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

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Abstract

Big data and related technologies have the potential to transform healthcare sectors by facilitating improvements to healthcare planning and delivery. Big data research highlights the importance of aligning big data implementations with business needs to achieve success. In one of the first studies to examine the influence of big data on business-IT alignment in the healthcare sector, this paper addresses the question: how do stakeholders' perceptions of big data influence alignment between big data technologies and healthcare sector needs across macro, meso, and micro levels in the New Zealand (NZ) healthcare sector? A qualitative inquiry was conducted using semi-structured interviews to understand perceptions of big data across the NZ healthcare sector. An application of a novel theory, Theory of Sociotechnical Representations (TSR), is used to examine people's perceptions 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.

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

1 Introduction

In the past decade, with the advent of ever more sophisticated information technologies, and addressing increasing demands due to significant health issues 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 (including public health emergencies such as Covid-19), 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). 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/wearable devices, and sensors (Emani 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 complex data (Wyber et al., 2015). However, recent technological developments 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; Lv & Qiao, 2020). Some notable examples of application of big data technologies to healthcare 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, Weerasinghe et al., 2022b; Lv & Qiao, 2020; Williams et al., 2018). 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 (Williams et al., 2018; He et al., 2017).

Similar to other developing countries, New Zealand (NZ) healthcare system is exploring the potential applications of emerging technologies, such as big data. 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 strategies for the NZ health system from 2016 to 2026. From an information and societal 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). Five key themes are identified which provide the needed direction for the desired future. These are: (i) people powered, (ii) closer to home, (iii) value and high performance, (iv) one team, and (v) smart system. The identification of "smart system" is a key starting point for technological advancements in the NZ healthcare sector, including big data technologies. As such it is important to understand stakeholders' perspectives of these technologies.

Research in the field of big data shows that the success of big data technologies depends on their alignment with business/sector needs (Bean & Kiron, 2013; Watson, 2014; Weerasinghe et al., 2018a). Addressing this importance of alignment between big data technologies and healthcare sector needs, this paper presents a study exploring alignment of big data technologies across multiple levels (identified as macro-meso-micro) within the New Zealand (NZ) healthcare sector. The NZ healthcare sector is led by the Ministry of Health (MoH) (Ministry of Health, 2014) and the Minister of Health develops policy with input from the MoH, Cabinet and the government (Ministry of Health, 2017). District Health Boards[1] (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.

[1] This research was conducted prior to NZ health sector reforms in July 2022 which disestablished DHBs.

Due to the association of many different organisations, actors, and structural divisions in the NZ healthcare system, it is understood to be 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, 2012; Weerasinghe et al., 2018a).

Studying the implications and applications of big data in a complex system can be done by exploring two types of elements: social and technical. As a technological phenomenon big data research often focuses on technical elements, 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 elements around big data, such as understanding, commitment, value and perceived challenges are often given less attention in big data research (Shin & Choi, 2015). Social elements involve the subjective understanding of a technological phenomenon that often affect its use (Dulipovici & Robey, 2013). Thus, understanding how social elements impact big data implementation and use are crucial for its success (Shin, 2015, Weerasinghe et al., 2018a). Political, organisational and managerial decisions concerning big data technologies are all greatly influenced by social elements (Shin, 2015). The implementation of big data technologies is challenging and involves all healthcare sector levels, thus requiring the support of multiple stakeholders (Weerasinghe et al., 2018a). For example, the implementation of big data technologies must accord with how different stakeholders implement health strategy. Security measures, necessary funding, available skills and technology, and willingness to use are all considerations, alongside responsibilities, which reside at different stakeholder 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, 1984). This notion of studying different perceptions and social elements aligns well with studying social dimension in a business-IT alignment study (Chan & Reich, 2007). As such in this paper we explored the social dimension of alignment which refers to how stakeholders at different levels perceive the technological phenomenon and the alignment of such perceptions. Based on this understanding the research question addressed in this paper is

how do stakeholders' perceptions of big data influence alignment between big data technologies and healthcare sector needs across macro, meso, and micro levels in the NZ healthcare sector?

Business-IT alignment refers to the fit between business (strategy or approach) and information technology (Chan & Reich, 2007; Henderson & Venkatraman, 1993; Luftman, 1996; Grant, 2010; Jenkin & Chan, 2010; El-Mekawy et al., 2015). In this context it is defined as the fit between perceptions of big data and healthcare sector needs. Studying big data as an emerging technology in the early stages of its introduction, implementation and adoption in the healthcare sector through a business-IT alignment lens can provide a more comprehensive understanding, as well as identify potential issues (Bean & Kiron, 2013; Watson, 2014). 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 (Weerasinghe et al., 2022a) 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.

2 Big data in Health

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).

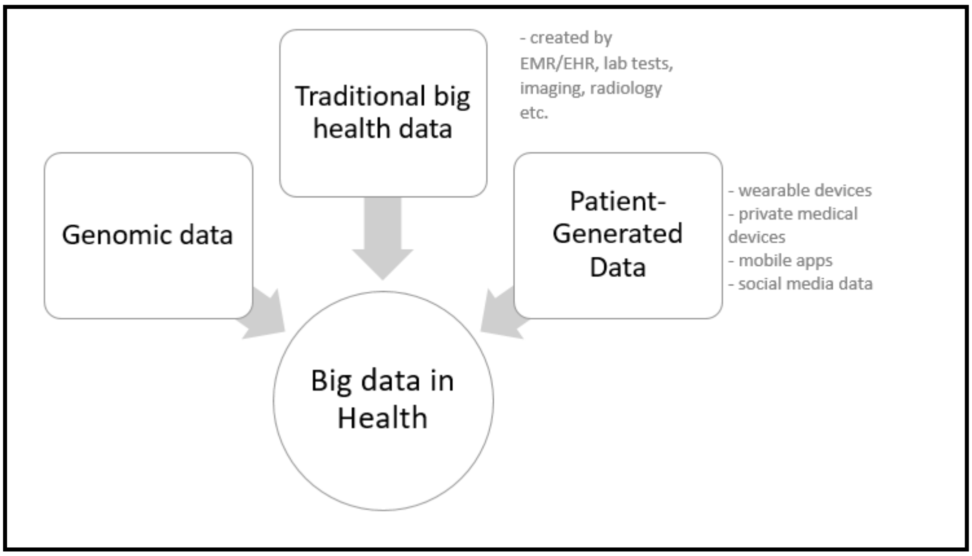

Figure 1. Types of big data in health

Big data in health refers to large and complex data across healthcare that may potentially be used to improve healthcare management and service delivery. 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 1 illustrates the types of data that can be considered big data in the healthcare context.

Genomic data is used to understand a person's genome through sequencing techniques[2] . A genome (DNA) has nearly three billion base pairs, which results in approximately 100 gigabytes worth of data for a single person (O'Driscoll et al., 2013). Due to its complexity and enormous volume, genomics data is categorised as big data (He et al., 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; Weli, 2018).

Patient-generated data is data produced by patients outside of clinical settings in normal daily life (Petersen & DeMuro, 2015; Jim et al., 2020). 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 et al., 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; Williams et al., 2018). Data from social media is also a form of patient-generated data that healthcare sectors can utilise for improved healthcare management and delivery. Use of artificial intelligence technologies (such as machine learning/ML, natural language processing/NLP) have gained increased attention to improve efficiencies in healthcare practises (Shailaja et al., 2018). 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 (Zadeh et al., 2019).

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 use or analyse 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 (Tormay, 2015; Wyber et al., 2015; Lv & Qiao, 2020). 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 which is formatted in different ways (structured, semi-structured and unstructured) and found in different systems (e.g., Electronic Medical Records, Patient Management Systems, clinical systems, etc.) to be linked and analysed together (i.e., connected care).

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

Compared to other industries like retail merchandising and banking, the uptake of big data technologies in the healthcare sector has been limited and slow (Groves et al., 2013; Bakker et al., 2020). However, the healthcare sectors around the world is increasingly catching up (Weerasinghe, 2019). 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; Guo & Chen, 2023). Health-IT researchers highlight the importance of alignment and a comprehensive approach to the aligning, planning, executing and governing technology components in the healthcare sector (Krey, 2018; Weerasinghe et al., 2018a; Fattah & Arman, 2014).

Recently, developed countries have recognised the importance of big data analytics for healthcare (Jim et al., 2020). 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; Lv & Qiao, 2020). 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 (Jim et al., 2020, Williams et al., 2018, Roski et al., 2014).

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 elements (analytics, privacy and security measures, IT infrastructure) involving big data implementations have been extensively researched (Chen et al., 2014; Davenport, 2013; Bag et al., 2023). As a technological revolution itself, big data research naturally leans towards these technical elements. As a result, adequate research has not been carried out to investigate the social elements of big data (Shin, 2015; Shin & Choi, 2015). Social elements refer to users' understanding, commitment, perceived value and challenges of big data in a given context. Social elements reflect the actual and potential use of a technological phenomenon, and so investigating them is important. Limited research on the effects of the social elements on big data technologies has shown that people's understanding of big data technologies influences implementation and adoption (Shin, 2015; Weerasinghe et al., 2022). But empirical work identifying and discussing such social elements is limited. Nonetheless, while uptake of big data is increasing in healthcare, social elements (e.g., a doctor's understanding of an AI risk assessment tool) can play a significant role in its use in healthcare. Thus, to address this, the research investigates social elements around big data in the NZ healthcare context.

3 Theoretical Foundations

The theoretical foundations of this paper are twofold. First, to investigate business-IT alignment, the Taxonomy of Alignment Conceptualisations (Weerasinghe et al., 2018b) is used. The taxonomy helps identify and define the scope of the study. Second, the Theory of Sociotechnical Representations (TSR) developed by Weerasinghe et al. (2022a) is used as a foundational theory to understand sociotechnical representations of big data in health to investigate its influence on alignment.

3.1 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 et al., 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 and 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 et al. (2018b) created a taxonomy (Table 1) that identifies existing conceptualisations of alignment and explains how they can be used to define the scope of an alignment 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		

Table 1. Taxonomy of Alignment Conceptualisations

This taxonomy identifies five classes of alignment: types, levels, dimensions, states and environments. The properties of each type are identified, based on literature. The taxonomy encourages the study of at least one property within each class for an alignment study to be complete . The selected properties for this alignment study are shaded in the taxonomy (see Table 2) and explained below.

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		

Table 2. Selected conceptualisations of alignment for the study

Strategic fit is selected as the **type** of alignment for this study (from the first row in the taxonomy). Strategic fit investigates alignment across domains of business strategy, business structure, IT strategy and IT structure (Henderson & Venkatraman, 1992). As big data implementations demand change in business and IT strategy and structure, it is necessary that all these domains are explored through strategic fit. As the research question relates directly to understanding the influence of big data perceptions across the healthcare sector, the **level** of alignment to be investigated is the sector level (second row of the taxonomy). By investigating sector level alignment the study will provide insights into understanding agreements and gaps in alignment across the whole healthcare sector under investigation.

Highlighting the lack of knowledge and the need to investigate the social elements around big data, the social dimension of alignment was selected as the lens through which to conduct this alignment study. It is important to note that the strategic/intellectual dimension here refers to exploring fit of documented strategies to the organisations needs and other elements such as people, and therefore is not the focus of this research. 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), such as MMM levels. 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 elements of big data (Weerasinghe et al., 2022b). Dulipovici and Robey (2013) identify two aspects of technology use as intended use 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 elements 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 (macro-meso-micro), 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.

3.2 Theory of Sociotechnical Representations

The Theory of Sociotechnical Representations (TSR) is a novel theory explained in Weerasinghe et al. (2022a) which integrates key elements of two well-known theories: Sociotechnical Systems Theory (SST) (Emery, 1959) and Social Representations Theory (SRT) (Moscovici, 1984). 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-created with the people around it (policy makers, planners, implementers and users): not just in what people do with it (e.g., tasks, 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 (as modelled in Figure 2). Therefore, the roles and responsibilities of people are affected by what technology is intended to do and can do. However, the Theory of Sociotechnical Representations uses SRT (Moscovici, 1984) with SST, to explain that this interdependence of technology and people goes beyond concrete factors like roles, responsibilities, or pre-determined ways of usage, and posits that perceptions of technology (identified as sociotechnical representations) are critical to the success of technology.

As shown in Figure 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. Further, researchers such as Orlikowski and Scott (2008), Leonardi (2011) and Cecez-Kecmanovic et al. (2014) have also acknowledged the importance of taking a social lens to technology adoption in their work on Socio-materiality. Because Social Representations Theory (SRT) is a tool to explore user perceptions of technology (the technical subsystem) using the potential social capabilities (of the social subsystem), the Theory of Sociotechnical Representations (TSR) uses SRT to inform Sociotechnical Systems Theory (SST).

The SRT literature highlights two processes: anchoring and objectification. Anchoring refers to identifying a phenomenon within a group based on the aspirations, perceptions, collective sense making by the group, while objectification supports the anchoring process through an individual's mapping of the phenomenon. These two processes (anchoring and objectification) processes impacts/complements each other. For example, consider a healthcare organisation that has had cyberattacks in the past which compromised patient information. The employees may anchor their understanding of data security to strict access controls, encryption, and firewalls. They perceive data security as the need to protect sensitive information from unauthorized access, which becomes the common understanding in the organisation (anchoring). However, if there is an employee who is well versed about data privacy regulations and has studied cybersecurity, they may objectify data security as the need for data governance, proactive monitoring and employee awareness and training. This objectification is informed by their past experience/knowledge with cybersecurity. This then reshapes the groups anchored perception of data security. This is acknowledged in Figure 2 by showing a recursive relationship between the two. Also, the shape of representation is different to that of the actual technical subsystem highlighting that the representation may not always be the same as the technical subsystem as it is shaped by the social elements.

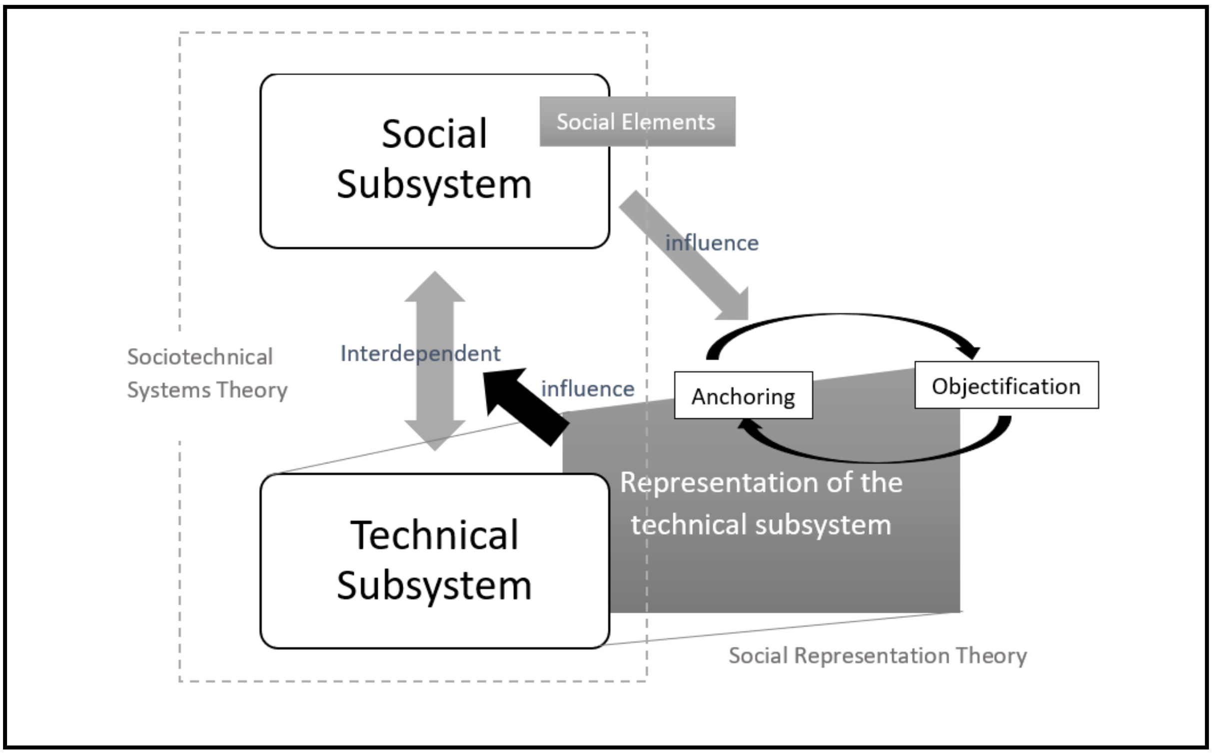

Figure 2. Theory of Sociotechnical Representations (based on Weerasinghe et al. (2022a))

SRT acknowledges that representations are anchored and objectified within a group, which influences TSR to promote exploring stakeholder groups (Moscovici, 1988). 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. By understanding anchoring and objectification, TSR acknowledges that the representations of the technical subsystem are continuously evolving or being shaped because anchoring and objectification complementary each other. Box 1 illustrates an application of TSR to explain anchoring and objectification.

> A health insurance company adopts a new system for project management. The system is the technical subsystem and the people (employees, management) are the social subsystem. The management team in an attempt to shape the representation of the new system begins by trying to anchor an understanding of this system by emphasizing its efficiency in automating tasks, streamlining workflows, and increasing productivity. They promote the idea that this system will revolutionize how projects are managed and lead to improved outcomes. This anchoring process happens within the organisation and is influenced by the social subsystem in accord with their responsibilities. However, individual employees may objectify the new system differently based on their own experiences and perspectives. For instance, some employees might objectify the technology as a source of surveillance or control, perceiving it as a means for management to monitor their performance. Others may objectify it as a potential problem as they have experienced system failures in the past. This is the objectification process. As such, the representation the management wants to create may be shaped by social elements. As the implementation and adoption of the new project management system takes place, anchoring and objectification will continue to shape and re-shape the representation of the technological system.

Box 1. An Example Application of TSR

Using TSR, the present study focuses on the social elements 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 (e.g., MMM levels) 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 Table 3 explains the Distinctions of SST, SRT and TSR.

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 formed, 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. As such TSR explains that when people interact with technology, it may be that people are interacting with the representation of the technology. Another important aspect of TSR is that it can explain why/how perceptions of technology can change over time. For example, as new actors/people get involved, their objectification can change group perceptions influencing the sociotechnical representation. Use of TSR also has an important impact on the methodology and selection of participants compared to a typical SST-based study. Because it focuses on sociotechnical representations, the use of TSR promotes the value of understanding the perceptions of people over physical documents or systems.

Sociotechnical Systems Theory	Social Representations Theory	Theory of Sociotechnical Representations
People and technology are interdependent	People create a representation of a phenomenon (e.g., technology)	People and their representations of technology are interdependent
Social subsystem includes occupational roles, tasks and activities of people; technical subsystem includes technologies, technical capabilities and processes	Representation of a phenomenon (concept, object or situation) is created within the social group for the purpose of understanding and communicating and is influenced by thoughts, feelings and behaviours of the actors. The creation of the representation happens through anchoring and objectification.	Social subsystem (people) creates a representation of the technical subsystem which may or may not be similar to the actual technical phenomenon. This is impacted by anchoring and objectification.
When using SST the focus of research questions/ objectives will be the use/adoption of technology	When using SRT the focus of research questions/ objectives will be the perceptions (representations) of technology and the factors that influence these perceptions.	When using TSR the focus of a RQ/research objectives will be the perceptions of technology and how it impacts use/adoption
RQ example: how are big data technologies used in the healthcare sector?	RQ example: how do people perceive big data in the healthcare sector? And what influence those perceptions?	RQ example: how do perceptions of big data influence the use of big data technologies in the healthcare sector?

Table 3. Distinctions of SST, SRT and TSR

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) 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)'. It is important that perceptions (social dimension of alignment) at each MMM level is investigated to understand similarities and difference between these levels within the sector (i.e. sector level alignment).

4 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 elements around big data adds a further level of complexity because social elements 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 stakeholders' perceptions of big data influence alignment between big data technologies and healthcare sector needs 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. Previous literature has identified NZ health sector to have three levels (macro, meso, and micro/MMM) and has emphasised the importance of exploring technology phenomena through these levels (Cumming, 2011; Scahill, 2012; Weerasinghe et al., 2018a). These MMM levels 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 (MMM) to understand perceptions of big data at each subsector level. A cross-group analysis was then undertaken to understand influence on alignment across the NZ healthcare sector. Within the NZ 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 procedure are shown in Figure 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 was used as a guide in reporting the findings and discussion identifying alignment and misalignment of big data in the NZ healthcare context.

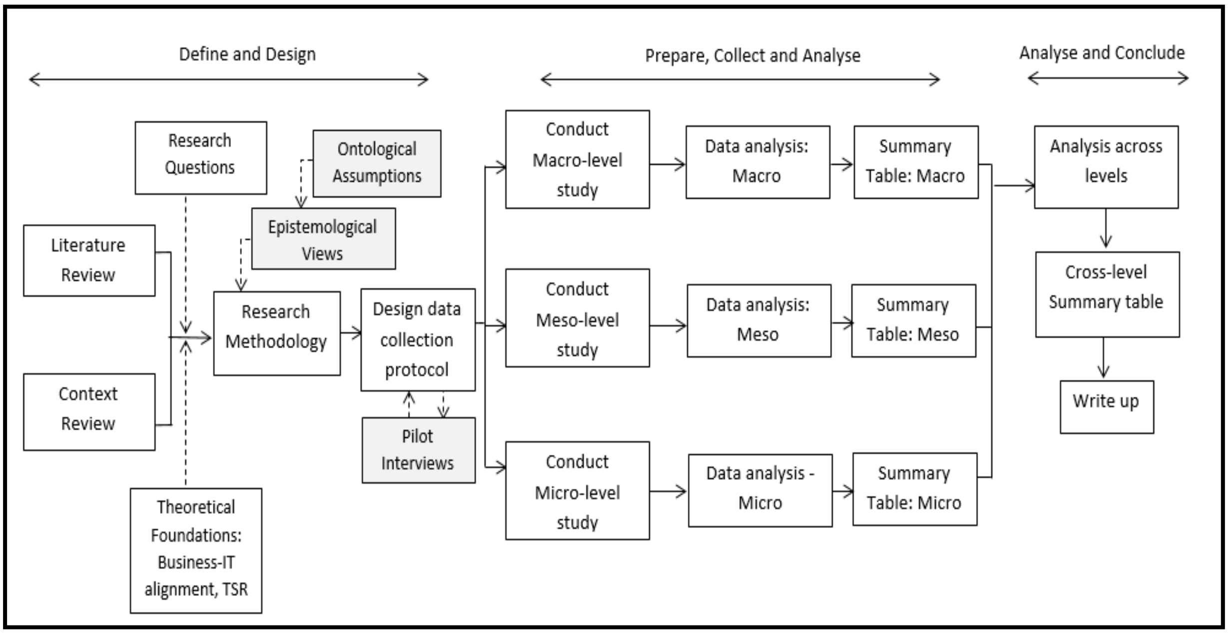

Figure 3. Research Procedure

Semi-structured interviews were conducted to gather rich data from participants at each MMM level (Merriam, 2009) (interview schemas can be found in Appendix 1). Purposive sampling techniques were used as the research required gathering data from informants who were involved in constructing policies (macro), planning and implementing (meso), or using (micro) (current or future) big data technologies (Miles et al., 2014; Patton, 2015). A snowball sampling strategy was also used, asking informants to direct the researcher to other participants (Miles et al., 2014). Overall, 32 interviews were conducted, with six at macro level[3], 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 2. As similar themes continue to emerge through data, theoretical saturation was reached, which allowed the researchers to determine the sample size (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 the first author was fully familiar with the data, transcripts were coded and themes were identified (example of coding themes and descriptions can be found in Appendix 3). 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. 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. In the next section, the findings are presented at each MMM level, and the cross analysis then identifies the alignment/misalignment issues which are presented in the Discussion section.

5 Findings: Summary Findings across MMM levels

Through a TSR lens this research investigates the social subsystem (people in MMM levels) and the technical subsystem (big data) and their interdependencies to business-IT alignment in the context of NZ healthcare. In this research 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). Five key categories emerged from data analysis that influence the sociotechnical representations of big data. These are: (i) absence of a clear definition, (ii) understanding 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.

This section describes findings of the three levels (MMM) separately, analysing how big data is socially represented in the NZ healthcare context.

[3] 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.

5.1 Macro Level: Policy Makers

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. 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).

The macro level participants talked about their experience (relates to objectification in TSR) 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.

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. The participants talked about the NZ health strategy[4] 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.

5.2 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 District Health Boards (DHBs) and Primary Health Organisations (PHOs) often voiced their confusion of how it differed from 'small' data. When asked about what influenced their understanding of big data academics spoke of their work (teaching or research) in a related field. 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.

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. The IT vendors and PHOs showed a great deal of interest in patient-generated data, but claimed that "it's a pipe dream"

[4] New Zealand health system (including the health strategy) has undergone reforms after data collection took place.

(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 planners and funders saw a lack of understanding by the micro level (clinicians) about the use of big data for clinical care and overall health system, 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 (anchoring).

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'. Since 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 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).

5.3 Micro Level: Clinicians (General Practitioners 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 in the healthcare context, particularly for clinical care and decision making.

Discussing the applications that used data, 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. 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.

Clinicians also talked about how cumbersome the systems in use are in sharing data, being fragmented in nature and typically not effectively communicating with each other. For example, different General Practitioner (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).

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.

6 Discussion: Alignment of Big Data Perceptions across NZ Healthcare

Typically the result of an alignment study is identifying alignment and misalignment present through the investigated context/phenomenon. As a business-IT alignment study, further analysis into the above findings through a cross level analysis 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. Table 4 summarises alignment and misalignment issues found through further analysis of the findings. Alignment in this study means that all three levels (macro, meso, micro/MMM) 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.

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

Table 4. Areas of alignment and misalignment of big data in New Zealand Healthcare

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

6.1 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 (IoT) 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 et al., 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 et al., 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 (which helped with anchoring and objectification, based on SRT in TSR) 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 et al., 2018; Roski et al., 2014).

6.2 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 et al., 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, 1984) 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[5] , 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 (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[6]) 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 data ownership. Because primary care (e.g. 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 et al., 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

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

[6] 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.

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[7] and SNOMED[8] 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 incompatible systems and

[7] 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/).

[8] SNOMED International determines standards for clinical terminology (http://www.snomed.org/). SNOMED standards are used in electronic health records.

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, 2012), 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.

7 Practical Implications

The practical implications of this study include implications for healthcare policy and practice. As reported 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. As such, a key implication of this study 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. Clear articulation of concepts of big data and related technologies across the sector needs to be facilitated by the macro and meso levels. Through member checking the findings of alignment and misalignment was reported back to the participants and 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, and highlights the importance of clear guidelines through health policy to facilitate better understandings about data ownership across the sector.

In addition the findings suggest the need for an open discussion around the importance of data sharing. Policy makers need to be more open to revisiting policy, making required adjustments while also ensuring privacy of patients in this big data era. Another implication of the study is the possibility of a whole of sector approach (e.g., the need for a countrywide electronic patient management system) as opposed to a fragmented approach. It is recommended that policy makers carefully consider this alongside strengthening policies around interoperability before making changes[9] .

Based on the findings around issues in communicating/information flow of technology driven projects such as precision medicine, we highlight the importance of a robust plan for providing information to the lower levels. This will facilitate a more positive environment in the future when precision driven medicine becomes more available and applicable to front-line clinicians. Further to this is the lack of prioritisation on the role of big data technologies for clinical decision making. 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. Consultation with clinicians is important when developing and implementing tools as this leads to the successful adoption of such tools.

8 Conclusions, 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

[9] NZ moving into a nation-wise health system as a part of sector reforms in 2022 is a step towards this direction.

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 elements influencing the sociotechnical representations around big data. The paper shows the applicability of the business-IT alignment taxonomy (Weerasinghe et al., 2018b)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 et al., 2018b), 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. TSR provides a specific tool for investigating perceptions of technology and provides a way of understanding how perceptions of technology are formed at individual and group levels (objectification and anchoring). By extension, this understanding allows for interventions to shape objectification and anchoring. The practical implications of the study include the identification and discussion of areas of alignment and misalignment (which has been covered in detail in the previous section in detail).

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.

References

Andreu-Perez, J., Poon, C. C., Merrifield, R. D., Wong, S. T., & Yang, G.-Z. (2015). Big data for health. *IEEE journal of biomedical and health informatics,* 19, 1193-1208.

Ashley, E. A. (2016). Towards precision medicine. *Nature Reviews Genetics,* 17, 507-522.

Bag, S., Dhamija, P., Luthra, S., & Huisingh, D. (2023). How big data analytics can help manufacturing companies strengthen supply chain resilience in the context of the COVID-19 pandemic. *The International Journal of Logistics Management,* 34, 1141-1164.

Bakker, L., Aarts, J., Uyl-De Groot, C., & Redekop, W. (2020). Economic evaluations of big data analytics for clinical decision-making: a scoping review. *Journal of the American Medical Informatics Association,* 27, 1466-1475.

Bates, D. W., Kuperman, G. J., Wang, S., Gandhi, T., Kittler, A., Volk, L., Spurr, C., Khorasani, R., Tanasijevic, M., & Middleton, B. (2003). Ten Commandments for Effective Clinical Decision Support: Making the Practice of Evidence-based Medicine a Reality. *Journal of the American Medical Informatics Association,* 10, 523-530.

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

Blasimme, A., Fadda, M., Schneider, M., & Vayena, E. (2018). Data Sharing For Precision Medicine: Policy Lessons And Future Directions. *Health Affairs,* 37, 702-709.

Burns, W. A. 2014. Healthcare Data's Perfect Storm: Why Healthcare Organizations Are Drowning in the Data They are Creating and Why They Need Even More Data to Weather this Storm [White Paper]. Available: https://s3.amazonaws.com/rdcmshimss/files/production/public/HIMSSorg/Content/files/HitachiDataSystems_BR-458_perfectStorm.pdf [Accessed 26 Feb 2016].

Cecez-Kecmanovic, D., Galliers, R. D., Henfridsson, O., Newell, S., & Vidgen, R. (2014). The sociomateriality of information systems. *Management Information Systems Quarterly,* 38, 809-830.

Chan, Y. E., & Reich, B. H. (2007). IT alignment: what have we learned? *Journal of Information Technology,* 22, 297-315.

Chawla, N., & Davis, D. (2013). Bringing Big Data to Personalized Healthcare: A Patient-Centered Framework. *Journal of General Internal Medicine,* 28, 660-665.

Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile Networks and Applications,* 19, 171-209.

Collins, B. (2016). Big Data and Health Economics: Strengths, Weaknesses, Opportunities and Threats. *Pharmaco Economics,* 34, 101-106.

Cumming, J. (2011). Integrated care in New Zealand. *International Journal of Integrated Care,* 11, e138.

Dang, A., & Mendon, S. (2015). The value of big data in clinical decision making. *International Journal of Computer Science and Information Technologies,* 6, 3830-3835.

Davenport, T. H. (2013). *Analytics 3.0: in the new era, big data will power consumer products and services* [Online]. Harvard Business School Press. Available: https://hbr.org/2013/12/analytics-30 [Accessed 12 Jun 2016].

Davenport, T. H., & Dyché, J. (2013). Big data in big companies. *International Institute for Analytics*. https://www.iqpc.com/media/7863/11710.pdf

Dhawan, R., Singh, K., & Tuteja, A. (2014). When big data goes lean. *McKinsey Quarterly,* 24, 97-102.

Dopfer, K., Foster, J., & Potts, J. (2004). Micro-meso-macro. *Journal of Evolutionary Economics,* 14, 263-279.

Dulipovici, A., & Robey, D. (2013). Strategic Alignment and Misalignment of Knowledge Management Systems: A Social Representation Perspective. *Journal of Management Information Systems,* 29, 103-126.

El-Mekawy, M., Rusu, L., & Perjons, E. (2015). An evaluation framework for comparing business-IT alignment models: A tool for supporting collaborative learning in organizations. *Computers in Human Behavior,* 51, 1229-1247.

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

Emery, F. E. (1959). Characteristics of Socio-Technical Systems. London, UK: Tavistock Institute.

Emery, F. E., & Trist, E. L. (1965). The Causal Texture of Organizational Environments. *Human Relations,* 18, 21-32.

Esposito, C., De Santis, A., Tortora, G., Chang, H., & Choo, K. R. (2018). Blockchain: A Panacea for Healthcare Cloud-Based Data Security and Privacy? *IEEE Cloud Computing,* 5, 31-37.

Eynon, R. (2013). The Rise of Big Data: what does it mean for education, technology, and media research? *Learning, Media and Technology*, 38, 237-240.

Fattah, F., & Arman, A. A. (2014). Business-IT Alignment: Strategic Alignment Model for healthcare (case study in hospital bandung area). *2014 International Conference on ICT For Smart Society (ICISS)*, Bandung, Indonesia, 2014, 256-259, doi: 10.1109/ICTSS.2014.7013183.

Gal, U., & Berente, N. (2008). A social representations perspective on information systems implementation: Rethinking the concept of "frames". *Information Technology & People*, 21, 133-154.

Ginsburg, G. S., & Phillips, K. A. (2018). Precision Medicine: From Science To Value. *Health Affairs*, 37, 694-701.

Grant, G. (2010). Reconceptualizing the concept of business and IT alignment: from engineering to agriculture. *European Journal of Information Systems*, 19, 619-624.

Groves, P., Kayyali, B., Knott, D., & Van Kuiken, S. (2013). *The 'Big Data' revolution in healthcare: Accelerating value and Innovation* [Online]. Available: https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/the-big-data-revolution-in-us-health-care [Accessed].

Guo, C., & Chen, J. (2023). Big data analytics in healthcare. *Knowledge Technology and Systems: Toward Establishing Knowledge Systems Science.* Springer.

Halamka, J. D. (2014). Early Experiences With Big Data At An Academic Medical Center. *Health Affairs*, 33, 1132-1138.

He, K. Y., Ge, D., & He, M. M. (2017). Big Data Analytics for Genomic Medicine. *International Journal of Molecular Sciences*, 18, 412. https://doi.org/10.3390/ijms18020412

Henderson, J. C., & Venkatraman, N. (1992). Strategic Alignment: A Model for Organizational Transformation through Information Technology. *In:* Kochan, T. A., & Useem, M. (eds.) *Transforming organizations.* New York, USA: Oxford University Press.

Henderson, J. C., & Venkatraman, N. (1993). Strategic alignment: leveraging information technology for transforming organizations. *IBM Systems Journal* 32, 472-484.

Herland, M., Khoshgoftaar, T. M., & Wald, R. (2014). A review of data mining using big data in health informatics. *Journal of Big Data*, 1, 1-35.

Jameson, J. L., & Longo, D. L. (2015). Precision medicine - personalized, problematic, and promising. *Obstetrical & Gynecological Survey*, 70, 612-614.

Jenkin, T. A., & Chan, Y. E. (2010). IS project alignment - a process perspective. *Journal of Information Technology*, 25, 35-55.

Jia, Y., Wang, N., & Ge, S. (2018). Business-IT Alignment Literature Review: A Bibliometric Analysis. *Information Resources Management Journal*, 31, 34-53.

Jim, H. S., Hoogland, A. I., Brownstein, N. C., Barata, A., Dicker, A. P., Knoop, H., Gonzalez, B. D., Perkins, R., Rollison, D., & Gilbert, S. M. (2020). Innovations in research and clinical care using patient-generated health data. *CA: A Cancer Journal for Clinicians*, 70, 182-199.

Kaisler, S., Armour, F., Espinosa, J. A., & Money, W. (2012). Big Data: Issues and Challenges Moving Forward. In Proceedings of the 46th Hawaii International Conference on System Sciences, 7-10 January 2013. 995-1004.

Karkouch, A., Mousannif, H., Al Moatassime, H., & Noel, T. (2016). Data quality in internet of things: A state-of-the-art survey. *Journal of Network and Computer Applications,* 73, 57-81.

Krey, M. (2018). Facing business-IT-alignment in healthcare. In Proceedings of 51st Hawaii International Conference on System Sciences (HICSS), Waikoloa Village HI, USA, 3-6 January 2018. 3090-3099.

Kyriazis, D., & Varvarigou, T. (2013). Smart, Autonomous and Reliable Internet of Things. *Procedia Computer Science,* 21, 442-448.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS quarterly*, 147-167.

Liamputtong, P., & Ezzy, D. (2005). *Qualitative Research Methods,* Oxford, UK: Oxford University Press.

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic Inquiry,* London, UK: SAGE Publications.

Luftman, J. (1996) . *Competing in the Information Age : strategic alignment in practice,* New York, USA: Oxford University Press.

Lv, Z. & Qiao, L. (2020). Analysis of healthcare big data. *Future Generation Computer Systems,* 109, 103-110.

Mason, M. (2010). Sample Size and Saturation in PhD Studies Using Qualitative Interviews. *Forum: Qualitative Social Research,* 11, 1-19.

McAfee, A., & Brynjolfsson, E. (2012). Big Data: The Management Revolution. (cover story). *Harvard Business Review,* 90, 60-68.

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

Merriam, S. B. (2009). *Qualitative research: a guide to design and implementation,* San Francisco,, CA, USA: Jossey-Bass.

Miles, M. B., Huberman, A. M., & Saldana, J. (2014). *Qualitative data analysis: a methods sourcebook,* Thousand Oaks, CA, USA: SAGE Publications.

Minister of Health (2016). New Zealand Health Strategy: Future Direction. Wellington, New Zealand: Ministry of Health

Ministry of Health (2014). Briefing to the Incoming Minister 2014. Wellington, New Zealand. https://www.treasury.govt.nz/publications/bim/briefing-incoming-minister-health-2014

Ministry of Health (2017). *Overview of the Health System* [Online]. New Zealand: Ministry of Health. Available: http://www.health.govt.nz/new-zealand-health-system/overview-health-system [Accessed 29 Jan 2019].

Moscovici, S. (1984). The Phenomenon of Social Representation. *In:* Farr, R. M., & Moscovici, S. (eds.) *Social representations: European Studies in Social Psychology.* Cambridge, UK: Cambridge University Press.

Moscovici, S. (1988). Notes Towards a Description of Social Representations. *European Journal of Social Psychology,* 18, 211-250.

Nash, D. B. (2014). Harnessing the Power of Big Data in Healthcare. *American Health & Drug Benefits.*

O'driscoll, A., Daugelaite, J., & Sleator, R. D. (2013). 'Big data', Hadoop and cloud computing in genomics. *Journal of Biomedical Informatics,* 46, 774-781.

Orlikowski, W. J., & Scott, S. V. (2008). Sociomateriality: challenging the separation of technology, work and organization. *Academy of Management Annals,* 2, 433-474.

Paré, G., Sicotte, C., Jaana, M., & Girouard, D. (2008). Prioritizing Clinical Information System Project Risk Factors: A Delphi Study. In Proceedings of the 41st Annual Hawaii International Conference on System Sciences, Waikoloa, HI, USA, 2008. doi: 10.1109/HICSS.2008.354.

Patton, M. Q. (2015). *Qualitative research & evaluation methods : integrating theory and practice,* Los Angeles, CA: SAGE Publications.

Petersen, C., & Demuro, P. (2015). Legal and regulatory considerations associated with use of patient-generated health data from social media and mobile health (mHealth) devices. *Applied Clinical Informatics,* 6, 16-26.

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

Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: promise and potential. *Health Information Science and Systems,* 2, 3.

Reich, B. H., & Benbasat, I. (1996). Measuring the Linkage Between Business and Information Technology Objectives. *MIS Quarterly,* 20, 55-81.

Roski, J., Bo-Linn, G. W., & Andrews, T. A. (2014). Creating Value In Health Care Through Big Data: Opportunities And Policy Implications. *Health Affairs,* 33, 1115-1122.

Russom, P. (2011). Big data analytics. *TDWI Best Practices Report, Fourth Quarter*. https://tdwi.org/research/2011/09/best-practices-report-q4-big-data-analytics.aspx?tc=page0&tc=assetpg&tc=page0&tc=assetpg&m=1

Saporito, P. (2013). *The 5 V's of big data: value and veracity join three more crucial attributes that carriers should consider when developing a big data vision* [Online]. A.M. Best Company, Inc. Available: https://www.thefreelibrary.com/The+5+V%27s+of+big+data%3A+value+and+veracity+join+three+more+crucial...-a0350676739 [Accessed 7].

Sathi, A. (2012). *Big data analytics: Disruptive technologies for changing the game*. Boise, USA: Mc Press.

Scahill, S. L. (2012). The 'Way things are around here' : organisational culture is a concept missing from New Zealand healthcare policy, development, implementation, and research. *New Zealand medical journal (Online).*

Shailaja, K., Seetharamulu, B., & Jabbar, M. (2018). Machine learning in healthcare: A review. In Proceedings of the 2nd International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2018. IEEE Xplore, 910-914.

Shapiro, M., Johnston, D., Wald, J., & Mon, D. (2012). Patient-generated health data [White Paper]. *RTI International, April*. https://www.rti.org/publication/patient-generated-health-data-white-paper.

Shin, D. H. (2015). Demystifying big data: Anatomy of big data developmental process. *Telecommunications Policy,* 40, 837-854.

Shin, D. H., & Choi, M. J. 2015. Ecological views of big data: Perspectives and issues. *Telematics and Informatics,* 32, 311-320.

Smith, J. A., Flowers, P., & Larkin, M. 2009. *Interpretative phenomenological analysis : theory, method and research,* London, UK: SAGE Publications.

Strome, T. L. 2014. *Healthcare analytics for quality and performance improvement,* Hoboken, NJ, USA: John Wiley & Sons.

Thomas, D. R. 2006. A General Inductive Approach for Analyzing Qualitative Evaluation Data. *American Journal of Evaluation,* 27, 237-246.

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

Ward, M. J., Marsolo, K. A., & Froehle, C. M. 2014. Applications of business analytics in healthcare. *Business Horizons,* 57, 571-582.

Watson, H. J. (2014). Tutorial: Big data analytics: Concepts, technologies, and applications. *Communications of the Association for Information Systems,* 34, 1247-1268.

Weerasinghe, K. (2019). Transformation through Big Data Analytics: a Qualitative Enquiry in Health. *30th Australasian Conference on Information Systems.* Perth, Australia.

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

Weerasinghe, K., Pauleen, D. J., Scahill, S. & Taskin, N. (2022a). Theory of Sociotechnical Representations: A Novel Approach to Understanding Technology Perspectives. Pacific Asia Conference on Information Systems, 5-9 July 2022 Taipei/Sydney. Association for Information Systems. https://aisel.aisnet.org/pacis2022/314

Weerasinghe, K., Scahill, S. L., Pauleen, D. J., & Taskin, N. (2022b). Big data analytics for clinical decision-making: Understanding health sector perceptions of policy and practice. *Technological Forecasting and Social Change,* 174, 121222.

Weerasinghe, K., Scahill, S. L., Taskin, N., & Pauleen, D. J. (2018b). Development of a Taxonomy to be used by Business-IT Alignment Researchers. *22nd Pacific Asia Conference on Information Systems.* Yokohama, Japan: AIS Electronic Library.

Weli, A. R. (2018). Precision Medicine. *Health Affairs,* 37, 687-687.

Williams, M. S., Buchanan, A. H., Davis, F. D., Faucett, W. A., Hallquist, M. L. G., Leader, J. B., Martin, C. L., Mccormick, C. Z., Meyer, M. N., Murray, M. F., Rahm, A. K., Schwartz, M.

L. B., Sturm, A. C., Wagner, J. K., Williams, J. L., Willard, H. F., & Ledbetter, D. H. (2018). Patient-Centered Precision Health In A Learning Health Care System: Geisinger's Genomic Medicine Experience. *Health Affairs*, 37, 757-764.

Wyber, R., Vaillancourt, S., Perry, W., Mannava, P., Folaranmi, T., & Celi, L. A. (2015). Big data in global health: improving health in low- and middle-income countries. *Bulletin of the World Health Organization*, 93, 203-208.

Yin, R. K. (2014). *Case study research : design and methods,* Los Angeles, CA: SAGE Publications.

Zadeh, A. H., Zolbanin, H. M., Sharda, R., & Delen, D. (2019). Social Media for Nowcasting Flu Activity: Spatio-Temporal Big Data Analysis. *Information Systems Frontiers*, 1-18.

Appendices

Appendix 1: Interview Schemas

1.2. Macro Interview Schema

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?)

Sociotechnical Representation of Big Data (TSR)

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?

1.2. Meso Interview Schema

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 - Sociotechnical Representations (TSR)

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 – Business-IT alignment

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?

    Or,

    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>1.3. Micro Interview Schema</u>

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?

Sociotechnical Representations (TSR)

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 <u>help</u> 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 <u>big data</u>? 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?)

<u>Alignment</u>

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 2: Participant Demographics

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 years	No
MIC9	General Practice	GP Z	GP	Health	29 years	No

Appendix 3: Sample themes and data (Data analysis)

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)

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