy maker is talking about it [patient-generated data]" (MES13). They argue that even if using patient-generated data is not currently being planned for clinical decision making or application elsewhere, the government has to be ready to cater to future needs by capturing it or identifying this likely direction in health policy.

7.7.3.3. Micro: Clinicians (GPs and Hospital Doctors)

At the micro level, big data was represented as "large datasets" (MIC5) or "national datasets" (MIC2). There was no other understanding about what big data was but the participants had a very good idea of how data can be used for clinical care and decision making.

From an SST perspective of clinical decision making, doctors expressed that a few tools are used such as Health Pathways (online tool that guides clinicians to manage health conditions of patients), and risk calculators. Some doctors (specialists in hospitals) talked about how they still use manual disease risk calculators. From an SRT perspective, the doctors raised concerns over data quality and hinted that because of their individual experience as well as experience of fellow colleagues with poor data quality (anchoring and objectification), they are reluctant to use tools for clinical decision making unless they are sure that the systems work. They explained that clinical decision making tools should be as rigorously tested as medications are if they are to be relied on in patient health care.

The clinicians explained how people outside of the clinical areas do not understand their profession, and the consequences they have to bear if something goes wrong. They said "people (referring to patients) do not have an undo button" (MIC1). These claims directly relate to the nature of the profession and are explained by SRT as objectification. SRT's application on SST can explain this as the nature of the profession not being understood by other people who may question the doctors' reluctance to use a certain system, creates a frustration and influences the sociotechnical representation negatively. Another gap highlighted by the doctors about their profession and modern expectations was that the medical training (as a part of the social subsystem) they received did not teach data analysis. Therefore, understanding modern tools is difficult for them (objectification). However, they acknowledged that contemporary medical training may be different.

Clinicians talked about how cumbersome the systems in use are, being fragmented in nature and typically not effectively communicating with each other. For example, different GP practices use different patient management systems (PMSs) (e.g., MedTech, MyPractice) and hospitals use a completely different one. The GPs showed a level of frustration with not being able to link real time to hospital data, and hospital doctors explained how it is an utter waste of money repeating tests because "I'm blind, I can't see any of that data [data on reports done by the GP]" (MIC6). Also highlighting the issues of funding and structure in the NZ health system, the GPs explained that because funding is calculated based on frequency (patient encounter) and not per service (not based on the complicatedness). This is deemed difficult because GPs are only funded for 10 or 15 minutes for a consultation. And they said that they want to just talk to the patient in that short time and not use any tools other than the PMS system. Because they claim more tools will consume more time leaving them even less time with the actual patient. While these examples emphasise the issue of not or mis-identifying the interdependencies between the two subsystems it also shows the frustrations that influence the representations through objectification of participants experiences (not linked systems and values, time per consultation).

GP's also talked about patient-generated data and thought it was a good way to get to know the patients better. As the patients themselves can record data about their health with greater frequency (e.g., seven consecutive readings of blood pressure done at home verses one reading at the clinic) and share at (or bring along to) the consultation. However, micro level participants claimed that most of the apps that patients use (or they share with the patients) are apps that are made for a different market and may be problematic when used in NZ with the existing funding system that does not fund more than a 15 minute medical consultation. This links back to the previous point about how GPs see more tools or apps will consume more time that according to them is best to be used talking with the patients. In addition, some participants claimed that most patients do not use apps saying "we've shared this [mobile app to capture blood pressure] with probably 300 people. Only one or two sent back data" (MIC2). Another GP highlighted an issue saying doctors do not work 24/7 in the GP practice and if a patient record was shared with him on his mobile he does not want to look at it when he is not working and this could be potentially life threatening to a patient.

7.7.4. Summary Findings across MMM levels

Summary findings with regard to big data and clinical decision making can be categorised into five areas: (i) potential of big data for clinical decision making, (ii) healthcare policy for better data future, (iii) work underway for better data future, (iv) role of clinicians, and (v) overarching issues of the health system influencing the use of tools for clinical care. These categorizations are discussed both within and across levels and differences and similarities are drawn out. Key implications of social representations of big data and clinical decision making are stated. These will be discussed in the next section in the context of TSR.

Potential of big data for clinical decision making: At the policy and planning levels (macro and meso) the participants identified that the use of big data tools and techniques have significant potential but they see it as a low priority compared to all other more pressing problems. At the micro level, while there is some use of clinical decision support tools like Health Pathways, GP's, in particular, were not sure whether they would have enough time to use more tools during the short time they have for clinical care with their patients. The hospital doctors were also a little wary of the idea of more tools for clinical decision making because of their experience in poor quality data.

> Key Implication: Macro and meso levels show a low priority to use big data for clinical decision making and the micro level demonstrates a lack of interest to use more tools.

Healthcare policy for better data future: Participants at the macro level talked mostly about the healthcare strategy as a good starting point to the big data era through the promotion of data standards and connected systems. While agreeing with this, some of the meso level participants spoke of their frustrations about health strategy not addressing patient-generated data which they believe to be important for the future of both clinical care and health administration. Although unprompted by interview questions, most participants at the meso level voluntarily identified patient-generated data as a part of big data, while that did not seem to be the case for the macro level. This lack of awareness and interest in patient-generated data may be the reason behind the lack of policy initiatives in this area. GPs, on the other hand, explained that they have shared mobile apps with their patients that *they thought were useful*. But they were unclear of the accountability or the use of this data professionally or legally. They highlighted that PMS do not allow capturing data created by patients through such mobile apps. This links back to the need for policy and standardising the use of mobile apps to capture patient-generated data which has to come from policy and planners rather than the doctors themselves.

> Key Implication: Healthcare policy needs improvements in various aspects to utilise big data for better clinical care.

Work underway for a better data future: The macro and some meso level participants talked to a great extent about the plans for precision medicine – a project currently in place funded by the Ministry of Health. While this is still in the research stage they highlighted that it is a project that is heading in the right direction to provide big data tools for clinical decision making in the future. The micro level, however, did not comment on the use of genomics or precision medicine, which could be because it has not yet come to their level. However, it is important to note that the doctors are aware of such projects and that they understand the potential benefits precision medicine can have on providing improved care to patients.

> Key Implication: There are different levels of awareness across MMM about technology use in the future and about how the technology can be used in clinical decision making.

Role of Clinicians: While the macro level participants have come across inspiring GPs and hospital doctors initiating useful clinical care tools (even with approaches close to genomics), at the meso level (specifically DHBs and PHOs) participants claimed that the clinical people lack an understanding of the potential of big data in clinical care. But the meso level participants argued that if evidence was shown to the clinician they will be interested in sophisticated tools that will facilitate care. Additionally, participants at PHOs explained that clinical personnel are a great influence for them, pushing them to work on better tools as well as improve data quality. At the micro level both GPs and hospital doctors alike claimed that their profession is not well understood by the other levels. The clinicians claimed that they will not use tools in their clinical practice unless they are shown evidence of the accuracy, as they are dealing with human lives and they have to be accountable for the decisions they make. Nonetheless, they highlighted that their training did not include information analysis, which is important for the modern data world, and is something that policy makers might look at for the future.

> Key Implication: A broader understanding by the clinical profession across the sector is needed to facilitate clinicians' needs using technology.

Overarching issues of the health system: The biggest issue all three levels agreed on is the quality of data available within the health system. Experiences of participants from all three levels highlighted cases of poor data in the systems. Doctors blamed the systems being in silos for the issues of quality, highlighting the importance of a single connected system for the whole of NZ. Policy makers highlighted their initiatives towards standardising data collections in systems through health strategy. Funders and planners also talked through the same lines as that of policy makers. Nevertheless, it is important to highlight that addressing data quality issues is crucial for improved decision making in both clinical care and healthcare planning.

> Key Implication: All the levels (MMM) highlighted issues of data quality suggesting importance of taking necessary measures to improve quality of health data.

7.8. The Case for a Theory of Sociotechnical Representations

This case demonstrates that SRT can enhance and deepen understanding of socio technological scenarios that have traditionally been the domain of SST studies. Using SRT, we have been able to gain a useful understanding of big data in clinical decision making across the whole of the NZ healthcare sector by examining and comparing different representations of big data across the MMM levels. Based on these representations, we have drawn out key implications that we believe would need to be addressed to achieve a coherent and effective implementation of big data in clinical decision making in the NZ health care sector. In this section, we show that by using SRT in a SST study we have essentially developed a new and potentially important variation of SST, which we call the Theory of Sociotechnical Representations.

SST perspectives allow us to understand how new social technologies (like big data) are implemented and used. It acknowledges how such new technological phenomena become a social practice, and emphasise the appropriateness of using theory from social sciences to gain a better understanding hopefully resulting in better systems (Berg & van der Lei, 2003).

The sociotechnical system in our case is the clinical decision support tools that could utilise big data. Given the current situation it would be difficult to undertake a traditional sociotechnical investigation because clinical decision making using big data is still evolving, and there are no (or a few) clearly identified big data tools in New Zealand. The use of SRT on a sociotechnical investigation allows examining new phenomena that are at initial stages of design and implementation. By extending SST with SRT through the Theory of Sociotechnical Representations, we can now better understand a new phenomenon (in this case big data in clinical decision making) by not only identifying interdependencies but also acknowledging the fact that the perception (representation) of the new phenomenon is critical in establishing the conditions for successful planning, design and implementation of the 'technology' under consideration.

The use of TSR also adds to the investigation by identifying that there are often different groups/levels of people involved in sociotechnical systems as is the case in the context of a multi-level healthcare sector. Multilevel study or considerations are facilitated by SRT which acknowledges the presence of different representations by different groups. An SST investigation will allow a multilevel analysis but does not support it to the extent of the TSR framework. As shown in Table 7.2, using TSR in this investigation has allowed a richer understanding of the phenomenon of big data by allowing the various perceptions of the various stakeholders (policy, planning, and use) to be investigated across multiple levels of the NZ healthcare sector.

Table 7.2: Application of SST vs. TSR

Levels	**Sociotechnical Perspective (SST)**	**Sociotechnical Representations (TSR)**
Macro	Investigates policy around clinical decision making and big data	Investigates policy makers perceptions of: policy, tools (application) and users (clinicians)
Meso	Investigates current tools and their implications on planning and funding changes to clinical decision making	Investigates funders and planners perceptions of: tools, policy, and users (clinicians) with a focus on implications for funding and planning
Micro	Investigates actual tools in use and how they align with the clinicians daily work	Investigates clinicians perceptions of: potential tools and their use, policy, funding and planning

As highlighted in Table 7.2 at the macro level, a sociotechnical investigation informs understanding of policy around clinical decision making tools and use of big data. The use of TSR enabled us to understand the perceptions of policy makers and how they see the potential of big data in the context of clinical decision making; discussing policy, the tools, and the users (clinicians). At the meso level we explored funders and planners views on initiating and building projects that are used for big-data-based clinical decision making. This exploratory study investigated the way people perceive the potential of big data in clinical decision making, rather than just the clinical decision making tools. However, the participants did talk about clinical decision making tools that have been in use, or future plans for tools using big data which adds to their representation of big data in the clinical care context as well as our understanding. Finally, we investigated the micro level – the doctors (general practitioners and hospital doctors) to look at the sociotechnical representation of using big data for clinical decision making. The doctors did not have as clear an idea of big data as the other levels. However, they were able to talk about the use of big-health-data for clinical decision making which helped us in understanding the evolving representation of big-healthcare-data at the micro level.

As perceptions are often reality (Tornow, 1993), we believe that examining sociotechnical representations generates important insights through examining the perceptions and potential motivations of policy-makers (and not just the policy itself), funders, and users and their values around the technical system. We see significant potential in the use of TSR, especially in the context of novel phenomena such as big data because the initiatives around such phenomena are still emerging and therefore representations are evolving, and are not yet embedded in actual policy or projects. Additionally, investigating sociotechnical representations will allow early detection of strengths, issues and opportunities around the novel technology that will eventually come into play.

Additional theoretical reasoning provided on the basis of SRT are anchoring and objectification which allows us to explain certain findings in sociotechnical research. For example, by studying *anchoring* - the formation of the representation by the group through activities (discussions, communications, documentations and the like) within the MMM levels – we found that there is a lack of anchoring activities around the concept of big data. There was no common discussion of the concept of big data or its application (e.g. clinical decision making) at any level. One implication of this for sociotechnical initiatives might be to facilitate single and cross-level discussions about big data, its areas of potential, issues and opportunities as part of the planning process.

Further to this we found that characteristics in the social subsystem can also be used when explaining anchoring and objectification of SRT. As explained, the macro level identified clinical decision making or looking for the potential benefits of improving clinical decision making using big data as not being the role of the Ministry of Health. The role is a part of the social subsystem, but the role of an individual directly influences objectification, while the perceived role of the organisation influences anchoring. Thus using TSR we can explain macro level's sociotechnical representation of big data for clinical decision making as "low priority" by drawing on the perceived role of the organisation (anchoring) as fixing overarching issues of the health system.

Objectification – the mapping of individual's values to the representation - was seen throughout most of the discussions with the participants as they mapped their own past experience, education background, roles and even age to their understanding of the concept of big data. As explained by MAC1, his "love for data" was influenced by his background as a mathematician. Another interesting example from the micro level was GP's position that tools for clinical decision making may not be very useful. The reasons they objectify were: (i) they do not have the necessary skills in using tools (e.g. slow typist so do not want to use systems), and (ii) spending time interacting with the patient has more value than spending time looking at tools.

7.9. Conclusion, Implications and Future work

This paper sets out to explain a novel theory, the Theory of Sociotechnical Representations. We believe that this paper makes a solid theoretical contribution – the extension of SST using SRT to introduce the Theory of Sociotechnical Representations and empirically apply the theory to the New Zealand healthcare setting. This is a novel approach as the authors are not aware of literature making the linkage of SRT with SST. The case explained in this paper used the theory of sociotechnical representations to investigate the phenomenon of big data in the context of clinical decision making. The methodological direction provided by SRT enabled the authors to investigate different groups (MMM) in order to understand their representations. The analysis found that within the healthcare sector there are varying representations of big data in the context of clinical decision making. While these differences may have been found by any multi-level study or a group study, TSR provides a solid basis to understand the causes of these differences as explained in the discussion section.

The paper therefore adds to the body of literature on both SST and SRT through the development and application of TSR, creating a novel theoretical approach to IS research. In the modern era of emergent technology, and evolving technical concepts TSR can provide a holistic grounding to understand such novel technical phenomenon by investigating the perceptions around new technology and addressing the social dynamics that influence the social representations. Understanding the subcomponent processes (anchoring and objectification) that underlie a social representation and the influence the subcomponent processes has had from the social subsystem was highlighted in the discussion. We believe that this is only a starting point. Taking TSR as a foundational theory, researchers will be able to produce rich sociotechnical research.

When investigating the NZ healthcare sector, the identification of MMM levels allows the formulation of an understanding that the work systems explained in SST perspectives by Trist (1981) demonstrate a linkage to MMM levels and their definitions. However, further research is needed to understand and better establish the connection.

In a sense, technological emergence or implementation happens at various levels, whether these are acknowledged or not. Each of these levels has its own anchored or developing representation of the technology. Facebook, for example, was designed by technologists who have their own understanding of the technology and its uses, while Facebook users have another. Government regulators and policy makers are another level of participant in the Facebook context. In the beginning of Facebook's rise and its establishment of its own representation, government representations of Facebook were non-existent, irrelevant, or at best laissez faire. But over time as Facebook and its users (including hackers) representations began to clash, government was forced to take a closer look at Facebook, thus developing its own representations. Facebook as a sociotechnical system is undergoing quite radical re-representation due to competing views of it at various social levels. The lesson here is that all technologies that are part of sociotechnical systems should, as part of their design and implementation, undergo a phase of sociotechnical representation, that is be examined and understood at all levels so a common understanding of their uses and effects can be developed before they are widely implemented. Developments in artificial intelligence, robotics, genetic mapping, and other technologies come to mind as areas ripe for sociotechnical representation research.

These examples of "sociotechnologies" have potentially overwhelming implications for society as a whole (Dalal & Pauleen, 2018), but TSR also has relevance for organizations, where relevant levels of representation in a technology-based project implementation may include, among others, senior management, line management, the technologists and the users. Each level may have its own representation of the technology project and unless these are understood and harmonised beforehand, the project may suffer or even fail.

One limitation of TSR is the focus on investigating the social dynamics around a technology. Although the social dynamics around technologies are extremely important, we also understand that the technical dynamics (the actual technical features) need to be investigated. However, that is not the aim of TSR, resulting from its use of SRT. In studies where technical dynamics play an important role other theories may need to be used in conjunction with TSR.

7.10. References

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Chapter 8: Findings and Discussion – Part II (Paper IV)

8.1. Overview of the Paper

This chapter presents Paper IV, which is an empirical application of the Business-IT Alignment Taxonomy (Chapter 3, Paper I) and uses the Theory of Sociotechnical Representations (TSR) (Paper II) as the theoretical basis to conduct an alignment study. This paper presents the findings around alignment and misalignment of big data perceptions (using a social dimensions lens) across the healthcare sector.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of the candidate:	Kasuni Weerasinghe
Name/title of Primary Supervisor	Professor David J Pauleen
Name of Research Output and full reference:	
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In which Chapter is the Manuscript/Published work:	Chapter 8
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	90%
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
This paper presents the key empirical findings of this thesis around alignment. This paper was drafted by the candidate, and has been through four rounds of revision with the co-authors. The paper brings together Paper I and Paper III and presents an empirical application of the Theory of Sociotechnical Representations (TSR).	
For manuscripts intended for publication please indicate target journal:	
Journal of Information Technology	
Candidate's Signature:	
Date:	20 May 2019
Primary Supervisor's Signature:	
Date:	20 May 2019

Alignment of Big Data Perceptions in Healthcare: The case of New Zealand

8.2. Abstract

Big data and related technologies have the potential to transform healthcare sectors by facilitating improvements to healthcare planning and delivery. In one of the first studies to examine the influence of big data on business-IT alignment in the healthcare sector, this paper asks the question: how do perceptions of big data influence alignment across macro, meso, and micro levels in the NZ healthcare sector? A newly developed theory, the Theory of Sociotechnical Representations (TSR), is used to examine people's sociotechnical representations of big data technologies and their applicability in their day-to-day work. These representations are analysed at each level and then across levels to evaluate the degree of alignment. A social dimension lens to alignment was used to explore mutual understanding of big data across the sector. The findings show alignment across the sector through the shared understanding of the importance of data quality, the increasing challenges of privacy and security, and the importance of utilising modern and new data in measuring health outcomes. Areas of misalignment include the differing definitions of big data, as well as perceptions around data ownership, data sharing, use of patient-generated data and interoperability. Both practical and theoretical contributions of the study are discussed.

Key words: Big data, New Zealand healthcare, business-IT alignment, Theory of Sociotechnical Representations, business-IT alignment taxonomy

8.3. Introduction

In the past decade, with the advent of ever more sophisticated information technologies, the healthcare sector has undergone major changes targeting improved patient care (Paré et al., 2008; Roski et al., 2014). A wide range of clinical and operational information systems are used by healthcare systems around the world (Menon et al., 2009). This growing use of information systems in the healthcare sector, 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; Wyber et al., 2015). Until recent times data-driven approaches in healthcare were considered difficult, if not impossible, because technology itself was not mature enough to handle such data (Wyber et al., 2015). However, recent developments of technology around big data analytics have opened promising avenues for healthcare to make use of big-healthcare-data for improved healthcare delivery (Herland et al., 2014; Mace, 2014; Nash, 2014). Some notable examples include: precision medicine, discovering the most effective treatments, identifying patterns related to medication side effects and hospital readmissions, and advances in pharmaceutical research (Groves et al., 2013; Nash, 2014; Tormay, 2015). Although the healthcare sector has not been an early adopter of big data analytics (Groves et al., 2013; Ward et al., 2014), currently, developed countries demonstrate a great interest in the potential of big data to improve healthcare planning and service delivery (Raghupathi & Raghupathi, 2014; Ward et al., 2014).

Research in the field of big data shows that the success of big data technologies depends on its alignment with business needs (Bean & Kiron, 2013; Watson, 2014; Weerasinghe, Pauleen, et al., 2018). Addressing this importance of alignment, this paper presents a study investigating the influence of big data on business-IT alignment in New Zealand (NZ) healthcare across multiple levels. The NZ healthcare sector is led by the Ministry of Health (MoH) (Ministry of Health, 2014a) and the Minister of Health develops policy with input from the MoH, Cabinet and the government (Ministry of Health, 2017). The Minister is advised by the Ministry and its directorates (e.g., Directorate of System Strategy and Policy, Data and Digital Directorate), Health Workforce New Zealand and other advisory committees (Ministry of Health, 2017, 2019). District Health Boards (DHBs) and Primary Health Organisations (PHOs) and their member general practices are the main organisations that are responsible for healthcare delivery. Healthcare services are provided by these organisations to the NZ population and are directed by the MoH.

Due to the association of many different organisations, actors, and structural divisions in the NZ healthcare system, it is defined as a complex system. When studying complex systems it is helpful to take an approach that incorporates the macro-meso-micro (MMM) perspective of the system to arrive at a holistic understanding (Dopfer et al., 2004). Within the NZ healthcare sector macro has been identified as policy makers, meso as planners and funders, and micro as frontline care providers (Cumming, 2011; Scahill, 2012b; Weerasinghe, Pauleen, et al., 2018).

Big data can be studied through two dynamics: social and technical. As a technological phenomenon itself, big data research often focuses on technical dynamics such as analytic capabilities, security measures, infrastructure requirements and so on (e.g., Chen et al., 2014; Davenport, 2013; Dhawan et al., 2014). The social dynamics around big data such as understanding, commitment, value and perceived challenges are often given less attention in big data research (Shin & Choi, 2015). However, because social dynamics involve the subjective understanding of a technological phenomenon and it often reflects and affects the use of this (Dulipovici & Robey, 2013), the positive social dynamics of big data are crucial for its success. While there exists some research examining the social dynamics of big data (Eynon, 2013; Shin & Choi, 2015), more knowledge around social dynamics is required (Shin, 2015; Shin & Choi, 2015). Political, organisational and managerial decisions about implementing big data technologies are greatly influenced by the social dynamics around big data (Shin, 2015). The implementation of big data technologies is challenging and spans the sub-sectors of healthcare, requiring the support of multiple stakeholders (Weerasinghe, Pauleen, et al., 2018). For example, the implementation of big data technologies must accord with health strategy in the first instance. Security measures, necessary funding, available skills and technology, and willingness to use are considerations, alongside responsibilities which reside at different levels. It is important to note that perceptions about big data by stakeholders at different levels (MMM) may be different due to the range of roles they play, their experience and many other factors (Moscovici, 1984b).

Based on this understanding the research question addressed in this paper is how do perceptions of big data influence alignment across macro, meso, and micro levels in the NZ healthcare sector? Although the general understanding of business-IT alignment concerns maintaining consistency between technology and formal documentation (such as policy, design documents, and the like), the successful implementation of technology also depends on stakeholders' perceptions, understanding and commitment. These are the focus of the social dimension of alignment (Dulipovici & Robey, 2013; Gal & Berente, 2008). The social dimension of alignment fits well with the intent of the Theory of Sociotechnical Representations (TSR), which is a novel theory developed to examine people's sociotechnical representations of big data technologies and their applicability in their day-to-day work. TSR is a new theory and this paper presents an early application of it.

The next section provides a review of literature on big data in the context of health, identifying definitions and explaining potential opportunities and issues. The discussion in the theoretical foundations section is twofold: it explains TSR and its use and discusses a taxonomy derived from the alignment literature that guides an alignment study and identifies the scope and boundaries for the present study. The methodology section outlines the qualitative methods used in this study. The findings section reports on both alignments and misalignments around perceptions of big data in relation to each MMM level. The final section identifies important implications, limitations and directions for future work.

8.4. Big data in Health

Big data in health refers to large and complex data across healthcare that may potentially improve healthcare management and service delivery. In general, big data refers to enormous amounts of unstructured and complex data produced by a wide range of sources such as computer applications, mobile devices, and sensors (Emani et al., 2015; Groves et al., 2013). There is no universally agreed upon definition for big data (Herland et al., 2014) and phrases such as "massive amounts of data", "enormous growth of data" and "large datasets" are typically seen across the literature as defining big data (Chen et al., 2014; Eynon, 2013). Big data can be defined and distinguished from standard data based on three characteristics, known as the 3Vs: volume (enormous amounts of data), variety (many different types and sources of data) and velocity (data that is generated and used at a high speed) (McAfee & Brynjolfsson, 2012; Russom, 2011). Two additional Vs – veracity (accuracy of data) and value (data that is able to create value) – are also commonly cited, extending the characteristics of big data to 5Vs (Emani et al., 2015; Saporito, 2013; Sathi, 2012).

Typically, big data in health are data generated by health information systems such as Patient Management Systems (PMS), laboratory systems, radiology and imaging systems and the like, within the health system itself. Genomics data (data obtained through genomic sequencing) and patient-generated data (data created by patients outside of the healthcare system) are also identified as other types of big data in health (Roski et al., 2014). With this understanding, Figure 8.1 illustrates the types of data that can be considered big data in the healthcare context.

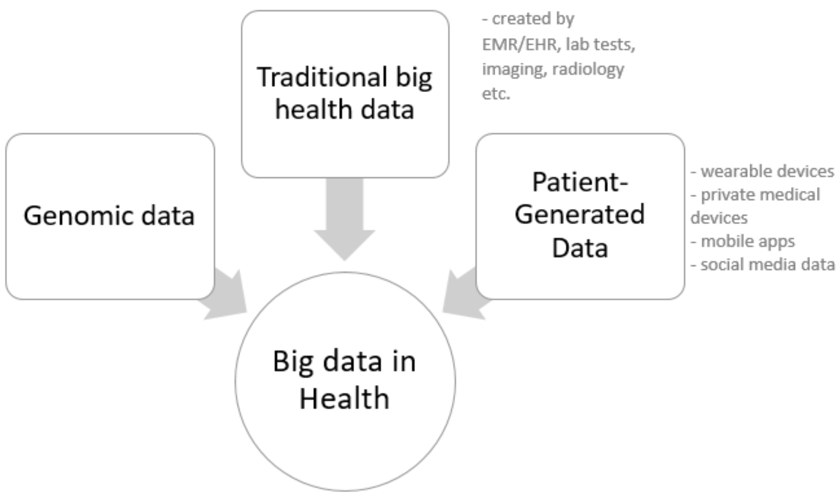

Figure 8.1: Types of big data in health

Genomic data is used to understand a person's genome through sequencing techniques[29]. A genome (DNA) has nearly three billion base pairs, which results in approximately 100 gigabytes worth of data for a single person (O'Driscoll, Daugelaite, & Sleator, 2013). Due to its complexity and enormous

[29] Sequencing techniques refer to technology (technologies) which allows inspection of DNA

volume, genomics data is categorised as big data (He, Ge, & He, 2017). Genomics in healthcare may enable precision medicine. Traditionally medications are prescribed to patients on a trial and error basis because they do not cater to the individual or their genomic makeup. Some medications work well for some patients but not for others. With genomics, precision medicine can more clearly define a disease and facilitate precise targeting of disease subgroups to allow better treatments (Ashley, 2016). Precision medicine uses big data technologies to facilitate personalised treatments by identifying a person's genomic makeup (Jameson & Longo, 2015).

Patient-generated data is data produced by patients outside of clinical settings in normal daily life (Petersen & DeMuro, 2015). Such data is generated by mobile apps, wearable devices or other medical devices used by patients to monitor their health; for example, blood pressure monitors (Shapiro, Johnston, Wald, & Mon, 2012). The use of such patient-generated data provides benefits including customised care plans, assessing patients' functional status, understanding outcomes after surgery to predict the length of hospital stay, and so forth (Petersen & DeMuro, 2015). Data from social media is also a form of patient-generated data that healthcare sectors can utilise for improved healthcare management and delivery. Healthcare research increasingly discusses the benefits of capturing patient experience through social media as opposed to getting patient feedback on the services through traditional methods (Greaves, Ramirez-Cano, Millett, Darzi, & Donaldson, 2013).

Although data with characteristics of big data have been generated by the healthcare sector for some time, historically data-driven approaches in healthcare were often considered complex, if not impossible, because technology was not mature enough to handle such data (Wyber et al., 2015). For example, only around 15% of data from health records (which are in a structured form) is used at present, mostly through traditional analytics (Roski et al., 2014). Recent developments in big data analytics have opened up promising avenues for the healthcare sector to make better use of big-healthcare-data for improved healthcare delivery (Mace, 2014; Tormay, 2015; Wyber et al., 2015). Examples include: Hadoop clusters, which can be used to economically store massive amounts of data;

data science experts, who are capable of making sense of large and complex data generated nearly in real time; and advanced analytical capabilities, which allow for health data to be formatted in different ways (structured, semi-structured and unstructured) to be linked and analysed together.

Compared to other industries like retail merchandising and banking, the uptake of big data technologies in the healthcare sector has been limited and slow (Bates et al., 2014; Groves et al., 2013). The complex nature of the healthcare system, resistance to change by healthcare practitioners, uncertainty of returns, and privacy concerns are identified as possible reasons for this lag (Groves et al., 2013). Nonetheless, due to increasing IT expenditures and the enormous amounts of under-utilised, complex data, the healthcare sector needs more efficient practices, research and tools to analyse and maximise the utility of big data (Chawla & Davis, 2013; Groves et al., 2013).

Recently, developed countries have recognised the importance of big data analytics for healthcare (Prewitt, 2014). As big data analytics allows for discovering associations and recognising patterns and trends it has the potential to improve care, save lives and lower costs (Raghupathi & Raghupathi, 2014). McKinsey & Company estimates that with the use of big data analytics tools and technologies for healthcare, the United States can save between $300 billion to $450 billion per year (Groves et al., 2013). Harnessing big data for enhanced applied knowledge could have significant implications for healthcare. Some of these benefits include: improved clinical decision support, detecting gaps in care delivery, discovering the most effective treatments, identifying patterns related to medication side effects and hospital readmissions, delivery of personalised medicine through genomics, improving pharmaceutical research, reliance on patient-generated data for diagnostics and lastly, fraud detection (Groves et al., 2013; Nash, 2014; Roski et al., 2014; Tormay, 2015).

Although such benefits can be achieved, the very nature of big data catering to multiple different areas creates huge challenges on its own. Some of these challenges include maintaining data quality, patient privacy, obtaining skills, changes to IT infrastructure, and re-visiting policy (Halamka, 2014; Roski et al., 2014). Technical dynamics (analytics, privacy and security measures, IT infrastructure) involving big data implementations have been extensively researched (Chen et al., 2014; Davenport, 2013; Dhawan et al., 2014; Jagadish et al., 2014). As a technological revolution itself, big data research naturally leans towards these technical dynamics. As a result, adequate research has not been carried out to investigate the social dynamics of big data (Shin, 2015; Shin & Choi, 2015). Social dynamics refer to users' understanding, commitment, perceived value and challenges of big data in a given context. As such, social dynamics reflect the actual and potential use of a technological phenomenon, investigating social dynamics is important. Thus, to address this, the research investigates social dynamics around big data in the NZ healthcare context.

8.5. Theoretical Foundations

The theoretical foundations of this paper are twofold. First, to investigate business-IT alignment, the Taxonomy of Alignment Conceptualisations (Weerasinghe, Scahill, et al., 2018) is used. The taxonomy helps identify and define the scope of the study. Second, the Theory of Sociotechnical Representations (TSR) is used as a foundational theory to understand sociotechnical representations of big data in health to investigate its influence on alignment.

8.5.1. Taxonomy of Alignment

For over 30 years business-IT alignment has been a key concern in academia and industry, making it an important field of IS research (Chan & Reich, 2007; Jia, Wang, & Ge, 2018). 'Alignment' refers to the degree of fit between the business and information technology and involves strategy, structure and/or people (Chan & Reich, 2007; El-Mekawy et al., 2015; Henderson & Venkatraman, 1992; Luftman, 1996). The business-IT alignment literature is vast and has many different conceptualisations as a result of being studied for years across many domains (Chan & Reich, 2007). Weerasinghe, Scahill, et al. (2018) created a taxonomy (Table 8.1) that identifies existing conceptualisations of alignment and explains how they can be used to define the scope of an alignment study.

Table 8.1: Taxonomy of Alignment Conceptualisations

(Weerasinghe, Scahill, et al., 2018)

Classes	**Properties of Each Class**					
Types	Bivariate fit	Cross-domain alignment	Strategic fit			
Levels	Organisational	Operational	System	Project	Individual	Sector
Dimensions	Strategic/Intellectual	Structural (Formal/Informal)	Social	Cultural		
States	End (Result)	Process				
Environments	Internal	External				

This taxonomy identifies five classes of alignment: types, levels, dimensions, states and environments. The properties of each type are identified, based on literature (a complete definition of all properties can be found in Paper I – Section 3.4). The taxonomy encourages the study of at least one property within each class for an alignment study to be complete (Weerasinghe, Scahill, et al., 2018). The selected properties for this alignment study are shaded in the taxonomy (see Table 8.2) and explained below.

Table 8.2: Selected conceptualisations of alignment for the study

Classes	**Properties of Each Class**					
Types	Bivariate fit	Cross-domain alignment	Strategic fit			
Levels	Organisational	Operational	System	Project	Individual	Sector
Dimensions	Strategic/Intellectual	Structural (Formal/Informal)	Social	Cultural		
States	End (Result)	Process				
Environments	Internal	External				

Strategic fit is selected as the type of alignment. Strategic fit investigates alignment across domains of business strategy, business structure, IT strategy and IT structure (Henderson & Venkatraman, 1992). As big data implementations demands change in all of these domains, it is necessary that all the domains are explored, as opposed to investigating two or three domains through bivariate fit or cross-domain alignment. Secondly, the research question relates directly to understanding the influence of big data perceptions across the sector. Therefore, the level of alignment to be investigated is the sector level. By investigating sector level alignment the study will be able to understand agreements and gaps in alignment across the whole sector.

Highlighting the lack of knowledge and the need to investigate the social dynamics around big data, the social dimension of alignment was selected as the lens through which to conduct this alignment study. Big data implementations involve the utilisation of a set of technological, social and organisational interactions. This could mean having to deal with groups of stakeholders with different interests, interpretations and perceptions (Gal & Berente, 2008). Therefore, the social dimension of alignment is used to explore how big data is perceived by different players across the sector. This further fits with the identified gap in the literature – a lack of research around the social dynamics of big data. Dulipovici and Robey (2013) identify two aspects of technology use as intended and situated use. Intended use is the planned purpose of technology/IS while situated use is the subjective understanding of technology/IS. Investigation through a social dimension lens will facilitate the study of social dynamics around big data, allowing an understanding of its situated use. Because the implementation of big data is still in progress in the New Zealand healthcare sector, it will continue to evolve; thus this study considered alignment as a process, as opposed to an end state. This definition of alignment as a process allows us to capture different stages of understanding of big data as well as big data initiatives across the sector. Although many different organisations and healthcare bodies were examined, because all the organisations are within the NZ healthcare system itself, it is regarded as a study of the internal environment within the healthcare sector.

8.5.2. Theory of Sociotechnical Representations

The Theory of Sociotechnical Representations (TSR) (Paper III – Chapter 7) integrates key elements of two well-known theories: Sociotechnical Systems Theory (SST) (Emery, 1959) and Social Representations Theory (SRT) (Moscovici, 1984b). TSR combines IS views of technology (through SST) with social psychology perspectives (through SRT) to explore and understand individual perspectives of technology and the effects of these perspectives on technology implementation and use. TSR explains that given any technological phenomenon is co-dependent with the people around it (policy makers, planners, implementers and users), not just in what people do with it (e.g., roles, responsibilities) but also in terms of how people perceive it (e.g., usefulness, commitment to use, value). As explained in SST by Emery and Trist (1965) the social subsystem (people) and the technical subsystem (technology) interact with each other and are interdependent with each other. Therefore, the roles and responsibilities of people are affected by what technology is intended to do and can do. However, TSR using SRT (Moscovici, 1984b) with SST (Paper III – Chapter 7), explains that this interdependence of technology and people goes beyond concrete factors like roles and responsibilities or structures and that the perception of technology (identified as sociotechnical representations) is critical to the success of technology.

Through the previous explanation of TSR and as shown in Figure 8.2, TSR uses SRT as a theoretical tool to deeply examine the technical subsystem. It does not ignore the social subsystem. Instead, it looks into the interdependencies between the social and technical subsystems, highlighting that the social subsystem influences the representations of the technical subsystem. Because SRT is a tool to explore user perceptions of technology (the technical subsystem) and the potential social capabilities (social subsystem), TSR uses SRT to inform SST. The SRT literature highlights two component processes: objectification and anchoring. Objectification is the individual mapping of the phenomenon while anchoring refers to how the people around it (the group) influence the perception. Further, TSR highlights that the social subsystem influences anchoring and objectification of the technical subsystems' representation. Therefore, SRT supports a deeper and richer understanding of sociotechnical systems. It does this by facilitating the examination of sociotechnical representations created by the social subsystem about the technical subsystem through anchoring and objectification. As explained in SRT, these two subcomponent processes (anchoring and objectification) are complementary to each other.

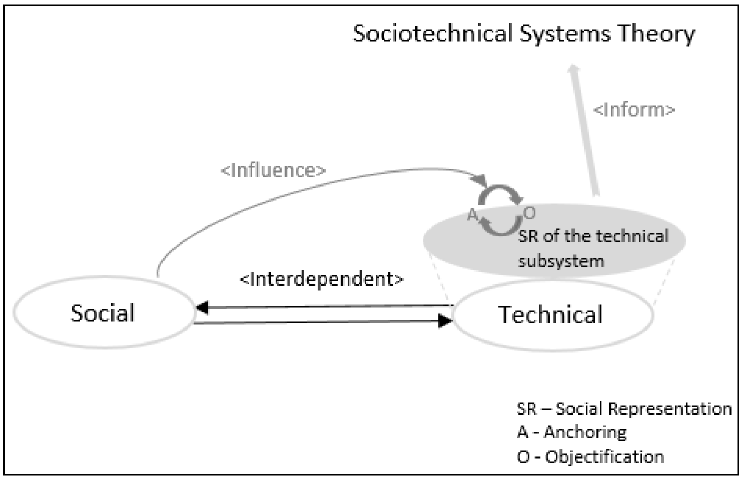

Figure 8.2: Theory of Sociotechnical Representations

(adopted from Paper III, Section 7.6)

Using TSR, the present study focuses on the social dynamics of technology (i.e., how technology is perceived in terms of value and challenges, and the commitment of people involved). It contributes to understanding how the technical subsystem is perceived and appreciated (or not) by the stakeholders themselves who are the social subsystem. This understanding helps researchers to identify issues and derive understandings about social interpretations and reasons why the technical subsystem influences sociotechnical interdependencies. The SST perspective explains that the social and technical subsystems are interdependent in the sense that peoples' skills, values and other humanistic characteristics are interrelated with the technological aspects, such as the systems, IT infrastructure and tools.

TSR also argues that the social representation of the technical subsystem by the stakeholders of this subsystem plays an important part in the success and acceptance of technical systems. Because a social representation of the technical subsystem is created, TSR uses the term "sociotechnical representation" as opposed to the term "social representation" used in SRT. A sociotechnical representation alludes to a technological phenomenon that is created through social interpretations of technology by an individual's objectification and the groups' process of anchoring. Use of TSR also has an important impact on the methodology and selection of participants compared to a typical SST-based study. Because it is a sociotechnical representation, use of TSR promotes the value of understanding the perceptions of people over physical documents or systems.

The use of a social dimension lens (based on the business-IT alignment taxonomy) promotes the investigation of the "level of mutual understanding" (Reich & Benbasat, 1996, p. 58) in a business-IT alignment context. Similarities and differences in sociotechnical representations around big data technologies and their use can inform big data's influence on business-IT alignment. The use of TSR is appropriate for a study that investigates the social dimension of alignment. In this study, alignment is defined as 'the fit between perceptions of big data and healthcare sector needs at each subsector level (macro, meso, and micro)'.

8.6. Methodology

The aim of this paper is to explore how big data analytics is perceived (represented) in the healthcare sector and how this representation influences business-IT alignment. An exploratory qualitative approach is used (Liamputtong & Ezzy, 2005). The very nature of the healthcare sector and implementing and aligning big data technologies across this multi-level system potentially has unidentified complexities. Considering social dynamics around big data adds a further level of complexity because social dynamics may vary from person to person as well as in each MMM level. Accordingly, the research is not hypothesis testing in nature, but rather is guided by the research question: *"how do perceptions of big data influence alignment across macro, meso, and micro levels in the NZ healthcare sector?"*

The use of TSR promotes collecting data from individuals and interpreting it at a group level. Individual sector levels (MMM) were identified as the smallest unit of analysis. Data was collected from individuals and was analysed and interpreted at each of the three subsector levels to understand perceptions of big data at each subsector level. A cross-group analysis was then undertaken to understand influence on alignment across the healthcare sector. Within the healthcare sector, the identified MMM levels have different tasks and responsibilities associated with big data initiatives, and are likely to construct different sociotechnical representations of big data. Analysing the groups separately minimises the abstract level of analysis, allowing for examination of operational details within the sector (Yin, 2014).

The research design and procedures are shown in Figure 8.3. The research question, literature and context along with the theoretical foundations influenced the selected research methodology. The data collection protocol was decided and three interview schemas for each of the MMM levels were piloted. Data was collected from MMM groups and data from each individual level was separately analysed and individual summary tables were created (Smith et al., 2009). Using the three summary tables, a cross-level analysis was done to understand the situation across the healthcare sector. The cross-level summary table (see Section 6.3.2) was used as a guide in reporting the findings and discussion identifying alignment and misalignment of big data in the NZ healthcare context.

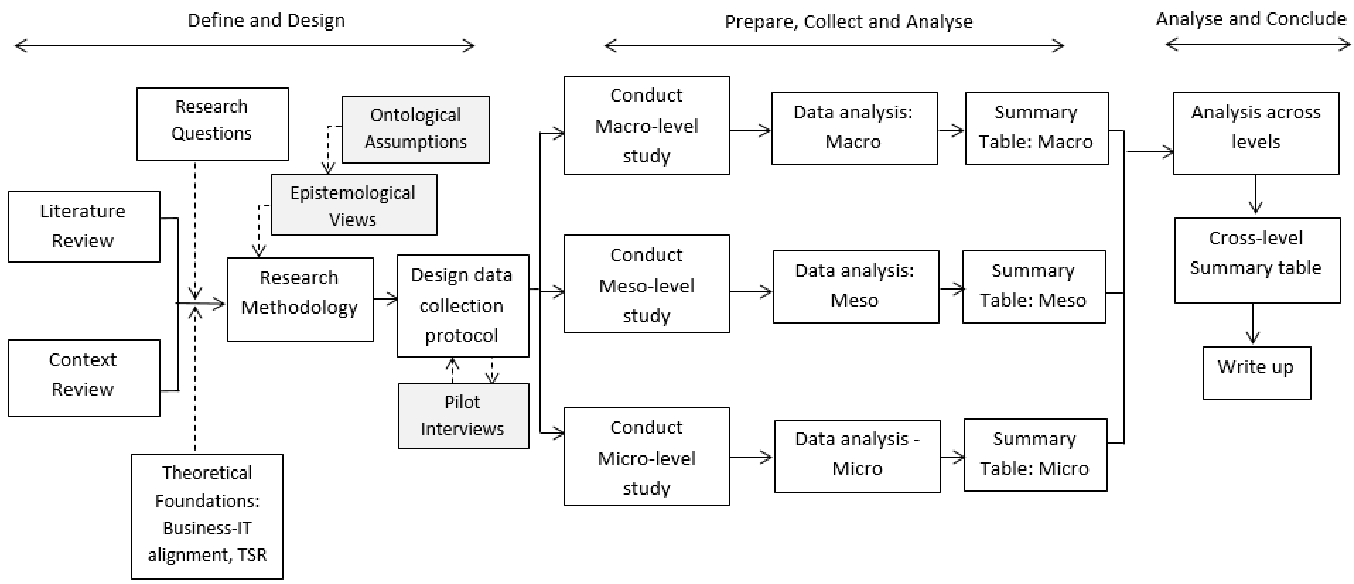

Figure 8.3: Research Procedure

Semi-structured interviews were conducted to gather rich data from participants at each MMM level (Merriam, 2009). Purposive sampling techniques were used as the research required gathering data from informants who were involved in constructing policies, planning and implementing, or using (current or future) big data technologies (M. B. Miles et al., 2014; Patton, 2015). A snowball sampling strategy was also used, asking informants to direct the researcher to other participants (M. B. Miles et al., 2014). Overall, 32 interviews were conducted, with six at macro level[30], seventeen at meso and nine at the micro level. Four participants at the meso level, who had clinical duties, also answered questions relating to the micro level. Participant demographics are provided in Appendix 7. Sample size was determined upon reaching theoretical saturation (Mason, 2010). Interviews were audio recorded and transcribed verbatim.

General inductive thematic analysis (Thomas, 2006) was used to analyse data, supported by NVivo software. An inductive approach was adopted and its intent was to see what ideas emerged from the data rather than the literature around big data. The first step in the inductive analysis was to clean the raw data files and to bring all transcripts into a similar format using Microsoft Word. Then reading and re-reading along with writing memos was done by the first author. When fully familiar with the data, transcripts were coded and themes were identified. All themes at each MMM level were analysed separately to identify categories. These categories were re-analysed to remove less consequential categories and to merge similar ones. Three summary tables were created for each of the MMM levels for analysis, which guided the report writing for each level (An example of categories and themes along with representative quotes can be found in Section 6.3.2- Table 6.3).

8.7. Findings and Discussion: Alignment of Big Data Perceptions across NZ Healthcare

Five key categories emerged from data analysis that influence the sociotechnical representations of big data. These are: (i) absence of a clear definition, (ii) valued characteristics of big healthcare data, (iii) issues and challenges of big data, (iv) applications (current and future potential areas), and (v) influence of healthcare strategy and policy. A table summarising key categories and themes identified across MMM levels is provided below (Table 8.3). As a business-IT alignment study, further analysis

[30] The data was collected between February 2016 and June 2018. During this period the government of NZ changed, and the Ministry of Health went through a restructure and NZ health strategy was revised. Consequently, some of the participants who were interviewed in 2016 talk about things that are no longer in use. Some of the business units that were thought to have a major role in the health system with regard to health-IT were disestablished.

into these findings showed areas of alignment and misalignment of big data technologies across the sector. It is important to iterate that this is not a traditional business-IT alignment study (investigating the strategic dimension of alignment), but instead a study that investigated the social dimension of alignment. Therefore, the study's focus was on how participants perceived big data technologies and the technology's potential/application for their day-to-day work. The results in Table 8.3 comprise alignment and misalignment issues based on these perceptions across the New Zealand healthcare sector. Alignment in this study means that all three levels have similar perspectives. If only two of three levels aligned, this was considered misalignment. However, if one of the MMM levels did not talk about a certain issue/topic while the other two did and had similar views it was taken to be alignment.

Table 8.3: Areas of alignment and misalignment of big data in New Zealand Healthcare

Alignment	Misalignment
• Importance of data quality is well understood by all three levels. • Privacy and security of data is seen as a challenge across the sector. • Agreement around use of more data for improved measures of health outcomes • Agreement by macro and meso around changes to skills and technology infrastructure to facilitate big data • Aligned views (of macro and meso) around health policy and strategy as providing initial direction towards the future of big data	• Ambiguity and differences in defining big data within and across levels • Differing views on velocity as a characteristic of big data • Misaligned views around definitions of data ownership • Disagreements around data sharing practices and privacy laws influencing data sharing • Differing opinions around interoperability • Misalignment around areas of application (precision medicine and clinical decision making) • Invisibility of patient-generated data in health policy and strategy

These examples of alignment and misalignment are discussed below in light of the related literature. When discussing misalignment, TSR underpins the explanations and recommendations.

8.7.1. Areas of Alignment

Importance of data quality is well understood by all three levels of the healthcare sector. While big data brings many opportunities to healthcare, it also adds significant challenges around data quality that need to be addressed (Halamka, 2014). Perceptions of all three MMM levels showed that participants understood the importance of data quality. While arguing that data quality is not just about accuracy, participants across all levels identified factors that influence data quality such as relevance, completeness, timeliness, level of summarisation and availability of contextual information. The analysis also showed that those at the macro level are working on ensuring data accuracy through implementation of standards and policies, which will facilitate the capture of correct and complete data. Those at the meso and micro levels agreed on the importance of ensuring standards through appropriate policy to maintain data quality. While this aligns with discussions in the literature around health policy (e.g., Roski et al., 2014), this finding adds to the literature by identifying the agreements and acknowledgements at other levels around the importance of policy as a facilitator of data quality.

Another area of interest for improving accuracy is enabling the direct input of data to health information systems from digital devices (explained as the use of Internet of Things technologies) without the need for a human interface (e.g., blood pressure monitors entering the reading directly into patient records). IoT technologies improve the reliability of data which increases data quality due to the connectedness brought through IoT and sensor technologies (Kyriazis & Varvarigou, 2013). However, the IoT literature also highlights data quality issues due to dropped readings, multi-source inconsistencies, and unreliable readings (Karkouch, Mousannif, Al Moatassime, & Noel, 2016). Participants from the meso level emphasised their work around implementing proper measures to ensure the capturing of accurate data, through collecting correct and complete data. Doctors at the micro level also talked about the value of data quality, explaining the importance of quality data for clinical and administrative decision making. All of the MMM levels have dealt with issues around poor data accuracy and therefore see it as important to tackle accuracy issues with modern technology around data.

Privacy and security around health data is seen as another major challenge by all of the participants across the sector. All participants agreed that privacy around personal health data must be secured. Privacy and security are great concerns in the big data era, especially due to the amount of data being held by organisations, as well as potential use of cloud service providers (Esposito, De Santis, Tortora, Chang, & Choo, 2018). Moreover, healthcare organisations have an added responsibility because of the sensitivity and the personal nature of healthcare data, which demands greater requirements around privacy and security measures. Roski et al. (2014) argue that current practices, policies and security measures around the use of data need to be revisited by policy makers to facilitate better data security in the big data era, this does currently seem to be the case in New Zealand.

Improved measures of health outcomes is facilitated by big data. When talking about the possible applications of big data technologies, all three levels talked about improvements to measuring outcomes within the healthcare sector. From clinicians who talked about the importance of getting a detailed view on how their patients are doing to policy makers wanting to see how they are achieving health targets (or not), there was a clear acknowledgement of how more data as well as new types of data can improve current practices of measuring outcomes. Measuring health outcomes has been standard practice and the healthcare sectors are constantly looking for practices and technologies to improve these measurements (Strome, 2014). Globally, improvements to the measurement of outcomes are identified as a key area in which big data technologies can be utilised (Groves et al., 2013).

Agreements around changes in skills and technology. Another important challenge identified by macro and meso levels (and not by micro, as it is not relevant to them and their work) is changes to skills, IT infrastructure, and IT architecture. Meso level also identified organisational structure changes around transformation of data. These show similarities with existing literature around big data transformation

(Davenport & Dyché, 2013). At the macro level there was no data around organisational structure changes in the data collected in 2016, but there has been a recent restructure in late 2018 at MoH to include a Data and Digital Directorate. This is a significant step towards better policy, implementation, use and management of big health data.

Health strategy provides initial direction toward big data. Macro and meso levels also identified and accepted that health strategy is providing initial direction toward big data technologies in the NZ healthcare sector. The macro level believed the term "smart systems" (MAC1) in health strategy is related to initiatives around big data, and the meso level agreed. Further, meso level participants claimed that having this term included in strategy provides a good platform to discuss big data technologies and their application across many domains. The literature also highlights the importance of health policy and strategy in providing direction around big data technologies as an important factor for big data success (Blasimme, Fadda, Schneider, & Vayena, 2018; Roski et al., 2014).

8.7.2. Areas of Misalignment

In this section identified areas of misalignment are discussed, drawing on findings and literature. TSR is used to identify likely reasons for these misalignment issues. Recommendations are made at the end of each point that can potentially overcome identified issues of misalignment.

Ambiguity and differences in defining big data within and across levels. The initial overall analysis showed that there was a lack of understanding and knowledge around defining the term 'big data' within all levels of healthcare. People across the sector defined big data in different ways. For some participants, big data is not seen as something new (e.g., MIC6) while some saw big data as something they did not clearly understand (e.g., MES3), or were reluctant to use the term due to confusion around it (e.g., MAC5). Some participants saw big data as a buzzword (e.g., MES14), with a few exceptions who were able to clearly define big data (e.g., MAC1). While big data has as of late turned into a buzzword, the literature highlights that there has to be a common understanding that big data concerns data that is too large, too fast and too complex to be dealt with through traditional/existing technologies (Andreu-Perez et al., 2015).

There is an unanswered question as to whether big data is genuinely a new phenomenon, or whether large scale datasets consisting of data routinely collected for years are also classed as big data (Collins, 2016). However, modern technologies developed around big data have increased the capabilities for making use of such large-scale datasets (Collins, 2016). Similarly, most participants acknowledged that evolving technology is what generates big data and new possibilities around health data. Big data literature in the health domain explains that big data is not just about existing forms of health data but about utilising new forms of data that can be linked to health systems to improve healthcare management and delivery of care (Ginsburg & Phillips, 2018; Zadeh, Zolbanin, Sharda, & Delen, 2019). There was an understanding across sector levels that technology is changing how healthcare is delivered and data plays a prominent role. However, it was observed that these understandings are misaligned (e.g., some identified big data as new, some as a buzzword, some as not new) and are not heading in the same direction.

While it is acceptable to have evolving representations as explained in TSR foundational theory (i.e., SRT) (Moscovici, 1984b) and alignment as a process (Jenkin & Chan, 2010), ambiguity is not the same as evolving representations. Ambiguity shows unawareness, lack of understanding and confusion. Understandings through TSR can explain this ambiguity by drawing on data that shows there is a lack of anchoring of the term across the sector. Many participants did not have anchoring experiences (group conversations, presentations, documentation such as policy) to understand big data and its possibilities. Therefore, participants objectified the term 'big data' based on their background, past experience, understanding and other individual components (e.g., MAC2, being an epidemiologist[31], has seen a lot of data for many years of her career and claims big data is not new). Thus, they did not get to anchor the term through discussions within or across their levels. This results in many

[31] A person who analyses populations to understand certain aspects of health (population health analysis)

(mis)alignment issues across the sector. It is recommended that this gap needs to be addressed, mainly facilitated by macro and meso level organisations across the sector. Such initiatives could include initiating discussions around the concept of big data and its applications.

Differing views on velocity as a characteristic of big data. In the big data literature, velocity is discussed as the real-time use of data (McAfee & Brynjolfsson, 2012). However, one of the macro participants (MAC5[32]) emphasised that they opposed the views on real-time data, claiming "the real information comes through analysing both historical data and the most recent data". While other macro participants talked about speed of data creation as velocity, there was a lack of explanation around using data in real time at the macro level. However, there was evidence at the meso level that participants saw timely use of data as a part of velocity and they saw using real-time data as desirable (but not currently being done in practice). These misaligned perceptions relating to the definition of big data can also be linked to the lack of anchoring across the sector. However, such alignment gaps may result in policies not capturing the potential use of data in real time as desired and valued by the other levels. Similarly, to address unclear definitions of big data, in order to get everyone on the same page a common discussion is recommended.

Misaligned perceptions around data ownership. All three levels showed uncertainty around who owns patient data. At the macro level, it was highlighted that "primary care has a view that they own the patient information, and the patient information is a commercial asset" (MAC4). Meso participants also showed their confusion around data ownership. A senior technical specialist from a PHO explained this confusion, saying "[t]he problem is there's always the big question of 'who owns the data?' So if you ask this from a doctor, GP or a specialist or a DHB or the Ministry of Health I'm not sure they will answer you" (MES8). While the GPs at the micro level were not sure whether they, the PHOs or the government owned patients' data, hospital doctors did not have any comments about

[32] MAC5 is a senior executive leading a team at the macro level; he has had extensive experience in IT and over 6 years of healthcare experience.

data ownership. Because primary care (PHOs) has a responsibility to collect patient data, this may imply to those at the primary care level that they own this data. However, not having clear policies to facilitate anchoring and objectification of what data ownership means may result in confusion and a lack of clarity for all parties. Data ownership has been a common concern in big data literature (Kaisler, Armour, Espinosa, & Money, 2013); specifically in health, it is said that policy makers are required to redesign policies around data ownership when health systems are starting to utilise big data technologies (Roski et al., 2014). Therefore, it is highlighted that transparent guidelines through health policy are needed to facilitate clear understandings about data ownership.

Misalignment around data sharing practices and privacy laws influencing data sharing. While all three levels agreed on the importance of privacy and security around big health data, there seems to be disagreements around practices and privacy laws. Macro level participants stated that "in New Zealand we have good privacy laws" (MAC1). While micro and meso levels agreed that the privacy laws are protecting patient data, they highlighted that these laws may in fact be going too far, claiming privacy laws were hindering their ability to use data when it is required to help a patient. One meso level participant explained that "it [privacy law] would not allow me, as an interested party who had the capability, to help people who are disadvantaged at the moment [identified by the IDI]" (MES4). Tackling concerns around sharing big health data is often seen as a huge challenge to healthcare policy throughout the literature (Blasimme et al., 2018).

The literature highlights that policies around data sharing need to be updated and policies guiding data stewardship need to be adopted for better use of big data in the healthcare context (Roski et al., 2014). Similarly, meso and micro level participants recognised the need for flexible privacy laws along with clear ethical standards around sharing and use. TSR can explain this discrepancy through the definitions of tasks in different social subsystems at each level. Because macro has a role in securing trust of patients through privacy laws, their understanding around the difficulties of using data is limited. On the contrary, meso and micro levels need to use data and they do report coming across these difficulties. To overcome these different perceptions, it is recommended that there is more open discussion around the importance of data sharing, requiring the policy level to be more open to revisiting policy, making necessary adjustments but also ensuring privacy of patients in the modern era.

Differing perceptions around interoperability. Views around interoperability and the nature of the health system seem to have discrepancies. While all three levels identified the importance of interoperability, their thoughts and solutions around it showed misalignment issues. For example, the policy level acknowledged the semi-autonomous nature of the NZ health system, claiming "it has always been like [semi-autonomous] that and it will probably always be like that" (MAC3). They saw the semi-autonomous nature as allowing innovative organisations (PHOs or DHBs) to initiate new inventions without being driven by the government. However, the meso level participants saw this fragmented nature as something that created an "attitude of competitiveness" (MES14) between DHBs, causing DHBs to go in different directions and use "different systems and different methods" (MES3). The same was seen at the primary care level with PHOs (and their GPs) using various systems (primarily PMSs) that are provided by different software vendors (e.g., MedTech, MyPractice).

Doctors from hospitals reported the difficulties they go through on a daily basis due to the use of different health information systems. They also highlighted the amount of money and time wasted by having to repeat investigations, due to unlinked systems not providing them access to previous investigations done elsewhere. While implementing standards like HL7NZ[33] and SNOMED[34] will facilitate interoperability, a few micro level participants felt that the government needs to mandate a single PMS across the country as a starting point to fix issues around incompatibility. Although the semi-autonomous nature may be an advantage, not managing it creates interoperability issues across the sector and becomes a larger problem to deal with. It was highlighted by the participants that while

[33] HL7NZ is the New Zealand affiliate of Health Level Seven International. HL7 is the global developer of standards for health information systems to promote interoperability (http://www.hl7.org.nz/).
[34] SNOMED International determines standards for clinical terminology (http://www.snomed.org/). SNOMED standards are used in electronic health records.

incompatible systems and interoperability issues are not issues specific to big data, moving forward into big data technologies will be difficult and may create more challenges if these issues are not dealt with in the traditional data environment. While the data suggested that there is a need for a countrywide PMS, it is recommended that policy makers carefully consider this possibility alongside strengthening policies around interoperability before making changes. Further research is needed to make informed recommendations.

Misalignment around areas of application. As identified by participants across the three levels, big data has multiple areas of application, such as: measuring outcomes (within-sector and cross-sector analysis), precision medicine, population health, and clinical decision making. These areas of application were not seen in the same manner (in terms of potential and priority) by the three MMM levels. Although several participants at macro and meso levels identified population health as an area with big data potential, there was little dialogue from across the sector to discuss alignment, and is not covered in this section. While perceptions about measuring outcome seemed to be in alignment as explained in the alignment section above, identified misalignment issues across precision medicine and clinical decision making are discussed below.

Precision medicine is a key interest of the big data area identified by the government. A precision medicine initiative by the MoH is currently underway (at a research stage) in partnership with a DHB, a vendor and a university. As explained by one of the macro participants, health strategy through its identification of “smart systems” promotes fields like precision medicine. Therefore, such initiatives align with overall objectives of NZ healthcare. Both macro and meso levels saw this initiative focussing on precision medicine as favourable. They explained that “precision medicine will at some point facilitate improved clinical care” (MAC5) through understanding a person’s genomic structure. However, currently there was not enough information made available to clinicians about this precision medicine initiative, and they were not clear about the value of precision medicine.

TSR can expose and elaborate this issue by explaining that the social subsystem at the macro level (being the policy makers) identifies that it is a macro level role to set futuristic strategy. As explained by MAC1 and MAC4, they are looking out for modern areas that NZ health can benefit from. Thus, because of their role, their thoughts about precision medicine are positively objectified and further anchored through discussions, allowing them to perceive the importance of precision medicine for improved healthcare in the future. Similarly, those at the meso level (specifically participants from DHBs, vendors and universities) work closely with the Ministry and have the opportunity to get involved in the project or in the discussion (objectification). Further, because of their role (social subsystem) in planning and funding and implementing government policy (Scahill, 2012b), the social subsystem influences their objectification, allowing them to perceive precision medicine as a beneficial area of application for NZ healthcare.

In contrast, clinicians' roles and responsibilities are around providing healthcare, and not many of them are involved in these discussions. Unless they are informed, there is little opportunity for them to get information around new areas such as precision medicine. For example, MES5, who was interviewed for both meso and micro groups as they have a strategic role in a DHB while also practising as a specialist doctor in the hospital, talked about the potential of precision medicine – this shows a clear reference to TSR's explanation of how the social subsystem influences the sociotechnical representations. Therefore a robust plan for providing information to lower levels is important, and will facilitate a more positive environment in the future when precision-driven medicine becomes more available and applicable to front-line clinicians.

Clinical decision making is the other area of application discussed under misalignment. While literature has identified clinical decision making as an area that can greatly benefit from big data technologies (Dang & Mendon, 2015), differing perceptions were seen across the sector. The big data literature identifies clinical care and decision making as an ideal area to utilise big health data (Roski et al., 2014). Clinical decisions supported by data from health systems can assist decision makers to achieve gains in performance, reduce gaps between knowledge and practice, and improve patient safety (Bates et al., 2003). However, macro level participants were very much focused on other areas (specifically measuring outcomes and population health) rather than looking into application of big data technologies for clinical decision making. Several of the macro participants acknowledged that big data has potential in clinical care settings; they claimed "it's not our [Ministry's] role" (MAC2) to initiate the use of big data for clinical care and decision making.

While the government and the MoH has a broader role and is participating through its active role of understanding the overall health system and how it can be improved through modern data, clinical decision-making initiatives need support from policy for successful implementation (Roski et al., 2014). Identifying current clinical decision support and its use of data to be at a "rudimentary stage" (MES2), meso level participants identified the application of big data for clinical decision making as having great potential. At the micro level there seems to be confusion about the potential of big data tools to facilitate clinical decision making. These participants talked about tools like Health Pathways and Atlas, and explained that they were wary of using any new tool without seeing evidence of its benefits. This echoes understandings of TSR, as TSR explains that experiencing something first-hand helps in terms of objectifying and anchoring it. As both the literature and the participants agree that clinical decision making can benefit from big data technologies, it is recommended that clinical decision making be made a priority and discussions initiated across the sector. Prioritising clinical decision making as an important area of application will lead to development of tools; however, it will also require the greater involvement of clinicians.

Ignorance of patient-generated data from policy-making levels. Patient-generated data (a source of big health data), while accepted and understood to have huge potential by meso and micro levels, did not seem to get much attention from the policy level. Some clinicians at the micro level currently use patient-generated data through mobile apps; yet this presents many difficulties due to a lack of guidance from the policy-maker level as well as from their meso level DHBs and PHOs. The meso level identified the use of patient-generated data as important and something they are interested in (specifically PHOs). However, these meso level participants admitted that they are not doing anything in the area of patient-generated data yet, saying “on our priority list it’s probably well down” (MES9). The meso level participants explained that policy makers need to discuss patient-generated data, and need to provide better direction to the sector through policy around capturing and using patient-generated data. Understandings through TSR can explain that this voluntary identification of patient-generated data as an area of interest by meso and micro level participants is due to their direct experience in dealing with patients (a few GPs explained how patients bring data recorded by them for consultations). At macro levels the absence of patient-generated data in policy may hinder their ability to objectify or anchor patient-generated data as beneficial. As one of the key action areas of health strategy is being ‘people-powered’ (Minister of Health, 2016), it is recommended that patient-generated data be incorporated into health policy for other levels to make effective use of it.

8.8. Conclusions, Implications, Limitations and Future Work

This study set out to investigate perceptions around big data and how business-IT alignment is influenced by such perceptions (identified as sociotechnical representations) in the NZ healthcare sector. The theory of sociotechnical representations (TSR) was used as the theoretical basis to investigate perceptions, identified as sociotechnical representations in TSR at multiple levels of macro, meso and micro. Through investigating sociotechnical representations, this study identified the social dynamics influencing the sociotechnical representations around big data. The paper shows the applicability of the business-IT alignment taxonomy (Weerasinghe, Scahill, et al., 2018) and uses TSR to conduct an alignment study. The paper identified areas of alignment and misalignment across the sector around perceptions of big data and its application. Understandings generated through TSR are used to explain misalignment and provide recommendations where necessary.

Using the business-IT alignment taxonomy (Weerasinghe, Scahill, et al., 2018), different lenses were used to frame the research. Examining strategic fit allowed us to investigate people, strategy and policy, and technology (Henderson & Venkatraman, 1993) to understand how business-IT alignment is influenced by sociotechnical representations of big data. The findings demonstrate that the sociotechnical representation of big data in the NZ healthcare sector is formed through the influence of perceived definitions, valued characteristics, identified issues and challenges, identified areas of application, as well as direction provided through policy and strategy. While there was no clearly formed sociotechnical representation of big data, this was expected when investigating business-IT alignment as a process (Chan & Reich, 2007).

NZ healthcare is an early adopter of electronic devices and computer systems in comparison to other parts of the world (Protti & Bowden, 2010). This habit of early adoptions has now resulted in huge amounts of data and this will increase exponentially. With data being generated for nearly 30 years, along with datasets like the National Minimum Dataset of NZ and other health datasets held by the Ministry of Health, 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 big data technologies to be applied to facilitate improved healthcare delivery and management in NZ.

The implications of this paper are both theoretical and practical. Theoretically the paper contributes specifically to TSR literature, making this one of the first applications of TSR and illustrating its potential contribution to IS research. The practical implications of the study include the identification and discussion of areas of alignment and misalignment. Alignment across the sector was found in the shared understanding of the importance of data quality, the increasing challenges of privacy and security, and the importance of new types of data in measuring health outcomes. Aspects of misalignment included the differing definitions of big data, as well as perceptions around data ownership, data sharing, use of patient-generated data and interoperability. While participants identified measuring outcomes, clinical decision making, population health, and precision medicine as potential areas of application for big data technologies, the three groups expressed varying levels of interest, which could cause misalignment issues. These findings will enable policy makers to understand the situation around big healthcare data at lower levels, influencing improved policy around big data. Similarly, meso and micro levels can get a better understanding about their current practices causing alignment issues that they can address and change in the future.

One of the key observations brought to light with TSR is that there is a lack of anchoring activities about big data across the sector. To create a common understanding about big data, its potential and application, it is important to initiate open discussions across the sector, possibly initiated by macro and meso levels. This was identified by several meso level participants who highlighted that there was no common discussion around what big data is, which was leading to confusion and possibly missed opportunities.

While MMM levels were separately analysed before the cross-group analysis, some subgroups within levels were also observed. Specifically, within the meso level, there were differing representations in some areas of application among subgroups such as DHBs, PHOs, vendors and academics. While presentation of such subgroups is accepted in TSR (through SRT), prominent differences are noted in the discussion. It was identified that data from participants from DHBs show many similarities to those of the macro level. This can also be explained by TSR: because DHBs work closely with the government, many DHB participants were involved, or have been involved in government discussions around health-IT. This could have allowed them to shape their perceptions (sociotechnical representations), through anchoring, to become similar to that of the government (and vice versa). Participants at universities and vendors also had experience working with the government, but their roles seemed more independent (e.g., independent research funded by the Ministry) – which could explain why their representations are not always as similar.

One of the limitations of this study is that at the micro level, there are other clinicians that have not been included as participants (nurses). The researchers tried getting nurses involved but did not succeed, and due to time constraints around research, the decision was made to go ahead with hospital doctors and general practitioners. Another study limitation is that pharmacy-related policy, funding, planning and use were not investigated. However, pharmacy is a different area and it is identified as a potential topic of study for the future.

Other future work could include investigations into specific issues around interoperability through a TSR lens, and investigating policy in more depth, existing use of standards and actual use in the clinical frontline. Investigations into patient-generated data from a policy perspective are also suggested. Quantitative studies would also be useful in generalising issues of alignment and misalignment within the NZ healthcare sector and also for formalising the applicability of TSR.

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Chapter 9: Conclusions

This chapter highlights the implications and contributions of this research. As a thesis by publication, this thesis utilises four research papers. Implications and contributions from these four research papers are first highlighted and then the overall contributions and limitations of this study are discussed. Future areas of research are also identified in this chapter.

9.1. Overview of the thesis

The growing use of information systems in the healthcare sector, on top of increasing patient populations, diseases and complicated medication regimens, is generating enormous amounts of unstructured and complex data that have the characteristics of 'big data'. Until recent times data driven approaches in healthcare to make use of large volumes of complex healthcare data were considered difficult, if not impossible, because available technology was not mature enough to handle such data. However, recent technological developments around big data have opened promising avenues for healthcare to make use of its big-healthcare-data for more effective healthcare delivery, in areas such as measuring outcomes, population health analysis, precision medicine, clinical care and research and development.

Big data research has often leaned towards technical dynamics such as analytics, data security, and infrastructure requirements (Davenport, 2013). A lack of research around social dynamics (such as people's understanding and their perceptions of its value, application, challenges and the like) has been observed in big data research (Shin & Choi, 2015). To address this research gap, this thesis explored the social dynamics around the concept of big data in the New Zealand healthcare context. Three subsector levels have been identified within the NZ health sector as: (i) macro (policy-makers), (ii) meso (funders and planners), and (iii) micro (clinicians) (MMM levels). Investigating and comparing social dynamics of big data across these levels is important, as big data research has highlighted the importance of business-IT alignment to the successful implementation of big data technologies.

While business-IT alignment can be investigated through many dimensions, to investigate social dynamics around big data, this thesis adopted a social dimension lens, which promotes investigating alignment through people's understanding of big data and its role in their work. Taking a social dimension lens to alignment fit well with the aim of this thesis, which was to understand perceptions around the notion of big data technologies that could influence the alignment of big data in healthcare policy and practice. With this understanding, the research question addressed was: *How do perceptions of big data influence alignment across macro, meso, and micro levels in the NZ healthcare sector?* Structured as a thesis by publication, the thesis consists of four research papers structured to answer these research questions. The four research papers explain different stages of a large single study. Further explanations about these four papers and their contributions are given in the following section.

9.2. Research papers

9.2.1. Paper I

> Weerasinghe, K., Scahill, S. L., Taskin, N., & Pauleen, D. J. (2018). Development of a Taxonomy to be used by Business-IT Alignment Researchers. Paper presented at the 22nd Pacific Asia Conference on Information Systems, Yokohama, Japan.

This paper is presented in the thesis as an important finding from the literature review around business-IT alignment. It presents an in-depth analysis of business-IT alignment literature and develops a taxonomy based on past alignment conceptualisations. Novice and experienced researchers alike face the daunting task of selecting the right lens for a business-IT alignment study given the number of conceptualisations present in business-IT literature over the past 35 years (Weerasinghe, Scahill, et al., 2018). Therefore, this taxonomy is a much-needed contribution to business-IT alignment literature. This paper identifies relationships between different conceptualisations in order to develop the taxonomy. It also presents the case study of this thesis as New Zealand healthcare and demonstrates how the taxonomy can be used for an empirical study.

9.2.2. Paper II

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

Presented in Chapter 5 this paper discussed the development of the theoretical framework used to guide the data collection of this thesis. While also using findings from the literature and an understanding of the NZ healthcare context, this paper discussed the use of Social Representation Theory (SRT), a theory from social psychology, as a methodological lens in developing the theoretical framework to conduct a business-IT alignment study. A methodological lens as explained in Paper II methodologically guides the development of a framework (Weerasinghe, Pauleen, et al., 2018). Use of SRT as a methodological lens is deemed a novel approach in using SRT. This is further explained below in the Research Contributions section (Section 9.3).

9.2.3. Paper III

Weerasinghe, K., Pauleen, D. J., Scahill, S. L., and Taskin, N., Theory of Sociotechnical Representations: Concept and Application. Awaiting submission.

This paper discussed the development of a new theory, the Theory of Sociotechnical Representations (TSR) as one of the key contributions of this thesis. TSR was developed by merging SRT with a well-known IS theory: Sociotechnical Systems Theory (SST). The understandings through SST perspectives highlight the interrelationships and interdependencies between people and technology. From SST perspectives, this interdependence is acknowledged as people's roles, responsibilities and tasks (Fox, 1995). Merging SST with SRT, this paper highlighted that while people and technology are interdependent, people may create representations of technology that are different from the actual technological phenomenon itself. As such, the representations may have an influence on these sociotechnical interdependencies. Therefore, the perceived understanding of a technological phenomenon as well as the perceived interdependence between people and technology may be different from the actual technology itself.

Although the concept of TSR was articulated after findings were analysed, because the study was designed to look at interdependencies between people and big data (without implicitly acknowledging SST), TSR could be applied to collected data. Thus, Paper III not only explained the concept of TSR but also discussed the application of TSR by explaining findings through TSR. TSR is believed to be a theory with wider applicability than just this situation. In this context, it has been used to explain findings as well as highlight misaligned perceptions. However, TSR can potentially be applied to studies other than alignment studies in any IS domain.

Paper III discussed the application of TSR through the case of big data for clinical decision making in NZ healthcare. The reason behind selecting clinical decision making as opposed to the overall discussion of big data (as captured by collected data) was that the main focus of this paper was to articulate the concept of TSR and to provide an understanding of its applicability. Thus in order to contain the paper and make it manageable, the decision was made to use a subset of data as opposed to the complete dataset. However, it is important to highlight that a separate, richer, deeper representations analysis for this paper around clinical decision making data obtained from the general inductive thematic analysis of the main dataset was conducted. Nonetheless, this paper also discussed practical implications identified through the application of TSR within the context of clinical decision making.

9.2.4. Paper IV

> Weerasinghe, K, Scahill, S. L., Pauleen, D. J., and Taskin, N. Alignment of Big Data Perceptions in Healthcare: The case of New Zealand. Awaiting submission.

This paper brought together the taxonomy of business-IT alignment (Paper I) as well as TSR (Paper III) to present an empirical study addressing the research question of the thesis. The paper investigated representations of big data across macro, meso, and micro levels within NZ healthcare, and is a presentation of the whole research study conducted through the theoretical framework developed in Paper II. The aim of Paper IV was to contribute to healthcare policy and practice by identifying the areas of alignment and misalignment present around big data technologies across macro, meso and micro levels. Paper IV discussed alignment issues through TSR, highlighting possible causes of misalignment, and provided recommendations.

9.3. Research Contributions

The contributions of this thesis are three fold: theoretical, methodological and practical. Theoretically, the research contributes to literature around big data, health information systems, business-IT alignment (development of a business-IT alignment taxonomy) as well as to IS theory (through the development of TSR). Methodologically, the concept of methodological lens in the development of the theoretical framework (presented through Paper II) is seen as an important contribution. Practically, the findings of this thesis contribute towards policy and practice by identifying alignment issues, identifying potential reasons behind alignment issues (through TSR) and making recommendations. The following sections further explain these contributions.

9.3.1. Theoretical Contributions

The development of TSR is a major theoretical contribution of this thesis. The thesis developed (Paper III) the concept and applied (Paper III and Paper IV) TSR to understand perceptions of big data within the New Zealand healthcare context to understand alignment. The uses of TSR are three fold. Firstly, TSR can be used as an underpinning perspective (similar to SST) in IS research. Secondly, TSR can be used as methodological lens in guiding the theoretical framework or even the research design. Thirdly, TSR can be used as a theoretical lens to explain research findings through data. However, as explained in Paper III, TSR has wider applicability to modern technological phenomena in understanding policy, design, implementation and use of such technology.

Other theoretical contributions of this thesis include contributions to literature around big data, business-IT alignment, and healthcare as well as contributions to SRT and SST literature. The thesis specifically addresses research gaps such as: (i) lack of research around social dynamics of big data, (ii) lack of guidance for business-IT alignment research in using its various conceptualisations, (iii) lack of research around the social dimension of alignment, and (iv) lack of research around big data within the New Zealand healthcare context.

9.3.2. Methodological Contributions

Methodological contributions of the thesis include the use of SRT as a methodological lens to develop the theoretical framework of the study, as explained in Paper II. The concept of methodological lens refers to the guidance provided by the theory (SRT) in defining the theoretical framework, and also identifying what, where, how and whom to study. The central idea of SRT is ‘social representation’ created by an individual about a phenomenon (Moscovici, 1984b). SRT characterises representations through three elements: (i) the object represented, (ii) the individual who builds the understanding, and (iii) the group to which the individual belongs (Dulipovici & Robey, 2013). These three elements, along with guidance from the literature and context, form the basis for the theoretical framework. Additionally SRT identifies two processes as: (i) anchoring, and (ii) objectification. Objectification is the individual’s mapping of the phenomenon to their experience, background or the like, while anchoring is the group’s influence on the representation through interactions (Wagner et al., 1999). This understanding facilitated conceptualising the relationships within the theoretical framework. The understandings of SRT acted as a methodological lens in developing the theoretical framework that was used to guide the empirical study of this research. The concept of using SRT as a methodological lens is a novel approach and has broader applicability within the IS domain than this study alone (Weerasinghe, Pauleen, et al., 2018).

9.3.3. Practical Contributions

The practical implications of this thesis include implications for healthcare policy and practice. As highlighted in Paper IV, five key categories were identified after cross group analysis, highlighting areas influencing sociotechnical representations of big data: (i) perceived definition, (ii) perceived challenges, (iii) concerns, (iv) potential areas of application, and (v) the influence of health strategy and policy (further explained in Appendix 12). This understanding of areas that influence sociotechnical representations of big data is important and provides greater insights into alignment across the sector.

The discussion in Paper IV addressed the research question identifying areas of alignment and misalignment of big data through a social dimensions lens. Across the three levels, alignment was found in the shared understanding of the importance of data quality, the increasing challenges of privacy and security, and the importance of new types of data in measuring health outcomes. Aspects of misalignment included the differing definitions of big data, as well as perceptions around data ownership, data sharing, use of patient-generated data and interoperability. While participants identified measuring outcomes, clinical decision making, population health, and precision medicine as potential areas of application for big data technologies, the three groups expressed varying levels of interest. This caused misalignment issues with implications for both healthcare policy and practice.

In addition, the focus on clinical decision making in Paper III provided further detailed understanding of the context of clinical decision making and the role of big data in this context. The practical implications highlighted in Paper III across the sector are: (i) the low priority given to applying big data technologies to clinical decision making, (ii) the need for policy improvements around big data technologies, (iii) varying levels of awareness around current big data initiatives at lower levels (specifically micro), (iv) the need for a broader understanding by the clinical profession to facilitate clinicians' use of technology, and (v) wide acknowledgement of the importance of data quality and the need to manage issues.

Papers III and IV reported that the NZ healthcare sector has issues around anchoring (as explained in TSR) of big data technologies which is the cause of some misalignment issues. Participants objectified big data based on their experience and background as well as their roles, but a lack of anchoring through discussions across the sector around big data was causing ambiguity around this concept. A key recommendation of this thesis is the importance of having a common discussion around the notion of big data, and identifying, agreeing on and prioritising potential applications of big data technologies based on the needs of the sector.

These findings were further validated through member checking (Lincoln & Guba, 1985). A summary of findings was sent to the participants. Out of the twenty-six participants who could be contacted, four participants responded with feedback. The feedback confirmed that they agreed with the findings. One macro level respondent commented that lack of understanding about the concept of data ownership at other levels is particularly surprising given how policy around data ownership clearly identifies the patient as the owner of health information. This further confirms the finding on misalignment around data ownership. However, two out of four respondents explained that the current situation might have changed since data collection due to the rapid developments around data and analytics within the sector.

9.4. Limitations

This thesis had several limitations. Some of these limitations suggest avenues for future research.

As qualitative research, the findings may not be statistically generalisable to a larger population. Despite this, it is expected that TSR will have a degree of applicability that goes wider than this study alone. Additionally, considering the scope of the health system, getting a representative sample size was challenging. While every effort was made to find participants from all demographic locations, and nationalities, across DHBs, this proved difficult and the sample did not (and could not) include all DHBs/PHOs, or participants from all geographic locations. Some applications of big data discussed by DHBs and PHOs might be of specific interest to only that region (e.g. precision medicine) and not relevant for others. However, a quantitative study (survey) based on the findings of this study may potentially provide further understanding about big data in the NZ healthcare context.

Interviews were conducted between 2016 and 2018 and during this period many changes took place within the NZ healthcare sector: changes to the NZ government, restructuring of the Ministry of

Health, and the health strategy revamp, to name a few. Additionally, once the data collection phase was completed some structural changes within the Ministry of Health were noticed (i.e., the introduction of new units like the Data and Digital Directorate (Ministry of Health, 2019)). The representations captured may still be changing and the findings may not represent the actual situation at the present time. This is understood and is expected by TSR (through SRT). SRT identifies that hegemonic representations (further explained in Section 5.5), such as big data, will be continuously evolving.

Finding micro participants, particularly GPs, was extremely challenging. The first round of interviews only had one micro participant, while the second round only had two micro participants. Although at the beginning it was anticipated that most interviews were likely to be at the micro level, the study was completed with only nine participants at the micro level (along with four meso level participants who had clinical responsibilities, creating a total of thirteen micro participants). After the first round of interviews, changes were made to the information sheet to make the introduction to the study more about the use of modern types of data (instead of using the term 'big data'). Nonetheless, the response rate was low throughout the study. Local clinics were contacted by email and by phone, with no success. Two GPs were recruited by walking into clinics. The only other success was through contacts of one of the supervisors and snowballing techniques (this was the only way doctors in hospitals were recruited). Thus the study might not have achieved a representative sample. However, a follow up quantitative study can provide further verifications and a more generalised understanding.

As explained in the methodology chapter, there was concern that the snowballing technique might result in similar representations. Therefore, snowballed participants were carefully monitored to see whether such similarities arose. Typically similarities in perceptions were seen more across snowball participants within the same level compared to across levels generally. Across levels, snowballed participants tended to have more diverse perceptions, although a few similarities were still present.

In such cases data was carefully analysed to ensure these resemblances were also present in participants who were not snowballed.

The notion of groups in SRT is typically tighter than the macro-meso-micro levels that were investigated in this study. Original SRT research investigates sub-groups within well-established groups such as those in organisations (e.g., departments or project teams) which are ideally working closely together. Nonetheless, some researchers have used SRT in a general way in less cohesive groups (e.g., Vaast, 2007), or even in non-group environments (e.g., Liu, 2006). Through macro-meso-micro levels as groups, the explored groups are not very closely tied together. However, similarities of representations were clearly seen in analysis at each macro, meso, and micro level and not having cohesive groups was not seen as an issue. As highlighted in Paper II, it was expected that sub groups (like DHBs, PHOs, academics, GPs etc.) might be identified through data collection. However, it was observed that the representations were not greatly different from each other, except in areas of application (e.g. DHBs saw precision medicine as an important area of application while PHOs saw patient-generated data as having more potential). Therefore, it was decided to keep the discussion at macro-meso-micro levels rather than breaking it down into sub groups within main groups to get a sense of big data at each of the MMM levels. However, where distinctions were identified they were addressed in the discussion as necessary. Original SST theory explains three levels of work groups: macrosocial systems, whole organisation systems, and primary work systems (Trist, 1981). While at a high level, these definitions seem to align with MMM levels, further research is needed to clarify the connections.

An identified limitation of TSR is the focus on investigating the social dynamics around a technology. Although the social dynamics around technologies are extremely important, we also understand that the technical dynamics (the actual technical features) need to be investigated. However, that is not the aim of TSR, resulting from its use of SRT (nor was it the aim of this thesis). In studies where technical dynamics play an important role other theories may need to be used in conjunction with TSR.

The research was conducted in New Zealand. The theoretical framework is based on the structure of the NZ health system, thus may not be wholly transferable to a different country context (Fusch & Ness, 2015). However, the study may be replicated using the same theoretical basis by adapting it to the context of the country to be studied. Similarly, other public sectors that have a similar structure (within or outside NZ) may be able to use the theoretical framework to conduct research around big data, with careful attention to changes that may be needed prior to data collection.

As presented in the theoretical framework the expectation was to investigate big data's alignment with government, business, and user objectives. However, the participants found it extremely difficult to explain how they see big data playing a role in objectives (specifically at meso and micro levels). The reason behind this was that big data was a novel concept to most participants, as well as being a broader technological concept, which they were unable to place within the objectives of their work or organisation. Thus following a pure social dimensions lens, mutual agreement around the concept of big data was investigated as alignment in this thesis. As Paper II was published before making this change, the theoretical framework uses the term “objective” which ideally should be “need”.

Finally, doing a thesis by publication resulted in some limitations of the ability to present research data. While it seemed important to have participant quotations in the thesis, papers were rejected by reputable journals when quotations in the discussion were given priority. Thus not many quotations were used in the thesis body. However, descriptions of the five key categories are given in Appendix 12, which also presents quotations from participants across MMM levels. Writing journal papers also limited the amount of data that could be used due to the need to make short and concise representations of the research. Although originally there were two research questions (*RO1: How is big data perceived at macro, meso, and micro levels? RQ2: How do these perceptions influence alignment across the sector?*), with the possibility of producing two different publications addressing both questions prior to analysis, it was considered that because of TSR and its identification of representations of big data as perceptions and its application in this research to investigate alignment, it was impossible to separate perceptions and alignment in this research to produce two different publications. Therefore instead of creating two different papers, the two original questions were brought together to create one research question (*how do perceptions of big data influence alignment across macro, meso, and micro levels in the NZ healthcare sector?*) allowing it to be addressed in one research paper.

9.5. Future work

A few avenues of future work are proposed in this section. As explained in the limitations section (Section 9.4) a quantitative survey based on the findings of this study is identified as a possible future research avenue to gain greater understanding of representations of big data across the sector. TSR, through its use of SRT and SST, can be applied to quantitative studies. Development of a quantitative survey based on TSR will be a significant future contribution to IS research.

While this research promotes insight into big data representations and their influence on alignment within the healthcare sector, patients' representations of big data technologies (such as genomics and precision medicine or use of patient-generated data) were not examined in this research. Therefore, this is identified as an interesting avenue to explore in the future as it too may have an impact on alignment.

As explained earlier, TSR is deemed to have wider applicability in IS research. More future research around TSR, applying it to technological phenomena other than big data, is needed to further clarify its applicability and use. In addition, lessons learned through TSR will provide much needed understanding of how people perceive a technological phenomenon which influences its presence in policy, design, implementation, and use. Therefore, future research is desirable using TSR to understand the role of technology in any context.

Researching big data around other dimensions of alignment (presented in the business-IT alignment taxonomy, Paper I) will also be useful future research. While great potential is seen in the strategic dimension to investigate documented strategies around big data, other dimensions are also deemed beneficial. While the theoretical framework developed for this thesis (in Paper II) may be adopted for alignment studies, with other dimensions it may need changes depending on the dimension of alignment being used. In such research, careful investigation to amend the theoretical framework may be necessary.

Smaller more focused research within organisations around big data representations is also possible (investigating organisational level alignment as opposed to sector level, Paper I). Such focused alignment studies will allow understanding of specific alignment issues within organisations, which are contributing to the overarching issues of alignment within the NZ healthcare sector. Looking into project alignment with big data representations will also be useful for large-scale projects like precision medicine to understand project specific alignment issues and get greater understanding of big data representations in such projects.

9.6. Concluding Remarks

This thesis aimed at contributing to the understanding of the notion of big data, which is deemed an important concept in both academic and business worlds. Since there was limited research around understanding social dynamics of big data, this thesis set out to investigate such social dynamics around big data across the NZ healthcare sector. The purpose behind understanding social dynamics through perceptions was to investigate alignment of big data in the NZ healthcare sector. Taking a social dimension lens to business-IT alignment fitted well with the notion of investigating social dynamics.

This thesis is set out as a thesis by publication and four papers have been presented. All four papers were developed based on a single study as opposed to multiple studies. Paper I is an output of the literature review targeting business-IT alignment. Although developed as a conceptual paper, Paper II provides methodological contributions with its use of SRT as a methodological lens in developing a theoretical framework that can be (and has been in this thesis) used for alignment studies. As an important theoretical contribution of this paper a novel theory, the Theory of Sociotechnical Representations, was developed by merging SRT and SST. The concept of the theory and application is presented through Paper III. Paper IV addresses the broader research question around alignment, identifying areas of alignment and misalignment of big data across the NZ healthcare sector. Paper IV also applies TSR in its explanation of findings.

The contributions of TSR are not just applicable to this research, nor just to business-IT alignment studies. TSR is a theory that seems applicable to wider IS phenomena. It will provide theoretical tools to investigate representations that can be created by groups that are different from each other, such as: policy makers, developers, planners, funders, vendors, researchers, academics and users. This understanding of representations will promote creating appropriate strategy and policy, more useful and needed technology and also promote resolving issues around use. TSR is deemed most beneficial for new or emerging technological phenomena, because of its ability to identify differences in representations and what might be causing them in early stages of the technology. TSR has the potential to investigate representations and interdependencies between people and technology even in well-established technical domains. In such situations, TSR might even be able to identify issues of design, development, policy or use.

Chapter 10: Researcher Reflections

Technologies have always excited me for what they can do, rather than how they can be developed. During my undergraduate studies in Information and Communications Technology I found the "soft side" of information systems the most interesting. I have always loved data, and the increasing potential of using data to do incredible things fascinates me.

After working for two years in the IT industry as a Software Quality Assurance Analyst, I decided to follow my mother into academia. I loved this new path, the role of being a teacher and seeing how education transforms lives, and the opportunities it brought my way. In order to further my career as an academic, I decided to investigate undertaking a PhD. As part of my search for a potential doctoral topic I started reading about big data. I immediately knew big data would be a part of my doctoral research as not only did I find it fascinating, but also I could see it was going to be a megatrend and I wanted to be part of that future. I was lucky enough to find the right supervisors, with the required experience and knowledge, and enrolled to do my doctoral studies early in 2015.

My initial thought for a topic was to look at managing the IS risk around big data technologies that I believed existed and yet remained under researched. However, I realised the more I read about big data, the more confused I got. Every time I spoke with a researcher, or someone from the corporate sector, the explanations were different. Realising that people's perceptions of what big data was, and its potential to help them manage their businesses, were still so nascent, made me decide that this was where I wanted to focus, instead of IS risk. The path my PhD journey took once I made this decision is modelled in Figure 10.1.

In Figure 10.1, the black dots show different stages of progress, while the large black circles highlight important decisions or developments. The grey circles represent the underlying investigations, realisations, issues, or changes that occurred along the way. The stars signify key publishing milestones.

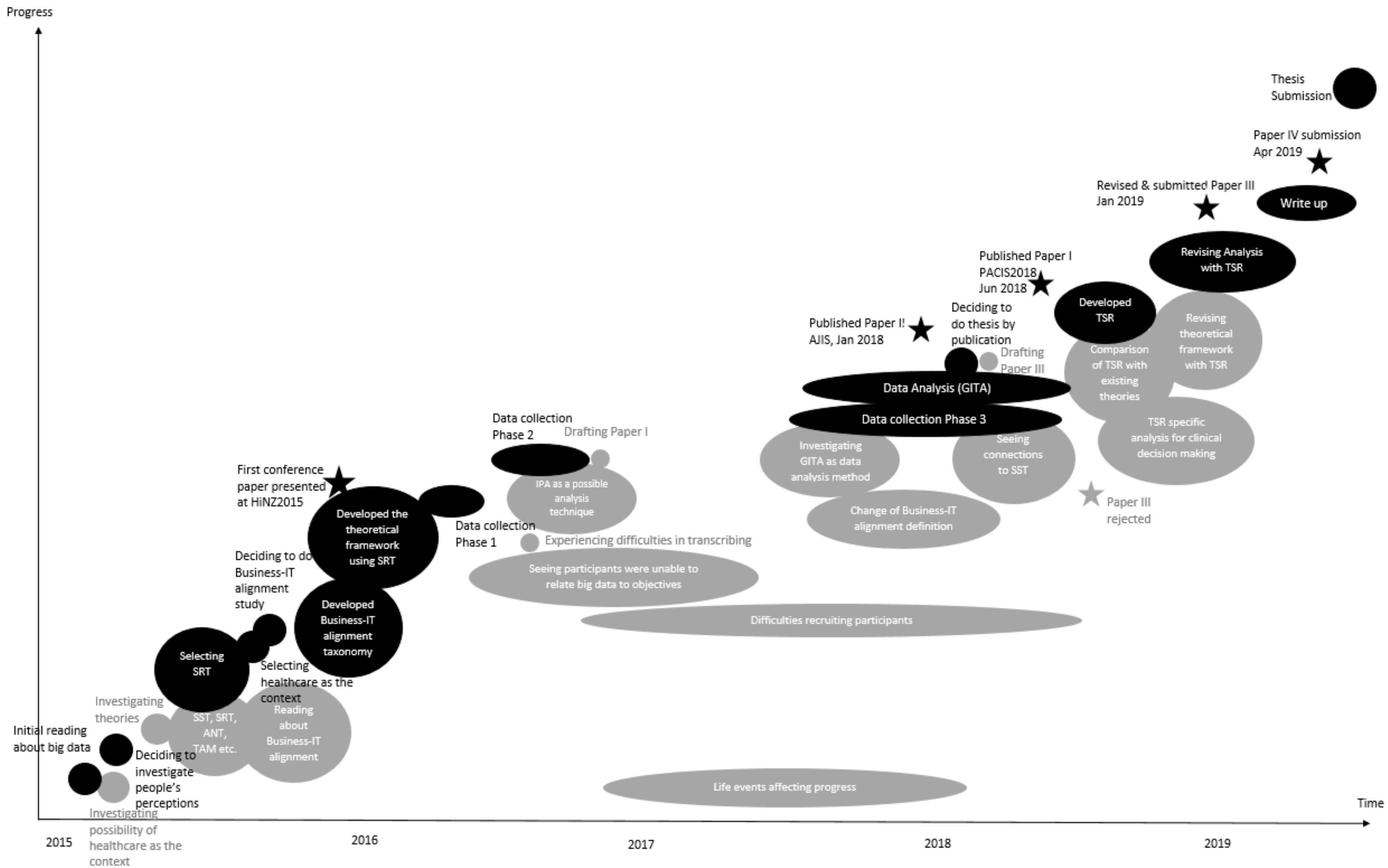

Figure 10.1: Timeline of events leading to submission of the thesis

Having identified my interest in people's views on big data, deciding to investigate the social dynamics (perceived understanding, values, commitment, understandings about challenges and the like) of big data was one of the foremost decisions of my PhD. I initially investigated theories including Sociotechnical Systems Theory (SST), Actor Network Theory (ANT), and the Technology Acceptance Model (TAM), before settling on Social Representations Theory (SRT): a theory from social psychology that looks into how people perceive phenomena. Using the tools provided by SRT to investigate differences in perception I conducted a business-IT alignment study, using the social dimension of alignment to investigate the social dynamics around people's views on big data.

As I continued my reading, it became apparent that much of the exciting big data research was based on commercial/business fields. However, a new article (at that time) by global management consultants McKinsey & Company (Groves et al., 2013) highlighted how the healthcare sector could potentially benefit from the application of big data technologies. This was the starting point for considering healthcare as a context. Moreover, there was very little information about the use of big data in the New Zealand healthcare sector, which further drove me to select healthcare as my context for investigating big data perceptions. Around the same time, I was also able to get a supervisor with a background in health to join my supervisory panel.

As shown in Figure 1, the original theoretical framework was developed using my initial understanding of business-IT alignment and SRT. It was first presented as a conference paper at the Health Informatics New Zealand conference in 2015 (HiNZ2015). Attending HiNZ2015 was a great opportunity, allowing me to make connections and to recruit participants for my study. Moreover, the comments from the reviewers and the audience influenced further development of the theoretical framework, to the point where it was subsequently submitted (2017) and accepted (2018) for publication (Weerasinghe, Pauleen, et al., 2018).

Around the same time as the business-IT alignment taxonomy was implemented, Paper I was written and submitted to the 22nd Pacific Asia Conference on Information Systems 2018. In the early days of my research, as highlighted in Paper II, I defined business-IT alignment as "how well technology is realised to make sense out of big data to create value. Creating value in the business context signifies achievement of business goals and objectives" (Weerasinghe, Pauleen, et al., 2018, p. 5). Drawing on the proposed theoretical framework, the plan was to investigate people's perceptions of big data and how they perceived its link with their business goals and objectives. However, as data collection progressed it became apparent that my participants struggled to relate big data to their business objectives or their clearly identified goals. Because of big data's potential applicability in multiple areas (e.g., population health, measuring outcomes, precision medicine and the like), participants found it difficult to place big data as a concept. These observations during my data collection and the early stages of analysis resulted in an updated definition of business-IT alignment. However, as Paper I and II were published by then, no retrospective change could be made to those papers.

Recruitment of participants, at all three levels, was one of the greatest challenges I faced during my PhD journey. At the macro level, given the topic under discussion and the definition of the macro level itself (those who are involved, or who will be involved, in contributing to policy), there was always a limited number of potential participants. While purposive sampling was initially undertaken (by looking at the Ministry website as well as with the help of my co-supervisor who has a health background), a few additional participants were able to be successfully recruited through snowballing techniques. At the meso level, the challenge was the differences that existed between organisations and the need to make sure the organisations selected played a planning and funding role around big data (potential big data applications).

The most challenging participants to recruit were those at the micro level. While it was anticipated that the micro level would have the highest number of participants, this was not the case. The success rate of getting an interview after contacting potential micro level participants (either by email, phone or in person) was less than 30%. Their busy schedules and a reluctance to talk about information systems affected their willingness to take part. In an attempt to address this, while at first I shared the same information sheet with potential participants at all three levels, a separate information sheet was created, simplifying technical terms and replacing big data with “modern types of data” for the micro level. This change resulted in several additional participants being recruited for the micro level.

Another challenge I encountered in relation to my participants was that although theoretically each of the levels were clearly divided, it became apparent that people may have more than one role, and thus belonged to more than one level. While during the interview I asked participants to answer questions based on a selected role, sometimes it was impossible for them to do so. However, in certain cases I also found these multiple roles advantageous (e.g., when my meso level participants were able to answer the micro level questions).

Anticipating a low participant response rate and the need to deeply investigate the data, I looked at the possibility of using Interpretative Phenomenological Analysis[35] (IPA) to analyse my data. I analysed five macro interviews and three meso interviews manually through IPA (Appendix 1 provides a snapshot of this analysis). While it was interesting to see the individuals’ perceptions in detail, I realised that IPA was leading into three levels of analysis (individual, MMM level, and healthcare sector), making the analysis very complex. In addition, my participant numbers were increasing beyond the recommended number of participants for an IPA study. Moreover, understanding individual representations was not the aim of my theoretical framework. Therefore, I decided to look into other options for data analysis. I had looked at thematic analysis during the time of my confirmation. Because of the need to do within group and cross-group analysis, I decided to use general inductive thematic analysis (GITA) as I found it to be straightforward and clear.

A final significant change, in this case to the theoretical foundation of my thesis, came about during my data analysis. While data collection was based on SRT, I began to realise that there were some connections between SRT and SST, a theory that I had previously considered. When I wrote the first

[35] IPA is a phenomenological method of analysing data (Willig, 2013). It allows the researcher to understand personal experiences of research participants (Smith et al., 2009). IPA takes an idiographic approach that investigates individuals within groups (Pringle, Drummond, McLafferty, & Hendry, 2011).

version of Paper III, explaining the connections between SRT and SST I noted how SRT can be applied to investigate an SST perspective. The paper was initially rejected with many comments from three reviewers. After meeting with my supervisors, we decided to revise the paper to address the comments from the reviewers. This process made me realise that SST was not just an underlying perspective to SRT, but SRT can be specifically connected to the technical subsystem of SST, leading to the development of my Theory of Sociotechnical Representations (TSR). The second version of Paper III was significantly changed from the original and is now awaiting a review decision.

It is important to highlight that Paper III is based on big data in the context of clinical decision making as opposed to overall use of big data in health. This is a reflection of the word count limitation of journal papers. The main purpose of Paper III was to articulate the concept of TSR, and therefore the decision was made to select a subset of data to avoid an abstract level of data presentation in the paper. Clinical decision making was seen as the best choice because all three levels talked about the application of clinical decision making. Furthermore, interview schemas had clinical care as a prompt around the application of big data. We had also looked into the possibility of looking at one level (MMM) but because I wanted to highlight issues across levels, it was decided that selecting an area of application was the best choice.

The final paper of my thesis reflected each of the changes I had made throughout the PhD process. After the development of TSR, I revisited the theoretical framework and my analysis. I wrote paper IV to address the research question of the thesis. In Paper IV, I applied TSR as the theoretical underpinning to the study, however again due to limitations around paper length, I was unable to present a theoretical framework in it. In Paper IV TSR was also applied to findings when explaining misalignment issues. Once paper IV was completed, the thesis was able to be written, bringing all the pieces together, as a complete package. The choice to do my thesis by publication has certainly introduced additional challenges, such as having to work within often restrictive word counts but the input from journal reviewers has proven invaluable in moulding and shaping my ultimate contribution.

My journey as a PhD student over the past four and half years has had both ups and downs, with a number of factors significantly affecting how long my journey has taken. Halfway through my PhD, I gave birth to my son. Around the same time, I was offered the opportunity to work at Massey University as a full-time Assistant Lecturer. Managing two new roles (as a first-time mom and a full-time teacher) on top of being a PhD student was extremely challenging. I took time off from my PhD until my son was four months old, and then as we had no family support in New Zealand, I found I was initially still putting very few hours into my PhD. After my son turned one, my husband changed his work hours to give me more time to work on my PhD. As I have explained in the methodology chapter, data collection was influenced by these life events and it took a longer time than I anticipated to complete the data collection and the PhD. While I would not change my personal circumstances for anything, in hindsight looking back I think I would have requested help from our family. However, this extremely challenging experience has made me strong, given me experience and the capability to successfully multi task.

Another significant event that affected my PhD journey was the somewhat belated decision to undertake my thesis by publication. While I started doing my PhD thesis as a monograph, I have always liked publishing, having already published eight conference papers prior to commencing my Doctoral studies. Even when I was spending little time on my PhD during the first year after my son was born, I found writing papers to be milestones I was able to successfully achieve. My primary supervisor saw this as a strength and suggested I look into doing the thesis by publication. The decision to change to a thesis by publication was not made overnight. I spoke to several colleagues who had completed a thesis by publication and had discussions with the Research Director at that time to understand the process and to understand my options. I also made a plan with my supervisors to identify potential papers that could go into my thesis. Based on all these discussions and the possibility of lining up papers according to the plan, we decided to go ahead with the thesis by publication. While the original plan did change along the way, it guided me, shaping the ideas around papers and the structure of my thesis. While I believe I made the right decision to change to thesis by publication, I strongly believe that success depends on an individual's desire to publish as well as having supportive supervisors.

Looking back at the four and half years of my PhD journey, while there may be some things I would have liked to change, overall I am pleased with the majority of the decisions I made, including my decision to look into people's views of big data. As big data is becoming more and more commonplace, my contributions around theory and practice are not only for those working in healthcare but for contemporary society as a whole.

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Appendices

Appendix 1: Participant Information Sheets

1.1. Information sheet used for all participants

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND
MASSEY BUSINESS SCHOOL

Exploring the Influence of Big Data on Business-IT Alignment in NZ Healthcare

INFORMATION SHEET

Researcher Introduction

I, Kasuni Weerasinghe, am the lead/ student researcher of this study which is carried out as a part of my PhD (Management) research at Massey University.

Project Description

This study aims to understand how people at different levels of the healthcare sector perceive big data analytics and how it influences business-IT alignment in the NZ healthcare sector. With an objective to understand the fit between big data analytics and government, business and user objectives, the study aims to get perspectives from health-IT policy setters, planners /funders, implementers and users of health-IT solutions. Big data analytics is identified to benefit the healthcare sector in many ways such as: decision making, pattern recognition, population analysis, and personal health. However individuals' understanding and commitment towards such tools is the key to success of big data initiatives.

Through your participation I will be able to understand the dynamics around the current situation of implementing big data analytics within the NZ healthcare sector. Thus the study aims to contribute towards early detection of alignment issues and/or recognition of best practices as possible outcomes of this study.

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND

MASSEY BUSINESS SCHOOL

An Invitation

You are invited to share your views about big data analytics and how and whether healthcare objectives could be achieved by using big data analytics for healthcare planning and delivery. I'm hoping to talk to approximately 40 participants across the NZ healthcare sector to gain a broad understanding.

Project Procedures

I would like to interview you in person, over the phone or by Skype for about 45 minutes. If you are involved in health-IT policy making I would like to ask you about your view of big data analytics and how it may help to achieve government and health care providers' objectives. If you are involved in planning, funding or implementing big data analytics tools I would like to talk to you about your experience on big data analytics implementations. If you are a healthcare provider, I would like to talk to you about your opinions and views on using big data analytics for healthcare delivery.

Data Management

The interviews will be audio recorded, then transcribed verbatim and returned to you for checking and editing if you choose. When you are happy with the transcript I will analyse the data using NVIVO qualitative data analysis software. Electronic data collected will be kept secure on password protected devices.

Information about you will remain confidential to the study and any identifying details about you or the organisation for which you work will be removed from the transcript and from the report I write. I'll use a pseudonym or numbering system instead of your name.

Participant's Rights

You are under no obligation to accept this invitation. If you decide to participate, you have the right to:

- decline to answer any particular question;
- withdraw from the study (up until one week following the interview);
- ask any questions about the study at any time during participation;
- provide information on the understanding that your name will not be used unless you give permission to the researcher;
- if you wish, you will be given access to a summary of the project findings when it is concluded.

Te Kunenga ki Pūrehuroa

School of Management
Massey University, Private Bag 102904, Auckland 0745 T +64 9 414 0800 http://management.massey.ac.nz

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND

MASSEY BUSINESS SCHOOL

If you'd like to participate in this research please contact me by text or email and I will get back to you to organise a meeting. My details are given below along with details of my supervisors. Please contact me or the supervisors if you have any questions about this project.

Project Contacts

Student Researcher: Kasuni Weerasinghe

Phone: +64 9 414 0800 ext 43379

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Email: w.m.k.g.weerasinghe@massey.ac.nz

Supervisor: Prof David Pauleen

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Supervisor: Dr Shane Scahill

Phone: +64 9 414 0800 ext 43394

Email:s.scahill@massey.ac.nz

Supervisor: Dr Nazim Taskin

Phone: +64 9 414 0800 ext 43402

Email:n.taskin@massey.ac.nz

Ethics

This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named above are responsible for the ethical conduct of this research.
If you have any concerns about the conduct of this research that you wish to raise with someone other than the researcher(s), please contact Dr Brian Finch, Director, Research Ethics, telephone 06 356 9099 ext 86015, email humanethics@massey.ac.nz

1.2. Information sheet for micro participants

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND
MASSEY BUSINESS SCHOOL

Exploring the Influence of Big Data on Business-IT Alignment in NZ Healthcare

INFORMATION SHEET

Researcher Introduction

I, Kasuni Weerasinghe, am the lead/ student researcher of this study which is carried out as a part of my PhD (Management) research at Massey University.

Project Description

This study aims to understand how people at different levels of the healthcare sector perceive (big) data and analytics (modern technology that uses big healthcare data). With an objective to understand the fit between modern data and government, business and user objectives, the study aims to get perspectives from health-IT policy setters, planners /funders, implementers and users of health-IT solutions. Use of big health data is identified to benefit the healthcare sector in many ways such as: decision making, pattern recognition, population analysis, and personal health. However individuals' understanding and commitment towards such tools is the key to success of big data initiatives.

Through your participation I will be able to understand the dynamics around the current situation of management and use of data within the NZ healthcare sector. Thus the study aims to contribute towards early detection of alignment issues and/or recognition of best practices as possible outcomes of this study.

Te Kunenga ki Pūrehuroa
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MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND

MASSEY BUSINESS SCHOOL

An Invitation

You are invited to share your views about big healthcare data, its potential for healthcare and possible issues. I'm hoping to talk to approximately 40 participants across the NZ healthcare sector to gain a broad understanding.

Project Procedures

I would like to interview you in person, over the phone or by Skype for about 45 minutes. As you are a healthcare provider, I would like to talk to you about your experience of, opinions and views on using data and modern technology for healthcare delivery.

Data Management

The interviews will be audio recorded, then transcribed verbatim and returned to you for checking and editing if you choose. When you are happy with the transcript I will analyse the data using NVIVO qualitative data analysis software. Electronic data collected will be kept secure on password protected devices.

Information about you will remain confidential to the study and any identifying details about you or the organisation for which you work will be removed from the transcript and from the report I write. I'll use a pseudonym or numbering system instead of your name.

Participant's Rights

You are under no obligation to accept this invitation. If you decide to participate, you have the right to:

- decline to answer any particular question;
- withdraw from the study (up until one week following the interview);
- ask any questions about the study at any time during participation;
- provide information on the understanding that your name will not be used unless you give permission to the researcher;
- if you wish, you will be given access to a summary of the project findings when it is concluded.

Te Kunenga ki Pūrehuroa

School of Management
Massey University, Private Bag 102904, Auckland 0745 T +64 9 414 0800 http://management.massey.ac.nz

If you'd like to participate in this research please contact me by text or email and I will get back to you to organise a meeting. My details are given below along with details of my supervisors. Please contact me or the supervisors if you have any questions about this project.

Project Contacts

Student Researcher: Kasuni Weerasinghe

Phone: +64 9 414 0800 ext 43379

Mobile: +64 21 0860 7547

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Supervisor: Prof David Pauleen

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Supervisor: Dr Shane Scahill

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Email:s.scahill@massey.ac.nz

Supervisor: Dr Nazim Taskin

Phone: +64 9 414 0800 ext 43402

Email:n.taskin@massey.ac.nz

Ethics

This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named above are responsible for the ethical conduct of this research.
If you have any concerns about the conduct of this research that you wish to raise with someone other than the researcher(s), please contact Dr Brian Finch, Director, Research Ethics, telephone 06 356 9099 ext 86015, email humanethics@massey.ac.nz

Appendix 2: Participant Consent Form

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND

MASSEY BUSINESS SCHOOL

PARTICIPANT CONSENT FORM – INDIVIDUAL

Project Title:	Exploring the Influence of Big Data Analytics on Business-IT Alignment in NZ Healthcare Sector
Researcher Name:	Kasuni Weerasinghe

I have read the Information Sheet and have had the details of the study explained to me. My questions have been answered to my satisfaction, and I understand that I may ask further questions at any time. (YES | NO)

I agree to the interview being sound recorded. (YES | NO)

I understand that my participation is completely voluntary. (YES | NO)

I understand that I may request a summary of the results from this project to be emailed to me. (YES | NO)

I agree to participate in this study under the conditions set out in the Information Sheet. (YES | NO)

Signature: .... **Date:** ....

Full Name ....

Appendix 3: Demographics Sheet for Participants

Project Title: Exploring the influence of big data analytics on business-IT alignment in the NZ healthcare sector

Researcher: Kasuni Weerasinghe

Supervisors: Prof David Pauleen, Dr Nazim Taskin, Dr Shane Scahill

Demographics

1. **What is your age group? Please circle the appropriate value.**

20-25 years   26-35 years   36-45 years

46-55 years   56-65 years   >65 years

2. **Gender: Please tick the appropriate box.**

☐ Female   ☐ Male

3. **Ethnicity. Please tick the appropriate box.**

Ethnicity	**Which do you identify with?**
European not further defined	
NZ European	
Other European	
NZ Maori	
Pacific Island not further defined	
Samoan	
Cook Island Maori	
Tongan	
Niuean	
Tokelauan	
Fijian	
Other Pacific Island	
Asian not further defined	
Southeast Asian	
Chinese	
Indian	
Other Asian	
Middle Eastern	
American	
Latin American/ Hispanic	
African	
Other ethnicity	
Don’t know	
Refuse to answer	
Response unidentifiable	
Not stated	

Appendix 4: Low Risk Notification Obtained from Massey University Human Ethics Committee

MASSEY UNIVERSITY
TE KUNENGA KI PŪREHUROA
UNIVERSITY OF NEW ZEALAND

Date: 24 November 2015

Dear Kasuni Wannitilake Mudiyanselage

Re: Ethics Notification - **4000015287 - Exploring the influence of big data analytics on business-IT alignment in the New Zealand healthcare sector: A socio-cognitive approach**

Thank you for your notification which you have assessed as Low Risk.

Your project has been recorded in our system which is reported in the Annual Report of the Massey University Human Ethics Committee.

The low risk notification for this project is valid for a maximum of three years.

If situations subsequently occur which cause you to reconsider your ethical analysis, please go to http://rims.massey.ac.nz and register the changes in order that they be assessed as safe to proceed.

Please note that travel undertaken by students must be approved by the supervisor and the relevant Pro Vice-Chancellor and be in accordance with the Policy and Procedures for Course-Related Student Travel Overseas. In addition, the supervisor must advise the University's Insurance Officer.

A reminder to include the following statement on all public documents:
"This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named in this document are responsible for the ethical conduct of this research.

If you have any concerns about the conduct of this research that you want to raise with someone other than the researcher(s), please contact Dr Brian Finch, Director - Ethics, telephone 06 3569099 ext 86015, email humanethics@massey.ac.nz. "

Please note, if a sponsoring organisation, funding authority or a journal in which you wish to publish requires evidence of committee approval (with an approval number), you will have to complete the application form again, answering "yes" to the publication question to provide more information for one of the University's Human Ethics Committees. You should also note that such an approval can only be provided prior to the commencement of the research.

Yours sincerely

B J Finch.

Dr Brian Finch
Chair, Human Ethics Chairs' Committee and Director (Research Ethics)

Research Ethics Office, Research and Enterprise
Massey University, Private Bag 11 222, Palmerston North, 4442, New Zealand **T** 06 350 5573; 06 350 5575 **F** 06 355 7973
E humanethics@massey.ac.nz **W** http://humanethics.massey.ac.nz

Appendix 5: Interview Schemas

5.1. Macro Interview Schema – Version 1

Project Title: Exploring the influence of big data analytics on business-IT alignment in the NZ healthcare sector: A socio-cognitive approach

As at: 6th Jan 2016

Researcher: Kasuni Weerasinghe

Supervisors: A/P David Pauleen, Dr Nazim Taskin, Dr Shane Scahill

Section A: General Questions

1. What is your current position?
2. How long have you been in this position?
3. How many years have you been working in a policy making role?
4. Apart from healthcare, do you have a background in other business or IT?

Section B: Interview Questions

5. Can you describe the role of health-IT policy making undertaken by your organisation?
6. Can you describe your role and responsibilities? To whom do you report to?
7. What other business units/government organisations are aiding/advising the ministry in health-IT policy making?
8. There's a big discussion around the use of big data analytics in healthcare, which you probably are aware of. What do you know about big data analytics?
   Note: big data analytics refer to making use of tools and technologies to analyse large amounts of data that comes from a variety of sources.
9. Do you think big data analytics could be used for better delivery of healthcare?
   a. If so how?
   b. If not why not?
10. What position does big data analytics have in the health-IT plan/health policy?
    a. If it is included: can you explain the government objectives that will be facilitated by big data analytics? How does it align with the government's healthcare objectives?
    b. If it's not included: what are the reasons big data analytics is not included in the health-IT plan/health policy? Any concerns?
11. Have you discussed incorporating big data analytics in the health-IT plan/health policy in formal/informal meetings? Can you recall what decisions were made and why?
12. Who are the potential users of big data analytics applications? As per your understanding whose work will be facilitated by such tools?
13. Does the NZ healthcare system have any large data repositories that are being used for any recognition of patterns? Population analysis tools? If there are can you give me some information about these repositories, e.g. what sort of data do they have? Who uses this data and for what purposes?
14. Can you introduce me to some more people who are involved in health-IT policy making?

5.2. Macro Interview Schema – Late Version

Project Title: Exploring the influence of big data analytics on business-IT alignment in the NZ healthcare sector: A socio-cognitive approach

As at: 10th Jul 2016

Researcher: Kasuni Weerasinghe

Supervisors: A/P David Pauleen, Dr Nazim Taskin, Dr Shane Scahill

Section A: Demographics Interview Questions

1. How many years have you been working in the healthcare sector?
2. How many years have you been working in a policy making or advisory role?
3. What is your current position(s)?

Select which role to go forward with.

4. How long have you been in this position?
5. Apart from working in the healthcare sector do you have a background in
    a. Business
    b. IT
    c. Other: …………………………………….

Section B: Interview Questions

General Information

6. Looking from a health-IT perspective, what are the responsibilities of your organisation towards the NZ healthcare system?
7. Can you describe your role and responsibilities within your organisation?
   To whom do you report? And who reports to you? (Where do you fit in the company structure?)

Social Representation of Big Data

8. There have been on-going discussions around the use of big data analytics in healthcare. In the literature there are different ideas relating to big data. I'm really interested in getting to know what your perception of big data is. What do you understand by the term big data?
9. I am interested in your view on the contribution that big data could make in the health care sector. Do you think using big data and big data analytics could be used for better planning and delivery of healthcare?
    a. If so how?
    b. If not why not?
    c. Not sure?

Note for interviewer: big data analytics refers to making use of tools and technologies to analyse large amounts of data that comes from a variety of sources. The sources could be a variety of healthcare information systems – clinical care, and administrative decision making as well as consumer generated data.

10. Could you talk a bit about what might have influenced or informed your understanding of what big data is?
    Prompt: Do you think your understanding of big data was influenced by discussions you had with other board members or any other factors?
11. Do you think that this (your) perceptions/ understandings are common across the board/organisation/department? Or have you seen any different views in others?

Business-IT Alignment (through a social dimension lens)

12. I've looked at the health-IT program 2015-2020 on the NHITB's website/MOH health strategy. So where do you see big data analytics within this program?

13. Can you explain to me the reasons why big data is presented in that way (or not presented) in the health-IT program/strategy? (What were the reasons for including big data in the health-IT program/health strategy?)
    Note: history of IT success? Big data analytics in healthcare success stories from other countries? Industry pressure? Need?
14. In your opinion is there anything missing or included which shouldn't be included (related to big data)?
15. Can you give me some examples of use of big data, big data analytics tools that you might know of?
16. I am interested in better understanding degrees of alignment in health care. Do you think the big data analytics initiatives (outlined within the health-IT plan/health strategy or the example you've given) align to the government's healthcare objectives? If so can you elaborate, if not why not?
    To what extent do you think the big data analytics will actually facilitate the government objectives?
17. So far we have talked about big data as a concept and the involvement in it from a top level view. Have you experienced a need for big data initiatives coming from regional or local level at healthcare provision as opposed to a strategic level?
18. We are looking at Macro, meso and micro level alignment. What is your perspective of DHBs' (meso) and healthcare providers' (micro) role in successfully implementing such big data initiatives?
19. Who do you think might be the potential beneficiaries of big data initiatives, and why? (Sub groups? Researchers? Medical centres? Consumers?)
20. Big data initiatives are identified in the health-IT program. Who do you think are going to be running them? Also, who are the potential users?
21. Who else do you recommend I talk to at a policy making level about big data? Are you able to introduce me to other high level people who are involved in health-IT policy making?

5.3. Meso Interview Schema – Early Version

Project Title: Exploring the influence of big data analytics on business-IT alignment in the NZ healthcare sector: A socio-cognitive approach
As at: 15th Mar 2016
Researcher: Kasuni Weerasinghe
Supervisors: A/P David Pauleen, Dr Nazim Taskin, Dr Shane Scahill

Section A: Demographics Interview Questions

1. What is your current position?
2. How long have you been in this position?
3. How many years have you been working in the healthcare sector?
4. Apart from working in the healthcare sector do you have a background in
    a. Business
    b. IT
    c. Other: …………………………………….

General Info

5. Can you explain to me what responsibilities your organisation has towards NZ healthcare? What are its activities?
6. Can you describe your role and responsibilities?
   To whom do you report? And who reports to you? (Where do you fit in the company structure?)
7. Do you know of any big data initiatives of your organisation? Can you tell me a bit about this project(s)?
8. I would like to know about how involved you are in these project(s). What is your role towards these projects?
9. Do you think you can place yourself as an adviser to the organisation/government? Do you belong to any advisory bodies of NZ healthcare?

Social Representation of Big Data

10. You may be aware there has been on-going discussion around the use of big data analytics in healthcare. I am interested to know how you would define big data, and can you also tell me a bit about how you understand big data?
11. I am interested in your view on the contribution big data could make in the health care sector. Do you think big data analytics could be used for better planning and delivery of healthcare?
    a. If so how?
    b. If not why not?
    c. Not sure?

Note: big data analytics refer to making use of tools and technologies to analyse large amounts of data that comes from a variety of sources. The sources could be a variety of healthcare information systems – clinical IS and administrative IS as well as consumer generated data.

12. In your view how can big data initiatives improve services of your organisation?
13. Do you think that is the common understanding across the board? Or have you seen any different views in other members?
14. Do you think your understanding of big data and its importance was influenced by discussions you had with other board members or any other factors?
15. Have there been any discussions about big data and analytics in formal or informal discussions? Can you recall what those discussions were and what decisions were made? Any concerns raised?
16. Are you aware of any concerns your organisation may have in the application of big data analytics to healthcare data?
17. Have you had past experience working with any sort of analytics tools? If yes can you explain how it was?
    Prompt: Clinical care/decision making, administrative decision making, consumer generated data

Business-IT alignment

18. It is interesting that your organisation is currently working on a big data project(s). Can you explain a bit about the planning and implementation of these projects?
19. I'm interested to know about the business objectives these project(s) facilitate. Will you be able to explain that to me?
20. I'm also interested to know what healthcare objectives these projects are catering to. What benefits does it bring to the patients?
    Are you aware of how involved the users are when implementing big data initiatives? What input is received from them?
21. Will you be able to identify the potential users of this/these initiative(s)? In your view how does this project(s) facilitate user objectives?

a. How does big data meet needs of clinicians?

22. Would you like to describe your perspective on policy makers' role in the success of big data initiatives?
    a. Are you aware of any government concerns regarding big data applications?
    b. What improvements do you think are necessary for the success of big data implementations?

If no idea on consumer generated data comes up

23. There seems to be increasing dialogue around the applicability and use of consumer generated data (e.g. self-monitored blood pressure readings). Does the organisation have a view on how to deal with this idea? Do you have a personal view?
24. Who else do you think I can talk to, to get an understanding of how things are happening around planning and implementations of big data initiatives?

5.4. Meso Interview Schema – Late Version

Project Title: Exploring the influence of big data analytics on business-IT alignment in the NZ healthcare sector: A socio-cognitive approach

As at: 1st Feb 2017
Researcher: Kasuni Weerasinghe
Supervisors: A/P David Pauleen, Dr Nazim Taskin, Dr Shane Scahill

General Information

1. Can you tell me a bit about your educational background?
2. From a health-IT perspective what are the responsibilities of your organisation towards NZ healthcare?
3. How many years have you been working in the healthcare sector?
4. What is your current position(s)?

(If many, select which role to go forward with.)

5. How long have you been in this position?
6. What is your role and responsibilities?
7. To whom do you report? Who reports to you?
8. Have you done any work with the MOH or its business units? If so can you talk a bit about that?
9. Do you interact with (other) PHOs/ DHBs/ other organisations? how?

Big Data

10. What does big data mean to you?
11. What contribution does it make to healthcare? Do you think big data and big data analytics could be used for better planning and delivery of healthcare?
12. What might have influenced or informed your understanding?
13. Do you think this view of big data and its use is common across your organisation and the people you work with? Or have you seen any different views?
14. Why is big data different from the normal data that we have?
    a. Is it types of analytics?
    b. Does it require new skills?
    c. Does big data influence the organisation's structure and roles?
    d. Is it the change in IT infrastructure?

e. Do you see IT architecture changing with big data? (methods, models and technologies used)

Current situation

15. Are you aware of any current or planned big data analytics projects by your organisation? Can you describe them a bit? Are you involved? (Clinical care, outcomes, precision medicine etc.)
    a. Are you aware of the business objectives of these project/s?
    b. What healthcare objectives (overall heath objectives) are these projects catering to? What benefits does it bring to the patients?
    c. Who benefits from these projects?
    d. Who are the (potential) end users? How involved are they in these kinds of projects?
    e. In your view how does this/these project/s facilitate user objectives?

    <u>Or,</u>

    What is the current position of your organisation's use of big data?

    What is your understanding of the current situation of big data in NZ health sector?

16. Do you think big data can be used to improve services of your organisation? If so how?
17. Do you have any concerns about big data use in health?
18. What do you think the policy-makers' role is with regard to the success of big data initiatives?
19. Do you think any improvement is needed with regard to health IT policy for the successful use of big data?
20. Do you see a need for any improvements by your organisation to cater to the big data hype?
21. Who else do you suggest I talk to?

<u>5.5. Micro Interview Schema – Early Version</u>

Project Title: Exploring the influence of big data analytics on business-IT alignment in the NZ healthcare sector: A socio-cognitive approach

Researcher: Kasuni Weerasinghe
Supervisors: A/P David Pauleen, Dr Nazim Taskin, Dr Shane Scahill
As at: 18th Jun 2016

1. Can you tell me a bit about your educational background?
2. How many years have you been working in the healthcare sector?
3. What is your current role? How long have you been in this role?
4. What are your responsibilities?
5. To whom do you report? Who reports to you?
6. Are you able to talk about the responsibilities of your organisation towards NZ healthcare from a health IT perspective?
7. How often do you use IT applications?
8. How would you describe the use of data to help you do day to day work?
9. Are you using any systems for clinical decision making? Can you explain?
10. Can you explain your best and worst experience of using system generated data/systems?
11. Do you like to have more information with you to improve the consultation?
12. Have you been involved in doing any work with the MOH or the NHITB? If so can you talk a bit about that?
13. How would you describe your interactions with the PHO?
14. How would you describe your interactions with the DHB?
15. Have you ever heard of the term big data? What have you heard?

16. What are your thoughts on patient-generated data? i.e. collecting data from a blood pressure monitor or from a patient's phone?
17. Do you see any issues with using systems or data from systems or patient-generated data?

    How can these issues be mitigated? Can the government or the PHO or the DHB do something differently to mitigate these issues?
18. What do you think might have influenced you to think about systems and data in this manner?

5.6. Micro Interview Schema – Late Version

Project Title: Exploring the influence of big data analytics on business-IT alignment in the NZ healthcare sector: A socio-cognitive approach

Researcher: Kasuni Weerasinghe
Supervisors: A/P David Pauleen, Dr Nazim Taskin, Dr Shane Scahill
As at: 02nd Jan 2018

1. Can you tell me a bit about your educational background?
2. How long have you been a doctor?
3. Do you have experience working in any other industry? Do you have any IT experience?
4. What is your current role? How long have you been in this role?
5. What are your responsibilities both clinical and administrative/managerial?
6. GPs: Do you own the practice or are you a salaried employee here?
   Hospital Doctors: To whom do you report? Who reports to you?
7. Are you able to talk about the responsibilities of your organisation towards NZ healthcare from a health IT perspective?
8. What sort of IT systems do you use at your practice/work? Can you talk a bit about what they are and how they help your work?
9. How would you describe the use of data in these systems? How does the data help you do your daily tasks?
10. Do you see any issues around using data in these systems?
    a. How can these issues be mitigated? What can you (doctors) do better?
    b. What can PHOs do to mitigate such issues?
    c. What can the government do to mitigate such issues?

    (data quality, privacy and security)
11. Are you using any IT systems for clinical decision making? Can you explain?
12. Would you prefer to have more information available to improve the consultation (or do you think the information you have is sufficient)? Can you explain?
13. Have you ever heard of the term big data? What does big data mean to you?

IF no, define – big data is data that's large in volume, complex in the sense of lots of different varieties, so in health obviously things like text with scans, x-rays, other reports and even most modern things like data from patients' Fitbits maybe. And also there's an element of real time in big data so something like collected now and used in near real time. The use according to international research says that this type of health data has a huge potential for things like measuring the performance of the health system and population health and even to be used in the clinical frontline to improve clinical care.
What do you think about this in the NZ context?

14. What are your thought about using such data for clinical decision making?
    a. What are the issues that you see in using such big data in clinical decision making?

b. Is there anything that bodies like the PHO, DHB or the government can do to mitigate such issues? (OR improve the use?)

15. What are your thoughts on patient-generated data? i.e. collecting data from a blood pressure monitor or from a patient's phone?

(prompt: What about patient-generated data in huge volumes that constitutes big data not just own practice clinical data)

16. Do you see any issues around using patient-generated data?

    a. How can these issues be mitigated?
    b. What can PHO do to mitigate such issues?
    c. What can the government do to mitigate such issues?

17. Are there any other technologies or information systems that you see or know of or have heard of which could improve your quality of work?
18. What do you think might have influenced you to think about data (both about data in systems and patient-generated data) in this manner?
19. Have you seen any different perspectives about data from others around you?
20. Can you explain your best and worst experience of using system generated data? (you might even talk about an experience of a colleague?)
21. From a health-IT perspective how would you describe the role of your PHO? What do they do to help you (or not) do your work?
22. From a health-IT perspective how would you describe the role of the Ministry of Health? How do they help you (or not) do your job better?
23. Have you been involved in doing any work with the MOH or the NHITB from a health-IT perspective? If so can you talk a bit about that?
24. If GP only: How would you describe your interaction with the PHO, from a health IT perspective?
25. If GP only: How would you describe your interaction with the DHB, from a health-IT perspective? IF hospital doctor: Can you talk about how the DHB administration communicate with you about health IT?

Appendix 6: Snowballed Participants

Snowballed Participant	Referred by
MAC2	MAC1
MAC3	MAC1
MAC4	MAC3
MAC6	MAC3
MES1	MAC1
MIC1	MES1
MES2	MES1
MES13	MES2
MES5	MAC5
MES7	MES4
MES9	MES7
MES10	MES7
MES12	MES9
MES15	MIC5
MIC8	MIC7

Appendix 7: Demographics of the Participants

Participants	Organisation type	Organisation	Role	Main focus of the role (IT or health)	Number of years of experience in healthcare	ICT experience (research)
MAC1	Policy Making Body	Macro organisation X	Senior Executive	IT	15 years	Yes
MAC2	Policy Making Body	Macro organisation X	General Manager	Health	> 20 years	No
MAC3	Policy Making Body	Macro organisation X	General Manager	Health	> 16 years	No
MAC4	Policy Making Body	Macro organisation X	Manager	Health	> 35 years	No
MAC5	Policy Making Body	XYZ Board	Senior Executive	IT	10 years	Yes
MAC6	Policy Making Body	Macro organisation Y	Manager	Health	> 10 years	No
MES1	Funding and Planning (Secondary Care)	DHB X	Clinical Lead	Health	23 years	Yes
MES2	Funding and Planning Body (Secondary Care)	DHB X	Clinical Director	Health	> 30 years	Yes
MES3	Funding and Planning Body (Secondary Care)	DHB Y	Manager	IT	< 6 months	Yes
MES4	Funding and Planning Body (Primary Care)	PHO A	Senior Manager	Health	26 years	Yes
MES5	Funding and Planning Body (Secondary Care)	DHB Z	Clinical Director	Health	45 years	Yes
MES6	Funding and Planning Body (Primary Care)	PHO B	Manager	IT	> 10 years	Yes
MES7	Funding and Planning Body (Primary Care)	PHO C	C-level Manager	IT	< 1 year	Yes
MES8	Funding and Planning Body (Primary Care)	PHO D	Technical staff	IT	> 4 years	Yes

MES9	Funding and Planning Body (Primary Care)	PHO E	Knowledge Manager	IT	25 years	Yes
MES10	Funding and Planning Body (Primary Care)	PHO F	C-level Manager	IT	< 2 years	Yes
MES11	Funding and Planning Body (Primary Care)	PHO F	Technical staff	IT	< 2 years	Yes
MES12	Funding and Planning Body (Primary Care)	PHO C	C-level Manager	IT	> 10 years	Yes
MES13	University	University X	Academic	Health-IT	40 years	Yes
MES14	University	University X	Academic	Health-IT	> 15 years	Yes
MES15	Funding and Planning Body (Secondary Care)	DHB X	Epidemiologist	Health-IT	20 years	Yes
MES16	Vendor organisation	Vendor X	Manager	IT	> 10 years	Yes
MES17	Vendor organisation	Vendor X	General Manager	Health	> 20 years	No
MIC1	Hospital	Hospital X	Specialist Doctor	Health	10 years	No
MIC2	General Practice	GP W	GP	Health	> 35 years	Yes
MIC3	General Practice	GP X	GP	Health	29 years	Yes
MIC4	Hospital	Hospital Y	Specialist Doctor	Health	25 years	No
MIC5	Retired	-	GP	Health	50 years	Yes
MIC6	Hospital	Hospital Z	Doctor	Health	29 years	Yes
MIC7	General Practice	GP Y	GP	Health	29 years	No
MIC8	General Practice	GP Y	GP	Health	10	No
MIC9	General Practice	GP Z	GP	Health	29 years	No

Appendix 8: A Snippet of the Google Doc maintained as a data collection/analysis journal

8.1. Memos

Getting Started | hotmail | my HR | Massey Library | RIMS | Google Scholar | SMSportal | Leave Forms - Home | Pearson - Using MIS, ...

i - Data Collection - 2016

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B	C
6/5/2016	**7 Interviews completed**
	3 people were not clear about what big data is and they pointed out that it's just a term. Data is evolveing, and they are all interested in making use of the data. But since there are no ongoing projects that are in use (except for research projects - precision medicine no other project seems to USE big data)
	SRT?! Would business-IT alignment make sense if there are no big data projects? Not sure! For now it seems like its just alignment across the sector!
14/07/2016	thoughts while transcribing
	Big data is user/tobe used for healthcare planning rather than clinical services. It seems to be a part of health IT strategy. Not a part of clinical decision making or decision support. So I'm not sure if it's worth talking to the GPs!
	BD analytics/ Big data is a part of the health IT plan. It is in the early stage -> it seems to be having stages
	Data generating -> see the importance of big data -> Apply techniques to make use of big data -> generate knowledge from big data
	Seems like NZ healthcare is passing the 2nd stage and are somewhere inbetween 2nd and 3rd stages
20/7/2016	**5 interviews transcribed**
	Big data related projects are for healthcare planning - strategy development. Mostly research projects (precision medicine)
	Projects seems to be in planning for big data itself instead of actually using big data.

8.2. Interviews

[redacted]	16-May-2016	2:00 PM	[redacted]	Face-to-face	Yes	44.27	Joint interview	done- Mac3	Macro V8	E E S
	17-May-2016	2:00 PM	[redacted]	Face-to-face	Yes	94.07	[redacted] called in Sick [redacted] in the discussion for about 45 mins they had NZ Health Strategy in the meeting room.		Vendors V2	
[redacted]	18-Aug-2016	3.00 PM	Massey Uni	Telephone	Yes	47.04			Meso V7	D
[redacted]	19-Aug-2016	10.30 AM	[redacted]	Face-to-face	Yes	53.43	email sent to get potential participant		Meso V7	
ormation Officer	30-Aug-2016	3.30 PM	Massey Uni	Telephone	Yes	33.1			Meso V7	G G
	2-Sep-2016	10.30 AM	[redacted]	Face-to-face	Yes	42.18	requested the questionnaire before the interview and had ma		Meso V7	M A F H F
eam	14-Sep-2016	2:00 PM	Massey Uni	Telephone	Yes	26.55				
[redacted]	25-Sep-2016	12:00 PM	Massey Uni	Face-to-face	Yes	55.58		done	Meso - New v7	
[redacted]	10-Nov-2016	4:00 PM	Massey Uni	Telephone	Yes	66.42			Meso - New v8	S
ta Officer s Intelligence Analyst	16-Nov-2016	2:00 PM	[redacted]	Face-to-face	Yes	51.31	[redacted] not answer some questions related to projects - he requested me to email them and he will send back some documents [redacted] had to leave after 45 mins and he asked me to call to continue the discussion - emailed asking for a time or asked if its more convenient for him if I email the questions			
ic	18-Nov-2016	11:00 AM	Massey Uni	Telephone						

Potential Participants | Contacted People | Pilot Interviews | Interviews | Interview Schema changes - Memos | Books Referred | Intersting Press Releas

Appendix 9: Findings Shared with Participants

ALIGNMENT OF BIG DATA IN NEW ZEALAND HEALTH

Perceptions across policy, planning and clinical care

Participant Report

Doctoral Researcher: Kasuni Weerasinghe

Supervised by: Prof David Pauleen, Dr Nazim Taskin, Associate Prof Shane Scahill

Massey University, School of Management, Auckland

EXECUTIVE SUMMARY

This study looked into how people at different levels of the New Zealand healthcare system perceive big data analytics and how such perceptions align across the sector. With the objective to understand the fit between big data analytics and government, business and user objectives and needs, perspectives from health-IT policy setters (macro level), planners/funders/implementers (meso level), and users (micro level) of health-IT solutions were interviewed. Big data analytics is predicted to benefit the healthcare sector in many ways such as: decision making, pattern recognition, population analysis, and personal health. However, individuals' understanding and commitment towards such tools is the key to success of big data initiatives.

The data was collected between March 2016 and June 2018. A total of 32 participants were interviewed across the sector, which included six from the macro level, seventeen across the meso level - from District Health Boards (DHBs), Primary Health Organisations (PHOs), universities and technology vendors, and nine participants at the micro level - General Practitioners (GPs) and Hospital Doctors.

This report presents a summary of the key findings of this research for participants. It is shared with you as you have contributed to my study with your valuable time and comments. Please be mindful that this is for your personal use and not to be shared nor disseminated in any manner without the approval of the author.

Please provide your feedback on or before 10th May 2019 about these findings by visiting the link below: Feedback form

If you need to discuss it further please feel free to contact me.

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Ph: +64 9 414 0800 ext 43379 | DD: 09 213 6379

1. Overview of Findings

A majority of the participants showed a lack of clear understanding about the term “big data”. However, all participants agreed that “data” plays a key role in healthcare planning and service delivery in New Zealand. The findings show alignment of perceptions across the sector through the shared understanding of the importance of data quality, the increasing challenges of privacy and security, and the importance of utilising modern and new types of data in measuring health outcomes. Areas of misalignment include the varied definitions of big data, as well as perceptions around data ownership, data sharing, use of patient-generated data and interoperability. The lack of a shared understanding and dialogue around the concept of big data and its potential applications, which could lead to significant alignment issues across policy and practice, is identified as a key implication of this work.

2. Areas of Alignment

2.1. Importance of data quality is well understood by all three levels.

Perceptions of all three levels showed that participants understood the importance of data quality. While arguing that data quality is not just about accuracy, participants across all levels identified factors that influence data quality such as relevance, completeness, timeliness, level of summarisation and availability of contextual information. The analysis also showed that those at the macro level are working on ensuring data accuracy through implementation of standards and policies, which will facilitate the capture of correct and complete data. Those at the meso and micro levels agreed on the importance of ensuring standards through appropriate policy to maintain data quality.

2.2. Privacy and security of data is seen as a challenge across the sector.

All participants agreed that privacy around personal health data must be secured. Privacy and security is of great concern in the big data era especially due to the amount of data being held by organisations, as well as the potential use of cloud service providers. Healthcare organisations have an added responsibility because of the sensitivity and the personal nature of healthcare data, which demands greater requirements around privacy and security measures. The current practices, policies and security measures around the use of data need to be revisited by policy makers to facilitate better data security in the big data era. This does currently seem to be underway by New Zealand policy makers and is largely accepted across other levels.

2.3. Agreement around the use of more data for improved measures of health outcomes.

When talking about the possible applications of big data technologies, all three levels talked about the improvements required for measuring outcomes within the healthcare sector. From clinicians, who talked about the importance of having a detailed view on how their patients are doing, to policy makers wanting to see whether they are achieving health targets (or not), there was a clear acknowledgement that more data and new types of data will improve current practices of measuring outcomes.

2.4. Agreement by macro and meso levels around changes to skills and technology infrastructure to facilitate big data.

Macro and meso levels (not micro, as it is not relevant to their work) identified that modern types of data bring requirements around changes to skills, IT infrastructure, and IT architecture. Meso level also identified the need for organisational structural changes around transformation of data. At the macro level there was no dialogue around organisational structural changes during the interviews conducted in 2016 (all macro interviews were undertaken in 2016), but there was a recent restructure in late 2018 at the Ministry of Health to include a Data and Digital Directorate. This is a significant step towards better policy, implementation, use and management of big health data.

2.5. Aligned views (of macro and meso levels) around health policy and strategy to provide initial direction for the future of big data.

Macro and meso levels also identified and accepted that health strategy is providing the initial direction for big data technologies in the NZ healthcare sector into the future. They associated the term “smart systems” in health strategy (Minister of Health, 2016) with initiatives around big data. Further, meso level participants claimed that having this term included within strategy provides a good platform to discuss big data technologies and their application across many domains of healthcare.

3. Areas of Misalignment

3.1. Ambiguity and differences in defining big data within and across levels.

The analysis showed that there was a lack of understanding and knowledge around defining the term big data within all levels of healthcare. Participants across the sector defined big data in varied ways. For some participants, big data was not seen as something new while others saw big data as something more ambiguous - they did not clearly understand, or were reluctant to use the term due to confusion around it. Some participants saw big data as a “buzzword”; a few exceptions were able to clearly define big data along the lines of academic descriptions. There remains an unanswered question as to whether big data is genuinely a new phenomenon, or whether large-scale datasets consisting of data that has been routinely collected for years are also classed as big data. However, modern technologies developing around big data have increased the capabilities for making use of such large-scale datasets. Similarly, most participants acknowledged evolving technology is what generates big-health-data and creates new possibilities around health data.

3.2. Misaligned views around definitions of data ownership

Participants across all three levels showed uncertainty around who owns patient data. At the macro level, it was highlighted that primary care (PHOs) has a view that they own the patient information, and the patient information is a commercial asset. Meso participants also demonstrated confusion around the area of data ownership. A senior technical specialist from a PHO explained this confusion, saying that a doctor, a DHB or the Ministry of Health will not be able to answer the question about “who owns data”. While the GPs at the micro level were not sure whether they, the PHOs or the government owned patients’ data, the doctors from hospitals did not have any comments about data ownership.

3.3. Disagreements around data sharing practices and privacy laws influencing data sharing

While all three levels agreed on the importance of privacy and security around big health data, there are disagreements around practices and privacy laws. Macro level participants explained that New Zealand privacy laws are good. While micro and meso levels agreed that the privacy laws are protecting patient data, they highlighted that these laws may in fact be going too far, claiming privacy laws were hindering their ability to use data when it is required to help a patient. One meso level participant explained that “it [privacy laws] would not allow me, as an interested party who had the capability, to help people who are disadvantaged at the moment [identified by the IDI[36]]". Therefore, meso and micro level participants recognised the need for flexible privacy laws along with clear ethical standards around sharing and use.

3.4. Differing opinions around interoperability

Interoperability is the ability to connect and effectively communicate between systems across the healthcare sector. Views around interoperability and the nature of the health system showed discrepancies. While all three levels identified the importance of interoperability, their thoughts and solutions around it showed misalignment issues. For example, the macro level acknowledged the semi-autonomous nature of the NZ health system, claiming "it has always been like that [semi-autonomous] and it will probably always be like that". They saw the semi-autonomous nature as allowing innovative organisations (PHOs or DHBs) to initiate technological inventions without being driven by the government. However, the meso level participants saw this as fragmented and something that created an attitude of competitiveness between DHBs, causing DHBs to go in different directions and use different systems and methods.

Doctors from hospitals declared the difficulties they have on a daily basis due to the use of different health information systems. They also commented upon the amount of time and money wasted through having to repeat investigations, due to disconnected systems not giving them access to investigations undertaken elsewhere. A few micro level participants strongly believed that the government needs to mandate a single PMS across the country as a starting point to fix issues around disconnection between systems. It was highlighted by the participants that while disconnected systems and interoperability issues are not issues specific to big data, moving forward into big data technologies will be difficult and may create more challenges if these issues are not dealt with in the traditional data environment.

3.5. Misalignment around areas of application (precision medicine and clinical decision making)

Figure 1 highlights the types of health data that contribute to big data in health and potential areas of application thereof. Participants across the three levels acknowledged these areas of application, but only their perceptions around the importance of measuring health outcomes were aligned as discussed in section 2.3. Priorities, and perceived importance around other areas of application (specifically precision medicine and clinical decision making), seemed to vary across the sector.

[36] Integrated Data Infrastructure

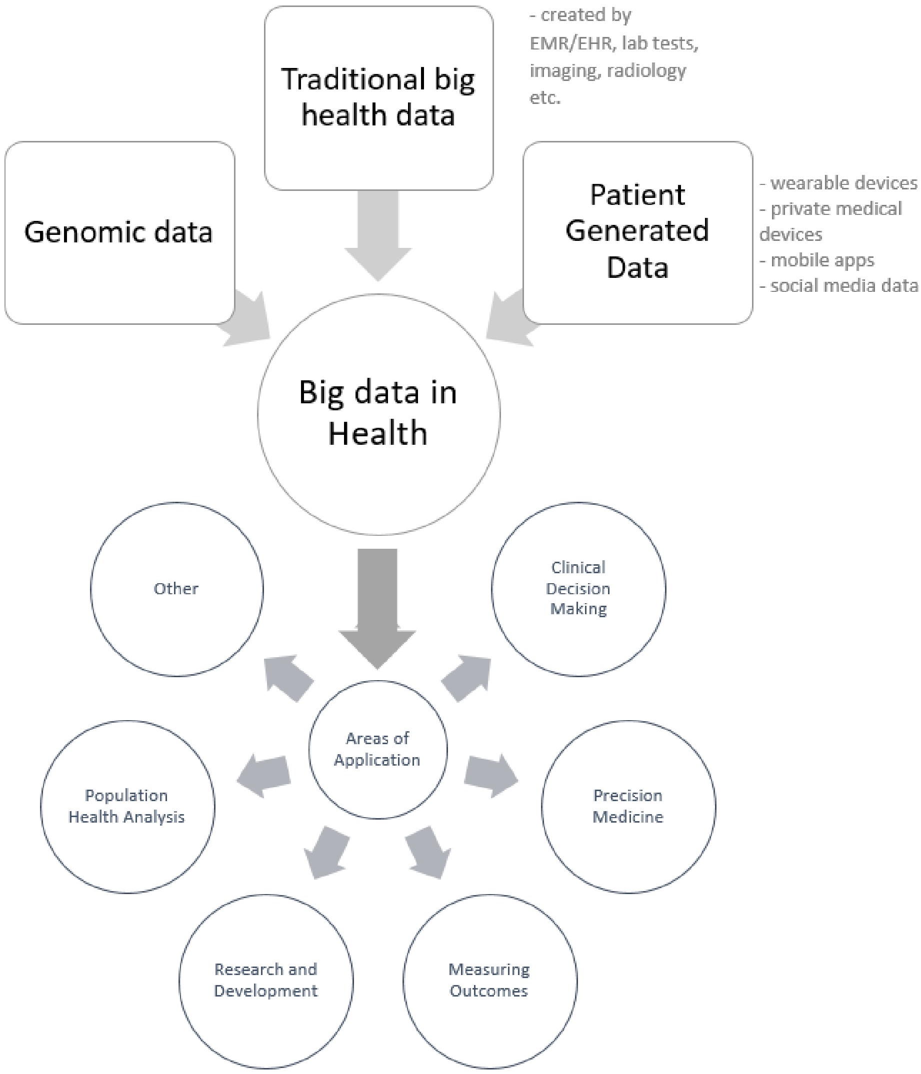


Figure 1: Types and applications of big data in health

Precision medicine is a key interest in the big data areas identified by the government. A precision medicine initiative by the MoH is currently underway (at a research stage) in partnership with a DHB, an IT systems vendor and a university. As explained by one of the macro participants, health strategy through its identification of "smart systems" promotes fields like precision medicine. Therefore, such initiatives align with overall objectives of NZ healthcare. Both macro and meso levels saw this initiative which focusses on precision medicine as being favourable. They explained that "precision medicine will at some point facilitate improved clinical care" through understanding a person's genomic structure. However, currently there is not enough information made available to clinicians about this precision medicine initiative, and they were not clear about the value of precision medicine as a concept.

Clinical decision making is the other area of application discussed under misalignment. While literature has identified clinical decision making as an area that can greatly benefit from big data technologies, differing perceptions were seen across the sector. Macro level participants were more focused on other areas (specifically measuring outcomes and population health) than looking into application of big data technologies for clinical decision making. Several of the macro level participants acknowledged that while big data has potential in clinical care settings, they claimed "it's not our [Ministry's] role" (MAC2) to initiate the use of big data for clinical care and decision making. While identifying current clinical decision support and its use of data to be at a "rudimentary stage", meso level participants identified the application of big data for clinical decision making as having great potential. At the micro level there was confusion about the potential of big data tools to facilitate clinical decision making. While these participants talked about tools like Health Pathways and Atlas, they explained that they were wary of using any new tool without seeing evidence of its benefits.

3.6. Invisibility of patient-generated data in health policy and strategy

Patient-generated data (a source of big health data), while accepted and understood to have significant potential by meso and micro level participants, did not seem to get much attention from the macro policy level. Some clinicians at the micro level currently use patient-generated data through mobile apps; yet this presents many difficulties due to a lack of guidance from the policy level as well as from their meso level DHBs and PHOs. The meso level identified the use of patient-generated data as important and something they are interested in (specifically PHOs). However, these meso level participants admitted that they are not doing anything in the area of patient-generated data yet, saying "on our priority list it's probably well down". The meso level participants explained that policy makers need to discuss patient-generated data, and need to provide better direction to the sector through policy around capturing and using patient-generated data.

3.7. Differences in the clinical profession that need to be understood by other levels

While the macro and meso level participants have come across inspiring GPs and hospital doctors initiating (and developing) useful clinical care tools (even with approaches close to genomics), there was a notion among these levels that the clinical people lack an understanding of the potential of big data in clinical care or decision making. Some participants (at macro and meso levels) also argued that if evidence was shown to the clinicians they would be interested in sophisticated electronic tools that will facilitate care. Additionally, participants within PHOs explained that front-line clinical personnel are a great influence on them, pushing them to work on better tools, as well as to improve data quality. At the micro level both GPs and hospital doctors alike claimed that their profession is not well understood by those at the meso and macro levels. The clinicians claimed that they will not use electronic tools in their clinical practice unless they are shown evidence of their accuracy and reliability, as they are dealing with human lives and they have to be accountable for the decisions they make. At the same time, GP participants highlighted that using more tools for clinical care is not practical due to enforced time constraints around patient consultations. They stated although tools are said to improve efficiency, using tools can consume more time in a consultation. Clinicians also highlighted that their training did not include information analysis, which is important for the modern data world, and is something that policy makers might look at for the future.

4. Key Recommendations

- A common dialogue about the concept of big data identifying its potential, challenges, and issues needs to be facilitated across the sector.
- Clear guidelines through health policy are needed to facilitate better understandings about data ownership across the sector.
- An open discussion around the importance of data sharing needs to be facilitated. Policy makers need to be more open to revisiting policy, making required adjustments but also ensuring privacy of patients in this big data era.
- While the dialogue suggested that there is a need for a countrywide electronic patient management system, it is recommended that policy makers carefully consider this alongside strengthening policies around interoperability before making changes. (Further research is needed to make informed recommendations.)
- A robust plan for providing information to the micro level is important, and will facilitate a more positive environment in the future when precision driven medicine becomes more available and applicable to front-line clinicians.
- Investigating potential applications of big data for clinical decision making needs to be made a priority by policy makers and discussions need to be initiated across the sector. Prioritising clinical decision making as an important area of application will lead to development of e-tools; however, it will also require the greater engagement and involvement of clinicians.
- As one of the key action areas of health strategy is being ‘people-powered’ (Minister of Health, 2016), it is recommended that patient-generated data be incorporated into health policy for the meso and micro levels to make effective use of it.
- More consultation with clinicians is required when developing and implementing tools and technologies (not just big data) that are relevant to clinical care.

Appendix 10: TSR and other IS Theories

Following many decades of studying technology use in society there is a vast body of literature with many theories acknowledging relationships between technology and people. Such theories in literature share some similarities with TSR and it is necessary to investigate them to determine whether TSR is truly offering a new theoretical perspective. Table A1 provides an overview of theories related to TSR.

Table A1: Relevant theories around sociotechnical perspectives[37]

Theory	Description
Social Shaping of Technology	Social shaping of technology is a theory that emerged from the critique of Technological Determinism[38]. It argues the development of technology is a social process and that people and social dynamics are central to technological change (MacKenzie & Wajcman, 1999). The theory holds that technology is shaped by social, political and economic values of society, and therefore takes a socio-economic view on technology (R. Williams & Edge, 1996). It is claimed that new technologies do not emerge through an inner technical logic but are developed as required by the society itself (R. Williams & Edge, 1996). *Originating authors: Donald MacKenzie and Judy Wajcman, 1985*
Social Construction of Technology (SCOT)	Opposing Technological Determinism and strongly influenced by Actor Network Theories the key underlying argument in SCOT is that human actions shape technology (R. Williams & Edge, 1996). To understand how technology is used it is crucial to understand how technology is embedded in its social context. SCOT also acknowledges social groups and how such social groups influence technology (Pinch & Bijker, 1987). *Originating authors: Trevor Pinch and Wiebe Bijker, 1984*
Sociomateriality	The Theory of Sociomateriality highlights the fusion of social aspects and material (technical) aspects in the context of information systems. It claims that social and

[37] Some of the identified theories in the table have underlying theories as their foundations (e.g. Structuration Theory by Anthony Giddens (1984) is the foundation of AST). We have excluded such theories from this table unless they show a specific similarity to TSR (e.g. TAM is UTAUT's foundational theory, but TAM has similarities to TSR which is important to this discussion).

[38] Technological determinism argues that technology determines the social structure and its values, and therefore shapes the society.

	technical aspects are inextricably related, and cannot be separated or separately studied. *Originating authors: Wanda Orlikowski and Susan Scott, 2009*
Technology Acceptance Model (TAM)	TAM theorises that users' acceptance and use of a new technology is influenced by its perceived usefulness and perceived ease of use. The technology acceptance model can be used to explain end user behaviour around technology use (Davis, 1985). *Originating author: Fred Davis, 1985*
Unified theory of acceptance and use of technology (UTAUT)	Acknowledging the importance of understanding acceptance of technology by users, the UTAUT model identifies four factors (performance expectancy, effort expectancy, social influence, and facilitating conditions) and four moderators (age, gender, experience, and voluntariness of use) that influence behavioural intention of using technology and actual use of technology in an organisation. *Originating authors: Viswanath Venkatesh, Michael Morris, Gordon Davis, and Fred Davis, 2003*
Work Systems Theory (WST)	WST, originating from General Systems Theory, views organisations as work systems. Within work systems, people and technology interact with each other to produce outputs. The central interest of WST is to understand how people think about information systems (Alter, 2013). *Originating author: Steven Alter, 2006*
Adaptive Structuration Theory (AST)	AST (based on Structuration Theory) focuses on social structures, rules and resources of technology as the basis for human activity. AST argues that technologies used by organisational groups trigger adaptive processes, which will bring organisational change (Gopal, Bostrom, & Chin, 1992). The theory claims that such change happens as members within organisational groups interact with technologies (DesSanctis & Poole, 1994). The 'spirit of technology' is identified as central to this change. DesSanctis and Poole (1994) explained that the spirit of technology is not the intended use of technology or the perceptions but something that is presented to the users by technology. Based on AST the structures adapted by the groups consist of this spirit and influence organisational change (Gopal et al., 1992). It is often used as a viable approach to investigate organisational change with information technology. *Originating authors: Marshall Poole and Geraldine DeSanctis, 1990*

While all these theories share an understanding about the relationship of technology and people, they all take different approaches in their explanations. For example, the theory of Social Shaping of

Technology argues technology is shaped by social, political and economic actions of the society, while SCOT emphasises that human actions create changes in technology. Sociomateriality on the other hand is about the inseparable tie between technology and people. Although Social Shaping of Technology, SCOT and Sociomateriality broadly explain the association between people and technology, their views on sociotechnical relationships are very different from that of TSR. As TSR is an extension of SST, SST principles claim technology and people are interdependent, and therefore TSR is different from views of technology being shaped or constructed by the society. Moreover, due to the foundation provided by SRT to TSR people create representations of technology and such representations evolve over time so TSR's view on the relationship between people and technology is not inextricable like that of Sociomateriality.

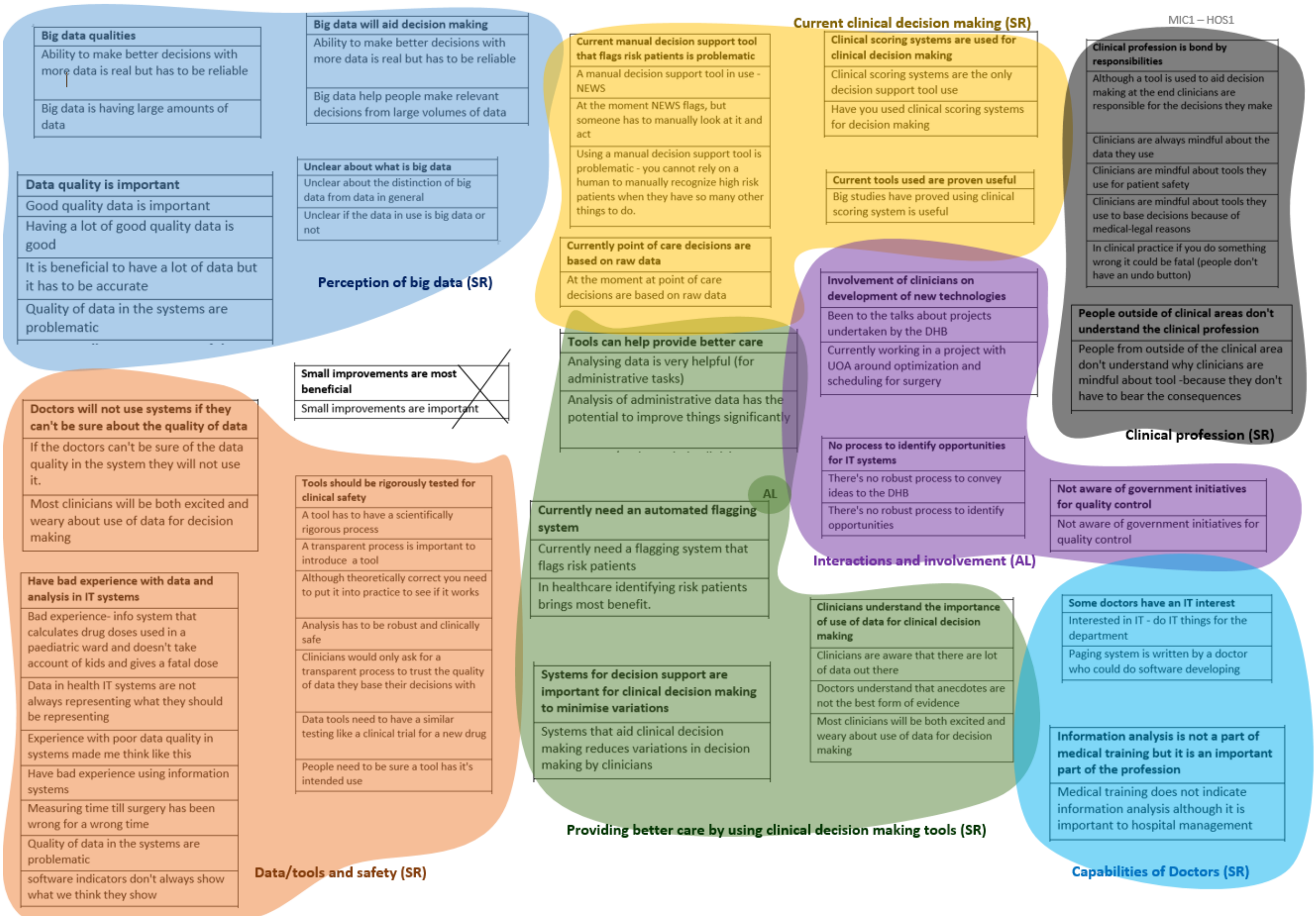
On the other hand, theories like AST, TAM and UTAUT show closer connections to TSR in understanding sociotechnical relationships and/or addressing the interrelationships and interdependencies between people and technology. TAM identifies two social dynamics influencing technology acceptance and use: perceived usefulness and ease of use (Davis, 1985). However, TSR is different from TAM (or its variants like TAM2) because TSR examines representations to understand what causes a certain perception of acceptance, importance and use. As explained in SRT, a representation is much more than a perception. It is a collective understanding that shapes an individual's perception about a phenomenon. UTAUT portrays more similarities to TSR in its definitions of factors and moderators that influence the use of technology. However, TSR takes a different approach to that of UTAUT by allowing the researcher to provide explanations behind such influencing factors. For example, UTAUT identifies performance expectancy as a factor that influences use of technology, while a TSR study may identify performance expectancy as influential, and it encompasses tools to explain what is behind these expectations (i.e., the type of work that needs fast processing and performance).

Similar to TSR, AST emphasises understanding the importance of social dynamics and acknowledges differences between groups (DesSanctis & Poole, 1994). However, because of its greater focus on organisational change triggered by the influence of social dynamics on technology (which is also influenced by the spirit of technology) (Gopal et al., 1992), the purpose of AST is different to that of TSR. In addition AST elaborates on the investigation of the spirit of technology by investigating technology through text (design material, features, user interfaces, training, and help) to understand the influence on social structures better. Social representations in TSR are clearly different from the spirit of technology investigated by AST, because the representations look into a more humanistic approach by understanding what influences an individual or a group to perceive and use a technology in a certain way.

WST, although developed from a broader SST perspective, claims social and technical subsystems are not two individual components, but rather a single system, and therefore goes beyond to explain completely automated systems and their performance without people's involvement (Alter, 2013). This is not the case for TSR. We believe that distinctive social dynamics are present even in fully automated systems within their process lifecycle and can be studied through TSR.

Although theories like Actor Network Theory (Callon, Law, & Rip, 1986; Latour, 1996), Contingency Theory (Fiedler, 1978) and Design Theory (Gregor, 2002; Walls, Widmeyer, & El Sawy, 1992) of Information Systems have minor similarities with TSR in some of its aspects, these are not substantial enough to be compared and are therefore not included in Table A.1. The above comparisons with similar theories provide justification that TSR is based on a contemporary discussion in the field of IS, yet is taking a novel approach in understanding social dynamics of technology in sociotechnical systems.

Appendix 11: IPA Analysis Snapshot of a Summary Map created in the Early Stages of Analysis



Appendix 12: Description of five categories through analysis of data

This is provided as a supporting document for the reviewers and is not to be published.

Detailed descriptions of five categories with direct quotations are given below. These five categories are the five key categories found as a result of cross-group analysis. It describes the findings, but does not talk about alignment or misalignment as that was done as the next step of analysis.

This document discusses the data from the interviews, with direct quotes. While the analysis of findings was done in three groups, the findings are presented here together around five important categories[39], which are: (i) perceived definition, (ii) challenges of big data, (iii) concerns around big data, (iv) applications (current and future potential areas), and (v) healthcare strategy and policy. The findings in these five aspects influenced the understanding of areas of alignment and misalignment.

Category 1: Perceived Definition

At all levels, there was ambiguity around the understanding of the term 'big data'. Even at the macro level where policy has to capture the use of big data, participants were unclear about the definition. At the macro level, a lot of participants saw big data as a buzzword, or a catch-all term. One participant claimed that he is reluctant to use the term 'big data', explaining that:

> "So you could say that the complexity and diversity of the data associated with the particular issues is much greater than it ever has been before, but in 10 years' time, that then would be enormously bigger. So big data or enormous data we are re-negotiating. The term doesn't make real sense to me." (MAC5)

Although this participant (MAC5) did not agree with the term 'big data', he did claim that modern data is more complex and diverse than it has ever been before and agreed that the issues around modern health data are much greater than before. This shows that while the participant acknowledges the growth of data, there is no clear understanding of the use of the term 'big data' to define modern types of data. Similarly, another senior manager at a macro level organisation claimed:

> "Big data to me is interpreted quite widely. I mean you get everything from the data… [it provides an] ongoing measurement of continuous factors. For example, blood pressure measurement, for a long period of time of an individual by medical type matrix. A lot of this

[39] The most relevant categories from findings around the research question are discussed.

information goes for monitoring a person… then there is lots of data like environmental data or radiological data, something very large and complex…. So to me, big data is about you either have a lot of depth in one system or small group or you have a lot of breadth. (MAC2)

Adding to this comment about big data, MAC2 highlighted that in her understanding, big data is not new, but people's awareness of the potential of big data has changed. These representations share a similarity: a lack of understanding as there is no clear definition of big data.

Interestingly, another senior manager at the macro level provided a complete definition for the term, identifying big data as: (i) expanding traditional health data, (ii) new types of data generated outside of clinical settings, and (iii) internet of things allowing health device data to be fed into systems directly. He explained that to him,

> "Big data is about realising technologies helping us to collect more data, more quickly with higher quality." (MAC1)

The commonality in these representations is that although there is ambiguity in the definition, there is agreement across the macro level participants that the modern technology is increasingly generating new types of data, attributing big data as a part of evolving technology.

Similar to that of the macro level, the participants at the meso level (particularly DHBs and PHOs) showed a lack of understanding about the term 'big data'. While some participants claimed that they are unclear about the meaning of big data, or see it as a buzzword, some highlighted that big data is already in use. One of the participants from the meso level showed lack of clarity around the term, saying:

> "It would be fair to say I am well aware of the term but poorly aware of the definition…. if by big data you mean a certain volume, whether we've got that volume or not I'm not sure." (MES4)

In contrast, some participants such as MES10, MES12 and MES15 explained that big data is not a new concept for health. They claimed that the NZ health system has been dealing with big data for a while now. Similar to the macro level, meso level participants also talked about how big data is just a buzzword as technology evolves. As explained by a IT specialist at a PHO:

> "For me personally, it's a terminology, like the Cloud. You know how some people coin the term Cloud, but basically it's just the internet." (MES8)

Although participants claimed to be unclear about what big data is and considered it to be a buzzword, they also understood the opportunities around the use of modern types of data. Participants agreed that it is better to have more data because more data helps with better analysis.

> "But we are able to see the big picture [with more data], we are able to see trends, we are able to see correlations. You know otherwise we couldn't pick [it] up [if] we didn't have all these data. And then we can use that back down to the individual patients to provide better healthcare for them. Because it's based on so much knowledge." (MES1)

With big data and modern technology allowing us to capture and store more data, the health system can get a better understanding of the patients – who they are, which doctors they see, and what treatments they are getting – creating a clear picture of a patient and also providing the ability to understand the effectiveness of treatments. Therefore, at the meso level there was also agreement by the participants that emerging technology is evolving and creating new types of data that can be used for the betterment of the health system.

At the micro level, as expected, most of the clinicians were not aware of the term 'big data'. However, a few were able to define big data, saying "big data is national data" (MIC2) or "monster datasets held by the Ministry" (MIC5).

> "I don't probably know exactly what people mean by big data but what I take from it is a very big database that we have in Wellington. Or in the cloud and things." (MIC5)

While at the micro level, definitions of big data literally refer to how large the data is, some clinicians claimed that big data is not new and the health system has been generating and using big data for a long time. However, there was some discussion around how big data studies in the area of population health may improve care going forward, but that did not seem to be new from their perspective. Although the clinicians were not aware of the term 'big data' or able to give a clear definition of it, they were able to talk about new sources of data (such as data from patient devices) and their applicability in healthcare delivery.

These findings show that the general understanding of the term 'big data' is lacking across the health sector. However, all three levels agreed that there are new types of data being generated that can improve healthcare.

Although there was a lot of ambiguity around the definition of the term 'big data', the analysis showed that there were distinguishing characteristics of modern health data identified by all three levels. The macro level participants talked about modern health data having 5V characteristics – volume, variety, velocity, veracity and value. There were perceptions about difficulty in accepting velocity as a characteristic.

Volume was acknowledged as the exponential growth of health data by almost all participants. They claimed that big data is large and complex data on a huge scale. MAC6 explained that:

> "It's sort of a catchall term to describe the insights that come from analysing large quantities of data that are collected about individuals and about other things." (MAC6)

The second V, **variety,** was discussed in aspects of complexity and diversity. Data from many locations, of many types environmental and radiological) and in different situations adds to the variety of big healthcare data. Participants also claimed that in health there are many collections of data sources and that it is about bringing together such collections, addressing the importance of data linkage/aggregation of these various types of data.

Commenting on the complexity and diversity of the health data itself, MAC5 claimed:

> "There's an aggregation of data at a system level related to an individual New Zealander, that could be from community, it could be from the GP, could be from hospital, it could be from your physiotherapist, could be from your obstetrician, could be from 1000 different places of the health system and over time you move around the country so it spreads geographically as well." (MAC5)

His claims show that the complexity and diversity of health data are inherent to the healthcare system due to its nature. However, participants (MAC3, MAC4, MAC6) pointed out that big data is not just within the health system but also about linking data from various other aspects. They talked about the Integrated Data Infrastructure (IDI) [40] and how it contributes to creating big data across the government by linking data across different sectors.

[40] Integrated data infrastructure (IDI) is a large database that contains data about New Zealanders. The data that IDI holds is from sectors across the government, data from censuses and non-government organisations surveyed by Statistics NZ (http://archive.stats.govt.nz/browse_for_stats/snapshots-of-nz/integrated-data-infrastructure.aspx).

The third V, **velocity,** refers to the speed of data. Analysis of participant perceptions found two qualities of velocity: (i) speed of data creation, and (ii) routine data. Participants agreed and appreciated that big data technologies allow very fast creation and capture of data, in near-real time. They explained that modern technology allows us to create more data, more quickly, and with better quality. However, one participant (MAC5) strongly believed speed of data creation does not make sense as a quality of big data. He claimed that collecting data from lots of different sources and bringing them together to make sense is not real time, but is where the value is. Additionally it was pointed out that good information comes from analysing and comparing historical data with present data, so the quality of "real time" was questioned.

The second identified aspect of velocity is continuity of data which is about routinely collected data over time about something specific and was seen as specifically useful for the healthcare sector in areas like population health analysis. Some participants claimed that no matter the scale of data, if the data is not continuous it cannot be categorised as big data. They also claimed that health data is big data because it has an element of being. MAC2 said:

> "I read a big study on a European state, several hundred thousand people being operated for years and years and years, so there's masses of data. But I don't see it as big data because it's quite compact, it's not quite that on-going…. With administrative data we've got big data because it just keeps coming." (MAC2)

The fourth V, **veracity** (accuracy), was particularly seen as an extremely important quality of big health data, highlighting the need for "right data" (MAC1). Some participants highlighted that although health data needs to be accurate, it is not always the case, talking about their experience with poor quality data. Macro level participants also talked about the data's ability to create **value** in the healthcare context. They perceived that just collecting health data is meaningless unless it can be used effectively.

Participants at the meso level also defined big data along the lines of 5Vs: volume, variety, velocity, veracity and value. The participants acknowledged the **volume** of big data, explaining that big data is data on a much larger scale and scope than the health system previously had. However, they highlighted that "it [big data] is not just about volume" (MES2), but it is more about the complexity of data and the availability of unstructured data. Such complexity was identified as a theme under the **variety** characteristic of big data. The meso level participants highlighted variety of data, acknowledging aggregating data from many sources including new sources like data generated by patients or genomics to make more sense. They talked about how such data could be unrelated at the point of creation but can be pulled together to make meaning. The meso level also talked about having unstructured data along with structured and semi-structured data as a defining variety of big health data. Such combining (aggregating) of existing and new data as discussed in the meso level links well to the complex and diverse nature explained by the macro level.

The velocity of data was discussed through three aspects: (i) speed of data creation, (ii) routine data, and (iii) timely use of data. Commenting about the speed of data creation, they talked about how modern technology allows them to create data in near-real time. MES1 explained that:

> "…it [big data] will be coming very quickly. We will be moving towards systems that are able to collect real-time, 24-hour sort of data, so there will be much more of it in that way".

Similar to that of the macro level, meso participants talked about routinely collected data as a defining characteristic of big data under velocity. They explained how big data is about "constant flow of data" (MES6) or "data that is coming" (MES9). Explaining more about the velocity characteristic than the macro level, meso participants highlighted the importance of timely use of big health data. MES6 highlighted how timeliness of big data is a very important characteristic for health, explaining:

> "But what we also need, from my perspective is, timeliness. Timely data around key predictive values so that we can actually predict back, down to the individual patient level to say when this starts to happen. Or when we see these test results and this combination of factors appearing for a patient, it means actually there is an 80% probability they are going to have a stroke within the next seven days. And then we can provide that information back to those who can in fact act and make a difference and prevent the stroke from happening or minimise the severity of the stroke because we had the advance warning." (MES6)

Meso participants also talked about veracity, referring to the importance of "honest data." Veracity was highlighted as the importance of having "honest data" (MES2), referring to accuracy of data. In addition to these 4Vs discussed at the macro level, the meso level also talked about the 5th V: value. Value was represented as "making meaning" (MES8) through data. Participants saw the importance of purpose in linking data or analysing data to make it meaningful and useful.

As expected, there was only a little understanding about what big data was at the micro level (this is acceptable as big data is something that known to technical and strategy sectors and not to the front-line people). At the micro level, characteristics of big data were defined through 2Vs – volume and variety. While explaining big data as "very large datasets held by the Ministry" (MIC5) they also talked about aggregating data from different places, hinting about the variety of data – however they did not specifically talk about variety as a characteristic.

Category 2: Challenges

Under this section the challenges participants saw in the big data environment around their work are discussed. Macro level participants identified skills, IT architecture, and IT infrastructure as challenges around big data. Highlighting the challenges around obtaining necessary skills, MAC2 explained that:

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

They 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 architecture and IT infrastructure. Meso level participants also identified similar challenges; however, apart from the three identified at the macro level, meso participants identified organisational structure changes that are happening around big data. 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)

There was no data around challenges from the micro level. Their role in the clinical frontline delivering healthcare necessarily does not face such challenges.

Category 3: Concerns

As concerns, macro level participants perceived accuracy, data ownership, making data available, data lakes, privacy and security of data, ability to misuse, and obtaining trust (or losing trust). While they saw accuracy as a characteristic of big data (under veracity) they also talked about how accuracy is a major challenge in the health industry. MAC1 claimed:

> “When you are dealing with such a complex industry like healthcare, you know, it’s not that you need lots of data, you need the right data that try and help you.” (MAC1)

The macro level participants talked about achieving data quality through collecting data at source (particularly by capturing data directly through digital devices – IoT approach) and storing data against a standard. Talking about data ownership as an issue around health data, they saw data ownership as questionable, claiming:

> “Primary care has a view that they own the patient information. And the patient information is a commercial asset.” (MAC4)

Talking further about data ownership, MAC2 explained:

> “It's not just somewhere where private enterprise can take ownership of this knowledge [genomics], they have tools to use big data. But, how do you help individuals and groups and communities to benefit from big data? It's a very important question.” (MAC2)

Along the lines of data ownership, participants also talked about making data available as a huge challenge. They talked about how there is data in silos but there is a desire to make data universally available so it can be utilised by relevant people depending on their need. Commenting about data lakes, while macro level participants acknowledge the recent concept of data lakes, some of the macro level participants did not seem to agree with this idea of pooling data without a clear focus. Privacy and security, misuse, and trust were other issues that the macro level participants talked about. They claimed that patients’ trust and confidence is extremely important, and in order to secure it, they believe taking necessary security measures to prevent misuse is the key.

Similar to the macro level, meso participants talked about issues of accuracy, data ownership, privacy and security, ability to misuse, and obtaining trust along with a few issues that were not seen at the macro level: context dependency of data and capturing context, ethical use, technology-enabled error and interoperability problems, and concerns around sharing data with other organisations. An interesting point was raised by MES8 about data ownership:

> “Well, it's people or the organisation that are holding the data. The problem is there's always the big question of "who owns the data?" so if you ask this from a doctor, GP or a specialist or

> a DHB or a Ministry of Health I'm not sure they will answer you. They will say the patient owns the data. So can you share it?" (MES8)

This shows that the macro level also claims that primary care thinks big data is a commercial asset, and there is confusion in primary care (MES8 is from a PHO) as to who owns patient data. While privacy and security was a major concern at the meso level similar to that of the macro level, the meso level participants talked about issues of misuse by both people who have access to the data as well as by potential hacking. There was also a discussion about how data can be misinterpreted, where they highlighted the importance of understanding the context as a major factor that influences correct understanding of data. Talking about the importance of acknowledging context dependency of data, MES9 claimed that:

> "I think there is some big challenges around interpretation. Within my team we talk about context and without having an understanding of the context in which the data was collected you actually create a whole raft of risk of interpreting it wrong." (MES9)

Other meso level participants also talked about the challenges around data sharing and ethical use of data, claiming "not everyone will make the same moral choices that you believe they should do" (MES2). Meso participants identified ethics as a very important issue that needs considerable discussion under big data. Other things that the meso level talked about was errors enabled by technology. One of the participants even explained how he experienced Hadoop-enabling errors and how dangerous such technology-enabled errors could be to the health system, as "we are dealing with lives here!" (MES14).

At the micro level the biggest and the most explained issue was data accuracy. The clinicians (both GPs and hospital doctors) were not satisfied with the quality of data, and often showed reluctance in using health data due to their experience with poor quality data. They highlighted the importance of a transparent and rigorous testing process for any data tools for them to be comfortable using it. Other issues and challenges around large amounts of data (not necessarily big data) were that doctors need summarised information to work fast in their jobs – so big data or normal health data has to be present in a summarised view for the doctors to make proper use of it. Doctors also highlighted ethical use of data as an important challenge.

Category 4: Application

This section explains perceptions across the healthcare sector on what big health data is expected to be utilised for, and in which fields it has great potential. Overall, the macro level participants identified measuring outcomes, population health analysis, cross-government data linkage and use, precision medicine and clinical decision making as fields big data can be applied to across health. Most participants talked about how measuring outcomes is important to understand how the health system is doing, and what is happening with health spending. While participants said there is considerable work being done on measuring outcomes, claiming "I think we do that in a reasonably sophisticated way" (MAC4), some highlighted that there are still areas that can be improved with data. One such comment was given by MAC5, talking about productivity and optimisation:

> "Then there is a whole area of analysis that needs to be done around productivity within the health system. How can you make sure that each individual is treated in the most effective way, minimising the expenditure of the person's time and the whole system's time? So there is [a] whole optimisation problem that needs to be addressed to the production type level within the system, which has not even been hardly touched." (MAC5)

MAC1 also talked about how big data could be used to capture measures of waste of time, highlighting an interesting area of potential from big data:

> "I think big data is a really great opportunity both to get the really accurate data about where the waste of time is, but also the perception that the doctors and the nurses and the consumers are having about that waste of time." (MAC1)

Macro level participants also highlighted that big health data has much applicability to population health. However, they also highlighted that plenty of work is already being done around population health (for example using data to understand relationships between conditions associated with different populations or different geographic situations). Much discussion took place around linking data across government to make big data and the use of such data for betterment of public services overall, and not just health. Participants talked about the Integrated Data Infrastructure as cross-government data linkage and how work is underway for such linked data infrastructure. Explaining the potential of IDI and how it is solving cross-government issues, MAC3 explained:

> "So for example the type 2 diabetes they have huge health and social costs, housing costs, and they don't participate in employment, they have quite [high] disability costs. So, the social

> investment unit is taking housing data and health data and employment data and economic data and actually saying, "this is what, if this condition poorly managed actually costs the country, and if you [healthcare] intervene at this point this is how it could be different.” (MAC3)

Thus the IDI and linking data across the government provides great opportunities to “understand how decisions made in healthcare actually shift cost and risks to other parts of the New Zealand system as a whole” (MAC4).

The other most talked-about area was precision medicine. Precision medicine is about understanding a patient’s genome and providing medications personalised to that patient based on the genomic structure. This differs from the existing generic way of treating illness based on an identified group of people. However, macro level participants highlighted that precision medicine is currently at its initial stage and the government is backing precision medicine projects as research.

The other area discussed was clinical decision making and the potential of big data. While a few participants at this level acknowledged that big data has promising potential in clinical care, they also highlighted that at the moment there are many issues that the health system is trying to tackle. Therefore, application of big data for clinical care is not something that they are interested in at the moment.

Analysis of meso level data showed that like the macro level, the meso level also has an interest in measuring outcomes, population health analysis, cross-government data linkage, precision medicine and clinical decision making. One of the things that was not discussed by the macro participants but was seen as valuable and as having a huge potential through big data is patient-generated data. Some discussion around applicability of artificial intelligence was also observed during the interviews at this level.

Similar to the macro level, meso level participants saw that while plenty of work has already being done around measuring outcomes there is still considerable work needing to be done with the help of big data. One such area discussed was effectiveness, and how it is important to know “not just the conceptually best answer but also what actually works within your environment” (MES2). Also highlighting the importance of measuring effectiveness, MES6 commented:

> “We're never going to improve our services to our patients or to our clients until we can actually monitor and track the effectiveness of what we're doing. It comes up all the time.

> Why we are spending this amount of money on this service, when it will be of more benefit to spend it elsewhere?" (MES6)

Therefore, such outcome measures will facilitate improved administrative decision making across the health sector. Meso level participants also talked about population health as an obvious application of big data. Some participants explained that big data has been used in population health analysis for many years; for example, MES13 explained that:

> "I've been working in Big Data Linkage studies [in epidemiology] since about 2000. So pretty much all of this century my work has been on Big Data Linkage." (MES13)

Some current big data projects in the field of population health as identified by the participants include Predict, ANZACS and Varienz which are all about data linkage. Some participants also talked about Atlas which is another population health tool that can be used for clinical decision support. A participant from a PHO talked about their huge repository of data about the whole enrolled population which can be used to provide all information about an enrolled patient whenever the patient uses the health system to facilitate providing good quality care. Moreover this participant from a PHO explained how they plan to aggregate this repository with three other large PHOs to provide a more nationally representative view of the health of New Zealanders. Another participant (MES3) explained how they are currently looking at extracting unstructured data from text-based notes of hospital doctors to create some meaningful understanding of it; this project is still at a very early stage (the discussion stage) and needs further understanding and design before implementing it. Such understanding through unstructured data is deemed to facilitate clinical and administrative decision support.

Like the macro level participants, the meso participants also talked about cross-government data linkage through the IDI. Highlighting that the IDI facilitates population research (not population health research) by "trying to create a more coherent picture of an individual to improve research. So that data linking between government services" (MES2), they saw that "IDI is not a full answer to big data but it's a very important or maybe the initial step" (MES15).

Many of the meso level participants from all four groups talked about the use of genomics for precision medicine. There were discussions either around how they have started looking into precision medicine through research, or how they saw genomics and precision medicine as an area with huge potential to use big data technologies. Explaining the potential of precision medicine for personalised care, one participant said:

> "What gets me excited about where we're heading as an organisation is that we will be in a position to personalise somebody's healthcare to a degree that we haven't even been able to dream about…. when you can start pulling all these bits of data together to say, "Anne is a very different person with Type 2 diabetes than Bob. Therefore, the care plan that we're going to put around her is going to look like this. It's totally different to Bob's care plan that needs to do this, this and this." (MES17)

While explaining that clinical decision support in the health system is at a "relatively rudimentary stage" (MES2), participants highlighted that the current clinical decision support mostly involves warnings. Hence the participants highlighted how precision medicine can in future build clinical decision support tools.

An area that was not discussed at the macro level but came up in the discussion with most of the meso level participants as relevant to the big data domain was patient-generated data. Patient-generated data is data created by the patients outside of the health system. With modern technology and mobile apps for almost everything, the participants said patients are creating valuable data about their health, and also data that could be linked to health as they go about their lives. Highlighting that there are lot of valuable data that the patients themselves create, one participant said:

> "Now ubiquitous computing is here, it's in everybody's home. We are collecting data about ourselves like it's going out of fashion. We need to think about what we can do with that data to transform the health system… We need to think about what we are going to do to make all that data that people collect about themselves useful." (MES14)

Patient-generated data is extremely frequent compared to data that is captured by the health system itself. For example, the health system may capture the blood pressure of a patient once every six months or 12 months. Whereas when the patient has a blood pressure monitor at home he/she can record the blood pressure every day (or even more frequently). Having such frequent data captured by the health system gives the ability to understand when there is a change and to do better predictive analytics around the blood pressure of a patient. Although these participants saw patient-generated data created by wearable devices or other personal devices as extremely beneficial for the health system in providing better healthcare, they claimed that are no deliberate approaches for doing so. MES9 explained that:

> "On our priority list it's probably well down. Although I think it's a chasm leap that I think has a potential to be a game changer. But actually requires a reasonable amount of investment to actually do it or to have a go." (MES9)

There was also some discussion about the use of Artificial Intelligence (AI) for the betterment of the health system, by the meso level participants. Some participants explained that big data has to be linked with technology like AI to utilise its full potential. One participant explained the potential of AI for clinical decision making:

> "America has already developed a tool that's for scanning CTs for cancer identification. Called the Watson. That system can scan the CT very quickly. And it can also do self-learning (so-called machine learning), which means it learns from itself, so it can correct errors or mistakes. So they can be supervised and unsupervised models. We consider that as the potential big data and artificial intelligence, but I think actually it's still not kind of mature. So sometimes if it is purely based on AI can be misleading. So we have to actually see the clinicians. Can't 100% rely on a decision made by AI. Clinical experiences that currently may not be captured by AI." (MES15)

MES15 also explained that while applicability of AI in the clinical care environment is extremely sensitive, they are currently looking at an AI tool to predict the length of a hospital stay. He explained they are yet to look at doing it in real time.

At the micro level, understanding about the application of big data seemed to be at a rudimentary level. However, there was general agreement that data is tremendously important and helpful in treating patients. They also talked about how big health data can be "used anonymously for wider epidemiological studies and health monitoring" (MIC3). Participants also talked about the possibility of preventative care through population health. For example MIC5 explained that:

> "…in the interface between those two sides [primary care and secondary care] you have population health. It's not acute work; it's preventive care and treating before it happens type care. So but New Zealand is probably more advanced than any country with that. New Zealand had an incredible advantage, because right from the 1930s I think every patient that came through a public hospital ended up with an NHI." (MIC5)

Participants also saw the use of big data in measuring outcomes within the health system. One example identified by a participant was around the use of ePrescribing and how ePrescribing data will allow understanding patterns of drug prescriptions within theatre. Another example given by MIC4 was around cost savings. He explained that:

> "The thing about anaesthesia is that potentially a lot of information can be collected, so every time we turn on an anaesthetic machine there is data on how much gas is being used and the cost of the gas and so on. And so one of our local researchers is looking at gas flows from individual anaesthetic machines, so he can then look at the whole theatre suite and create a dashboard of current anaesthetic gas flows. He's working with a company to actually incorporate a dashboard style monitor of gas usage which would ultimately be used to save money. So that is one clever way that data is being collected and then used to reduce cost." (MIC4)

Talking about the use of big health data (or large amounts of data) for clinical decision making, they talked about Health Pathways which are available to them to make decisions about certain conditions. However, there were mixed feelings about the use of Health Pathways, mainly due to the amount of time a GP has for a consultation.

> "There are heaps of them [Health Pathways], but if you actually have 45 minutes to consult a patient, it will be great. So, it's just impractical. Where do they think we are going to have time to read all this stuff every day?" (MIC1)

MIC1 also highlighted the importance of constant updates on such algorithms and gave an example of a health pathway that was updated in 2014 (the interview was conducted in 2017). Another tool for clinical decision making identified by MIC3 is Medimap, but he claimed that "it is pretty clunky and to actually use it in real time is very difficult because it just takes too long" (MIC3). Participants also talked about evidence-based decision-making tools that they use such as the Cardiovascular Risk Assessment Tool created by the Heart Foundation. MIC5 explained that:

> "If you use that tool you know it's evidence-based, you know if you treat somebody's cholesterol higher risk, other risk factors you know you can reduce his risk of another stroke or heart attack by 50% and that's huge." (MIC5)

However they were not sure whether such tools use big data or big data technology in making such assessments. A few micro level participants also talked about the use of patient-generated data for clinical care. They talked about how they have patients recording things like blood glucose levels or blood pressure and how they use that data to understand patient condition better. However, they explained that there is no way to capture these data into the patient management system other than scanning a printout of this data into the system, and that there is no guidance from the top levels (PHO) about apps they can use – instead they themselves have to research and select them. There were also some mixed thoughts about patients not wanting to record their health conditions as well.

While precision medicine was of great interest at the macro and meso levels there was little information about genomics, mainly from participants at the meso level who also had some clinical responsibility. One such comment was from MES5 who was in a management role at a DHB but also a consultant at the hospital.

> “Another area of big data which is not as well looked [at/after?] at the moment in my area of work but potentially will be, and that relates to genomics and precision medicine. And we know that with gout there's a particular gene which is expressed in the kidney and if you have this variant of gene then instead of excreting uric acid out your kidneys you retain it. If you have retained uric acid and it’s highly crystallised and gets into your joints and causes gout. And the research group that I am a part of with the Maori gout action group, we know there is a difference in the genetics with Maori and Pacific and Europeans…. We also know that there are certain genes, particularly in Chinese populations that actually cause side effects if you start on Allopurinol, which is the main treatment for gout.” (MES5)

He explained that through this understanding of the genomic makeup they are able to treat gout patients better as they will understand whether a treatment will work well, and how that will help the patient and the health system. The analysis showed that the micro-only participants did not talk about genomics and precision medicine at all. So the lead researcher went back to the doctors (emailed them) to ask about genomics and only one doctor replied. He claimed that:

> “We kind of use Genomics in the sense of getting as much accuracy with our Family History of illnesses for patients. In the future it is assumed this will simply become more sophisticated with DNA etc. I presume that is what you are referring to by Genomics. We already collect "old" genomics such as vertically transferred conditions such as Duchenne's Muscular Dystrophy. MD is the gold standard genomics indicator I guess, as the inheritance is precise and sex-linked. There are already databases at the DHB Genetic Services with regard to whanau-linked Genetic Disorders.” (MIC1)

However, after explaining to him that precision medicine is about how treatments can be personalised to treat a patient, and that it seems to be a big interest area for the government and funders and planners, MIC1 replied:

> “These guys are dreamers. That's next century stuff!” (MIC1)

Similar to the meso level, there were some discussions around patient-generated data by the micro level participants, particularly by the GPs. They explained how they use some mobile apps for patients to collect data about their health conditions and use that for treatments. Typically such apps are selected by them and the data from the apps cannot be linked into the PMS unless recorded manually.

Category 5: Healthcare Strategy and Policy

With big data, policy makers see the Ministry as an enabler, identifying their role as promoting the use of big data through sustainable policy and strategy – so that big health data can be used across many different areas. The participants talked about the NZ Health Strategy and how they saw the problems around big data being addressed in the strategy. They acknowledged that the health strategy provides opportunities for effective use of big health data through: (i) connected information, (ii) a well-defined National Health Index (NHI), and (iii) understanding of data collection settings. Therefore, the NZ health strategy is expected to lead to improved accuracy and quality of big healthcare data that will later be used for big data analytics to undertake population health analysis, achieve and measure health outcomes, and make clinical decisions and the like. The macro level participants however explained that health strategy and policy does not use the terminology ‘big data’ because:

> “At a government level, we use words like ‘we want a smart health system’. Then under a smart health system that means we want to see more of things like precision medicine. But sometimes we don’t come out and say we want big data. Because government policy should be more generalised than that.” (MAC1)

At the policy level there were also discussions about the health-IT plan and how it addresses big data-related issues. For example one participant explained that:

> “From the Health-IT Plan, you've got a lot of work around interoperability to ensure that systems used across health can exchange data.” (MAC2)

However, that research data was captured in early 2016 and by the time of analysis the Health-IT Plan was no longer in use, and the National Health-IT Board, which implemented the Health-IT Plan, was disbanded.

The meso level talked about health care policy around big data in terms of strengths of policy and strategy, issues they see, much needed improvements and DHB policy vs. government policy. Talking about the strengths of health policy and strategy, the meso level highlighted that health strategy is constantly updated and the current refreshed strategy captures a lot of technology-related issues. While acknowledging that the policy makers play a huge role in enabling big data technology they identified that the health policy captures big data through the term “smart systems”. Meso level participants saw this as an important first step towards a big data future. Explaining further about the term “smart system” in health strategy, MES14 explained that:

> “Smart Health Systems assumes big data analytics. I think it’s ambitious, but I think it’s an excellent place holder, it gives us licence to do big data stuff. (Whispering) I’m not entirely convinced that policymakers actually understood what they were putting into that strategy but they will come to learn when they see what we do with it. As I said earlier, I think everybody has got a different interpretation of what big data is. I think that the policymakers were brave in putting it in; although I think the people in the group that wrote that strategy knew what they were talking about from the IT side, I’m not convinced the others knew.” (MES14)

Talking about other strengths in health strategy and policy, the macro level participants talked about how information gathering and storage-related policies are good and how NZ health policy is about making the public feel safe about their health information.

Although they saw a few strengths in health policy, they also identified some issues that they saw in NZ health strategy and policy. A majority of participants complained that healthcare strategy, policy and information laws hinder the use of data, not necessarily big data. One participant explained his experience with past government policy (which has since been corrected):

> “Past government policy for example around data search, we sometimes supply data to government as part of big datasets. When we ask to use it we get told that we can’t see it for privacy reasons. And you’re going “well that’s completely ridiculous because we gave it to you so surely we can see it!” But that kind of stuff is just overly stupid when it comes to thinking about setting policy.” (MES4)

He also identified a current similar issue around the use of IDI, explaining that although you are able to find a patient with a disadvantage, the data is anonymised, and due to the privacy laws the IDI cannot not provide you with information about that patient even if you want to help that patient. Similar frustrations were seen across the meso level about sharing information. Meso level participants explained that it is the role of government to create sensible policy around the use of big data, to give the best balance between protection and advancement.

Some participants explained that some of the health policies around IT investments are misguided or contrasting to what the policies say. MES9 explained his perception in this regard:

> "I suppose what surprises me a little bit in the health IT policy is, you listen to the policy and the policy says prevention is the most important thing, we need it to enable general practice to manage more stuff in the community, better, sooner, more convenient, blah, blah, blah. The IT investment from the centre however focusses on District Health Board hospitals! How can we have systems and processes in the hospital setting? So it's almost like "primary care is the solution. But let's sort the hospitals out first because we control them!" So I think there is a need for some policy changes to actually focus on investment in the primary and community settings around IT systems that then enable the big data collection to actually happen." (MES9)

Another policy issue talked about by the meso level participants is that the policy is not capturing important areas like patient-generated data. While meso level participants saw patient-generated data as a valuable asset to understand a patient, they have doubts about how to go about utilising big data. Moreover, some of the meso level participants highlighted that it is an important area which needs to be captured by policy for them to be able to look into it in the future. The meso level participants also saw that it is important to have health informaticians involved in policy discussions because "those are the people who have the evidence, who know where the evidence is and they can present the evidence in those consultations" (MES14).

Along the lines of these issues the meso level participants discussed areas that they believed need to be improved: data ownership and ethical guidelines around sharing data. Meso level participants explained that the government policy needs to facilitate discussions around data ownership – "Who owns the medical record? Who owns the social data that goes into my big data story? So I think the policymakers have to be real grown up about that, and responsible" (MES16). Meso participants also explained that at the policy level they need to set moral and ethical standards/guidelines to provide the right kind of protection to health data without compromising its ability to be effective, and interoperable.

At the micro level, while they did not have a lot of understanding about health policy that may relate to health data or big health data, they saw issues around patient management systems which they believed that policy could address. While some of the doctors felt not having a mandated PMS was good as they can choose what they want, others saw that this openness creates many problems that are difficult to tackle. For example some PMSs in primary care do not talk to each other (e.g. MyPractice and MedTech) which therefore creates issues when patients move around. Highlighting the same issue in secondary care, hospital doctors talked about difficulties they face due to lack of interoperable systems across primary and secondary care as well as across pharmacy and radiology. The doctors felt that policy should address this issue:

> "Yeah what the government needs to do is show some backbone and just mandate one clinical software system for the whole of New Zealand. It's just ridiculous how you've got 21 District Health Boards and they all use different information systems. And you've got all the PHOs that use different information systems. And then the pharmacies use different information systems! It's ridiculous!" (MIC6)

Another issue that was talked about was the current model of care and how it hinders the doctors (particularly the general physicians) from using tools – even using PMS was seen to be time consuming and is not captured for their payments. Therefore most GPs said they do not want to use any more 'tools' because they do not have time. Some even commented that things like Health Pathways or patient-generated data presented through mobile apps are beneficial but they cannot really use them due to the lack of time – the time allocated by the funding system. They highlighted that without changes to the current model of care and funding they are restricted to using technology for the delivery of care. The GPs felt the policy makers need to understand and acknowledge this to create policy around care delivery to allow the doctors to use opportunities provided by technology to provide better healthcare. Some GPs even explained that other countries like Australia and the United States have a better service delivery model that allows the physicians to utilise technology in a better way.

Appendix 13: Defining Terms: Taxonomy, Theoretical Framework and Theory

The purpose of Appendix 13 is to clarify three theoretical terms used in this thesis: (i) taxonomy, (ii) theoretical framework, and (iii) theory. This appendix chapter aims to outline definitions of these three terms and how they were used in this thesis.

13.1. Taxonomy

Taxonomies provide structure and allow organising knowledge within an identified research context (Glass & Vessey, 1995). It is a form of classification which brings together related conceptual understandings into a pool, facilitatating improved investigations (Gregor, 2006; Nickerson, Varshney, & Muntermann, 2013). The importance of taxonomies has been well established in Information Systems (IS) research. Nickerson et al. (2013), based on a review of IS literature which discussed the development of taxonomies, identified three different types of taxonomies: (i) inductive, (ii) deductive, and (iii) intuitive. Inductive taxonomies are derived from empirical data, while deductive taxonomies are conceptualised through understandings of theory. Intuitive taxonomies on the other hand provides researchers with classifications of phenomena. The taxonomy presented in this thesis (Chapter 3/Paper I) is an intuitive taxonomy that brings together existing literature around business-IT alignment into one classification that can then be used for any alignment study (Weerasinghe, Scahill, et al., 2018).

13.2. Theoretical Framework

A theoretical framework acts as the foundation of a research study by providing support and rationale for the investigation (Osanloo & Grant, 2016). A theoretical framework explains the paths to a research, and is a researchers attempt to conduct meaningful and theoretically bounded research (Adom et al., 2016). Developing a theoretical framework prior to an empirial study allows the researcher to justify their research efforts by presenting how the study will be conducted (Lederman & Lederman, 2015). A theoretical framework may consist of assumptions based on the researchers understanding (Nickerson et al., 2013), which may change after empirical studies. In this thesis, theoretical foundations from the literature around big data, business-IT alignment and SRT as well as understandings about the New Zealand healthcare context were brought together to develop the theoretical framework (presented in Chapter 5/Paper II), which acted as a foundation for the empirical study.

13.3. Theory

A theory is a representation of how someone sees and describes the real world (around the phenomenon that was described) (Weber, 2012). Theory describes relationships between contructs (Mintzberg, 2017). Gregor (2006) claims that "[a]bstraction and generalization about phenomenon, interactions, and causation are thought to be at the core of a theory" (p. 616). Theory allows researchers to caputure, accumulate, and improve knowledge about phenomena (Niederman & March, 2019).

Walsham (2006) explains that theory can be used in three ways: (i) as an initial guide to design a study, (ii) as a part of the iterative process for data collection, and (iii) as an output of the research process. Discussing the structural nature of theories in information systems, Gregor (2006) identifies five different types of theories: (i) for analysis, (ii) for explanation, (iii) for prediction, (iv) for explanation and prediction, and (v) for design and action. In line with the views of Gregor (2006) and Walsham (2006) in this thesis, social representations theory (SRT) was used as a theory to design the research study (as explained in Chapter 5/Paper II).

However, development of Theory of Sociotechnical Representations (TSR) (presented in Chapter 8/Paper III) was not planned upfront at the research design stage[41]. As explained in Section 1.4 TSR was a result of sense making bounded by data and analysis. Building theory is a highly conceptual process that happens in the researchers mind (Mintzberg, 2017). Mintzberg (2017) highlighted the

[41] As it was not the aim of the research to develop theory, Grounded Theory was not considered as the methodological approach for this thesis (Wiesche, Jurisch, Yetton, & Krcmar, 2017).

unexpected nature of development of theory saying “[w]e get interesting theory when we let go of all this scientific correctness, or to use a famous phrase, suspend our disbeliefs, and allow our minds to roam freely and creatively” (p. 10). However, novel theory or extended theories should be open to be tested by different methods (Niederman & March, 2019). As explained in section 8.8, TSR needs to be further investigated through different research approaches.