The democratisation of decision-makers in data-driven decision-making in a Big Data environment: The case of a financial services organisation in South Africa.

by

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Declaration

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Abstract

Big Data refers to large unstructured datasets from multiple dissimilar sources. Using Big Data Analytics (BDA), insights can be gained that cannot be obtained by other means, allowing better decision-making. Big Data is disruptive, and because it is vast and complex, it is difficult to manage from technological, regulatory, and social perspectives. Big Data can provide decision-makers (knowledge workers) with bottom-up access to information for decision-making, thus providing potential benefits due to the democratisation of decision-makers in data-driven decision-making (DDD). The workforce is enabled to make better decisions, thereby improving participation and productivity. Enterprises that enable DDD are more successful than firms that are solely dependent on management's perception and intuition. Understanding the links between key concepts (Big Data, democratisation, and DDD) and decision-makers are important, because the use of Big Data is growing, the workforce is continually evolving, and effective decision-making based on Big Data insights is critical to a firm's competitiveness. This research investigates the influence of Big Data on the democratisation of decision-makers in data-driven decision-making.

A Grounded Theory Method (GTM) was adopted due to the scarcity of literature around the interrelationships between the key concepts. An empirical study was undertaken, based on a case study of a large and leading financial services organisation in South Africa. The case study participants were diverse and represented three different departments. GTM facilitates emergence of novel theory that is grounded in empirical data. Theoretical elaboration of new concepts with existing literature permits the comparison of the emergent or substantive theory for similarities, differences, and uniqueness. By applying the GTM principles of constant comparison, theoretical sampling and emergence, decision-makers (people, knowledge-workers) became the focal point of study rather than organisational decision-making processes or decision support systems. The concentrate of the thesis is therefore on the democratisation of decision-makers in a Big Data environment.

The findings suggest that the influence of Big Data on the democratisation of the decision-maker in relation to DDD is dependent on the completeness and quality of the Information Systems (IS) artefact. The IS artefact results from, and is comprised of, information that is extracted from Big Data through Big Data Analytics (BDA) and decision-making indicators (DMI). DMI are contributions of valuable decision-making parameters by actors that include Big Data, People, The Organisation, and Organisational Structures. DMI is an aspect of knowledge management as it contains both the story behind the decision and the knowledge that was used to decide. The IS artefact is intended to provide a better and more complete picture of the decision-making landscape, which adds to the confidence of decision-makers and promotes participation in DDD which, in turn, exemplifies democratisation of the decision-maker. Therefore, the main theoretical contribution is that the democratisation of the decision-maker in DDD is based on the completeness of the IS artefact, which is assessed within the democratisation inflection point (DIP). The DIP is the point at which the decision-maker evaluates the IS artefact. When the IS artefact is complete, meaning that all the parameters that are pertinent to a decision for specific information is available, then democratisation of the decision-maker is realised. When the IS artefact is incomplete, meaning that all the parameters that are pertinent to a decision for specific information is unavailable, then democratisation of the decision-maker breaks down.

The research contributes new knowledge in the form of a substantive theory, grounded in empirical findings, to the academic field of IS. The IS artefact constitutes a contribution to practice: it highlights the importance of interrelationships and contributions of DMI by actors within an organisation, based on information extracted through BDA, that promote decision-maker confidence and participation in DDD. DMI, within the IS artefact, are critical to decision-making, the lack of which has implications for the democratisation of the decision-maker in DDD.

The study has uncovered the need to further investigate the extent of each actor's contribution (agency) to DMI, the implications of generational characteristics on adoption and use of Big Data and an in-depth understanding of the relationships between individual differences, Big Data and decision-making. Research is also recommended to better explain democratisation as it relates to data-driven decision-making processes.

Keywords: Big Data, decision-making, democratisation, information systems, IS artefact, empowerment, generations, workforce.

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Frequently used Abbreviations and Acronyms

Abbreviation or Acronym	Expanded form
AI	Artificial Intelligence
ANT	Actor Network Theory
B2B	Business-to-Business
B2C	Business-to-Consumer
BDA	Big Data Analytics
BI	Business Intelligence
CGTM	Classical Grounded Theory Methods
CIO	Chief Information Officer
CoBD	Characteristics of Big Data
CoDM	Characteristics of Decision-makers
CT	Contingency Theory
DDD	Data-driven Decision-making
DIKW	Data-Information-Knowledge-Wisdom
DIP	Democratisation Inflection Point
DMC	Decision-making Capability
DME	Decision-making Entity
DMI	Decision-making Indicator/s

DMS	Decision-making Structures
EFQ	Empirical Findings Quote
GTM	Grounded Theory Methods
ICT	Information and Communication Technologies
IoT	Internet of Things
IS	Information Systems
IT	Information Technology
KBV	Knowledge-based View
KM	Knowledge management
KW	Knowledge Worker
PT	Practice Theory
RBV	Resource-based View
SGTM	Straussian Grounded Theory Methods
SMP	Sociomaterial Practice
SMT	Sociomaterial Theory
STP	Sub-theoretical Proposition
STS	Sociotechnical Systems
TH	The Habitus
TI	Technology infrastructure
TO	The Organisation

TOE	Technology-Organisation-Environment
TP	Theoretical Proposition

Table 1: Frequently used Abbreviations and Acronyms

Table 2: Definitions and working definitions of often-used terms and concepts

Actor	The concept of actor is based on the definition within Actor Network Theory (ANT) (Latour, 2005), which is expanded upon within Section 5.2.3.3. It is used in the context of the empirical findings, specifically the labelling of selective codes, namely Technology Infrastructure (TI), The Habitus (TH), The Organisation (TO), and Decision-making Entity (DME). An actor is described as a "moving target of a vast array of entities swarming toward it", results from many other actors (actions and acts), and is given equal agency in terms of language and treatment (Latour, 2005). Actors could be human, non-human, sociotechnical/sociomaterial, natural, and unnatural entities that contribute some value to the networks within which they participate.
Big Data	"Big Data is getting bigger" and could contain anything digital—voice, video, social media, mobile data, and databases (Lavalle et al., 2011, p. 29). Big Data is derived from firms' internal systems, as well as from external sources (Baesens et al., 2016). For instance, internal sources include systems and applications such as CRM, ERP, server logs, voice, audio, video, email, and sensor data (which could emanate from security systems, industrial machinery, and building utilities) (Baesens et al., 2016; Kitchin, 2014). External sources of Big Data include, but are not limited to, social media such as Facebook and Google, market information, people movement, and customer behaviour (Kitchin, 2014).

Big Data Analytics (BDA)	Several definitions exist to define BDA (Mikalef et al., 2018). A concise definition of BDA is the "holistic approach to managing, processing, and analysing" Big Data to create actionable insight that is valuable to the business (Wamba et al., 2016, p. 356). Business Intelligence (BI) is similar to business analytics and data analytics and "treat Big Data Analytics [BDA] as a related field", with the terms unified and used interchangeably (Chen et al., 2012, p. 1166). The purpose of these tools and processes is to transform raw data into information and possibly meaningful insight (Mikalef et al., 2018). BDA, BI, and business analytics entail the "full life cycle of enhanced data-driven decision-making" (Baesens et al., 2016, p. 808).
Data-driven decision-making (DDD)	DDD is the use of insight/s that results from [Big] data analysis; it is also referred to as evidence in support of decision-making (Provost & Fawcett, 2013). DDD is the use of analysed data (evidence), as opposed to intuition, to make decisions. "Intuition is a process of thinking" that relies on stored knowledge that is "automatically" and unconsciously invoked when confronted with decision-making (Salas et al., 2010, p. 943). DDD, in the context of this thesis, is centred on digital data and, specifically, on Big Data datasets.
Decision (and Decision-making)	Decision-making is defined as "commitment to action", which results in an action that facilitates the next steps (Mintzberg, 1979, p. 58) and, similarly, "'decision' implies the end of deliberation and the beginning of action" (Buchanan & O'Connell, 2006, p. 33). Decision[-making] is the conscious idea of the desired state that is different from the current state (Grünig & Kühn, 2009). Decision-making is said to comprise two parts: "generation of potential solutions and the evaluation of them" (Bonabeau, 2009, p. 46).

Decision-making Entity (DME)	DME, as related to decision-making, is centred on organisational design that takes into consideration structures and processes that support organisational strategies (Daft, 2010). Organisational design has been influenced by four paradigms: 1) Enhanced leadership power through power allocation based on loyalty; 2) accountability and authority assignments based on roles and responsibilities; 3) "structures and administrative processes that match the organization's production processes or operations"; and 4) "structures and processes that facilitate the making of organizational decisions" (Huber & McDaniel, 1986, p. 573). While paradigm 4 above appears to embrace DME closely, all paradigms mentioned are inextricably relevant to DME as they represent the evolution of organisational design and are inherently built into organisational structures. "Companies will need a power shift in their structures if they are to capitalize on Big Data Analytics capability" (Galbraith, 2014b, p. 5). Specifically, organizational design needs to focus on speed of decision-making (real-time), which BDA makes possible. DME helps to rationalise the decision at hand through considerations of decision-making structures and quality of decision-making.
Decision-making indicator/s (DMI)	DMI is the value contributed by each actor (actors were identified through GTM selective coding). It contains detailed information, rules, and a set of instructions for how information is treated and actioned. Effective decision-making does not rely only on objective information but "rather, it depends on tapping the tacit and often highly subjective insights, intuitions, and hunches of individual employees" (Nonaka, 1991, p. 193), which is an essential part of DMI. DMI is an aspect of knowledge management as it contains both the story behind the decision and the knowledge that was used to decide. For instance, BDA output includes 'information about the information', such as the age of data; KWs add the human element, such as summary and recommendations based on information; the organisation contributes DMIs that control risks to the

	organisation such as budget management, and, based on the organisational design, contributions to DMI include guidelines for adherence to decision-making processes. DMI, together with information, facilitate better decision-making; in their absence, decision-making is weakened. These all contribute to organisational learning, which is the "management of process, systems and structures of knowledge acquisition" (Alavi et al., 2010, p. 297), therefore knowledge management.
Democratisation	Democratisation espouses fair participation in the decisions that affect employees' lives, in exchange for responsibility and accountability (Potterfield, 1999).
Democratisation Inflection Point (DIP)	The DIP is the point at which the actors', i.e. Technology Infrastructure (TI), The Habitus (TH), The Organisation (TO), and Decision-making Entity (DME), DMI contributions and the information extracted through BDA are assessed for completeness. Prior to the DIP, the data is formatted for consumption, and merely represents processed data or information. The information has taken on no further meaning or insight, be it actionable or not. Information and DMI, collectively, are deemed an IS artefact. Therefore, the DIP is the point at which the decision-maker evaluates the IS artefact.
Democratisation of Decision-makers	Democratisation of the decision-maker (KW) in the context of the study is about effective value contribution through teaming and co-creation of the IS artefact, which provides a better picture of the decision-making landscape.
ICT/IT	ICT is the integration of hardware and software into systems that store, support and transmit unified communications comprising of voice (audio), video and data between homogeneous and heterogeneous

	systems (Murray, 2011). See below—Technology infrastructure (TI) for further elucidation of the concept.
IS artefact	An Information Systems (IS) artefact is the outcome of observations in a non-contrived setting, is self-describing, whole in terms of information, and represents a "pure instance", that is, it is not predefined (Nigam & Caswell, 2003, p. 430). The IS artefact "is a blend of data and process for a key business-relevant dynamic entity that captures its end-to-end journey" (Cohn & Hull, 2009, p. 7). An IS artefact, in the context of IS literature, and as adopted in this thesis, is the combination of the technical, social, and information aspects that comprise an IS artefact (Drechsler, 2017; Iivari, 2017; Lee et al., 2015). An IS artefact is not restricted to Information Technology (IT), it is not necessarily physical, and it is not mandatory that it has been forethought of by IT designers or others (Lee et al., 2015). These reasons allowed Lee et al., (2015) the freedom to re-conceptualise the IT artefact to an IS artefact. While Lee et al., (2015) describe an IS artefact as comprising technical, social, and information as subsystems that do not exceed the sum of the whole, Iivari, (2017) describes an IS artefact as comprising abstraction layers, for instance technical, semantic, and pragmatic. Both sources support the notion that an IS artefact is broader than an IT artefact, which suggests that the IT artefact is embedded within the IS artefact. The IS artefact, as related to this thesis, is discussed in Section 4.2.1. With respect to the subsystems and abstraction layers mentioned above, the IS artefact emanating from the case study and espoused herein, could be explained from both perspectives, as they fit the intended narrative.

Knowledge Worker (KW)	A decision-maker makes decisions. In order to narrow this down in light of the vastness and complexity of Big Data and data-driven decision-making (DDD), 'knowledge worker' (KW) resonates better. As mentioned in Section 1.1.2, the KW applies knowledge to solve problems, uses more mental than physical ability to realise work-related tasks, and manipulates data/information to find answers and insight (Pyöriä, 2005, p. 118).
Power	"The phenomena of power and influence involve a dyadic relation between two agents which may be viewed from two points of view: What determines the behaviour of the agent who exerts power? What determines the reactions of the recipient of this behaviour? (French & Raven, 1959, p. 259)". Dahl (1957) defines power "as the relationship between actors" or "collective entities" (Clegg et al., 2006, p. 208). Max Weber, a well-regarded sociologist, offers two definitions that captures the essence of power: 1) "'Power' (*Macht*) is the probability that one actor within a social relationship will be in a position to carry out his own will despite resistance, regardless of the basis on which that probability rests" (Weber, 2012, p. 152); and 2) "Power can be defined as every chance, within a social relationship, of enforcing one's own will even against resistance, whatever the basis for this chance might be" (Weber, 2019, p. 134). Power is centred on control, that is the ability of one to control rewards, punishment, results and consequences of others (Maner, Gailliot, Butz, & Peruche, 2007).

Technology infrastructure (TI) (ICT, IT)	TI is better characterized as two separate but closely connected and integrated concepts, which are the technical ICT infrastructure and the human ICT infrastructure (Byrd & Turner, 2000). The technical ICT infrastructure is "the consistent foundation on which the specific business activities and computer applications are built [... and it is] a set of shared, tangible IT resources forming a foundation for business applications" (Byrd & Turner, 2000, p. 169). The human ICT infrastructure "includes human and organizational skills, expertise, competencies, knowledge, commitments, values, norms, and organizational structures" (Byrd & Turner, 2000, p. 169)
The Habitus (TH)	TH brings to the fore the vastness of the human being's concious and unconcious mind from a decision-making perspective. Within these spheres of the mind, individual differences (and similarities) are profound and shaped by education, experience, and exposure to traditional belief systems and values, cultural background/practices, and environmental conditions such as socio-political and socio-economic factors (Bourdieu, 1989, 2013). "People show substantial individual differences, or variations, in how they respond to the same situation based on personal characteristics" (DuBrin, 2019, p. 23). Individual differences are forms of power within social classes, which comprise different levels of social, economic, and cultural capital (Bourdieu, 1989). Social classes are further discussed in Section 5.2.3.2. TH embodies culture, which is "a stock of assumptions, values, beliefs, and practices from which individuals selectively draw in order to make sense of situations and choose paths of action" (Geeling et al., 2019, p. 2). Equally, TH is a social artefact "that consists of, or incorporates, relationships or interactions between or among individuals through which an individual attempts to solve one of his or her problems, achieve one of his or her goals, or serve one of his or her purposes. We describe this artifact as social because

	relationships and interactions involve more than just one person; hence, they involve the social, not just the individual" (Lee et al., 2015, p. 9). Habitus is discussed further within section 5.2.3.2.
The Organisation (TO)	TO takes into consideration the organisation's strategy, mission, objectives, and cultural values, which are then formalised into goals, rules, processes, and procedures, which are actioned at tactical, operational, and administrative levels (Robbins & Judge, 2018). The key premise of TO is purpose and fostering organisational values that contribute to the success of the organisation through achievement of goals and objectives (Galbraith, 2014a). The performance of the organisation takes into consideration the effective and efficient use of firm resources, especially people, finances, and technology (Schneider & Barbera, 2014). Organisations are social entities (Daft, 2010, p. 11).
Unsolicited data	Unsolicited data is all the data that the firm receives involuntarily, which mainly stems from social media and through call centres; it is mainly unstructured (Davenport & Dyché, 2013). Data from social media mainly comprise the complaints, brand recognition mentions, third party website clicks-through, and related sponsored events. Call centre logs are related to enquiries, complaints, and administrative issues that are entering the firm. Ideally, these may appear to be solicited and valuable, but organisations may not be geared, technologically and strategically, to take advantage of the underlying insight through data and voice analysis. Unsolicited data is untouched, and is stored or discarded.
Value	Value is well defined from an exchange-transaction perspective, which is mainly grounded in perceived usefulness and worth (Bowman & Ambrosini, 2000). Value, in the context of this thesis, is when actors "enable a firm to conceive of or implement strategies that improve its efficiency and effectiveness" (Barney, 1991, p. 106). Value takes many

	shapes; expertise and decision-making are examples of value that emerges from the transformation of data into information, then knowledge, and finally into wisdom (Rowley, 2007). An example of the value contribution by an actor—TO, in this case—is as simple as indicating budget availability for procurement purposes. Another example is to block a decision due to insufficient evidence, which is a value contribution by all actors. Value contributions, no matter how small or big they are perceived to be, contribute to the IS artefact and are important to DDD. Other forms of value contribution could be context—that is, the circumstance relating to the event, the decision type (i.e., strategic, tactical, or operational), or the type of analytics (i.e., descriptive, predictive, or prescriptive) (Saggi & Jain, 2018). These are just some of the value contributions to the decision-making IS artefact that forms the basis for a decision. Without a value contribution by actors, the IS artefact is incomplete, thus causing a breakdown in the decision process.

1. INTRODUCTION

"If democracy is justified in governing the state, then it must also be justified in governing economic enterprises; and to say that it is not justified in governing economic enterprises is to imply that it is not justified in governing the state" (Dahl, 1986, p. 111).

Big Data is pervasive (Cukier, 2010). While the impact of Big Data on nations, organisations, and people varies, its adoption and use is challenging across all contexts (Mneney & Van Belle, 2016). The implications of these challenges can be profound, especially with respect to the insights derived for decision-making purposes (Malaka & Brown, 2015). Decision-making is said to comprise two parts: "generation of potential solutions and the evaluation of them" (Bonabeau, 2009, p. 46). Considering Big Data's pervasiveness, the evolving workforce now has access to decision-making insights (Abbasi et al., 2016). Insight/s could be thought of as knowledge (see Section 2.2.1 for definitions of data, information, knowledge, and wisdom) (Davenport & Prusak, 1998) that results from the application of data analytics to data and information (Lavalle et al., 2011). Newer insights result when linkages are created between older knowledge and newer information (Rowley, 2007). The challenges of Big Data, coupled with the possible insights, call for an understanding of the decision-making status quo, given that the granular control of data is in the past and the visibility of data, resulting from Big Data, is unprecedented (Berner et al., 2014). It requires the transformation of management practices to deal with data-driven decision-making (DDD) (McAfee & Brynjolfsson, 2012). DDD is the use of insight/s that results from [Big] data analysis; it is also referred to as evidence in support of decision-making (Provost & Fawcett, 2013). DDD is the use of analysed data (evidence), as opposed to intuition, to make decisions. "Intuition is a process of thinking" that relies on stored knowledge that is "automatically" and unconsciously invoked when confronted with decision-making (Salas et al., 2010, p. 943). DDD, in the context of this thesis, is centred on digital data and, specifically, on Big Data datasets.

Big Data has been viewed mainly from a technological perspective, but the effect of Big Data on organisations is not understood, although the impact is profound (Mikalef et al., 2018). DDD is taking centre stage as organisations realise the value and competitiveness that could be realised through Big Data analysis (BDA) (Abbasi et al., 2016; Walker & Brown, 2019). Several definitions exist to define BDA (Mikalef et al., 2018). A concise definition of BDA is the "holistic approach to managing, processing, and analysing" Big Data to create actionable insight that is valuable to the business (Wamba et al., 2016, p. 356). Business Intelligence (BI) is similar to business analytics and data analytics and "treat Big Data Analytics [BDA] as a related field", with the terms unified and used interchangeably (Chen et al., 2012, p. 1166). The purpose of these tools and processes is to transform raw data into information and possibly meaningful insight (Mikalef et al., 2018). BDA, BI, and business analytics entail the "full life cycle of enhanced data-driven decision-making" (Baesens et al., 2016, p. 808).

Taking advantage of, or just harnessing, Big Data will require viewing it from a multidimensional perspective that includes the workforce and workplace, especially decision-making processes, given the value and competitiveness at stake (Sheng et al., 2017). Gaining an understanding of the complexities embedded in the mindset of the workforce helps to address organisational design and workforce optimisation, and to facilitate the journey to organisational effectiveness (Arnold et al., 2005).

1.1. Background

Earning an income for sustenance purposes is an innate human desire (Arnold et al., 2005). A common realisation of this desire is to participate in workplace tasks, roles, and responsibilities through mutually beneficial employment relationships. The aim is to achieve the goals set by the firm for monetary gain and rewards, which is the foundation for the employment relationship (Hyman, 2016; Méda & Vendramin, 2016). Being productive and contributing to the firm's revenue, while reducing expenses, is a more concise description of the modern employment relationship (Méda & Vendramin, 2016). "Extract[ing] a surplus" is the driving factor of the relationship (Hyman, 2016, p. 12). Firms want to extract value and uniqueness from employees and strategic resources to command superiority and a competitive advantage in the marketplace (Wamba et al., 2016). As organisations strive to grow within markets, and employees strive to grow within organisations, decision-making is critical to facilitating actions that are mutually beneficial to both aspirations (McAfee & Brynjolfsson, 2012).

This section introduces Big Data in the workplace, and key aspects of decision-making that are influenced by, or have an influence on, the use of Big Data. It considers workplace decision-making, the potential influences on democracy and empowerment, and employee dynamics (as emanating from the presence of multiple generations).

1.1.1. Big Data

Big Data is growing exponentially and is a reality for most large firms as data is continuously generated, from sources that are both internal and external to the organisation (Baesens et al., 2016). "Big Data is getting bigger" and could contain anything digital—voice, video, social media, mobile data, and databases (Lavalle et al., 2011, p. 29). 'Big' in terms of dataset size is not as important as the insight gained from the many sources that constitute Big Data (Gerard George et al., 2014). A globally connected workforce has relatively easy access to externally generated data from social media sources such as Facebook and LinkedIn, and significantly more through search engines such as Google and Bing (Mayer-Schönberger & Cukier, 2013). Big Data is different data that has all the elements to disrupt and revolutionise traditional ways of working and thinking and, in the process, to effect radical changes to current business processes, strategy, and decision-making (Constantiou & Kallinikos, 2015).

With access to more data, considerations of privacy, security, and regulatory matters become pressing concerns to address (Malaka & Brown, 2015). While these concerns appear restrictive, insight is abundant where decision-making and decision-makers are concerned (Bharadwaj et al., 2013). Therefore, this aspect draws attention to decision-making: is it the right to decide based on widely available data, thereby invoking democratic principles?

1.1.2. Workplace Decision-making

Decision-making is defined as “commitment to action”, which results in an action that facilitates the next steps (Mintzberg, 1979, p. 58) and, similarly, “'decision’ implies the end of deliberation and the beginning of action” (Buchanan & O’Connell, 2006, p. 33). Decision[-making] is the conscious idea of the desired state that is different from the current state (Grünig & Kühn, 2009). Decision-making takes place throughout organisations, and is a function of organisational design, capabilities, and power centres (Galbraith, 2014b; Mintzberg, 1979). There are constraints to decision-making due to the influence of internal and external forces that may or may not be within the control of the organisation (Harrison & Freeman, 2004). Decision-making is a critical aspect of organisational success or failure, which is mainly attributed to optimum choice (Buchanan & Connell, 2006). The extent to which the choices are [perceived as] right or wrong becomes clear in the outcomes, which could be success or failure in a business context. Decision-making occurs mainly consciously, but also unconsciously (Kahneman & Tversky, 1984). “There is strong evidence supporting the notion that there are two distinct information processing systems in the human brain, one conscious and deliberative and the other unconscious and intuitive” (Salas et al., 2010, pp. 943–944).

The history of organisational decision-making coincides with the inception of firms, but the term has gained prominence in the business management realm since the middle of the 20th century (Buchanan & O’Connell, 2006). From an organisational perspective, decision-making processes or types are grouped into strategic, administrative, operational, and tactical (Bolman & Deal, 2017; Mintzberg, 1979). These decision-making types are differentiated by implications on the business, the level of authority involved, and the frequency with which they are made. Decision-making typically rests with owners in owner-operated businesses; with management (McAfee & Brynjolfsson, 2012); and/or is decentralised in some companies (Bolman & Deal, 2017; Mintzberg, 1979). “Decentralise” has two key connotations. First, formal power is delegated from top management to line managers. Second, informal (decisional) power is extended to the analyst, specialists, and operators (Anderson, 2015; Bolman & Deal, 2017; Mintzberg, 1979). For this study, analysts and specialists are referred to as knowledge workers (KW/s) because of their key capital contribution to the business which, in this case, is knowledge (Wright et al., 2018). KWs differentiate themselves from other workers as they apply knowledge to problem solving, “manipulate information”, and as their skills are appropriate to this environment in which mental work dominates the job role (Pyöriä, 2005, p. 118). The concept of the KW applies to non-managers and managers, as both process information to meet job requirements and both are considered decision-makers. While non-managers are deemed individual contributors with a specialised contribution, managers achieve job objectives through non-managers or individual contributors by directing them (Tiffan, 2009). Both types of workers, in modern organisations, are decision-makers. In a data-driven organisation, power in terms of decision-making is shifting towards experts that understand data and how to use data for decision purposes (Galbraith, 2014b).

Apart from evidence or data or insight-driven decision-making, intuition is another decision-making aid that is employed by decision-makers (Bakhshi & Mateos-Garcia, 2012). Historically, power centres within businesses relied on intuition as a decisional power, especially in the absence or scarcity of data. However, data (or evidence and insight) for decision-making purposes in the Big Data era is more accessible than in the past and is available for both strategic and operational decision-making, which unlike in the past, was largely restricted to strategy decision-making, which suggests that the organisation has more data-driven decision-makers than in the past (Berner et al., 2014; McAfee & Brynjolfsson, 2012).

Organisational structures represent configurations for how power is distributed across the organisation, and includes concepts of centralised and decentralised power distribution (Galbraith, 2014a). Power centres are evolving to improve firm performance and enhance competitive positioning to take advantage of Big Data, and is hence incorporating rational means of decision support (Blenko et al., 2010; Galbraith, 2014b). Data for decision-making purposes is not only available to management and data-scientists, but to a wider group of stakeholders that are closer to the problem area (McAfee & Brynjolfsson, 2012). With governance, accountability, and regulatory factors continuing to play a critical role in how decisions are made, evidence-based decision-making, also known as data-driven decision-making (DDD), is gaining momentum (McAfee & Brynjolfsson, 2012). DDD is a way to determine a course of action based on data quality, completeness, and analytical rigour (Kitchin, 2014). DDD does not necessarily minimise or completely negate intuition-based decision-making, but is complementary to it (Buchanan & O’Connell, 2006). “Decisions need not be based purely in intuition or purely in deliberation. Frequently, experts use a mixture of strategies" (Salas et al., 2010, p. 942). DDD is focused on decision-making based on digital datasets and, specifically, Big Data. The latter differs from traditional datasets, which were structured, very costly to generate and manage, internally controlled, limited in terms of accessibility, and scarce (Berner et al., 2014; Kitchin, 2014; NIST Big Data Public Working Group, 2018).

1.1.3. Employee participation in workplace decision-making

Decision-making is necessary to facilitate actions so that businesses achieve goals—this has been established in Section 1.1.2. Employee participation in managerial processes such as decision-making, which is giving decisional voices to employees, not only supports businesses achieving goals but also accelerates decision-making (Pausch, 2014). This is realised through the decentralisation of decision-making power centres, which entails devolving decision-making privileges down the hierarchical structures of organisations (Motammarri et al., 2017). Another way to think of this is the sharing of decision-making responsibilities with others, typically subordinates or experts, and at times peers through delegation of authority (Lincoln et al., 2002). The shift from a situation where owners or the highest-paid persons make decisions to one where line managers and KWs share decision-making responsibilities is continually happening, albeit with control mechanisms in place to mitigate risks (Lincoln et al., 2002). Several employee participation concepts are relevant, including freedom, emancipation, empowerment, and democracy (Potterfield, 1999). However, the literature is laden with democracy and empowerment knowledge as the concepts fit with business practices; this aspect will therefore be explored further (see Section 2.6 for more information) (Baack, 2015; Humborstad, 2014; Maynard et al., 2012; Motammarri et al., 2017).

Democracy has diverse connotations, including collective decision-making, equality of people, parliamentary representation, participation, co-determination, and individual freedom (Matten & Crane, 2005). Political democracy is associated with inalienable rights to equal participation, freedom of speech/information/expression, and choices in representation (Kerr, 2004). Political and workplace democracy are mostly similar, but roles and responsibilities within the workplace afford different levels of power, while in political democracy, different power levels are acquired through being afforded representational privileges. Workplace democratisation principles have grown for well over 300 years, having been elevated through trade unions, workforce bargaining power, and resistance-based activities (Fraser, 1998). Another view is that workplace democracy, based on worker rights and privileges, originated in the nineteen century (Hatcher, 2007). Workplace democracy is principled on co-determination and participation by employees in organisational decision-making processes and strategy development (Foley & Polanyi, 2006; Humborstad, 2014; Pausch, 2014). Co-determination is defined as consultation and cooperation between employees and management in the firm's decisions across the organisation (Page, 2011). Workplace democracy, as an employee participatory process, coincides with the historical beginnings of businesses, but the importance of the concept emerged when democratic ideals and industrial relations came together (Pausch, 2014).

From the above, workplace democracy appears to be about entitlement and participatory privileges in organisational decision-making. In contrast, empowerment (discussed further in Section 2.6.2), typically implies an afforded privilege or bestowed authority in decision-making processes, but within strict "command-and-control" approaches (Humborstad, 2014, p. 392). Fundamentally, empowerment is shaping employees to organisational requirements and is effected "to make workers' capabilities and subjectivities conform to organisationally defined needs for self-discipline and self-mastery" (Yeoman, 2014, p. 110). While the concept of empowerment is trendy in the business world, the concept has been topical for well over sixty years (Maynard et al., 2012). Empowerment comes across as centralised power and control that, in effect, represents one person who is designing the work parameters of a person lower in the hierarchy, and forcing responsibility on that person "without instituting collective self-determination in decision-making" (Yeoman, 2014, p. 114). Democratisation, on the other hand, espouses fair participation in the decisions that affect employees' lives, in exchange for responsibility and accountability (Potterfield, 1999).

Democratisation and empowerment are explored further in Section 2.6.

1.1.4. Workplace Generations

From a workplace perspective, four distinct generations are converging and are required to cooperate (Bresman & Rao, 2017; Clark, 2017) (see Section 1.1.4). The study by Bresman and Rao (2017) suggests that these four generations have largely different characteristics, recognition and reward systems, aspirations, and ambition. This is bound to bring challenges to the firm as the diverse personalities, attitudes, work ethic, and communication styles may call for alternative methods to deal with each generation (Bencsik et al., 2016). While this diversity may appear intimidating to personnel management, it is unavoidable in such a diverse assembly of people (Bencsik et al., 2016). Understanding how to capitalise on this uniqueness could be beneficial and a unique competitive advantage for firms (Clark, 2017). Ascertaining how to make each individual's contribution respected and appreciated will require an evolution in organisational design, personnel management, and leadership style (Bencsik et al., 2016). Productivity tools, including decision-making aids, which are instrumental in the production of goods and services, may need to evolve accordingly (Potterfield, 1999).Different decision-makers and decision-making styles influence the use of Big Data, and the value that can be derived by organisations from improved decision-making practices (McAfee & Brynjolfsson, 2012). Two key considerations in decision-making is maturity and experience of the decision-maker, and the ease of engagement with data for decision-making (Turpin, 2004). The different generations in the workplace embody these aspects differently and, as such, could influence the value that could be derived from Big Data.

Generations are defined as groups of people born within a certain time period, share life experiences based on an era (see Figure 10), and exhibit similar characteristics such as behaviour, attitude, and value systems (Bencsik et al., 2016; Schullery, 2013). However, some literature opposes generational stereotyping and labelling people because of the lack of empirical evidence to support such classifications (Costanza & Finkelstein, 2015; Kriegel, 2016). On the other hand, diversity management is a focused human resources activity that aids minimisation of generational and cultural conflict (Mazibuko & Govender, 2017).

1.2. DEFINING THE RESEARCH PROBLEM

The use of data analytics within enterprises should produce insight from complex datasets. Data analytics tools enable the shaping of raw data into formatted information and simplifies the extraction of insight. These data analytics tools are effective for producing automated reports, self-service portals that help KWs to create custom information reports, and context-centric analytics that are built into functional applications such as asset, customer, people, and supply chain management (Yaqoob et al., 2016). Traditional datasets are mostly generated from in-house artefacts of a structured nature. They are shared, through business reporting tools, after analytical processes have been applied (Chen et al., 2014). The focus of data governance is largely on information and communication technology (ICT) asset management (software, hardware, networks) and control (Sharma et al., 2014). ICT is the integration of hardware and software into systems that store, support, and transmit unified communications, comprising voice (audio), video, and data, between homogeneous and heterogeneous systems (Murray, 2011).

Table 3 outlines the visibility of information as it was in the traditional data era, and how it is or will be in the Big Data era, specifically drawing attention to the availability of (Big) data at different levels within the organisation.

Characteristic	**Smart Machine Era**	**Big Data Era**
Information Timeliness	Historical data	Real-time data
Information Sources	Self-created, high-quality datasets	Large amount of data including unreliable external datasets
Information Reach	Strategic level	Strategic and operational levels
Information Relevance for Decision Making	Low (experience-driven decision making)	High (data-driven decision making)

Table 3: "Comparison of past and future information visibility" (Berner et al., 2014, p. 15)

With reference to Table 3, data for strategy and decision-making purposes traditionally resided with power centres within organisations (Berner et al., 2014). Operational data was made available to KWs to fulfill workplace decision-making requirements. In both instances, the data was internally created and controlled to maintain visibility and access control. However, with the emergence of Big Data, the sources of data are both internal and external to the organization (Baesens et al., 2016). Although Big Data leads to greater visibility, transparency, and accessibility of data, it is significantly more difficult to control and manage from a data integrity and data security perspective (Akter et al., 2016; Hashem et al., 2015). Traditional data access control was based on fairly static content that resided in a single domain, with access to data being dependent on roles that KWs occupied within the workplace (Qiu et al., 2019). Big Data access control management is complex because the content is dynamic (mobile, social media, IoT), with the environment being described as a "multidomain collaborative environment" (Qiu et al., 2019, p. 2). Access control policies enable the firm to be in complete control of the integrity and use of data in traditional datasets, insofar as decision-making is concerned (Bertino et al., 2010). Rules and role-based access control are achieved through granular control (Bertino et al., 2010).

The inference from Figure 1 is that data-driven decision-making (DDD) is traditionally bestowed upon the workforce through empowerment principles, from top management downwards, but with reasonable assurances on the outcomes of decision-making (IşıK et al., 2013). The firm is likened to a political state, nation, or country in that subjects (employees) are legally obligated to uphold (Dahl, 2001) the decisions made by government (leaders). In Figure 1, the Managing Director (MD) makes decisions—in isolation or through collaboration—and empowers senior managers through role-based access control privileges to action those decisions. In turn, line management grants role-based access control privileges to KWs, and so on. Role-based access control granularly permits or denies access based on predetermined roles, responsibilities, and privileges (indicated as dash line) (Bertino et al., 2010). A few examples of this are the blocking of access to employee salary information, firm profitability, and intellectual property. Granular access control is key to assurances that decision-making is constrained, predictable, and corrigible.

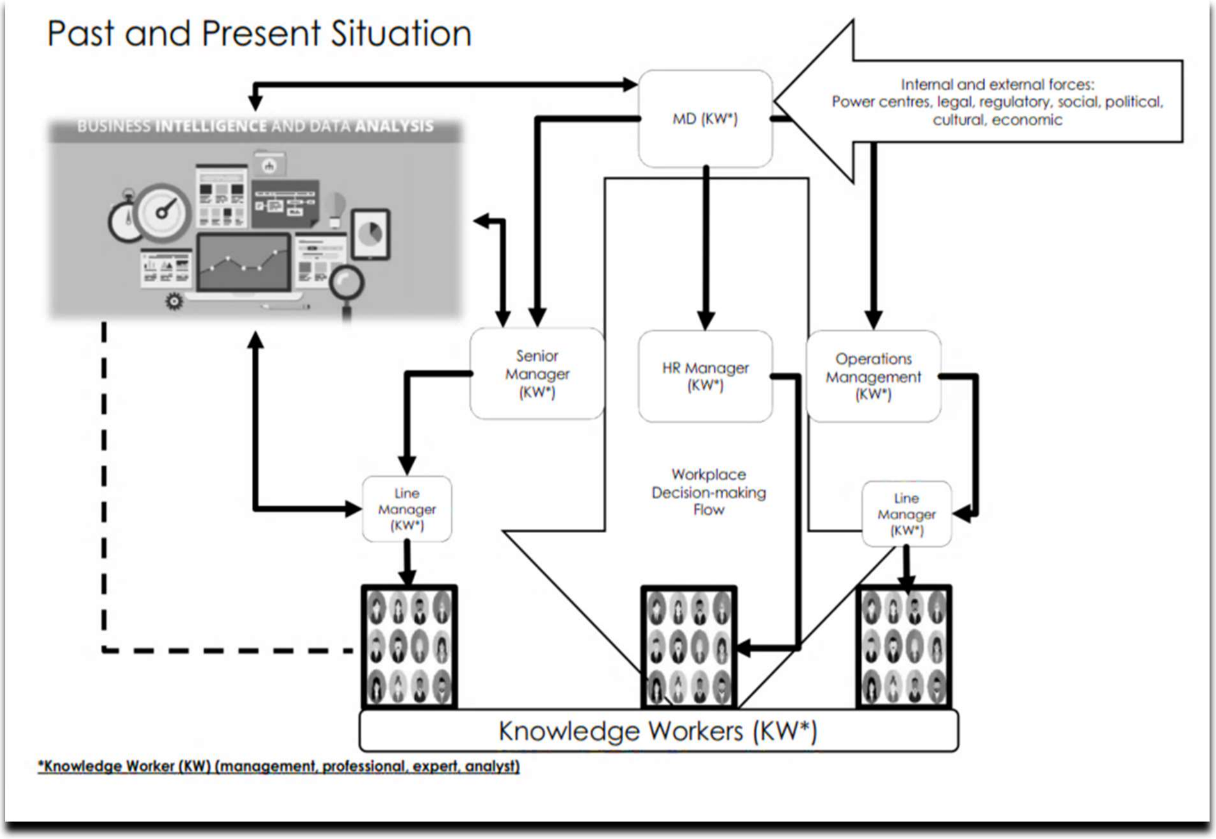

Figure 1: Researcher's view of traditional data-driven decision-making processes

Big Data datasets are produced from many sources and devices (Baesens et al., 2016). This new phenomenon creates an environment (Figure 2) in which it is difficult to command complete control, as the data sources are no longer just internal. Data sources now include customers, partners, suppliers, and the internet community (Günther et al., 2017). At the same time, the firm is under immense influence from controllable and uncontrollable factors such as regulatory affairs, shareholder pressure, and a diverse workforce.

When Big Data is compared to the traditional data era, data visibility is much greater; therefore, data is visible to KWs alike, that is management, professionals, and experts (Berner et al., 2014). Control and governance has to evolve to one of information management rather than role-based access control and empowerment, with supporting organisational structures that embrace wider decision-making processes (Sharma et al., 2014). The firm is no longer in complete control of the data repository, as data is entering from everywhere (Cukier, 2010). Therefore, it is contradictory that empowerment principles are applied to that which the firm does not control.

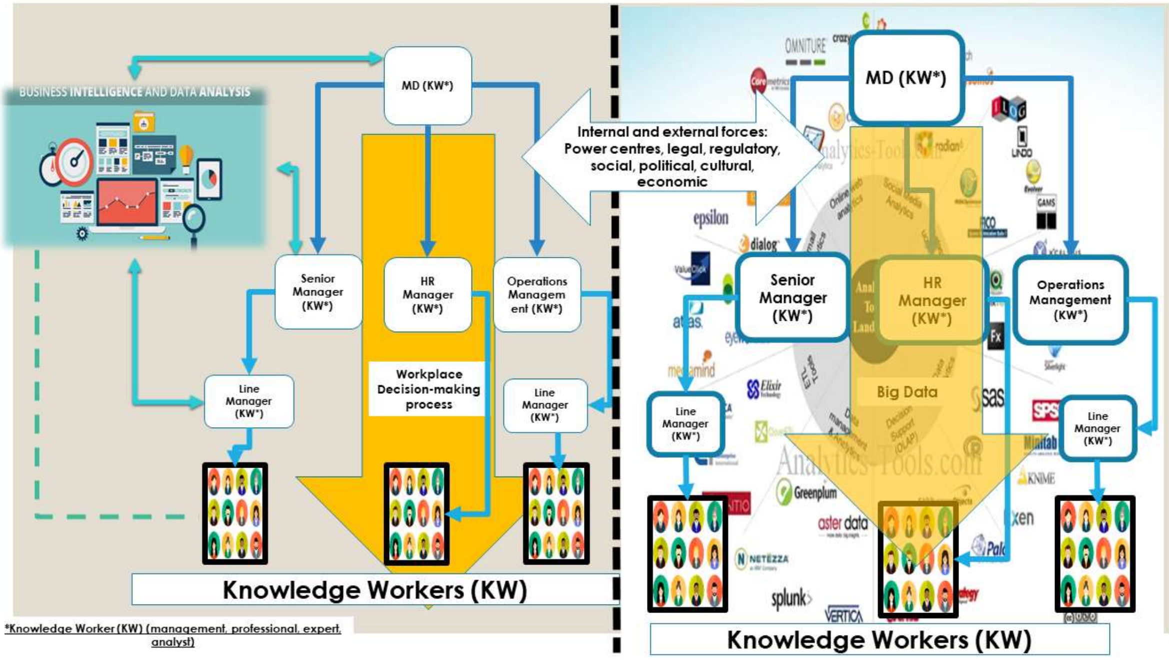

Figure 2: Researcher's view of the traditional and Big Data eras

Figure 2 and Figure 3 situates the research problem in illustrations that portray the differences between the traditional and Big Data eras from data visibility and decision-making perspectives. The key differences are visibility of data for decision-making and decentralisation of decision-making structures. Figure 3 shows that traditional data was visible to management in the form of information and insight, (denoted as hierarchical visibility). Controlled visibility to lower ranking KWs was afforded through operational data, that is, transactional and work-specific data. Conversely, Big Data is largely visible to management and KWs alike, which is denoted as horizontal visibility. In relation to horizontal visibility, the morphing of information-centric and process-centric systems is feasible because of declining ICT costs and availability of advanced Big Data Analytics that are capable of working across platforms (data warehouse, data lakes, storage systems, databases) (McAfee & Brynjolfsson, 2012). Cloud computing contributes to aggregation of services such as enterprise resource planning, supply chain management, customer relationship management, and business process automation (Hashem et al., 2015).

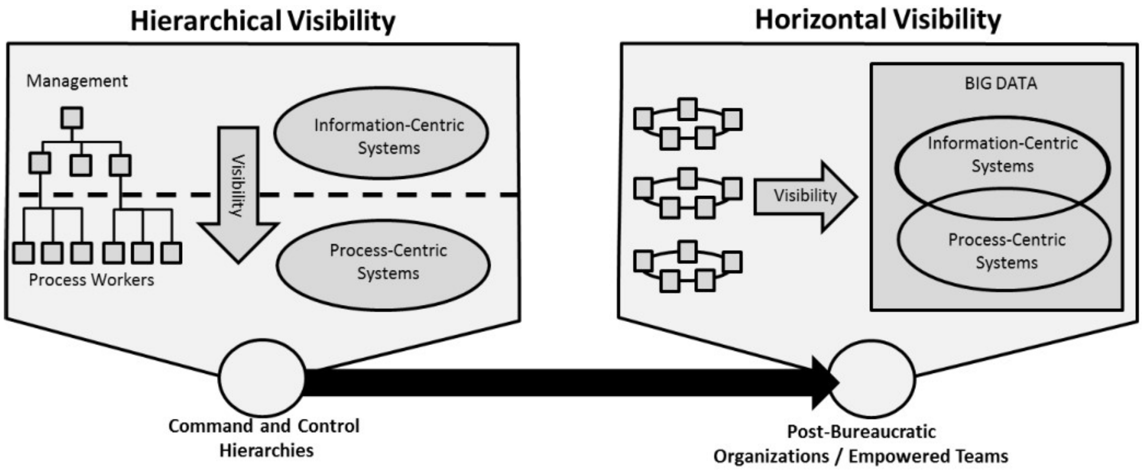

Figure 3: "Comparison of hierarchical visibility and horizontal visibility" to data (Berner et al., 2014, p. 16)

Big Data is disruptive, with characteristics that render it difficult to manage from technological, regulatory, and social perspectives (Carillo, 2017). With the prevalence of Big Data, democratisation in the workplace from a DDD perspective is a firm's quagmire—the extent of which is unknown. As explained, 'democratisation' as a participatory principle appears to be apt instead of 'empowerment' as a participatory principle, given the pervasive origination of Big Data, the challenges with control of Big Data, and the visibility of Big Data at all levels within the organisation. Empowerment appears to be applicable in a data environment that is controlled. This research investigates the influence of Big Data on the democratisation of decision-makers in data-driven decision-making in a financial services organisation in South Africa.

Democratisation of decision-makers in DDD and the influence of Big Data as a catalyst is not well understood, even more so in South Africa. Without understanding the influence and effect of the Big Data phenomenon on the workforce, especially KWs, firms cannot take advantage of the potential to have a participatory workforce (Humborstad, 2014). A workforce that is democratically enabled to make data-driven decisions is more productive, and DDD enterprises are more successful than those enterprises dependent on management's perception and intuition alone (Brynjolfsson et al., 2011).

1.3. Research Purpose and Objectives

1.3.1. Research Purpose

"Big data is an organisational and decision problem. It's not a technology problem. It's a business problem" (Weinberg et al., 2013, p. 190). With this in mind, the purpose of this study is to understand, through exploration, whether Big Data has influenced decision-making, specifically from the perspective of workplace democratisation of decision-makers in data-driven decision-making (DDD).

1.3.2. Research Objectives

The aim of the study is to ascertain whether Big Data enables or constrains the democratisation of decision-makers in data-driven decision-making in organisations.

Specifically, the goal is to:

a) Gather the most prominent of Big Data characteristics that affect data-driven decision-making;

b) Find out how Big Data use has or is changing organisational data-driven decision-making policies, processes, and procedures;

c) Determine whether power centres are changing, considering the use of Big Data;

d) Understand factors related to the internal and external environment that influence workplace democracy from a data-driven decision-making perspective; and

e) Develop a theory that explains the phenomenon in question.

1.4. Research Questions and Sub-Questions

1.4.1. Main Research Question (MRQ)

MRQ. Does Big Data influence the democratisation of decision-makers in data-driven decision-making (DDD) in organisations?

1.4.2. Sub Research Questions (SRQ)

SRQ1. In data-driven decision-making (DDD), what characteristics of Big Data affect decision-making processes and policies?

SRQ2. What internal and external environmental conditions inhibit or promote DDD in a Big Data environment?

SRQ3. How does data-driven decision-making (DDD) democratise decision-makers?

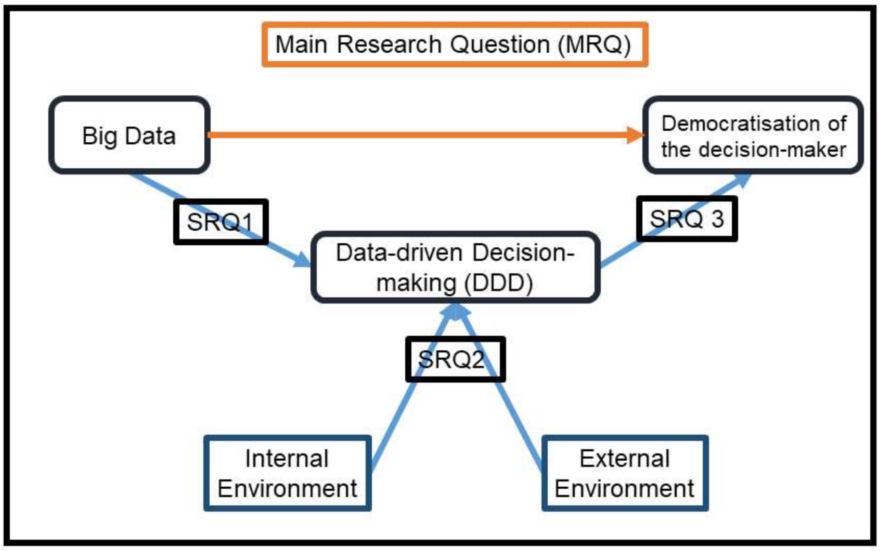

Figure 4: Illustration of Research Questions

As depicted in Figure 4, the sub research questions (SRQ) are meant to support and contribute to answering the main research question (MRQ). SRQ1 and SRQ2 focus on eliciting factors that are decision-making specific, meaning that processes and policies are under review as opposed to people. SRQ1 is intended to highlight characteristics of Big Data in relationship to DDD processes and policies. SRQ2 is directed at uncovering environmental conditions that lead to DDD in a Big Data environment. Outcomes of both SRQ1 and SRQ2 inform SRQ3, exposing a better understanding of the factors that influence the democratisation of decision-makers (people-centric).

1.5. Importance of research

Concurrently with the evolving workforce, Big Data is growing at a rapid rate and will continue to grow in future (Lavalle et al., 2011). The organisation does not exist in isolation, but as part of a network that comprises customers, suppliers, partners, and competitors that are materially influenced by internal and external forces, both within and without its realm of control (Andal-Ancion et al., 2003). Therefore, it is imperative to understand the influence that Big Data has—or not—on the workforce and the organisation, specifically from a data-driven decision-making perspective (Abbasi et al., 2016). Empowerment appears to be less fitting to decision-making processes in the Big Data era, as Big Data is not just internally created but multi-sourced, including external sources; it is therefore to some extent outside the control of organisations (Ekbia et al., 2015). Therefore, the workplace participatory concept of democratisation is fitting to help explain participation in DDD. Understanding this aspect helps businesses to evolve decision-making processes so that the possible insights from Big Data is harnessed and embraced rather than shunned. The literature, as demonstrated later, is limited; therefore, the knowledge contribution of this research is not only impactful, but also a point of departure for further discourse and contribution.

1.6. Overview of the thesis structure

The aim of the different chapters is to demonstrate the process and rigour adopted throughout the thesis in answering the research questions. These include surveying existing literature to find plausible gaps and adopting a fitting methodological approach to guide the thesis, thereby allowing theory to emerge that is grounded in the empirical situation. The substantive theory is situated against current literature to highlight the contribution to literature and practice (Urquhart et al., 2010). Finally, the research limitations, future research opportunities, and reflections conclude the thesis. Information is also provided in the form of references, appendices, and additional supporting evidence to support the thesis.

Chapter 1: **Introduction** contains the background to the research problem, research questions, research purpose, and objectives.

Chapter 2: **Literature review** aims to ascertain the current knowledge around the key concepts, and concludes with problematising the extant literature to demonstrate a persisting gap that is explored.

Chapter 3: **Research design** discusses the selection of the Grounded Theory Method (GTM), and in particular the Straussian GTM, as the guiding lens for the research. The research method aims to capture the empirical situation, the approach to data collection, and analysis.

Chapter 4: **Case study findings** is focused on the GTM steps followed, which resulted in empirical-based evidence and theory (Corbin & Strauss, 2014).

Chapter 5: **Discussion** compares the substantive theory to existing literature to find similarities, differences, and uniqueness through "theoretical integration" (Urquhart et al., 2010, p. 369).

Chapter 6: **Conclusion** contains thesis limitations, suggestions for future research, and reflections.

Following these are the chapters that provide supporting information. These include References (Chapter 7), Appendices (Chapter 8), and Additional supporting evidence (Chapter 9).

2. Literature Review

The aim of the literature review is to gain insights and a better understanding of the phenomenon or question under review (Levy & Ellis, 2006, p. 185)—in this case: does Big Data influence democratisation of decision-makers in data-driven decision-making in organisations? “The literature can be a stimulus to research. Sometimes the literature points to a relatively unexplored area or suggests a topic in need of further development” (Corbin & Strauss, 2014, p. 54).

2.1. Approach to Literature Review

Since Straussian Grounded Theory Methods (GTM) has been adopted to investigate the phenomenon, literature reviews were conducted throughout the development of the dissertation “for identifying a research gap, justifying the methodological approach, and informing data collection strategies” (Matavire & Brown, 2013, p. 126). This was specifically done when searching for knowledge gaps in existing literature, during the data collection-analysis stages and, finally, when the discussion section was compiled. However, this does not mean that the actual interviews, analysis, and development of the theory were explicitly influenced by existing literature. Reviewing the literature played an important role in ensuring theoretical sensitivity, adoption of current knowledge, and adherence to the methods (Corbin & Strauss, 2014).

An exploration of the literature throughout the study had the advantage that the knowledge gained helped to continually adhere to GTM guidelines, understand what has been done, and allow a theory to emerge through constant comparative analysis (Thornberg, 2012). For example, conducting the literature review during and after data collection helped to formulate codes, categories, and concepts that integrate more succinctly with existing literature, but “the literature is not the source of concepts” (Andrew, 2006, p. 30). A comprehensive search of accessible databases included, but was not limited to, EBSCOHOST, Elsevier Scopus, Emerald Insight, Science Direct, Springerlink, AIS Electronic Library, Jstor, Wiley online, Proquest, UCT Primo, and Google Scholar. The basket of eight journals[1] recommended by the Association of Information Systems (AIS)[2] was searched. In addition, journals

[1] MIS Quarterly, Information Systems Research, Journal of Management Information Systems, Information Systems Journal, Journal of Information Technology, European Journal of Information Systems, Journal of Strategic Information Systems, Journal of the AIS.

[2] www.ais.org

that were not part of the eight AIS journals were evaluated on the Scimago[3] Journal and Country Rank website for quality. Top journals that are not included in the AIS eight include, but are not limited to, Harvard Business Review, Communications of the ACM, and Decision Support Systems.

The initial step of the review necessitated searching through the mentioned knowledge repositories for seminal papers, articles, conference proceedings, and contributions by reputable practitioners. Practitioners such as IBM, SAP, and Microsoft are, amongst others, considered as industry experts in Big Data and in the aforementioned key concepts (Phillips-Wren et al., 2015). Gartner cited these practitioner enterprises for the last three years as the top ten producers of analytical software and business intelligence platforms (Aziza, 2018). This was reaffirmed by Datamation (Patrizio, 2019) and Information Week (Lisa, 2017). Practitioners are important to IS, and the perception that IS research is limited to academia is problematic and misleading (Ågerfalk, 2014, p. 594). The literature review results required a high-level parsing that involved, firstly, a review of the title (Günther et al., 2017). If the title appeared relevant to the research question, then the abstract and conclusion were searched for interesting and supporting information. If the paper appeared to be interesting based on relevance to the phenomenon at hand and included definitions, rebuttals, alternate views and critique, then the paper was read completely, or to the point that it was no longer interesting based on the immediate aspect being addressed.

This section presented the approach to uncovering existing literature, with the intention of transparently demonstrating the rigorous method adopted in discovering the extent of current knowledge. The following sections cover the key concepts, as related to the research problem identified in Section 1.2. Specifically, the various concepts are discussed from the perspective of definitions, the emergence of the concepts, differing viewpoints, use cases, and the relationships to other concepts.

2.2. Big Data

Big Data is derived from firms' internal systems, as well as from external sources (Baesens et al., 2016). For instance, internal sources include systems and applications such as CRM, ERP, server logs, voice, audio, video, email, and sensor data (which could emanate from security systems, industrial machinery, and building utilities) (Baesens et al., 2016; Kitchin, 2014). External sources of Big Data include, but are not limited to, social media such as Facebook and Google, market information, people movement, and customer behaviour (Kitchin, 2014). This short exposé is intended to demonstrate the vastness and

[3] http://www.scimagojr.com/index.php

complexity of Big Data. One possible reason for describing Big Data as 'big' is that traditional technology is inadequate from storage, computing, management, security, and analytical capability perspectives, because of the complexity of the datasets (Yaqoob et al., 2016).

The Gartner Hype cycle research report first mentioned Big Data as an emerging technology concept in 2011 (Fenn & LeHong, 2011). The heading in the report read as follows: “Big Data and Extreme Information Processing and Management” (Fenn & LeHong, 2011, p. 19). The report classified Big Data as “transformational”, which is further supported by Baesens et al., (2016); the report implied that the technology will fundamentally change business processes and the ways of doing business, and influence the firm’s competitive strategy—negatively or positively. Big Data and BDA is interesting to practitioners and academics, as it is “considered to be the most important technology disruption since the rise of the Internet” (Walker & Brown, 2019, p. 1).

Figure 5 illustrates the entrance of Big Data as an emerging technology in 2011, and Figure 6 outlines its status in 2014. From 2015 onwards, Big Data no longer appeared on Gartner Hype Cycle Emerging Technologies reports. Big Data is now relevant across hype cycles, for example IoT, AI, cloud computing, and virtual reality. The understanding of Big Data from a practice and academic perspective is at an early stage, with expectations of the potential of Big Data remaining high (Maass et al., 2018; Mikalef et al., 2018). Although Big Data is still largely in its infancy from an academic and practitioner perspective, Big Data is established within organisations globally (Pedro et al., 2019).

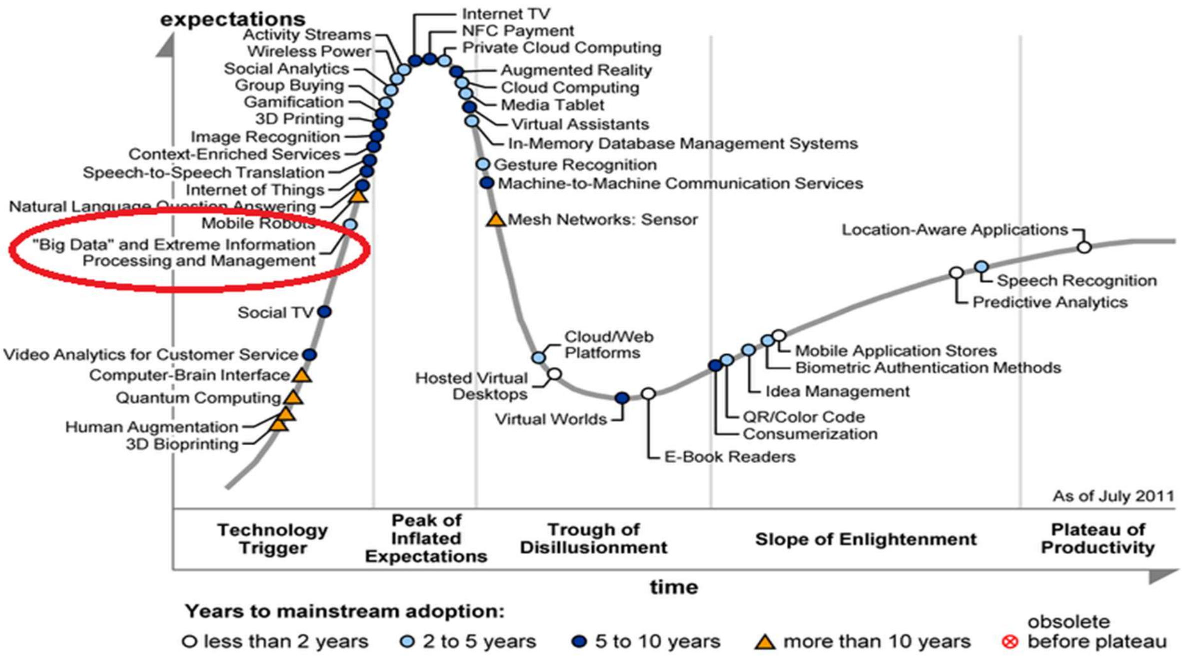

Figure 5: Gartner Hype Cycle for 2011 (Source: www.gartner.com)

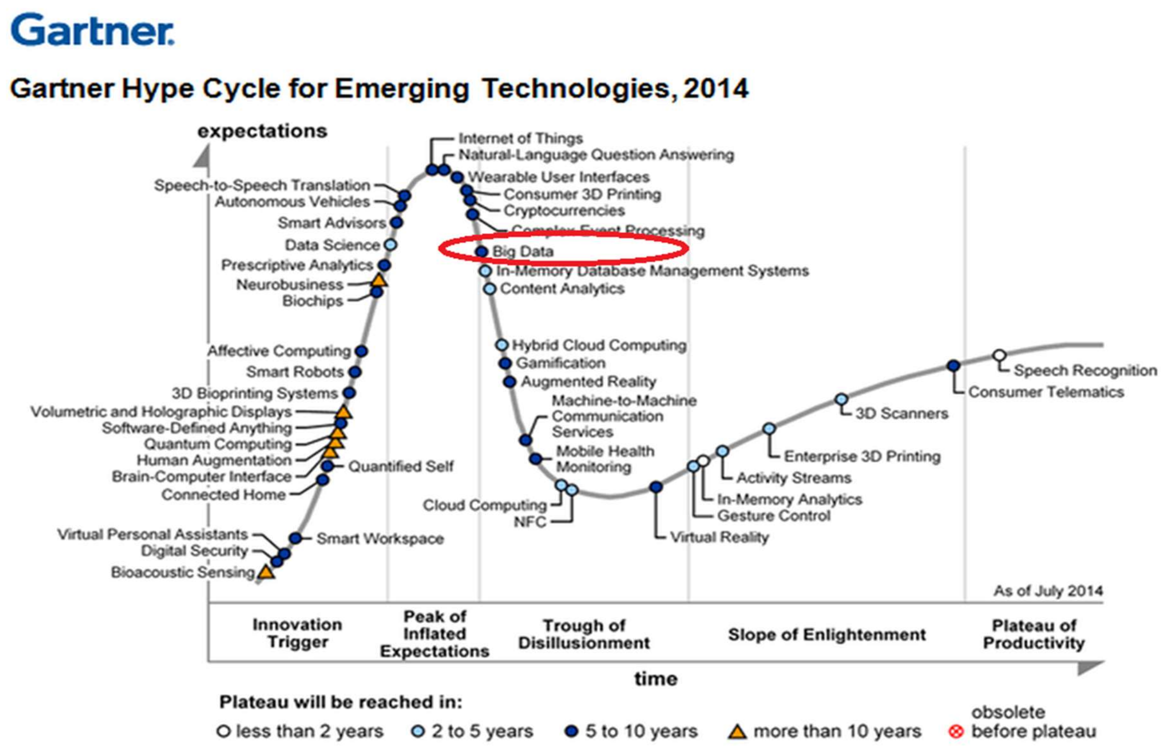

Figure 6: Gartner Hype Cycle for 2014 (Source: www.gartner.com)

2.2.1. Clarifying key terms – Data, Information, Knowledge, and Wisdom (DIKW)

Before proceeding, it behoves a discussion on these four key terms, as they are easy to misuse or use interchangeably. The four terms mean different things to different people. For the purposes of this study, the Data, Information, Knowledge, and Wisdom (DIKW) hierarchy model, (Figure 7) as explained by the systems theorist Ackoff (1989), is used to differentiate between these terms, albeit with limited explanation of wisdom. Although additional layers such as understanding and intelligence are sometimes included in iterations of these types of models, they are complex terms that bring different dimensions to the discussion. An instance of this is 'understanding', which is a layer between knowledge and wisdom in Ackoff's writings. However, 'understanding' is deemed to be a requirement at all layers of the pyramid since, without the understanding of characteristics of the layers, the pyramid serves no purpose (Bellinger et al., 2004). Big Data is at the core of the thesis; therefore, understanding the transformation of raw data by applying BDA necessitates an understanding of the different layers that emanate from data as value is added, thereby leading to information, knowledge and, at times, wisdom (DIKW) (Boell & Cecez-Kecmanovic, 2015). DIKW, as shown in Figure 7, appears to be largely accepted as the model to explain the transformations and, therefore, will be referenced in this study (Rowley, 2007).

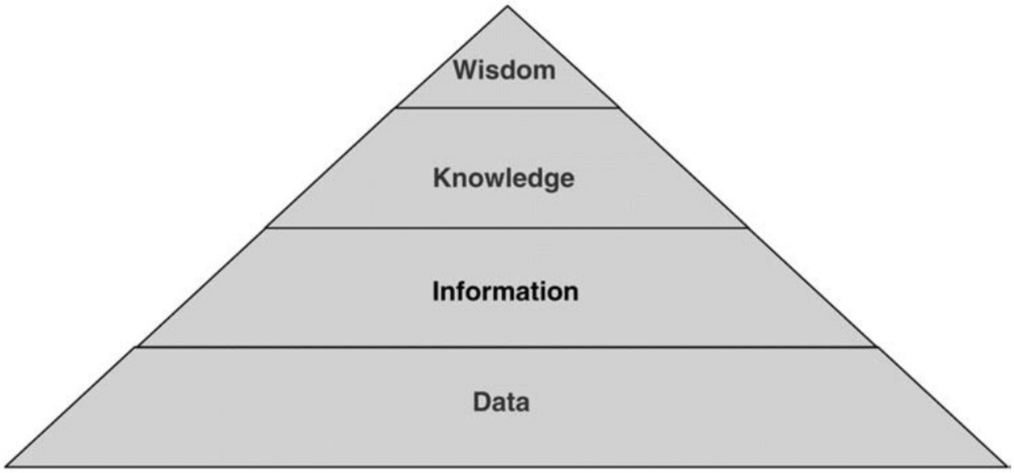

Figure 7: DIKW Hierarchy (Rowley, 2007)

The various explanations highlight that each layer, apart from the data layer, is an aggregation of the previous layer's attributes, with some value-addition and/or derivation to expand its usefulness and usability (Ackoff, 1989). The model is not without controversy, which mainly relates to consensus in the transformation criteria—that is, justification for the transitions from data to information to knowledge to wisdom (Rowley, 2007). Several criteria have been suggested for transitioning between layers, such as depth of meaning, value, algorithmic capability, levels of programmability, the extent of human agency, and order/structure (Boell & Cecez-Kecmanovic, 2015; Rowley, 2007). Another view is that DIKW is imprecise and lacks foundation in research; therefore, suggestions based on empirical evidence have been forwarded to enhance the model (see Section 5.2.4) (Boell, 2017). As the mentioned criteria are satisfied or achieved, the progression up the pyramid escalates. Hence, the progress moves to ‘how’ type inquiries rather than merely asking what/why/when/where questions. Given all this data, information and knowledge lead to deeper questions that are tied to consequences and judging of outcomes, both of which are critical to decision-making processes. Data, information, and knowledge consider historical events, while wisdom informs on the future implications and uses thereof (Bellinger et al., 2004). Although data, information, and knowledge appear to be subjectively different and interchangeable, these concepts differ profoundly (Davenport & Prusak, 1998). An interpretation of the four DIKW concepts that inform this thesis follows below.

2.2.1.1. Data

Data is the lowest layer in the DIKW pyramid (Boell & Cecez-Kecmanovic, 2015). It is the fundamental building block for the other layers (Merkus et al., 2019). Data could be characterised as disorganised facts, symbols, objects, and figures that lack meaning, but that relate to events such as transaction records, metadata, webpage clicks, and sensor communications (Davenport & Prusak, 1998). “Data has no meaning or value because it is without context and interpretation” (Rowley, 2007, p. 170). The base of the pyramid, data quality (i.e., veracity, fit for purpose, and use) is tantamount to usability in the subsequent layers. An apt phrase comes to mind, namely, “garbage in, garbage out” (GIGO), which holds true when the quality of the data lacks integrity and substance (Malaka & Brown, 2015; Mayer-Schönberger & Cukier, 2013). An extension of this is the quality of the analytical abilities and analytical tools that are used to interrogate the data. The lack thereof gives credence to the phrase GIGO.

Data integrity, analytical tools, and the abilities of the analyst contribute to the quality of information.

2.2.1.2. Information

Information is data that is organised, structured, and condensed; it is largely an outcome of interrogation-type questions—who, what, where, when; therefore, the processes that are applied to data (Lee, 2010). Within IS, information is typically conceptualised as: 1) data that has been processed, and 2) an increased level of understanding based on progressions within D→I→K→W (Boell, 2017). However, these conceptualisations are simplistic, given the multifaceted nature of information that have implications for the social, technical, and cognitive (separately and collectively), and the assumptions could lead to different consequences (Boell, 2017) Another perspective is that ‘inform’ means 'to give shape to', and ‘information’ is meant to shape the receiver in some way (Davenport & Prusak, 1998, p. 3).

Context is what allows the decision-maker to use information to answer questions, as data is no longer just random pieces of facts and symbols, but gathered for a purpose (Boell & Cecez-Kecmanovic, 2015; Davenport & Prusak, 1998). These are organised into something specific and coherent, for example, production schedules and financial balance sheets; information is more complete and tells a story. In this study, information is taken to mean processed data that is contextual, and the output based on questions put to BDA. Processed data is taken to mean that data has been interrogated by some analytical tool, for example, structured query language (SQL), to produce something meaningful that has relational associations. The output is often presented in tabular form (tables) for ease of use, for further and granular interrogation. Processed data is stored in relational databases and managed by relational database management applications.

Information can be conceptualised as integrating random pieces of data into something cohesive that is meaningful and useful, such as a message (Davenport & Prusak, 1998). However, the difference between data and information is functional, suggesting that is it is meaningful and useful rather than structurally different, and information is inferred from data (Ackoff, 1989; Dammann, 2018).

2.2.1.3. Knowledge

Explaining knowledge is complex, as the viewpoints vary—thereby contributing to multiple perspectives and hence complexity in interpreting these for decision-making. The viewpoint adopted in this study is as follows. Information that has been transformed into know-how or instructions is considered to be knowledge (Ackoff, 1989; Rowley, 2007). Knowledge is an awareness and an understanding of that which is a known reality (Davenport & Prusak, 1998). What is known—such as values, beliefs, culture, traditions, evidence, education, and experience—could be shaped by influencers (Davenport & Prusak, 1998). These influencers inform one’s perceptions, interpretations, and viewpoints, and have a bearing on how information is processed and used. It hence stands to reason that information, which is meant to influence the person, together with the mentioned shaping characteristics, result in knowledge (Rowley, 2007). Knowledge management “enables the optimal use of timely, accurate, and relevant information; it also facilitates knowledge discovery and innovation, fosters the development of a learning organization, and enhances understanding by integrating all sources of information, as well as individual and collective knowledge and experience" (Girard & Girard, 2015). Importantly, approaches to synthesising information, for instance the use of rationality and intuition, is central to decision-making and applies with or without evidence being present (Khatri & Ng, 2000).

2.2.1.4. Wisdom

From an organisational studies' perspective, an apt definition of wisdom is as follows: it is "the ability to use one's knowledge, skills, ethics, insight, and judgment and yet remain open to new ideas, experiences, and critique, and deal with the particular situation at hand" (Dalal & Pauleen, 2019, p. 227). Wisdom, insight, or judgement are the skills that people possess to allow them to see things differently and more meaningfully (Khatri & Ng, 2000). Wisdom is one way of applying knowledge. The wise are able to apply value-laden judgement in decision-making processes that transform into choices and actions (Ackoff, 1989; Rowley, 2007). Wisdom is understood to be the skill of making decisions based not only on available knowledge, but also on application of additional cognitive abilities such as rationality (logic) and intuition (experience) (Khatri & Ng, 2000).

In sum, there are multiple meanings and connotations for each of these concepts. However, these are the concepts and their associated meanings and connotations that have been adopted for this thesis. Based on several contributors (Ackoff, 1989; Bellinger et al., 2004; Rowley, 2007), the thesis adopts these definitions as the best possible. Data is deemed to be random and unprocessed chunks of text, video, and voice. Information is organised chunks of data that have some meaning, has been contextualised, and paints a better picture. Knowledge, together with underlying and innate influencers, helps to shape know-how and answers 'how' questions. Wisdom is the skill that applies judgement based on knowledge in order to realise choices and actionable insights.

Data, information, and knowledge describe the past, while wisdom focuses on the future (Ackoff, 1989).

2.2.2. Definitions and key characteristics of Big Data

A literature survey of over 1800 journal articles and conference papers led to the identification of several definitions of Big Data (De Mauro et al., 2016). Most definitions largely converge on four main characteristics (or 'V's), namely, volume, velocity, veracity, and variety. Volume refers to huge datasets. Velocity indicates the real-time nature and speed at which datasets are generated. Veracity attempts to address the authenticity of the data. Variety points to the heterogeneous composition of datasets (Kitchin & McArdle, 2016). As could be expected from an emerging phenomenon, the knowledge base is growing. Hence, additional Vs have been added over time to further characterise Big Data, such as value (Sharda et al., 2013), variability and visibility (Ylijoki & Porras, 2016), and/or visualisation (Seddon & Currie, 2017). The simplest definition of Big Data is the collection, processing, and analysis of large datasets (Van Es & Schäfer, 2017).

(Big) Datasets are structured, unstructured, and semi-structured, which are descriptions of the format and organisation of data (Mikalef et al., 2018). Structured datasets are organised in relational databases and easily searchable, which is unlike unstructured datasets that lack defined structure, and therefore lack relational database attributes and are difficult to search (NIST Big Data Public Working Group, 2018). A dataset could include just one type of content or combinations of content, which could include video, databases, audio, documents, pictures, social media content, text messaging, and voice (De Mauro et al., 2016). Unstructured datasets typically account for 95% of Big Datasets (Grover et al., 2018). According to a recent report, 80% of the unstructured data that a firm possesses is considered dark data, which means the data is not analysed for insight (Krisifoe, 2018). The report also claims that just 0.5% is analysed for insight.

While some contributions to a better understanding of Big Data includes value as a characteristic of Big Data, value is for the purposes of this thesis deemed to be an outcome after BDA has been applied to Big Data (Mikalef et al., 2018). Value or insight is a result of analysis and interpretation of the Big Datasets. Prior to the analysis, Big Datasets have little relevance, or lack relevance. For example, the speed at which data arrives is important to time-sensitive decision-making such as financial instruments trading, where the timing of data and decisions are critical to outcomes. Therefore, the application of analysis and interpretation to the dataset must be near real-time, resulting in value for decision-making. In this example, volume, veracity, variety, and velocity are present as Big Data characteristics that, together with BDA, yield business value (Lavalle et al., 2011; Mikalef et al., 2018).

2.2.3. Extracting Value and Insights from Big Data: Analytics and Intelligence

Previous writers, academics, and practitioners have covered Big Data Analytics (BDA), data analytics, and business intelligence substantially (Akter et al., 2016; Lavalle et al., 2011; Mikalef et al., 2018; Russom, 2011; Watson, 2014). The following concise explanation is provided to place BDA, which is an important concept, in the context of this thesis.

In order to extract insight and realise value from the immense volumes and variety that characterises Big Data, appropriate analytical tools (software, machines, processes, and people) are needed (Mikalef et al., 2018; Watson, 2014). Another perspective for gaining insight from Big Data is that the firm (business) has to ask the right questions (Rubinstein, 2018); these form the basis for implementing business processes, infrastructure, and data modelling architectures. Big Data analytical tools include the analytics/intelligence applications, Hadoop and Map Reduce. However, these may be too complex and unaffordable for many enterprises. Cloud computing and managed services are options for overcoming these obstacles through storage, dataset interrogation tools, and user-friendly dashboards to display results (Rubinstein, 2018).

Business or data analytics is fundamentally focused on producing insight from interrogating datasets, largely for decision-making and inquiry (Chen, Chiang, & Storey, 2012, p. 1174). This is achieved through data mining, statistical analysis, and machine learning. The traditional role of analytics is to answer questions based on scrutiny of largely structured data by means of analytical tools. BDA is intended to interrogate structured, unstructured, and semi-structured datasets that could include streaming of real-time data, social media, and sensor information (Baesens et al., 2016). Relevant analytics that are applied to traditional data and Big Data datasets could result in three key contributions, which are descriptive, predictive, and prescriptive in nature (Sivarajah et al., 2017; Watson, 2014). These are concerned with what happened, what is likely to happen, and what can be done (Saggi & Jain, 2018). Based on similar explanations by the aforementioned authors, descriptive analytics describes historical occurrences. Predictive analytics is forward-looking and algorithm-based; the output presents possible future events. Prescriptive analytics recommends possible actions to identified conditions.

Analytics is not just for business management purposes. It is widely used across most industries. For example, disease management, clinical data, patient care are some use cases of Big Data in healthcare (Amankwah-Amoah & Amankwah-Amoah, 2016; Sciascia & Radin, 2017). Geographic Information Systems (GIS) employ analytics to provide simple and advanced location-based services. For instance, a GIS map search of a location is simple, whereas more advanced GIS uses include the pairing of consumer preferences with location to advertise services such as hotels, restaurants, and gas stations (Abbasi et al., 2016). The key difference between BDA and business analytics is the technological ability to analyse large voluminous datasets that consist of a variety of structures, and data sources that flow at a near real-time rate (Malaka & Brown, 2015). The other significant difference pertains to the skills required, which are far more advanced than traditional analytical skills—hence the new term for the role, that is, data scientist and chief data officer as opposed to data analyst and business analyst (Davenport & Patil, 2012).

2.2.4. Big Data Use: Firm Capability and Motivation

Innately digital enterprises such as Google, Facebook, and LinkedIn do not necessarily face the same issues as traditional enterprises, as these businesses were born out of Big Data and have only operated with digital data (Davenport & Dyché, 2013, p. 2). Traditional firms, on the other hand, must contend with legacy-type business processes that require integration (Bindra, 2019). An example is the legacy paper-based records, which are still in use in banks including throughout South Africa (Firth, 2019). Traditional and digitally transforming organisations have been shaped to fit their state-of-the-art, with employees who are understandably accustomed to ways of work that fit with their business processes and models; however, achieving digital maturity or a sense that digital transformation is progressing requires strategic direction, investment in technology, and leadership (Heavin & Power, 2018).

In a joint practitioner and academic study of twenty large enterprises in the USA, including UPS, GE, and the Bank of America, Big Data is considered challenging; however, the realised and anticipated value justifies the effort and investment (Davenport & Dyché, 2013, p. 17). Hence, enterprises are incrementally allocating firm resources (budget, people, and technology) to extract value from Big Data. These resources are necessary to develop not only the technical skills of data scientists, but also the skills of managers to make evidence-based as opposed to intuition-based decisions. In another practitioner study fifty respondents, representing the largest enterprises in the USA, were expecting Big Data and BDA to have a significant bearing on their businesses—largely attributed to improved and smarter data-driven decision-making (Davenport, 2012). In a recent study of 260 participants within Pakistan, an emerging country, BDA adoption in the healthcare sector appears to be at an initial stage; however, the indications are that BDA is having an effect on the style of organisational decision-making (Shahbaz et al., 2019). Gauging the adoption, use, and success of BDA within organisations is not easy, as the implementations thereof varies across industry sectors and countries (Walker & Brown, 2019).

2.2.5. The role of Data and Big Data in Data-driven decision-making (DDD)

The role of data has already been established in previous sections. In summary, it represents the support and evidence mechanisms that are utilised to commit to an action or make decisions (Baesens et al., 2016). DDD relies on evidence in the form of data/information/insight, which is assumed to be of a good quality, reliable, and relevant, to determine a course of action (Provost & Fawcett, 2013).

To illustrate the importance and emergence of Big Data in DDD, some findings from market surveys are outlined below.

Excerpts from a practitioner market study of 1034 professionals in North America (Exasol, 2019) are as follows:

a) 80% of respondents use data for decision-making purposes;
b) Between 60-73% of data is not analysed by BDA because of inadequate technologies;
c) 71% of respondents said they use BDA; and
d) 51% adopt data science.

The following are outcomes of a survey of 241 global executives (Whelan, 2012):

a) 76% of respondents believe that more employees should have access to Big Data for decision-making purposes;
b) 74% believe that the more access to data, the better the decision-making;
c) More than half (53%) indicated that Big Data processes are driven outside of the Chief Information Officer (CIO)'s organisation, while 23% indicated that Big Data processes were driven by the CIO's organisation (24% were neutral);
d) 76% believe that adding additional data sources would have yielded better business decisions and outcomes;
e) Slightly over half (53%) indicated that their companies will be expanding DDD to more employees; and
f) 63% felt that better and faster DDD were possible outcomes if Big Data were more accessible to employees.

While point e) appears less than impressive, the surveyed executives did cite several barriers as possible limitations, including financial, security, culture, technology, and talent constraints. In the more recent (2019) survey outlined above, DDD is increasing.

2.2.6. Big Data in organisations in South Africa

Sabinet and Google Scholar were used to find research from a South African perspective. The search results indicate that previous work has largely focused on business intelligence and business analytics, with some studies on BDA readiness and BDA adoption (Dawson & Van Belle, 2013; Hartley & Seymour, 2011; Pedro et al., 2019; Ridge et al., 2015; Walker & Brown, 2019). However, an assessment of organisations and their use of Big Data in the democratisation of decision-makers in DDD is lacking. A review of the extant literature indicates that the retail and telecommunications segments have been explored from the perspective of the readiness and willingness to adopt Big Data (Mneney & Van Belle, 2016; Pedro et al., 2019). These studies affirm the adoption of data analytics by South African organisations for data interrogation purposes to develop business insight. It also confirms that DDD is lacking, organisational adaptation to data analytics is challenging, and the skills gap limits Big Data use. The skills gap is understandable, as there are 23 skills necessary to successfully fulfil work that is related to data analytics (De Jager & Brown, 2016). Another study of a South African telecommunications company reveals that DDD is challenging and not strategically driven, but instead as silo-based department-centric decision-making (Malaka & Brown, 2015). While this supports the phenomenon at hand, the issue is whether this is attributed to firm evolution or organisational design. These South African empirical studies prompt the question of how enterprises make decisions and design organisations in the Big Data era, under increasing complexity, as aspects such as culture, skills, privacy, and leadership unfold.

The context of the inquiry, namely, a financial services organisation in South Africa, is interesting, as South Africa could be classified anywhere between a developed and developing nation, with its extremely high inequality status (Sulla & Zikhali, 2018). From boasting first world infrastructure (roads, ICT, utilities) to having the majority of communities living in third world conditions, South Africa is an intriguing conundrum (Sulla & Zikhali, 2018). It is also thought-provoking to understand how Big Data affects decision-making from a workplace democracy standpoint, considering South Africa's history, cultural diversity, and the African perspective that "the art of decision-making is governed by communal thinking, consensus beliefs, elders' participation, and a shared goal" (Okonedo, 2018, p. 222).

2.3. Organisational Decision-making

"'Decision' implies the end of deliberation and the beginning of action" (Buchanan & O'Connell, 2006, p. 33).

As mentioned in Section 1.1, decision-making is fundamentally the commitment to action (Buchanan & O'Connell, 2006; Mintzberg, 1979) and a move to the desired state which is different from the current state (Grünig & Kühn, 2009). Grünig and Kühn (2009) succinctly explain the different approaches to decision-making. These approaches include intuition without reflection—a routine that is based on historical practices, influenced by expertise, completely random, and a "systematic rational thought supported by relevant Information" (Grünig & Kühn, 2009, p. 8). Intuition, briefly, "is a complex phenomenon that draws from the store of knowledge in our subconscious and is rooted in our past experience" (Khatri & Ng, 2000, p. 62). Furthermore, Khatri and Ng (2000) argue that intuition is influential in decision-making, despite the presence of evidence. From a historical perspective, decision-making (choice) goes back to prehistoric times and includes all disciplines (Buchanan &

O'Connell, 2006). For example; mathematics, philosophy, sociology, economics, and politics are just a few of the disciplines that aid decision-making processes. Organisations largely employ intuition and/or information/evidence/data-supported decision-making approaches (Brynjolfsson et al., 2011).

"Decision-making is *the* organizational activity" (Pettigrew, 2009, p. 5). Organisational decision-making comprises two parts, which is the identification of the problem and the selection of a course of action (Daft, 2010). Organisational decision-making is complex and multifaceted because there are several types of decision-making considerations. These considerations are programmed and non-programmed decisions; strategic, tactical and operational decisions; and organisational and individual decision-making (Daft, 2010). Some of these types of decision-making considerations are discussed below.

Programmed decision-making are decisions that are typically simple, repetitive and routine, therefore the organisation develops decision processes to address these proactively (Daft, 2010; Galbraith, 2014a). Non-programmed decision-making are decisions that are novel, unstructured, and non-recurring, therefore no process exists for solving the problem (Daft, 2010; Galbraith, 2014a).

Strategic decision-making or decisions are infrequent but have long term implications for the entire organisation insofar as the engagement of firm resources, the impact on the performance of the firm, the involvement of firm-wide functions and it is ambiguous so as to support flexibility and innovativeness in execution (Arendt et al., 2005; Eisenhardt, 1989b). Strategy type decisions have an effect on organisational positioning and direction the enterprise is choosing. "Strategic decisions have been described as committing substantial resources, setting precedents, and creating waves of lesser decisions" (Dean & Sharfman, 1996, p. 379). Tactical decision-making relates to the implementation of strategic decisions, have a medium to short term focus/impact and the impact is typically limited to departments, functional groups or a specific locus within the organisation (Awudu & Zhang, 2012). Middle management are typically the initiators of tactical decisions. Operational decisions relate to daily, weekly and monthly activities such as demand planning, production and supply chain management, and are repetitive (Awudu & Zhang, 2012). Operations supervisors and lower level management deploy operational decision-making and operational decision-making mostly fulfils the execution part of business processes (Varga, 2005).

Organisational decision-making is a process for the selection of the best alternative from the availability of two or multiple alternatives to solve a phenomenon (problem). A decision process normally entails a systematic set of steps that include problem detection, searching for information, evaluation of solutions, selection of solution, put into action the solution and evaluation of decision (Mintzberg &

Westley, 2001). Similar steps or phases to decision-making processes include “intelligence, design, choice and implementation” (Phillips-Wren, 2012, p. 2). “The process of decision making is a set of interactions through which demands are processed into outputs” (Pettigrew, 1972, p. 189). Pettigrew (1972) suggests that demands (problems, phenomena, questions) always flows systematically—rather than randomly—towards positions of power, thereby implying that the decision processes are always consistent. However, “sometimes decisions defy purely step-by-step logic” (Mintzberg & Westley, 2001, p. 89). So, alternatives such as intuition and action-oriented decision making are suggested when faced with unexpected occurrences (Mintzberg & Westley, 2001). Action-oriented decisions are triggered when the decision-maker is faced with an unexpected occurrence—so a divergence from what is expected or desired (Rudolph et al., 2009). IS tools to support and enhance decision-making processes include Management Information Systems (MIS), Decision Support Systems (DSS), Executive Information Systems (EIS), Management control systems and balanced scorecard (Daft, 2010). Decision-making tools are enhanced when decision-making—a human-intelligence driven activity—is attempted to be mimicked by AI tools, is combined with some decision-making tools mentioned, like DSS and EIS, to create intelligent DSS (IDSS) (Phillips-Wren, 2012). IDSS is meant to be intuitive, consistent and mimic decision-makers’ style (Phillips-Wren, 2012).

2.3.1. The Organisation as a Power Structure

“The phenomena of power and influence involve a dyadic relation between two agents which may be viewed from two points of view: What determines the behaviour of the agent who exerts power? What determines the reactions of the recipient of this behaviour? (French & Raven, 1959, p. 259)”. In most definitions of social power, the relationship dynamics between two or more people are described (French & Raven, 1959; Galbraith, 1983; Pfeffer, 1981; Weber, 2012). Dahl (1957) defines power “as the relationship between actors” or “collective entities” (Clegg et al., 2006, p. 208). Within the relationship dyad, a dominant actor imposes their will over another actor despite resistance, which suggests an imbalance of power within the relationship (Weber, 2012). Furthermore, the forcing of will by the assertive actor over the submissive, subservient, subordinate or resisting actor occurs consistently and despite the levels of resistance demonstrated (Weber, 2012). The basis of power is control, which is the ability of one to control tangible and intangible rewards, punishment, results/outcomes and consequences of others (Maner, Gailliot, Butz, & Peruche, 2007). In sum, the evidence suggests that power is central to control of organisational resources, organisational design and organisational structures through the dynamic relationships between individuals with one possessing power and the other yielding to power (Pfeffer, 1981).

2.3.1.1. Major types of power

To better explain power in relation to decision-makers and decision-making in organisations, earlier seminal work, "the bases of power", by social psychologists French and Raven is used to identify the major types of power (French & Raven, 1959). The work identifies the bases of power as coercive, reward, legitimate, expert and referent. Raven subsequently added informational power as the sixth basis of power (Raven, 1965). I briefly describe the six bases of power below.

Types of power	Definition	Examples
Reward Power	It is based on the offering of tangible, emotional, and spiritual rewards in lieu of desired behaviour.	Production bonus, time off, promotion, and salary increases.
Coercive Power	It is based on fear that the power holder has the ability to punish for non-conformance and non-compliance.	Poor performance review, salary decrease, demotion, and more work for less pay.
Legitimate Power	It is based on the recognition of authority—an appointment—to prescribe and control the behaviour of subordinate employees.	Recognition that the CEO directs the company and its resources, and management execute organisational strategy through delegation of work goals, objectives and authority.
Referent Power	It is based on affiliations, trust and respect that becomes an admiration of subordinates, peers and superiors.	Role model, change agent, and loyalty of subordinates.
Expert Power	It is based on a person's knowledge and experience.	Credentials, reputation and demonstration.

Informational Power	It is based on the possession of information on the one hand and the need for information on the other.	Access to information repositories, and information based on privilege (position, expert).

Table 4: Based on *The Bases of Social Power* (French & Raven, 1959; Raven, 1965)

The next sub section discusses power from a distribution perspective and expands on the concepts of centralised and decentralised decision-making strategies.

2.3.1.2. Distribution of decision-making

Legitimate power (authority) is distributed across the organisational structure, which is a hierarchy of roles and responsibilities that participate in decision-making processes (Daft, 2010). Other forms of power, apart from formal power, that could be found across the organisation structure is personal power, which emanates from individual's unique characteristics, differences and values (Robbins & Judge, 2018), Organisational decision-making could be centralised, decentralised, or a combination of both approaches (Galbraith, 2014a; Mintzberg, 1979). Firm decision-making is linked to organisational design, structures, and power centres (Galbraith, 2014b, 2014a). Mintzberg (1979) defines decision-making that is limited to a person (and single brain) as centralised power. The single brain is fraught with imperfections, is limited in its depth of experience and exposure, and is afflicted by human emotions (Elbanna, 2006). To overcome these cognitive limitations, decision-makers revert to rationality such that decisions appear to be reasonable, considering the myriad of organisational, environmental, and political influencing factors (Elbanna, 2006).

As opposed to centralised decision-making, which is mostly concentrated at the top of the organisation's hierarchy, decentralised decision-making is dispersed across organisational structures and power centres (Galbraith, 2014a). Within centralised decision-making, authority is limited to few people instead of cascading down the organisational structure, allowing more people to make decisions within or without predefined limits of authority (Galbraith, 2014a; Robbins & Judge, 2018). Centralised decision-making is deemed to concentrate decision-making power by limiting decision-making to few decision-makers. In decentralised decision-making, decision-making occurs at different levels of the organisational structures and by many decision-makers, each with limits of authority that is contextual in nature, meaning that decision-making is limited to specific roles and responsibilities, and for achieving organisational goals and objectives (Galbraith, 2014a; Robbins & Judge, 2018).

Four types of decision-making power centres are suggested (see Figure 8), which is illustrated as the decision-making continuum (Bolman & Deal, 2017; Galbraith, 2009; Mintzberg, 1979). On the one side of the decision-making continuum, decision-making is limited to [top] management of the firm, with centralised power. On the other side of the decision-making continuum, power rests with the members of the firm. Within the middle of the continuum, decision-making is decentralised, skills-based, and power rest with KWs, professionals, and experts (Galbraith, 2009; Mintzberg, 1979). “Sources of power” could be based on authoritative (managers), “information and expertise” (KW), and coercive (unions/members) (Bolman & Deal, 2017, p. 201)

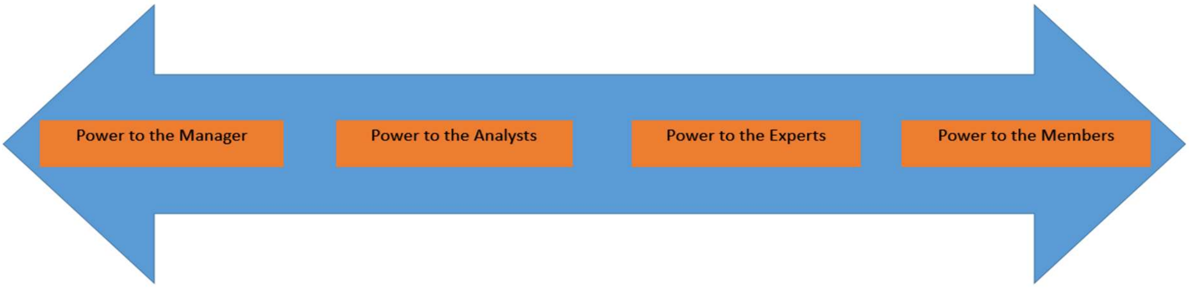

Figure 8: A synthesis of distribution of power explanations (Bolman & Deal, 2017; Clegg et al., 2006; Galbraith, 2014a; Mintzberg, 1979).

The distribution of power (i.e., its structural configuration, organisational structure) within organisations is driven by organisational design, in that it could be based on product groupings, functional groupings, and geography, which then brings the requirement for best fit in terms of decision-making processes, be it centralised or decentralised (Galbraith, 2009, 2014a). Decentralised decision-making is the dispersal of power through different organisational structures (Galbraith, 2014a). A similar view of structural configuration, but termed differently, is that of the “overbounded system” (centralised), which is tightly controlled, and the “underbounded system” (decentralised), which is loosely controlled and encourages competition and conflict (Bolman & Deal, 2017, pp. 205–206). The organisational structure emerges from the successive grouping of units into clusters (Galbraith, 2009; Mintzberg, 1979). The criteria for grouping units into clusters could, for instance, be based on product, geography, skills, and function. This, in turn, creates the 'formal authority' (power) system (Mintzberg, 1979). However, having the power to make decisions does not necessarily imply ability and capacity (Mintzberg, 1979). Clegg et al. (2006) posit that power is the ability to move someone from one place to another, as depicted in Figure 9, where A gets B to move from position B_1 to position B_2. In organisational design, location of experts (specialisation) is a key determining factor in the structural configuration of organisations (Galbraith, 2009).

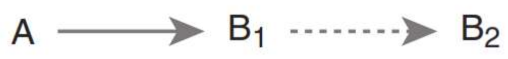

Figure 9: Simplistic illustration of power (Clegg et al., 2006, p. 209)

In terms of power, this thesis centres on the decentralisation method of distribution of power and the middle grouping of sources of power as being the KW. This research is important in understanding the aspects that determine workplace democratisation from a DDD (Big Data) perspective, as it relates to the KW (decision-maker).

2.3.2. Organisational Acceptance

"What is organization but the collective bending of individual wills to a common purpose?" (Clegg et al., 2006, p. 2).

There are limited evidence-based studies that explain the value of Big Data outcomes (insights) and DDD as they relate to organisational structure and enterprise processes (Sharma et al., 2014, p. 434). DDD without firm and individual-level (KW) acceptance will fail if profound behavioural changes, which are necessary to transform and evolve, are not effected within the organisation (Sharma et al., 2014, p. 434). The main concern for organisations, as gathered from a study that assessed the current state of Big Data initiatives in the largest enterprises in USA, is less about technology and more about the lack of leadership capabilities to effect organisational development and change (Davenport, 2012). Organisational success lies in developing and acquiring advanced skills so that information is meaningfully engaged to extract value, which leads to innovative behaviour and enhanced professionalism (Quinn et al., 1998). However, this alone is insufficient in the Big Data era given its characteristics, therefore appropriate decision-making processes, and control guidelines are necessary to support decision-makers to interrogate information, extract insight and make decisions. These all contribute to organisational learning, which is the "management of process, systems and structures of knowledge acquisition" (Alavi et al., 2010, p. 297).

2.3.3. Leadership and management style

"Organizations shape our lives, and well-informed managers can shape organizations" (Daft, 2010, p. 14). With respect to management motivation, the considerations are largely for management to take the lead in directing firms towards evidence (data insight)-based decision-making. For this to happen, decision-makers need to see, trust, and comprehend its value so that it informs decision-making

(Weinberg et al., 2013, p. 197). Blindly interrogating Big Data without a strategy is akin to looking for answers without knowing the questions (Lavalle et al., 2011; Weinberg et al., 2013). DDD does not completely negate human intuition and experience, especially considering that one characteristic of Big Data is that it is messy and requires expertise to tease out the value. The insights from data and management intuition are complementary to effective management and firm performance (Salas et al., 2010).

What is unknown, despite comprehensive literature search, is whether organisations in South Africa rely on intuition on the one hand or on data as the other extreme, or whether they fall somewhere in between. However, there are South African studies, albeit limited, that expose the post-implementation success factors of BI systems within organisations (Mudzana & Maharaj, 2015), discuss critical success factors for BI projects within financial services (Dawson & Van Belle, 2013), explore the role of user satisfaction in implementing BI (Serumaga-Zake, 2017) and explore analytics usage in organisations (Lautenbach et al., 2017). This thesis contributes to understanding decision-making as it relates to Big Data evidence-based decision-making in a South African financial services organisation.

In closing, "Direct participation in decision-making: participation in decision-making may be defined as the totality of such forms of upward exertion of power by subordinates in organizations as are perceived to be legitimate by themselves and their superiors" (Lammers, 1967, p. 205). The aforementioned statement draws attention to the power decision-makers possess and the suggestion that decision-making power has implications on the democratisation of decision-makers.

2.4. ORGANISATIONAL CULTURE AND DATA-DRIVEN DECISION-MAKING

In spite of the abundance of insightful data that is available for decision-making purposes, some enablers and obstacles come into play, such as the age of the firm, innovativeness, and business practices (Brynjolfsson et al., 2011). These enablers and obstacles are tied to the all-encompassing phenomenon of organisational culture that has been shaped through the many years of an organisation's history (Geeling et al., 2016). Organisational culture has many underlying meanings and connotations but is, fundamentally, the learning and adaptation that an organisation undergoes through its years of existence, as it adapts to changing external environmental conditions and shapes itself to deal with internal integration issues (Schein, 2017). External environmental conditions could include responding to marketplace dynamics such as competition and globalisation, regulatory requirements, and technological advancements (Porter, 2008). Internal considerations include the changes required to respond to external conditions, strategy changes, and product innovation, amongst others (Porter, 2008).

Every organisation has an identity that has culminated over time and is somewhat inimitable, as it is a combination of people and artefacts (Alvesson & Sveningsson, 2016; Hatch & Schultz, 1997). This identity is embedded in an organisational culture that is influenced by individual and group beliefs, assumptions, strategy, and leadership, and that culminates in an IS artefact such as a product, and branding (Schein, 2017). The collective beliefs and assumptions of stakeholders—employees, management, suppliers, competitors—come together and present broadly as organisational culture (Schein, 2017). Organisational culture is evident in the organisational behaviour, traits, and attitudes of individuals, and in organisational performance (Alvesson & Sveningsson, 2016).

2.5. WORKFORCE GENERATIONS AND DECISION MAKING

Different generations in the workforce are seen to have different behavioural characteristics, and hence have different implications on organisational decision-making (Alvesson & Sveningsson, 2016). These characteristics are important to understand, since the knowledge-based workforce is progressively comprising millennials and younger generations, who will be increasingly contributing to organisational decision-making over time (Bencsik et al., 2016). Decision-making entails processing information and making a judgement, which is largely based on experience even when evidence is available (Salas et al., 2010). Age diversity in the workplace has implications on decision-making—for example, the knowledge contribution toward decision-making by younger generations could be theoretical and technological in nature, whereas for older generations, experience could be the basis for decision-making (Janz et al., 2012). Behaviour in the workplace, including decision-making, is a function of the person and the environment; and the environment is influenced by, among other things, generational differences (Ketchen & Short, 2012).

Generational bands, commonly defined as ‘born between year x and y’, lack scientific foundation and are rather used as guidelines and tools to identify groupings of people based on the above definition (Dimock, 2019). Because of the lack of scientific studies, there are differing views on generational bands, and several versions exist (Bencsik et al., 2016; Schullery, 2013; Zemke et al., 2013). For this thesis, the bands and labels illustrated in Figure 10 are adopted.

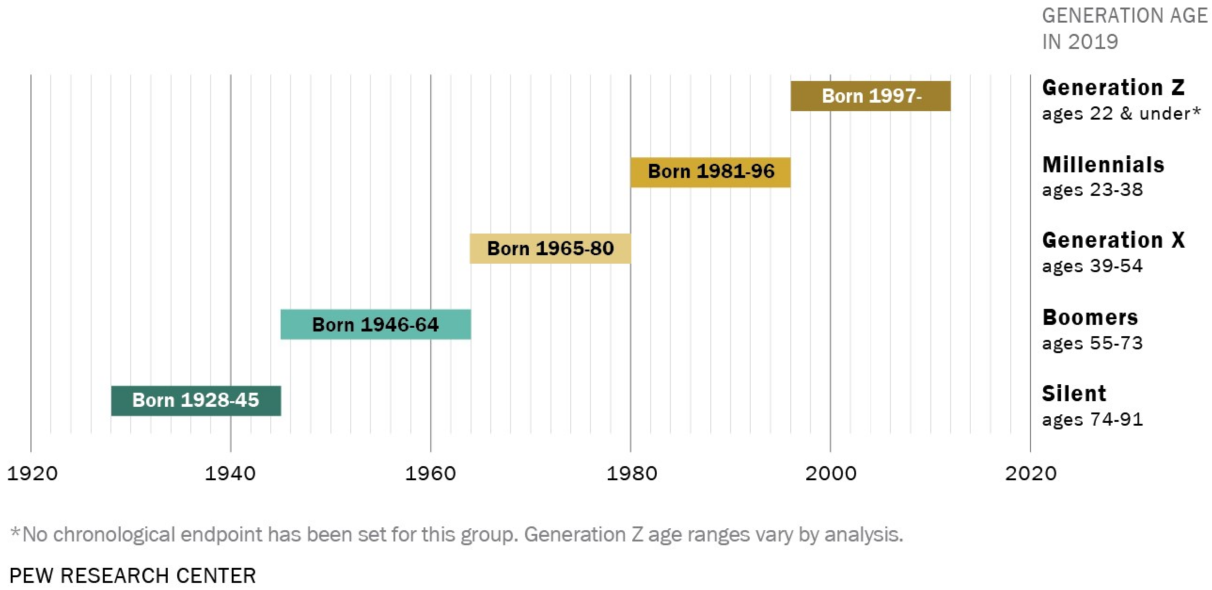

Figure 10: The Generations Defined (Dimock, 2019)

There are five known generations in existence, four of which are active in the workplace. The different generations are referred to as traditionalist or silent (born prior to 1945), Baby Boomers (1946-1964), Generation X (1965–1979), millennials or Generation Y (1981–1996), and Generation Z or the internet generation (iGen) or centennials (1997–present) (Dimock, 2019). The years between brackets are approximate birth year bands and not based on any scientific foundation (Dimock, 2019).

Some key but debatable characteristics of the generations are as follows (Bencsik et al., 2016; Zemke et al., 2013):

a) Traditionalists (the silent generation) value hard work and commitment, and are frugal;
b) Baby Boomers are politically savvy, considered big spenders, and take up either liberal or conservative positions;
c) Gen X are entrepreneurial, first adopters of technology, and cynical;
d) Gen Y or millennials are selfish, entitled, impatient, impulsive, technology-dependent, and social. Millennials are familiar with the digital era, do not recognise barriers in terms of race, and mobile technology is a critical pastime; and
e) Gen Z is still emerging in the workforce and is expected to be more prevalent in the next decade, with the first entrants starting to feature in the workplace already. Their work ethic, work style, and ambitions are yet to be seen. Judging from their current technology use—mainly internet and mobile—instant gratification and transparency are key descriptors.

These characteristics might be present across generations; however, the characteristics are more prevalent in specific generations (Bencsik et al., 2016; Bolton, 2013; Zemke et al., 2013).

'Instant gratification' is common to both millennials and Gen Z, but for different reasons. Instant gratification for millennials means wanting promotions quickly and requiring recognition (Kriegel, 2016). Instant gratification for Gen Z refers to the lifespan for which data is interesting to them, after which disinterest and boredom sets in (Bolton, 2013). The boundaries to what can and cannot be seen (i.e., transparency) is confusing to them as they are familiar with the ineffective controls of the internet; transparency is therefore assumed as given (Bolton, 2013).

2.6. Employee participation in workplace decision-making

There are many concepts that enhance the understanding of employee participation and contribution to workplace decision-making, including freedom, equality, emancipation, empowerment, and democracy (Potterfield, 1999). Freedom is defined, in the context of the workplace, as "people employ their self-reflective abilities to determine the conditions that determine them" (Potterfield, 1999, p. 3). This is taken to mean that employees exercise liberties that are determined by themselves within the workplace. However, it is reasonable to accept that freedom is not a privilege that organisations bestow—freely or not—on their employees, given the need to adhere to statutory laws, corporate governance rules, and creating shareholder value. All these are in place and enforced (Hyman, 2016). Freedom was explained to demonstrate the point that all participation approaches are applicable to this thesis.

Democracy and empowerment are concepts that are fitting for this thesis, as they are of a business-centric nature, and represent current and realistic approaches to employee participation and co-determination in decision-making.

2.6.1. Workplace Democracy

Workplace democracy was defined in Section 1.1.3.

Democracy, from a word and concept perspective, is a combination of the Greek words *demos* and *kratos*, which means people and power or rule, respectively (Ober, 2007). When combined, it essentially means the rule of the people. Democracy in the workplace has been described as "deconstructive self-determination" but, along with this description, it is open to critique in how it is interpreted, rationalised, and realised (Kokkinidis, 2012, p. 234).

Leaning on Mintzberg's (1979) seminal work, “Structuring of Organisations”, which is further corroborated (Anderson, 2015; Bolman & Deal, 2017), democratisation is closely linked to decentralisation in decision-making; the latter refers to the shifting of informal and formal power within organisational structures to the experts because of their knowledge. This is as opposed to a single individual with power or, on the other hand, the power of the entire organisation (comprising individuals with power because of their membership in the organisation) (Mintzberg, 1979).

In the context of this study, workplace democracy is not about strength in numbers, representation, or the right to equal participation in every facet of decision-making within the organisation. The focus is on the ability to self-determine, considering the available data and the application of knowledge to the data in the performance of knowledge-based tasks and the execution of responsibilities.

2.6.2. Empowerment

The concept of empowerment is not new, as it was described in literature over sixty years ago (Maynard et al., 2012). The meaning of empowerment is debatable and flexible in how and by whom it is used (Lincoln et al., 2002). Empowerment is also an ambiguous concept that is in most cases open to interpretation (Hill & Huq, 2004; Lincoln et al., 2002). Empowerment is defined as “imparting or bestowing power to an end or for a purpose” (Humborstad, 2014, pp. 392–393). This, in the context of the study, implies that management allows—but also controls—the use of data and resources, so that employees could accomplish the organisation’s goals and objectives (Lincoln et al., 2002, p. 272). These privileges are linked and tied to roles and responsibilities. Furthermore, the aforementioned authors describe ‘empowerment’ as the journey rather than the accomplishment itself. It “is not power itself” but “employee involvement techniques” such that employees’ “self-efficacy” is raised (Lincoln et al., 2002, pp. 273, 281). Without ‘empowerment’ to use necessary resources, it becomes difficult or unattainable to satisfy the requirement for the job role. This defeats the purpose of having the role in the first place, and consequently reflects negatively on management and the company.

‘Empowerment’ also brings with it control (access control, compliance, governance) that shapes the participation of the employee to conform with the organisation’s idea (and deployment) of self-determination (Yeoman, 2014). An example of this control is that, based on an employee’s role, only those resources necessary to fulfil the role —data, facilities, tools, assets—are made available. Limiting the resources brings reasonable assurances on the best and worst outcomes of that afforded privilege (Humborstad, 2014). If this cascaded across the organisation, the resulting effect is that management has effective control, albeit with minor deviation. ‘Empowerment’ has challenges in the Big Data era, as Big Data is pervasive and often not fully controlled by the firm—for example social media, which sees the shifting of power as related to online presence and organisational branding (Davids, 2017). Power is shared with the online community. Admittedly, the firm has the right—through processes, policies, and governance mechanisms—to control the effect of Big Data through granular control and veracity checks. However, controlling the vastness and embeddedness of Big Data in every aspect of the corporate fabric and lives of human beings that operate companies is increasingly difficult.

2.6.3. Employee participation in data-driven decision-making

Approaching the research problem from a workplace democracy perspective as opposed to a business-centric classification such as empowerment is intentional. Empowerment is described as an authority to achieve an end through the mobilisation of resources (Humborstad, 2014). It is the granting of permission to achieve a stated objective. Conversely, democracy is largely attributed to political determination—which is a right. However, in the context of this study, "co-determination" is more plausible as it brings the employee-employer relationship into the discourse. The inferences of the term 'democratic' enlightens the discourse around an individual's power in decision-making, which is the effective participation in matters and the outcomes that have a direct bearing on one's interest (Humborstad, 2014). Direct participation, a democracy theory, postulates that individuals with knowledge and influence should be afforded meaningful participation in policies and decisions that affect them. 'Real decision power' is effective, as individuals who follow the direct participation path in democratic processes think outside the box and take a longer-term perspective on matters (Laird, 1993).

Leaning on extensive earlier work, democratisation in decision-making in organisations focuses largely around centres of power and authority (Bolman & Deal, 2017; Clegg et al., 2006; Galbraith, 2009, 2014b; Mintzberg, 1979). On the one hand, power resides with management. On the other hand, power is equally distributed to all members of the firm, regardless of position or role. The middle of the power-authority continuum, that is, the knowledge-based decision-maker, is the focal point of this thesis. Consequently, the focus is on understanding the democratisation of the decision-maker in DDD from the expert's perspective (Mintzberg, 1979; Wright et al., 2018).

Democratisation, from a DDD perspective, is about having access to relevant and needed data. Importantly, workplace democracy is more than just participation in decision-making, it is also about having the necessary skills (education and training) to employ data analytical tools to derive useable insight, it is about having relevant information to make informed decisions, and it is about having meaningful choices (Pausch, 2014).

Empowerment and democratisation are critical concepts in this thesis. Both concepts are used to lead a discussion in a particular way.

2.7. PROBLEMATISING THE LITERATURE REVIEW

Big Data is not without its challenges. Enterprises are adopting Big Data to gain competitive advantage, whether it is through marketing and social media, banks and financial markets, production and supply chains, or governments and citizens (Boyd & Crawford, 2012). However, there are traditional considerations that will continue to play a role in how decision-making is cascaded throughout the organisation. These include legal, regulatory, and governance-related matters and might intensify, not abate, with respect to Big Data. Adherence to security and privacy processes are critical success factors insofar as the collection, analysis, and sharing of Big Data are concerned (Mikalef et al., 2018). Regulations and standards such as the Protection of Personal Information (POPI) Act[4] and Payment Card Industry (PCI) Data Security Standard (DSS)[5] are mechanisms to ensure that data is protected against fraud, privacy infringement, and theft (financial, identity, information,).

Workplace democracy is an established organisational concept and well researched (Foley & Polanyi, 2006; Pausch, 2014). Big Data and DDD are not new concepts to the IS community, and have been studied—albeit more so in recent times (McAfee & Brynjolfsson, 2012). The increased attention to Big Data and DDD concepts is largely because of practitioner hype (Phillips-Wren et al., 2015). However, the limited research around democratisation of decision-makers in DDD as a consequence of the use of Big Data in organisations is concerning. This is especially startling as the workforce is continually evolving. Variety, a characteristic of Big Data, specifically from an applications perspective, provides for the different age groups in the workplace. Tools such as WhatsApp, Facebook, and Twitter are legitimate business tools that are used to speed up decision-making (Bharadwaj et al., 2013). In the past, these tools were prohibited in the workplace (Boyd & Ellison, 2007). To grasp how variety and other characteristics influence democratisation of the decision-maker in DDD, the researcher has to be critical to organisational design, structure, and processes (Galbraith, 2014b). Research on the set of interrelated concepts of Big Data, democratisation, and DDD is scarce from a global perspective, and even more so from a local context perspective (i.e., South African organisations). This conclusion is based on a comprehensive literature search that followed a concept-centric approach (Webster & Watson, 2002).

[4] https://www.gov.za/documents/protection-personal-information-act

[5] https://www.pcisecuritystandards.org/

The risks with respect to researching the identified phenomenon, especially as it relates to a developing country, are that Big Data may not yet be considered essential; hence, the context and phenomenon may be mismatched (Allan, 2003). Reasons for this could include a lack of competence in Big Data analysis, a lack of resources, a lack of perceived value, a lack of interest by management, a lack of organisational structure that is conducive to change, or, possibly, a lack of Big Data (Van Es & Schäfer, 2017). These are real possibilities. However, these possibilities also create an environment in which to deliver a theory that is novel.

The absence of publications on Big Data within South African organisations, as related to democratisation of decision-makers in DDD, indicates the importance to expand the very limited knowledge base. The uniqueness of this context would result in novel contribution. Even creating awareness of the phenomenon would constitute a step in the right direction.

Empirical work is lacking with respect to the three main concepts of Big Data, democratisation, and data-driven decision-making, as well as the context. A brief summary of the open and persisting gaps that were uncovered during the literature review follows:

In a South African study, several research opportunities were identified (Malaka & Brown, 2015). One, in particular, pertains to DDD as related to Big Data, wherein decision-making is hampered because of organisational configuration, culture, and a lack of support at the strategic and firm level (Malaka & Brown, 2015). This leads to the dynamic capabilities of the firm and its adaptation to a Big Data environment (Braganza, Brooks, Nepelski, Ali, & Moro, 2017). Similarly, knowledge around the effect of DDD and organisational alignment—taking into consideration culture, politics, regulatory, economic, social, legal, and competitive matters—is lacking (Sheng et al., 2017).

Traditional decision-making has largely been based on authority. Whether it is the owner or management, it is increasingly based on intuition (Elbanna, 2006). As far as can be determined, there seems to be very little research, apart from studies in the United Kingdom (Bakhshi & Mateos-Garcia, 2012), United States (Brynjolfsson et al., 2011), and the EU (Côrte-Real et al., 2017), that produces empirical evidence to quantify the return on DDD. This explicitly implies that successful enterprises have higher proportions of data-driven versus intuition/experience-driven decisions. Based on the two extremes of decision-making, there is a dearth of empirical studies that better explain the enterprises in South Africa and where they lie within these two extremes. Additionally, the transition between these continuums is unknown (Abbasi, Sarker, & Chiang, 2016).

Despite the possibilities of Big Data in aiding better decision-making, the limitations do not lie solely with the technology (Davenport, 2012). Data analytics, which are the tools for extracting value, always start with people-driven questions. From the literature, it is not possible to gauge the capabilities of organisations in South Africa for producing usable DDD knowledge. This appears to be a global phenomenon, as further research is suggested into understanding the interrelationships between analytics, organisational decision-making processes, and firm performance (Akter & Wamba, 2016; Braganza et al., 2017). Top-performing firms use analytics five times more than lower-performing firms (Lavalle et al., 2011).

It is somewhat unclear from the current knowledge as to whether DDD is different in organisations where structured/internal datasets are supported by business analytics and operational business processes, compared to organisations that use Big Data in decision-making (Gupta & George, 2016).

The common thread in the identified gaps is centred on the continuum of [Big]DDD as evidence-based decision-making versus intuition-based decision-making, which is closely related to power centres (Bolman & Deal, 2017; Mintzberg, 1979). In decentralised firm structures, select employees—mainly management—are empowered to make decisions. However, the persisting phenomenon is around Big Data as an influencing factor of democratisation of decision-makers in DDD processes. The gaps identified indicate possible interrelationships between the key concepts, but the gravity thereof is yet to be determined.

Several gaps have been highlighted in the literature to support the focus of this thesis. Due to the lack of empirical research and supporting theoretical frameworks, the challenge is that, regardless of the pre-existing IS social theory that is used, it will result therein that the empirical situation and subsequent findings are tailored to fit the theory (Avison & Malaurent, 2014). An attempt to fit all concepts together to see the interrelatedness of the whole as influencing factors is not addressed by current social theories. For these reasons, this thesis utilised the Grounded Theory Method (GTM) to develop a theoretical framework from which to explain the phenomenon (Glaser & Strauss, 1967).

3. Research Design – A Grounded Theory study

3.1. Grounded Theory: An overview

GTM has been selected as the method that will guide this inquiry; it is appropriate to answer the research questions (Glaser & Strauss, 1967), as has been outlined in Section 1.4. GTM is intended to expose a theory through the systematic analysis of qualitative data that has been attained from an empirical situation, to explain a phenomenon (Glaser & Strauss, 1967). GTM is directed by rich research methodological guidelines. In its quest for new theory creation from empirical data, GTM is inherently aimed at circumventing theoretical stagnation (Heath & Cowley, 2004). GTM is "an inductive theory discovery methodology that allows the researcher to develop a theoretical account of the general features of the topic while simultaneously grounding the account in empirical observations of data" (Fernández, 2004, p. 43).

There are two distinct parts to GTM, namely, method and theory (Matavire & Brown, 2013). The method of GTM informs researchers through guidelines and techniques in coding, the conceptualisation of the identified codes, categorisation of the concepts, and exploration of relationships through capturing, recording, and analysis of the empirical data (Corbin & Strauss, 2014). The theory of GTM is largely an outcome of the coding-concept-category analytical steps and constant comparative analysis that results in the theoretical framework (Glaser & Strauss, 1967). GTM brings together data collection and analysis into a cohesive and iterative cycle, thereby creating a theory. The resulting theory is unhindered by preconceived ideas and is not an outcome of tailoring the results to fit the adopted theoretical framework, as is the case with traditional approaches to IS research. The results, through continuous confirmation, allow the empirical data and the situation to speak for itself.

GTM pivots around three main principles—emergence, constant comparative analysis, and theoretical sampling (Matavire & Brown, 2013).

a) The principle of emergence advances that the research does not begin with preconceived notions, but rather from perspectives that emerge from the empirical data. Emergence is the outcome of constant comparative analysis and theoretical sampling. Emergence is about the emergence of codes, concepts, and categories through the systematic and iterative interrogation of empirical data and by always asking "what's going on?" (Glaser & Strauss, 1967).

b) The foundation of the constant comparative analysis is to generate theoretical ideas systematically (Glaser & Strauss, 1967). These theoretical ideas are formed through analysis of empirical data to identify new and interesting properties, which are assigned code words. Apart from this, writing memos to capture the essence of the data is important for keeping in touch with the data and the formation of theory (Heath & Cowley, 2004). Assigning code words to interesting data, grouping these codes into higher-level concepts, and further grouping concepts into categories are the methods behind theory development. The constant comparative analysis process is iterative and continues to compare codes, memos, concepts, and categories until saturation is achieved—that is, until nothing new is discovered (Stol et al., 2016). From these high-level categories and the memos captured, a theory emerges based on the core categories identified.

c) Theoretical sampling is based on proven theoretical relevance (Corbin & Strauss, 2008). It comprises the collection of more data to develop the properties identified in codes, concepts, and categories, based on an analysis of the initial and earlier empirical data. Once new data is collected, the constant comparative process starts again and continues until no new properties emerge.

3.2. Different Grounded Theory approaches

Two well-known grounded theory models are classical GTM (CGTM) and Straussian GTM (SGTM) (Heath & Cowley, 2004; Matavire & Brown, 2013; Stol et al., 2016). The original authors of GTM, Glaser and Strauss, parted ways because of divergence in views on: a) how a theory emerges (or is forced) from and within the empirical situation; b) worldview perspectives; c) conducting literature reviews prior to data collection; and d) stating research questions as the precursor to research inquiries (Eisenhardt & Graebner, 2007; Heath & Cowley, 2004; Stol et al., 2016). These aspects are briefly described and compared below. Constructivist GTM is another prominent GTM approach, which extols that objective reality is non-existent, but that realities are "social constructions" of the individual (Charmaz, 2006, p. 131). The constructivist approach advances that data is constructed mutually between the participants and the researcher, with the theory being formulated through the researchers' paradigm, interpretations, and perspectives (Glaser, 2002).

As many as seven lesser-known GTMs exist (Stol et al., 2016). Apart from these, researchers sometimes claim that their studies are GTM-based. However, a recent study found that almost half of the investigated papers that claimed to be GTM-based were, in fact, using GTM techniques, concepts, and/or were inspired by the approach, but were not grounded theory studies (Stol et al., 2016). In a supporting paper, it was found that fellow contributors utilised GTM techniques, such as coding principles, to analyse empirically collected data (Matavire & Brown, 2013).

Although GTM had jointly been conceived by Glaser and Strauss (1967), Glaser retained the original version, while Strauss and Corbin have sought to evolve GTM (Heath & Cowley, 2004; Matavire & Brown, 2013).

Glaser continued with GTM, which originally emanated from a positivist perspective and is known as Glaserian GTM or CGTM (Seidel & Urquhart, 2013). CGTM follows an inductive reasoning perspective, and espouses flexibility and freedom in data analysis (Glaser & Strauss, 1967). It does not compel or ask for verification processes, as Glaser insists that the data must be allowed to tell the story which, in turn, becomes the theory. Purposely, limited guidelines are provided; this, according to Glaser, is the crux to unconstrained theory development.

Strauss partnered with Corbin to pursue GTM from a constructivist perspective that is known as Straussian GTM or evolved GTM (Babchuk, 2009; Heath & Cowley, 2004; Matavire & Brown, 2013). It is still considered an evolving GTM (Stol et al., 2016). SGTM insists on verification, validation, and elaboration processes. SGTM is restrictive in that guidelines are provided around coding and adherence to processes, which directly contradicts the CGTM principles of exploring the data for meaning, as opposed to trying to shape the theory with the paradigm model (Urquhart et al., 2010). However, the guidelines could also be considered as a benefit since GTM, in its original and current form—CGTM—is vague and left open to interpretation and the researcher's own devices.

A key fundamental difference between CGTM and SGTM pertains to theory development, which Glaser (CGTM) contends must emerge from the data (Duchscher & Morgan, 2004; Matavire & Brown, 2013). This is as opposed to SGTM, in which Glaser proclaims that theory is forced through the use of "preconceived categories" (Charmaz, 2006, p. 8). SGTM is seen to be rigid, which is contrary to grounded theory principles (Babchuk, 2009).

The other differences between Glaser's Classic GTM and Straussian GTM have been explored sufficiently in the literature (Heath & Cowley, 2004; Matavire & Brown, 2013; Seidel & Urquhart, 2013; Stol et al., 2016). A brief synthesis of these differences is as follows:

a) Philosophical position - Glaserian GTM follows a more positivist approach, with the data being viewed as a single truth. Straussian GTM posits a more constructivist perspective, which professes to embrace multiple realities rather than a single reality. These realities are discovered through interaction and communication with the actors (Charmaz, 2006).

b) Research question/s – Glaser's approach to research is to enter without any predefined research questions, but with an idea or area of interest (Heath & Cowley, 2004; Matavire & Brown, 2013; Stol et al., 2016). On the other hand, in the SGTM approach, the research question is deemed an important mechanism to focus the researcher, by formulating the identified research gaps into achievable objectives.

c) Literature – The need and/or place for literature reviews have been contentious since GTM's creation (Charmaz, 2006). Glaserian GTM (Glaser & Strauss, 1967) suggests that conducting literature reviews at the beginning of the research project has an influence and bearing on aspects of the inquiry, which might include data collection, interpretation, and data analysis. Instead, they suggest that literature reviews should be delayed until the theory begins to emerge (Stol et al., 2016). However, prominent scholars have ridiculed the incorrect assumption that producing a theory without prior knowledge and experience of the subject area is a characteristic of GTM (Suddaby, 2014). SGTM, on the other hand, promotes literature reviews throughout the empirical journey (Corbin & Strauss, 2008; Stol et al., 2016; Suddaby, 2014).

3.3. Limitations of Grounded Theory Methods

Although GTM offers flexible and practical approaches to uncovering a theory, some inherent limitations exist.

As discussed in previous sections, there are multiple approaches to GTM, such as Classical, Straussian, and Constructivist, which are at times confusing to the novice researcher (Hussein et al., 2014).

Constant comparative analysis, as related to large volumes of data, could lead to confusion, mistakes, and overlooking important pieces of information within the data (Corbin & Strauss, 2008). However, the data collection and analysis methods as prescribed by SGTM minimise this.

The nature of interpretive philosophy is that multiple, subjective realities exist (Creswell, 2007). Intentionally, SGTM is selected to construct a theory from the empirical data gathered; this is subjective, as the participants' and researcher's worldviews are interrogated (Creswell, 2007; Mills et al., 2006). There is also a (more beneficial) risk in the possibility that the theory is co-constructed as a result of "reciprocal" influences by the researcher and participant (Corbin & Strauss, 2014, p. 35).

Producing theory from the empirical situation is possibly tainted by researcher bias and subjectivity in interpretation; therefore, the theory and generalisation thereof for further use is challenging; however, GTM is grounded in data and rigour (Urquhart & Fernandez, 2006). Moreover, it is a myth that researcher bias and preconceptions limit theory building; the opposite is true in that it enables a continual assessment of "conflicting realities" that allows for freer thinking (Eisenhardt, 1989a, p. 546). SGTM conceptualises researcher involvement in the empirical situation through theoretical sensitivity (Corbin & Strauss, 2008). Theoretical sensitivity relates to researcher traits, professional and personal experiences, exposure to the empirical situation, and extant knowledge that has a bearing on theory building (Corbin & Strauss, 2008). The intention is to immerse the researcher in the research environment by interacting and communicating with the research group (Charmaz, 2006; Mills et al., 2006). In so doing, a theory is jointly developed between the participants and the researcher. However, in spite of this necessary involvement, the role of the researcher in this study is to remain largely in interrogation, learning, and scepticism mode, while consistently adhering to the principles of SGTM (Corbin & Strauss, 2008; Heath & Cowley, 2004). It behoves the researcher to ensure rigour in following GTM guidelines such as constant comparison, theoretical sensitivity, and theoretical sampling, since these present additional safeguards to mitigate the highlighted challenges.

As mentioned within the introduction to this chapter (see Section 3.1), GTM (and specifically Straussian GTM) has been selected for this research. The research strategy that is based on GTM is discussed further in Section 3.5.

3.4. Research philosophy

This section addresses the research philosophy of interpretivism, the ontology, and the epistemology that underpin the research (Myers et al., 1999). These have an influence on the research methods, data collection stages, interpretation of empirical evidence, and theoretical framework (Bryman, 2012).

In adopting Straussian GTM (SGTM) as the method of inquiry (see Section 3.5 for justification), the ontological and epistemological stances could be closely associated with GTM principles (Ralph, Birks, & Chapman, 2015). Alternatively, the researcher could adopt perspectives that facilitate better interaction with the actors in the empirical situation, such that the ontological position is that of the researcher and the epistemological stance aligns with the empirical data (Ralph et al., 2015). For the purposes of this study, the following philosophical perspectives are adopted.

3.4.1. Ontology

The perspective held by the researcher is that reality is constructed through interaction and communication within the research cohort (Stol et al., 2016). Therefore, the ontological position is aligned to social constructionism, constructivism, postmodernism, and interpretivism (Bryman, 2012).

This ontological stance aligns with GTM, as originally conceived, wherein the empirical reality is realised through observation and ongoing interpretation (Suddaby, 2014). Reality, from a GTM perspective, emerges from the empirical observation and from ascribing meaning based on the actual situation (Glaser & Strauss, 1967).

3.4.2. Epistemology

Leading on from the selected ontological position, the epistemological position is that there are underlying truth and deeper meanings that are waiting to be exposed. It is consistent with this belief to let the data expose the events and activities, such that data-driven theory emanates that could explain the research phenomenon. The epistemological stance taken in this thesis is that of an interpretivist; the empirical data will lead the researcher, which is consistent with SGTM (Mills, Bonner, & Francis, 2006). Interpretive studies centre on demystifying a phenomenon by understanding the meanings that participants ascribe to things and occurrences as they shape their understanding (Creswell, 2007).

3.4.3. Inference and Reasoning

GTM has come into existence to extract a theory from data that could explain a phenomenon that is impactful to society (Mills et al., 2006). It is an inductive method of theory development (Glaser & Strauss, 1967). Importantly, the research from an inductive reasoning perspective is suited to this research, as there are limited knowledge and theories that explain the phenomenon; hence, theory building is necessary (Eisenhardt & Graebner, 2007).

3.5. Research strategy: Grounded Theory Method Selection

Based on the key characteristics and limitations of the different GTM implementations, especially of CGTM and SGTM as the two prominent versions, the SGTM method is preferred and adopted for this research. The rationale for this decision is based on the method's key research principles, the ability to define the research via a research question, the consistent review of the literature throughout the empirical journey, and the nature of the guidelines stipulated within SGTM (Heath & Cowley, 2004; Matavire & Brown, 2013; Stol et al., 2016). The “forcing” accusations, which are attributed to axial coding and the paradigm model, are considered beneficial insofar as the grouping of codes after the initial/open coding processes allows for a deeper exploration into the interrelationships and contextual factors that arise from codes, categories, and sub-categories (Duchscher & Morgan, 2004; Matavire & Brown, 2013). Axial coding, which is the process of identifying relationships between codes (further defined in Section 3.7.4.2), was initially mandatory in SGTM; however, the method has evolved over time to become optional (Seidel & Urquhart, 2013). The aims of SGTM are to produce a theory that is abstract to the point that versions thereof explain other phenomena and incorporate sufficient rigour to ensure transparency and validity (Corbin & Strauss, 2008).

3.6. DATA COLLECTION

3.6.1. The case study as data collection strategy

Case study research was selected as the research strategy, of which data collection is a critical part (Myers et al., 1999). Case study research is focused on "understanding the dynamics present within a single setting" (Eisenhardt, 1989a, p. 534). This research adopted a mixed methods approach, which is the combined use of GTM techniques and case study research; this is consistent with Straussian GTM (Matavire & Brown, 2013). Although a case study research strategy for data collection is recognised, similar to that of surveys and experiments, caution is suggested around case study principles that advocate development of theory prior to case study data collection as an essential step to case study research (Fernández, 2004). This is counter to GTM principles in that theory building is the outcome of empirical data collection and observation.

A case study is the investigation of a phenomenon within a bounded system, which could mean a constrained context and setting (Creswell, 2007). Another definition is the investigation of a phenomenon in a natural setting, and employing multiple methods to collect data from individuals and organisations (Benbasat et al., 1987). A third definition is the study of a real-world case, in which the context suits the problem (Yin, 2018). Case study research is a research strategy for the emergence of theory when a real-world setting is warranted, especially when there is limited knowledge in the area of observation (Yin, 2018). It is pertinent for an exploratory inquiry into a real-life situation where the boundaries between phenomenon and context are not evident (Yin, 2018).

A single-case research strategy focuses the attention on the single setting, as opposed to a multitude of research settings that have their own forces-at-work that could shape the narrative (Eisenhardt, 1989a). Studying a single aspect of organisational decision-making fits a single case study research strategy (Creswell, 2007). Multiple case studies are appropriate for "replicating or confirming results", which is not the case here and is counter to GTM (Yin, 1981, p. 101). Having two or more cases strengthens credibility and affords better "theoretical replication" (Yin, 2018, p. 98). However, this is a "revelatory case"; therefore, theory generation rather than theory testing and triangulation is the intention of the research (Benbasat et al., 1987, p. 373).

3.6.2. Case Description

3.6.2.1. Case Study CSA – Company in the financial services and insurance industry[6]

CSA provides financial products and services to individuals, and businesses of all sizes. Financial products and services include life assurance policies, short term insurance, wealth management, asset management, financial planning and typical banking services like loans and savings facilities. The company has a national and international presence, and operates in 17 countries. CSA is listed on multiple stock exchanges. CSA has grown organically and through acquisitions over many decades. Approximately 31,000 people are employed by the firm. The routes to market include physical retail stores, digital channels, and third-party partners that act as brokers and financial advisors. The company's products and services are targeted at people of all ages, genders, and races.

As can be expected, the ICT assets of this case study are vast and extremely complex. The following (largely approximated) information has been provided:

- Servers (physical and virtual) - ~4000
- Applications - ~180-250 that are known and have dependencies on other services within the company. This excludes software that is installed on standalone servers, workstations, and laptops. It also excludes applications that are procured and consumed as a service from cloud service providers. Some ICT assets are listed below:
    - Databases – Oracle[7] and IBM[8] are key suppliers
    - ICT Asset management – Flexera[9]

[6] Section K: Financial and insurance activities. This section includes financial service activities, including insurance. http://www.statssa.gov.za/classifications/codelists/Web_SIC7a/SIC_7_Final_Manual_Errata.pdf

[7] www.oracle.com

[8] www.ibm.com

[9] www.flexerasoftware.com/

- ICT Service Desk - Cherwell[10]
- Business Analytical tools – Alteryx[11], Tableau[12], and DataRobot[13]
  - Various pre-emptive and well-known data reports are available to approved KWs.

- The current data storage capacity has not been established, as the company has several business units, each with data stored on-premises and hosted in the cloud.
- Several data warehouses are employed across the organisation, and are managed independently by business units.

Big Data sources are Public Data, Private Data, Community Data, and Self-Quantification Data (Gerard George et al., 2014). The organisation employs the first four types of data in various forms. A brief description of the data types, based on the work of George et al. (2014), follows.

Public data is government-generated and -stored data that is used for administration purposes (Gerard George et al., 2014). CSA accesses the South African government's Department of Home Affairs for citizen information such as confirmation of identity numbers, names, dependents, title deeds, births, and death details. The information is exchanged through an application programming interface (API) and provided by an individual citizen identity number rather than in bulk or in an offline manner, as that would transgress government regulations.

Private Data is data that is generated, stored, and managed by non-government organisations such as enterprises and individuals (Gerard George et al., 2014). Nearly all the data housed within CSA is CSA-generated data. Stored data is largely maintained in structured datasets, the extent of which is unknown because of multiple business units hosting independent, but accessible, data warehouses. CSA purchases marketing-related third-party data. From a CSA perspective, Big Data is relative, as just one terabyte of customer data in spreadsheet format is unheard of and will be challenging to use for end-

[10] www.cherwell.com

[11] www.alteryx.com

[12] www.tableau.com

[13] www.datarobot.com

user computing devices, such as desktop memory and processors. However, addition of multiple platforms and variety could easily exceed terabyte sizes[14].

Community data is largely social media-related data (Gerard George et al., 2014). CSA, from a social media perspective, does not utilise dedicated and automated tools for collecting relevant and interesting social media feeds from platforms such as Twitter, Facebook, and Instagram. While Twitter is largely visible in the public domain, other social media platforms such as Facebook and Instagram have privacy capabilities, which block unauthorised access to social media feeds (Tufekci, 2014). Monitoring of customer feedback and communication happens on CSA-controlled social media sites and web portals alone. This is a manual process and collated into business reports. A separate media team monitors the print and electronic media.

Self-quantification data is individual-centric data, and is linked to behavioural psychology (Gerard George et al., 2014). Self-quantification typically provides tracking and monitoring for mental, emotional, and physical well-being—for example, Fitbit exercise/activity monitoring.

Of importance is the fact that CSA survives and thrives through relationships with customers, that is, business-to-consumer (B2C) relationships. Business-to-business (B2B) relationships exist for supply chain purposes and, importantly, for the exchange of financial instruments such as equities, currencies, and bonds. The scope of the study did not venture into the realm of B2C or B2B engagements and relationships. However, the importance of customers and serving them optimally continually arose as discussion points during the interviews. The importance of financial and customer data—specifically from a privacy/confidentiality perspective, as related to investments/instrument trading and customer integrity, respectively—arose when discussing the critical nature of Big Data to the organisation. In CSA, keeping existing customers interested, increasing the wallet share of existing customers, and recruiting new customers across five very different generations, backgrounds, and statuses were challenging focus areas for the company.

CSA became the focus of the research, and eventually the only case study for this thesis. This was decided when CSA offered three very different departments, which were interesting to explore as diverse groups within a case study (Benbasat et al., 1987). The unit of analysis that will best inform the research questions is the KW—that is, an individual that is the ultimate decision-maker (Benbasat et

[14] 1000 terabytes equal 1 petabyte; 1 million terabytes equal 1 exabyte; 1 billion terabytes equal 1 zettabyte.

al., 1987; Frisch, 2011). CSA offered complexity in terms of their ICT deployments, multiple perspectives from the vastly different department, and diversity in terms of participants. The CSA case study was anchored by a common senior leadership, strategy, and vision.

3.6.2.2. Summary facts for the case study

No. of interviews	41
No. of departments participated	3
No. of generations participated	3 (Baby Boomers, Generations X and Y) (No participation from Generation Z)
Distribution KW Job Title/Role	Managers (KW): 19, Non-managers (KW): 22
Data Scientists, Data Analysts, BI Specialists	7 participants out of 41 participants
Data collection period	6 months (December 2018-May 2019)
Audio Recordings	~54 hours (excluding harmonisation and introductions)
Transcribed Words	~220,000

Table 5: Summary facts for the Case Study

Table 5 provides a summary of the case study. Further discussion on participants can be found in Section 3.6.3, while Section 8.3 provides a list of the participants, with details of the departments, generational classification, and job title/role. All other details—especially the participation code—has been omitted to protect the identities of the participants (Bryman, 2012).

3.6.2.3. CSA As A Big Data Environment

CSA is considered a Big Data environment, as the datasets of the organisations meet the key Big Data characteristics of volume, variety, veracity, and velocity. This reflected by the size of the organisation, its global presence, and a history (and hence data source) that spans over centuries. The variety of products, millions of clients, and multiple routes or channels to market via retail stores, online portals, telemarketing, and third-party providers create a significant amount of variety in the datasets and types of data housed, such as web, voice, and mobile. Veracity is fundamental when dealing with several sources of data to ensure the integrity of data—especially data that is unstructured in nature. Moreover, CSA is in an industry that is highly visible and actively monitored by the authorities. Due to the significant amounts of money under management, velocity is critical—especially real-time tracking of financial instruments (Trelewicz, 2017). Velocity is less important when near-real-time decisions are being made, and even less important for batch processing of data.

This research views Big Data as data that is largely comprised of internal datasets that are both historical (structured) and new (unstructured and semi-structured). The emerging notion around the concept of 'Big Data'—specifically within the case study— is that ALL information is considered part of the Big Data concept, including voice, video, sensor (IoT), traditional datasets, and newer type datasets (Baesens et al., 2016). Further clarification is important to understanding the empirical environment:

- CSA houses data repositories in company-owned and managed datacentres using key ICT assets such as storage, security systems, applications, business intelligence, BDA, servers, and networks.
- Several ICT assets, such as email systems, databases, applications, and third-party tools have been relocated to hosted environments. The extent of the hosting agreements have not been fully established, but could include platforms as a service, infrastructure as a service, and software as a service. Proprietary data is housed within CSA premises.
- The access to externally hosted services, whether it is company data or the mentioned services, is through Virtual Private Networks (VPN) and secure internet browsers.

CSA is in the customer-facing business, and interaction with customers is realised through retail, online, telephony, third party brokers, and direct engagement. The organisation's success is dependent on achieving high customer satisfaction levels. For this reason, telephony systems are critical, with their call centres providing a key interface to customers. Voice calls are recorded to enhance organisational effectiveness and customer satisfaction. In the few examples discussed (see Section 4.5.3.1), the insight contained within voice calls is invaluable.

3.6.3. The Participants

Participants represented three different departments, namely, ICT, Customer Services (CS), and Corporate Property Management (CPM) as highlighted in Section 3.6.2.2. All three departments report to the same executive leadership structure. The risk of having participants from the same department relates to the extent of exposure to the phenomenon, synchronised perspectives, or apprehension in expressing viewpoints. Multiple departments are not intended to test, verify, or validate information, but to expand the richness and contribute to the understanding of the phenomenon. The unit of analysis is the KW rather than the company, as the research focus is on the democratisation of the KW in DDD in a Big Data environment. From within the departments, representatives participated from sub-departments that included social media experts, facilities management, data scientists, data analysts, and wealth management experts. All participants interacted with Big Data and were deemed specialists by their companies from a roles and responsibilities perspective. There was a fair mix of managers and non-managers. The ages of participants spanned at least three generations, namely, Baby Boomers, Generation X, and millennials (Gen Y). Generation Z (iGen) was not represented, since this generation will only start to actively participate in the workforce from 2020, based on the assumption that they are currently engaged in some form of tertiary education.

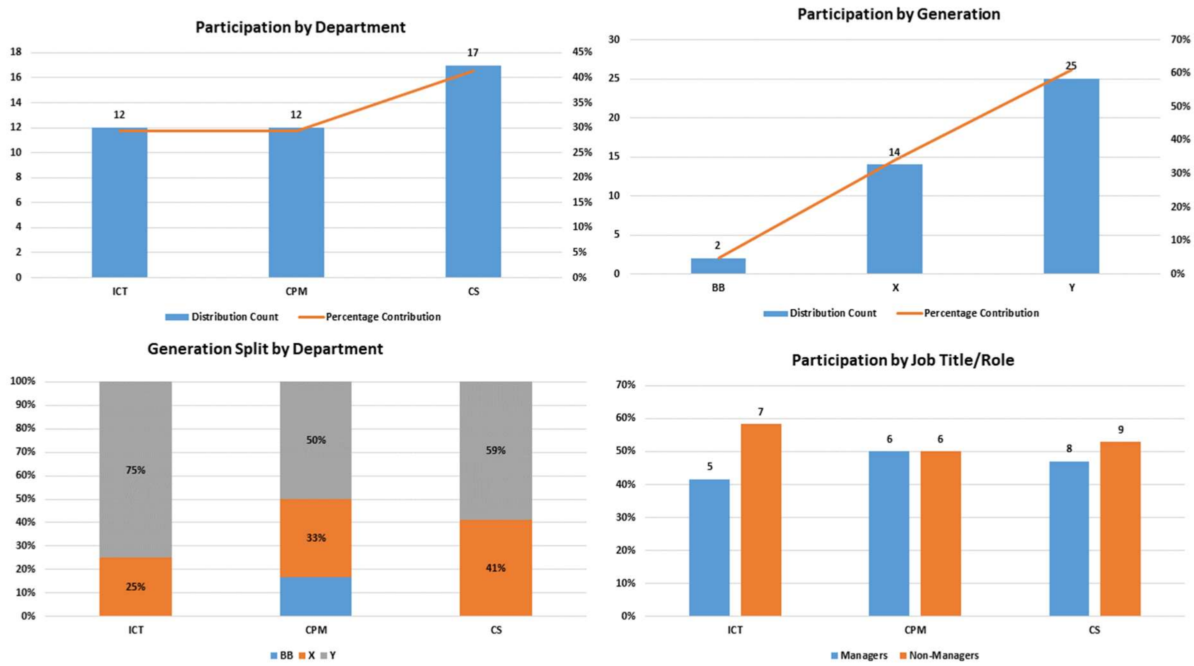

Figure 11: Participant distribution across case study

In reference to Figure 11, the figures (clockwise from top left) reflect the following:

- Participation by department: the distribution of participants across departments;
- Participation by generation: the generational composition for the entire case study;
- Generational split by department and;

- Participation by job title/role for each department: the role division per department.

Although multiple cases could have yielded additional insight based on the uniqueness of each case, the novel nature of the phenomenon necessitated the focus on a single case study (Yin, 2018). Multiple departments, within a single case study, facilitated richer understanding because of divergence in perspectives (Bryman, 2012; Eisenhardt, 1989).

3.6.4. Sampling

3.6.4.1. Theoretical Sampling

A GTM-aligned theoretical sampling approach was used, which is "controlled by the emerging theory" (Glaser & Strauss, 1967). Straussian GTM defines theoretical sampling as sampling based on proven theoretical relevance (Corbin & Strauss, 2008). Hence, the next sample is determined by the significance of concepts that are either missing or proving to be of importance due to repetition, and/or providing novelty in terms of knowledge (Charmaz, 2006). Sampling is not predetermined, but undertaken after the last sample has been subjected to the constant comparative analysis cycle.

The initial theoretical sampling process is non-specific and is based on a "general sociological perspective" (Glaser & Strauss, 1967, p. 45). There are suggestions that initial participants are chosen for their broader perspectives and general knowledge around the problem area which, in this case, is Big Data (Cutcliffe, 2000). For the purposes of this study, the data collection commenced with ICT staff to determine whether an organisation is a Big Data environment—the cornerstone of the research inquiry (Corbin & Strauss, 2008). Thereafter, either top management or non-managers, both of which are considered to be KWs, were recruited for data collection to develop a further understanding. The selection was based on pursuing interesting contributions and, importantly, fitting in with the availability of participants.

3.6.4.2. Ethical Considerations

In qualitative research, contributions made by participants and organisations become the centrepiece of the study, as it has the "potential to produce deep insights" (Myers et al., 1999, p. 67). However, qualitative research also demands more of the researcher in protecting the identities of contributors (Bryman, 2012). In order to collect data from participants out of their free will and, in doing so, collect data that is shared without fear or hesitation, reasonable assurances were provided to the participants, CSA management, and the university, namely, to anonymise identities completely. These assurances were conveyed in writing (see Section 8.6) and verbally during every interview session. Participants were also assured that CSA management will not have access to their contributions. All material that was used from the interviews was referenced with nondescript pseudonyms to protect the identities of the organisation and the participants (Bryman, 2012). All files are securely stored to protect the contributions made by participants. This thesis does not disclose any links between the case study participants and the analysis that is presented.

3.6.4.3. Sample Selection

The introduction of the theoretical sampling process is non-specific, in that there is no prescribed method for choosing the first participant (Glaser & Strauss, 1967). The first set of interviews was based on purposive sampling, since the researcher was ready to start the inquiry and was led by the availability of participants (Cutcliffe, 2000; Saunders et al., 2008). In accordance with the GTM, encouragement from the originators suggests that researchers “get on with doing it” rather than talk about it (Heath & Cowley, 2004). Therefore, the data collection phase was initiated with the organisation (CSA) that first received senior management approval to serve as a case study and provided names of participants, especially of those within an ICT department. In addition, three function-based departments within CSA separately authorised data collection.

After collecting data from five participants (with ICT-based roles), and following an open coding process, it was learnt that participants did not present sufficiently diverse views, and that a broader knowledge-base was needed. The initial five participants defaulted the conversation to technical aspects of ICT and Big Data which, although meaningful and helpful in understanding the Big Data deployment, was insufficient to address the phenomenon at hand.

Thereafter, from a sampling perspective, an SGTM-aligned theoretical sampling approach was followed. Corbin and Strauss (2008) define theoretical sampling as sampling based on proven theoretical relevance. Hence, the next sample is determined by the significance of concepts that are either missing or proving to be important due to repetition and/or novelty value (Charmaz, 2006). Sampling is not predetermined, but is undertaken after the last sample has undergone a constant comparative analysis cycle. Based on the participant’s demographic information and the interest to better understand an issue, interviews were based on a modified set of interview questions.

After open coding of the eleventh participant's interview data the story, as well as more prevalent gaps in data to answer the research questions, began to emerge.

3.6.5. Data Collection methods

The data collection methods were qualitative in nature, which is well suited to GTM (Charmaz, 2006; Creswell, 2007). Data, in a GTM empirical situation, is everywhere. Data was collected through semi-structured interviews (Saunders et al., 2008), and discussions occurred mostly in natural settings (Creswell, 2007). The interviews were conducted through semi-structured, “loosely guided”, and “non-judgemental” interview questions that facilitated an unhindered flow of information (Charmaz, 2006, p. 26). At the same time, in order to build credibility in the study—especially in terms of the quality of theory generation—open-ended conversations without time limits were practised (Glaser & Strauss, 1967).

In following GTM, and Straussian GTM in particular, empirical data collection, analysis, and theory development are parallel actions that have reciprocal relationships (Corbin & Strauss, 2014). This maintains the core fundamentals of GTM, which are that constant comparative analysis, theoretical sampling, and theory development are complementary and continuous processes (Bryant & Charmaz, 2007; Glaser & Strauss, 1967). According to Wiener, the core fundamentals of GTM begins with the first interview (Bryant & Charmaz, 2007).

The interview questions, although a guidance mechanism in GTM, were structured in such a way that three objectives were achieved. These were to: (1) collect demographic information; (2) harmonise key concepts; and (3) have interactive discussions.

3.6.5.1. Time Horizon

The study was cross-sectional, as data was gathered through interviews at a single point in time (Creswell & Creswell, 2018). As the study is based on SGTM, with theoretical sampling and constant comparative analysis being time-consuming and difficult to predetermine timeframes, the duration of iterative data collection and analysis was not known at the outset (Heath & Cowley, 2004). In practice, data collection and analysis took approximately six months.

3.6.5.2. Demographic Information

The participants' name, job role, title, age, and tenure were collected. In addition, a permission document was signed by the participants to provide consent for participation in the interviews.

3.6.5.3. Harmonisation of the key concepts

This became an important part of the interview process, as it emerged from the earliest engagements with sponsors that the terminology used was disconcerting, scary, and could possibly jeopardise the wilful participation of candidates. The objective of the harmonisation segment was to ensure that a common understanding of the key concepts was realised. The initial discussion focused on 'data-driven decision-making', 'democratisation', and Big Data.

'Data-driven decision-making' was the easiest concept for which to reach a consensus understanding, as participants were in most cases specialists in their fields and relied sufficiently on evidence, fact, and data to do their jobs.

The dialogue around 'democratisation' initially had political connotations. Moreover, concepts such as 'empowerment' and 'freedom' were brought into the discussions. However, after a short explanation as to the selection and use of the term 'democratisation', the participants embraced the concept.

The Big Data concept was new to most, apart from some participants in the Information Technology (IT) departments, and required a brief description with examples to create a common understanding for the rest of participants and the researcher. A common understanding is important to the research phenomenon. It was enlightening that, without prior exposure to Big Data as a [hype] concept (apart from a few), the participants confidently and correctly used the concept in their responses.

In order to gauge the harmonisation of concepts, the researcher asked questions related to the key concepts, which all participants were sufficiently able to explain in their own words.

3.6.5.4. Semi-structured interview

Although the main research questions and sub-questions remained the same throughout the study, the interview questions were changed a few times during the data collection stages (Corbin & Strauss, 2014). The reasons for the changes centred on reaching three key milestones. First, the initial questions were developed as guidelines, and were to a certain extent influenced by the literature. Second, after baseline information was gathered, there was a need for clarity after constant comparative analysis and open coding. Third, after no new information emerged, questions that clarified interesting pieces were discussed with select participants. Throughout the data collection and analysis stages, clarity questions were put to participants regarding unclear points, ambiguities, or misinterpretations, as it was important to obtain accurate stories from them. Subsequent interpretation is a core characteristic of qualitative research (Creswell & Creswell, 2018). In addition, some emergent and interesting categories were woven into the discussion to gauge importance and relevance. GTM allows for flexibility in questions and is largely used for guidance. Therefore, strict adherence is unnecessary when in pursuit of empirical realities (Corbin & Strauss, 2014).

Most questions were responded to by most participants. However, a very small number of participants did not respond to some questions, citing reasons such as lack of exposure and tenure. Another possible reason was 'stage fright' when given the daunting task of trying to string several concepts into a coherent response after having just been exposed to these. This problem was identified and partially remedied after five initial interviews; the interview questions were repeated at the end as a summary for subsequent interviews.

The summary section afforded participants the opportunity to mention information that they could have thought about during the interview process, but that did not come to mind when the actual question was asked. While most took advantage to put forth a confident response, others chose to skip the summary questions as they felt that they had sufficiently responded.

3.6.5.5. CSA-specific questions

CSA asked that a few questions related to Big Data be asked for purposes of organisational effectiveness. This was made known to the participants and all responded in full, based on the assurance of confidentiality. An executive summary of the participant contributions, without any analyses and researcher comments, was made available to management.

3.6.5.6. Refining the interview process

Refinement of the process allowed the researcher to establish the opportunity for future engagement, should further clarity be necessary.

The interview questions were refined after reviews of the transcripts and based on coding process outcomes (Urquhart et al., 2010). Questions that appeared redundant were removed, while questions that required clarity during the interview process were simplified for clarity. Questions were added based on a review of the audio recordings. The use of questions in GTM are controversial, based on the assumption that questions are intended to confirm existing knowledge rather than letting new knowledge emerge (Heath & Cowley, 2004). However, the interview questions were intended to guide the research and enable consistency from interview to interview. Importantly, participants were asked to allocate a certain amount of time for the interview; hence, another intention of having a set of prepared questions was to maximise the use of time.

3.7. Data analysis

3.7.1. Data Analysis Methods

The Straussian GTM (SGTM) approach is structured, methodical, and process-oriented (Heath & Cowley, 2004). This is considered restrictive compared with Classic GTM (CGTM). However, for the purposes of this study, following a set of guidelines adds rigour and validity to the data collection and analysis steps.

As discussed, SGTM analysis involves transcribing the collected data, searching through the data for codes (coding), and grouping the codes into concepts and the concepts into categories. Coding is the cornerstone to uncovering a theory. It begins by assigning labels to segments of data for comparative interpretation and helps to answer a key question in GTM, namely, "what is happening?" (Charmaz, 2006, p. 3). This iterative process is referred to as constant comparative analysis (Glaser & Strauss, 1967).

3.7.2. Unit of Analysis

The unit of analysis (participant/s) was the core and significant aspect of the analysis of the study (Creswell & Creswell, 2018). As the focus of the research was on the democratisation of the decision-maker in DDD, the essence of which was to understand democracy in the context of the individual's ability to participate in, and co-determine, in DDD (Pausch, 2014), KWs, as decision-makers, were the unit of analysis of the research. A key criterion for selecting a KW is their daily use of Big Data components, from a user's perspective rather than from a Big Data ICT technical perspective (Jung et al., 2018). Knowledge should include, but not be limited to, social media applications, analytics related to targeting customers, and call centres. Importantly, the perspectives of management may be different to those of individual contributors; therefore, theoretical sampling will be critical to how data collection proceeds.

3.7.3. Preparing case research data for analysis

Data was captured through handwritten memos and audio recordings of participant interviews. The audio recording was transcribed from audio to text—not only to grasp the essence of what the interviewees were saying, but also to apply analytical tools to obtain a deeper and more comprehensive picture.

Transcribing audio into text was challenging when speech-to-text (StT) and artificial intelligence (AI) tools were used. This was not because of the listening and transcribing skills that are required, but because of the preconceived expectations of using StT tools. Both options, that is, StT and AI, were explored extensively. However, the vast amount of editing required after applying the tools to the recorded audio proved to be time-consuming, rendering use of the tools a wasted effort.

One of the most highly rated StT software applications required an initial learning step before actual transcription could occur, that is, a sampling exercise. This required that a participant dictated a piece of prescribed text into a voice recorder for 4 minutes. The outcome after loading the sample recording into the StT software was very good. When the actual interview recording was loaded into the tool, the outcome was disappointing. Another problem with this method is that participants cannot be reasonably subjected to 4 minutes of voice sample training. In addition, interviews take place in an imperfect environment; the conversational, back and forth discussion between the researcher and participant complicated the use of the transcription software. Further, the interview was susceptible to environmental conditions such as noise and office distractions.

AI, through tools contained within IBM Watson Explorer, Google Docs, and YouTube, produced better results than the StT tool. However, this process was flawed, as several portions of the text did not make sense; at times, it appeared that the AI tool became too smart and appeared to override (invalidly so) portions of the speech by its own interpretation of the conversation.

Following these experiments, it was finally decided to use traditional methods, which is wholly supported by GTM. The audio was transcribed by listening to every word and capturing that into a document. This document was uploaded in Nvivo for tagging, searching, and collating. Throughout the journey, the recordings were key when doubt arose as to exactly what has been said or implied. The tones, enunciation, and emotions expressed in the spoken word helped to contextualise the written word.

3.7.4. The Coding Process

SGTM data analysis methods were followed (Corbin & Strauss, 2014). This entailed a coding paradigm that included constant comparative analysis through the three coding stages, namely, open, axial, and selective (Matavire & Brown, 2013). In addition to this, concept formulation and categorisation steps were followed.

3.7.4.1. Open coding process

The open coding stage comprises a first review of the data, with the objective of being open-minded and seeing properties and ideas that are interesting that could be further developed (Matavire & Brown, 2013; Seidel & Urquhart, 2013). Codes are assigned based on "interpretation" and "brainstorming" of data (Corbin & Strauss, 2014, p. 222).

Open coding largely involves taking an analytical first look at the data collected and trying to organise it into some manageable form by assigning labels or tagging sections of data (Corbin & Strauss, 2014). 'Open' attempts to signify an open-minded approach to the data without preconceived ideas (Bryman, 2012). The labels are assigned based on interpretations extracted during the interviews, as well as on descriptions found within the transcribed text that have some interesting meaning and that starts to shape into a high-level but meaningful taxonomy. The coding of data portions could be achieved by examining each line, a sentence or sentences, or whole paragraphs (Glaser & Strauss, 1967). The open coding approach in this thesis followed a mix of sentence-by-sentence coding, and coding at the paragraph level when it made sense to do so (Glaser & Strauss, 1967). It is impractical to follow just one method, as the data guides the approach taken.

3.7.4.2. Axial coding

The word 'axial' is a metaphor, as coding occurs around the axis of categories, thereby linking them at the property and dimension level (Matavire & Brown, 2013; Seidel & Urquhart, 2013). A key purpose of axial coding is to reassemble the codes created in the open/initial coding stages, such that categories (phenomena) begin to emerge.

Axial coding and coding for process is specific to SGTM methods, as CGTM excludes these steps (Urquhart et al., 2010). Axial coding is the aggregation and condensation of open coding into broader categories (Corbin & Strauss, 2014). Fundamentally, the axial coding process entails rebuilding the fragmented data that resulted from "break data apart", to identify concepts in the open coding stage and then rebuild by "relating those concepts" (Corbin & Strauss, 2014, p. 198). The rebuilding is based on identifying relationships and connections between open codes, and identifying causal and intervening conditions (Urquhart et al., 2010). The differences between open and axial coding are "artificial" (Corbin & Strauss, 2014, p. 198). Coding for process is facilitated moving iteratively (action-interaction) between stages as necessitated by what is being investigated and discovered in the data (Matavire & Brown, 2013). Action-interaction have implications for the findings, implying that if consequences in discovery are not found ("connected"), the findings lead to "descriptive" and informative knowledge and not theory (Corbin & Strauss, 2014, p. 180).

There are conflicting views around axial coding insofar as it is perceived to restrict the phenomena "from one particular view", for example, context or conditions (Urquhart et al., 2010, p. 362). However, the benefits of axial coding for this particular research centres on its use "as a general guideline to make sense of our data while remaining alert of emerging themes" (Seidel & Urquhart, 2013, p. 241). Well over 335 codes have been created. Axial coding helps with reduction by uncovering linkages in concepts (Heath & Cowley, 2004). Following the SGTM coding paradigm means that viewpoints and interpretation are applied to data in trying to understand the phenomenon, which holds true for interpretive and qualitative research (Corbin & Strauss, 2014). Contrary to some beliefs, SGTM does not purport rigidity in the coding process; instead, it promotes storytelling "that takes readers down a complex path of inter-relationships" (Corbin & Strauss, 2008, p. 130).

Regardless of the GTM that is adopted, following those recommended coding processes is ultimately intended to develop concepts that contribute to theory, which helps to explain the phenomenon (Urquhart et al., 2010). The empirical data is invaluable, and to force it into coding categories to adhere to any selected GTM method is a disservice to research stakeholders.

Although open and axial coding steps appear to be distinct and sequential, the steps are conducted in parallel (Strauss & Corbin, 2008). The aforementioned authors explain that the steps are "artificial" and "for explanatory purposes only" (Strauss & Corbin, 2008, p. 198).

3.7.4.3. Selective Coding

The aim of selective coding is to continue the process of consolidation by identifying relationships observed in the axial codes (Corbin & Strauss, 2008). The premise is to identify concepts and categories that collectively elevate a core (or "central") category that represents all the data (Matavire & Brown, 2008, p. 140). The core category links to all other categories (Stol et al., 2016); it is further developed into a theory, which is the final stage in SGTM (Seidel & Urquhart, 2013).

3.7.5. Memo Writing

Memo writing is a simple yet effective way to "write about one's research" so that pertinent points and events are quickly brought to the fore, especially considering the volumes of data collected (Bryant & Charmaz, 2007, p. 24). In social research, the engagement of readers through acclimatisation of the research process is key to understanding and knowledge contribution, which memo writing provides (Urquhart et al., 2010).

Memos were taken in written form throughout the research process; these included participant interviews and presentations to various members and organisations prior to selecting a case study organisation for the research. The memos helped with remembering key utterances and observations that do not necessarily come across in the audio recordings. For example, all candidates used visual body gestures and facial expressions when communicating. Some were more animated and expressive than others but, as a whole, the visual expressions that were captured in most conversations were valuable. These very valuable types of information could only be captured through interpretation by the researcher in memos. Some candidates preferred drawing when responding to questions, which was captured as a picture-type memo. A notable example of this was when a candidate found it easier to explain the differences—from their perspective—between 'intuition' and 'evidence', and illustrated it through a picture of an iceberg. The iceberg picture depicts a small visible icecap above the waterline and a megastructure below the waterline. The participant's idea is captured in Memo 10 and developed further in Section 4.7.3. The visible icecap above the waterline denotes the evidence part of the decision-making, while the megastructure below the waterline signifies the attributes of the person that inform their decision-making; it includes, but is not limited to, experience, exposure, education, culture, tradition, and value systems. The value of memos becomes evident during the coding process, where codes are liberally assigned to text. Without memos, the open codes become meaningless after a while.

Memos are located within the main thesis, especially Section 4, to contribute towards the storyline and within the Appendix: Section (8.1).

3.7.6. Emergence of a theory

The culmination of data collection and analysis from a social research environment results in the all-important emergence of a theory (Glaser & Strauss, 1967). The nature of theory in social research is to produce an explanation of a phenomenon, behaviour, or occurrence (Bryant & Charmaz, 2007). Of equal importance is that theory formulation is critical to answering research questions. Apart from this, the theory is meant to guide other research, instigate discourse, and minimise the knowledge gap (Bryman, 2012).

The theory that is produced from empirical data, according to the founding authors of GTM, is difficult to challenge as it is fundamentally tied to the empirical situation (Glaser & Strauss, 1967). However, the theory, as mentioned, is intended to encourage debate, discourse, and disagreement, thereby extending the theory or provoking new theory while the original theory stands. This then brings the quality of the theory to the fore.

The quality of the theory from a GTM perspective is challenged because of the original author's nonchalant stance—during the theorising stages—on the credibility of data, which entailed range, veracity, and volume of data as "all is data" (Bryant & Charmaz, 2007, p. 44). The theory is the end goal of social research, while theorising comprises all the parts of the research that precedes it (Swedberg, 2014). Therefore, to produce a theory that is steeped in rigour and validity, building blocks such as data collection and analyses processes need to be valid, consistent, and open to scrutiny. Failing this, the theory may stand but the credibility will be lacking.

3.8. Reliability and Validity

Validation and verification of the resulting theory are not the main aim of the thesis, as the intention is to build rather than test a theory (Eisenhardt & Graebner, 2007). However, it is important, as reliability and validity in qualitative research is based on consistency and the use of well-defined procedures, respectively (Creswell & Creswell, 2018). One way in which validity was realised is through the use of rich and descriptive evidence; further, ensuring reliability entailed well documented procedures, and consistency in coding and transcription of participants' contributions (Creswell & Creswell, 2018) Glaser posits that the emergent theory, without manipulation, validation and verification, is the crux of GTM, and that the rigour aspect is embedded in the constant comparative analysis steps (Glaser & Strauss, 1967). The objective of GTM is to allow the data that is grounded in the empirical situation to give rise to a theory, which could be considered flawed and imperfect. However, with constant comparative analysis techniques, theoretical sampling and theoretical sensitivity awareness, the theory is substantive and grounded in the empirical situation (Corbin & Strauss, 2008). This thesis has achieved "the principle of internal coherence" in that every effort has been made to ensure that the various components work together and are consistent across the thesis (Sarker et al., 2013, p. xii).

3.9. Summary of Chapter

The essence of GTM lies in the production of a theory from social research (Glaser & Strauss, 1967). The rigour and veracity of GTM theory realisation is attributed to constant comparative analysis, and being led through theoretical sampling approaches (Charmaz, 2006). Therefore GTM, and in particular SGTM, is suited to answer the research questions of this research. Moreover, the realised knowledge and the emanating theory could be used to understand similar phenomena experienced elsewhere.

4. CASE STUDY FINDINGS AND ANALYSIS - A CONCURRENT PROCESS

4.1. OUTLINE OF CHAPTER

This chapter presents the findings emerging from the GTM analysis. The chapter is structured as follows.

Section 4.2 provides an explanation for a few concepts that are frequently used.

Section 4.3 provides a high-level overview to familiarise the reader with the empirical findings. The study is inductive; however, the introduction presents—at a high level—all of the findings to familiarise the reader with some of the unique concepts that emerged and that will be encountered in this and subsequent chapters.

Sections 4.5, 4.6, and 4.7 present the findings based on outcomes of open, axial, and selective coding processes, respectively. Although the coding process was iterative, we present it as sequential steps in order to continually develop the storyline.

Section 4.8 provides a synopsis of the core category that emerged from the GTM analysis, and Section 4.9 introduces the emergent theory. Further elucidation is provided in Chapter 5.

Theoretical saturation is covered in Section 4.10 and Section 4.11 summarises this chapter.

4.2. EXPLAINING A FEW KEY CONCEPTS

In realising theory based on grounded theory methods, it is expected that some new concepts will emerge. These concepts, although seemingly common, have different connotations in the context of the study as they are contextual in nature, meaning that their richness is complementary to the findings. Herewith, a few concepts are explained.

4.2.1. IS artefact

An IS artefact has been defined based on literature at the beginning of the thesis. However, the explanation in this section is related to empirical findings and analysis. Below are excerpts that further an explanation of the IS artefact in the context of the thesis, which is based on literature (Lee et al., 2015, pp. 8–9).

- Technology artefact – “used to solve a problem, achieve a goal, or serve a purpose that is human defined, human perceived, or human felt”; in the context of the study, this could be a report.
- Information artefact – “form meaning” or “achieve viability” from the report, which in the context of the study is the application of knowledge to information.
- Social artefact – “relationships or interactions between or among individuals”, which in the context of the study could be translated to collaboration between KWs.

Technology, information, and social artefacts come together to form an IS artefact (Lee et al., 2015). IS artefact, IS application, or IS cannot be “organisationally” and “informationally” empty; therefore, the IS artefact espoused is valid and relevant (Iivari, 2017, p. 757).

An example of an IS artefact that is related to the empirical findings is presented in Section 4.3.1. Figure 13 is a graphical representation of an IS artefact in the context of the thesis.

IS artefacts are “always and already implicated in action and effect”, which is taken to imply that IS artefacts are not static, are interpreted differently, and comprise “often fragile and fragmentary components, whose interconnections are often partial and provisional and which require bridging, integration, and articulation in order for them to work together” (Orlikowski & Iacono, 2001, p. 131). Within the thesis, the IS artefact is realised through contributions of value (DMI) by actors (selective codes), based on the information extracted from BDA. The activities leading up to the realisation of an IS artefact and the activities that are consequences of the interrogation and interpretation of the IS artefact are considered as IS artefactual activities.

An IS artefactual instance begins with a question or request (an IS artefactual activity) which, in the context of the thesis, is Big Data-related and BDA-specific. An example is that a KW needs information to answer a question or fulfil a job requirement. This is put to a Big Data dataset via BDA, which results in context-specific information. Thereafter, the information traverses through an IS artefactual system (Democratisation Inflection Point (DIP) system: see Sections 4.3, 4.8, and 5.1) as depicted in Figure 12 and Figure 17, wherein value (DMI, see Section 4.2.1.1) is contributed, based on the information, resulting in an IS artefact. The IS artefact instance is related to a specific data-driven decision.

It is common to route IS artefacts back into the IS artefactual system (DIP system) for further processing. Reasons for further processing could include summary reporting for management consideration, expert input, and execution of authorisation processes. IS artefacts are part of multiple instances of co-creation of value of other IS artefactual instances and, as depicted in Figure 17, the production of processed data, that is, information, results from BDA, which is an IS artefactual system. The premise is that value breeds value, and so on. The co-created value is not necessarily new, but incremental, and has its origins in another IS artefactual system (the DIP system). The types of contributions (DMI) by the selective codes (actors) could vary based on the value that is required.

4.2.1.1. Decision-making indicators (DMI)

DMI is the value contributed by each selective codes (actors). It contains detailed information, rules, and a set of instructions for how information is treated and actioned. Effective decision-making does not rely only on objective information but “rather, it depends on tapping the tacit and often highly subjective insights, intuitions, and hunches of individual employees” (Nonaka, 1991, p. 193), which is an essential part of DMI. DMI is an aspect of knowledge management as it contains both the story behind the decision and the knowledge that was used to decide (Hibbard, 1997). For instance, BDA output includes 'information about the information', such as the age of data; KWs add the human element, such as summary and recommendations based on information; the organisation contributes DMI that control risks to the organisation such as budget management, and, based on the organisational design, contributions to DMI include guidelines for adherence to decision-making processes. DMI, together with information, facilitate better decision-making; in their absence, decision-making is weakened.

The evidence supporting the use of DMI is located throughout the empirical data within this chapter, which includes veracity of Big Data, decision-making structures, empowerment of people, controlling the business, and KWs’ abilities. These are just a few of the DMI or value contributions to decision-making.

4.2.2. DIKW Transformation

With reference to the DIKW model that has been discussed in Section 2.2.1, information is deemed to refer to data that has undergone interrogation and manipulation using Big Data analytical tools. Hence, the transformation has occurred from a raw and messy state to one that is organised according to user-defined filters and is contextual in nature, meaning that it is fit for purpose. The purpose relates to the question that is asked of Big Data.

The hype around Big Data is well-known and the impact on businesses, individuals, and academia is revolutionary— or will be—in terms of the vast insights that are possible. However, the contribution of

Big Data to the democratisation of the workforce, based on empirical findings, reveals that it is largely not obvious; hence, “it depends”.

It could be argued that ‘information’ is already value-laden, since BDA activities have transformed data into information. This is true. In a similar vein, each of the remaining actors could be artefacts resulting from other DIP systems.

4.3. OVERVIEW OF EMPIRICAL FINDINGS

The journey from early engagement with CSA executives, motivating their participation, and finally collecting participants’ worldviews has had profound implications for how the phenomenon is explained and understood by the researcher from a business perspective. Reading, re-reading, taking apart the conversations, and then slowly building it up again, based on discovered concepts, categories, propositions, and finally letting a theory emerge, reaffirmed the relevance of GTM for the study. Indeed, GTM allowed for raw and rich empirical data and insights to be uncovered. Trying to analyse that data through the lens of a framework would not have allowed for the intricate insights to be revealed from the rich data, and for theory to emerge.

In the age of Big Data, democratisation of the decision-maker in DDD is a consequence of the effective collaboration between key actors—animate and inanimate—such as the workforce, the organisation, Big Data, and decision-making entities (see Figure 12). Democratisation of the KW (decision-maker) in the context of the study is about effective value contribution through teaming and co-creation of the IS artefact, which provides a better picture of the decision-making landscape. Teaming involves the contribution of knowledge; organisational aspects such as culture, decision-making guidelines; and Big Data analyses in order to arrive at a decision-making point. Whether or not decision-making is democratised, is best answered with “it depends”. Democratisation of the KW in DDD is enabled when the actors mentioned above come together and contribute to the enhancement of information obtained from BDA, thereby facilitating a change from information to knowledge that is enveloped into a value-laden IS artefact. DIP is where various actors’ contribution of some value, in the form of decision-making indicators (DMI), are assessed based on the information extracted from BDA. The DIP has been identified as the core category; it is the central theme of the research and brings together related concepts (Corbin & Strauss, 2008). The DIP is the conflation of the contributions by the actors (DMI) and information resulting from BDA, thereby resulting in a decision-making IS artefact (see Section 4.3.1 for an example). The IS artefact is always knowledge, as adding value through the DIP has transformed the information and contributes to organisational learning. While the information may still be the verbatim output of BDA, it transformed as ideas, assumptions, and restrictions have been superimposed as a veneer over the information.

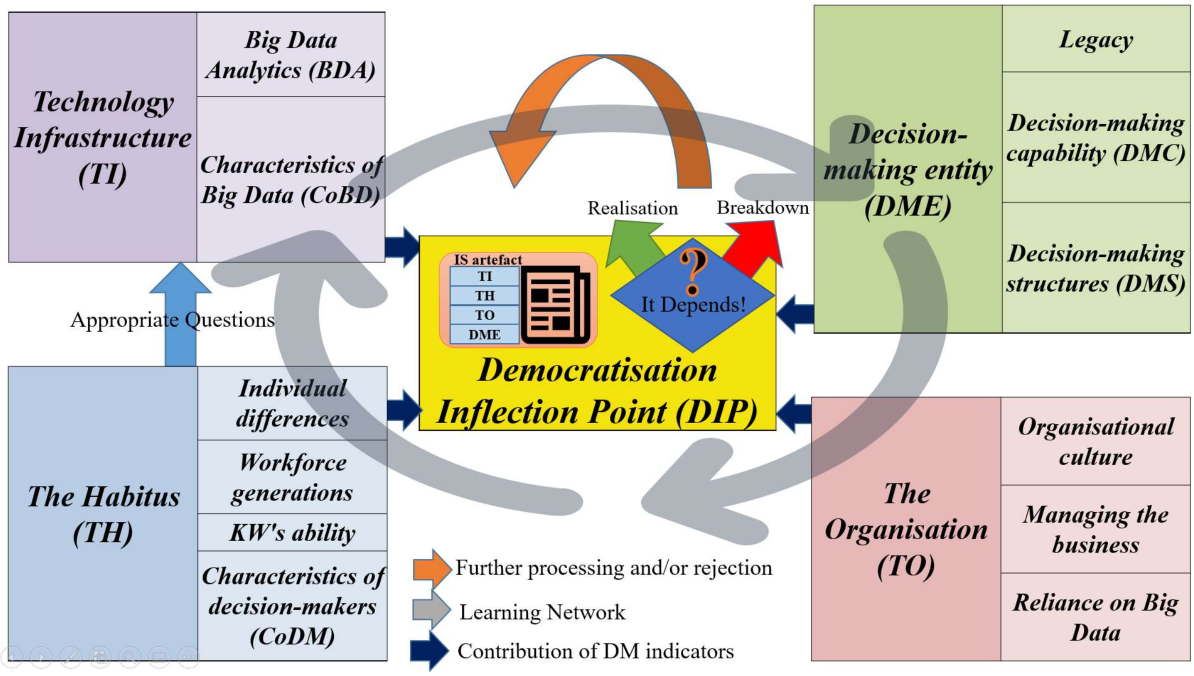

Figure 12: Democratisation Inflection Point (DIP) system IS artefact

Figure 12 presents the final theoretical outcome from the case study research at CSA. Although this theory emerged inductively through the GTM process, it is first presented in reverse order so that readers have an introductory level understanding of the unique concepts. These concepts will be further explained as the chapter progresses through the various stages of GTM analysis. It is the intention, as the chapter progresses, that the storyline becomes clearer. Following this approach could be confusing as concepts are not fully explained when introduced. However, in following the traditional approach by presenting the findings without introduction, the risk is that the reader may be more confused as unique concepts could remain disconnected until the end, and until the complete storyline has unfolded.

As shown in Figure 12, the core category is the DIP, which is defined as the point or place in which the KW assesses the completeness and quality of information and DMI that are available for decision-making purposes. The assessment for completeness and quality of information and for DMI within an IS artefact then causes a realisation or breakdown of democratisation of the decision-maker in DDD.

Democratisation of decision-makers (i.e., KWs) is the process by which KWs assess the completeness and quality of information through BDA and critical DMI that result from people, The Organisation, and decision-making structures. Democratisation of the decision-maker in DDD is realised when the information and DMI are sufficient for decision-making purposes. Democratisation of the decision-maker in DDD breaks down when the information and DMI are insufficient for decision-making purposes. Whether or not a decision is taken is beyond the outcome of the DIP. The outcome of the DIP is whether or not the decision-maker is democratised.

Table 6 defines the major selective codes and concepts, with reference to Figure 12.

Category	Definition
Technology Infrastructure (TI)	TI has been defined in Table 2 (page xviii), the crux of which is that TI comprises of the technical and the human ICT infrastructures. Both sets of infrastructures are interrelated because "the technical infrastructure is the choices pertaining to applications, data, and technology configurations. The human infrastructure is the choices pertaining to the knowledge and capabilities required to manage effectively the IT resources within the organization" (Byrd & Turner, 2000, p. 168). TI is akin to a technology artefact in that it comprises ICT hardware and software, and it is a "human-created tool whose *raison d'être* is to be used to solve a problem, achieve a goal or serve a purpose that is human defined, human perceived or human felt" (Lee et al., 2015, p. 8). Within the TI, Big Data Analytics (BDA) activities occur that fundamentally transform a question into information, therefore an information artefact (Lee et al., 2015). TI overlaps with TH as related to human-centric aspects such as technology acceptance, skills, capabilities, and analytical inquiry. However, TH is considerably more than this as TH draws into consideration attributes that are shaped by the individual's experience, exposure, education and emotion.
The Habitus (TH)	TH brings to the fore the vastness of the human being's concious and unconcious mind from a decision-making perspective. Within these spheres of the mind, individual differences (and similarities) are profound and shaped by education, experience, and exposure to traditional belief systems and values, cultural background/practices, and environmental

	conditions such as socio-political and socio-economic factors (DuBrin, 2019, Bourdieu, 1989, 2013). "People show substantial individual differences, or variations, in how they respond to the same situation based on personal characteristics" (DuBrin, 2019, p. 23). Individual differences are forms of power within social classes, which comprises different levels of social, economic, and cultural capital (Bourdieu, 1989). Social classes are further discussed in Section 5.2.3.2. Culture, an aspect of TH, is "a stock of assumptions, values, beliefs, and practices from which individuals selectively draw in order to make sense of situations and choose paths of action" (Geeling et al., 2019, p. 2). Equally, TH is a social artefact "that consists of, or incorporates, relationships or interactions between or among individuals through which an individual attempts to solve one of his or her problems, achieve one of his or her goals, or serve one of his or her purposes. We describe this artifact as social because relationships and interactions involve more than just one person; hence, they involve the social, not just the individual" (Lee et al., 2015, p. 9). Habitus is discussed further within section 5.2.3.2.
The Organisation (TO)	TO are aspects of the organisation that can be identified and have an influence on the performance of the organisation. TO takes into consideration the organisation's strategy, mission, objectives, and cultural values, which are then formalised into goals, rules, processes, and procedures, which are actioned at tactical, operational, and administrative levels (Robbins & Judge, 2018). The key premise of TO is fostering organisational values that contribute to the success of the organisation. The performance of the organisation takes into consideration the effective and efficient use of firm resources, especially people, finances, and technology (Schneider & Barbera, 2014). Organisations are social entities (Daft, 2010, p. 11). Therefore, TO and DME are considered social artefacts (Lee et al., 2015).
Decision-making Entity (DME)	DME, as related to decision-making, is centred on organisational design that takes into consideration structures and processes that support

	organisational strategies (Daft, 2010). Organisational design has been influenced by four paradigms: 1) Enhanced leadership power through power allocation based on loyalty; 2) accountability and authority assignments based on roles and responsibilities; 3) "structures and administrative processes that match the organization's production processes or operations"; and 4) "structures and processes that facilitate the making of organizational decisions" (Huber & McDaniel, 1986, p. 573). While paradigm 4 above appears to embrace DME closely, all paradigms mentioned are inextricably relevant to DME as they represent the evolution of organisational design and are inherently built into organisational structures. "Organizational design has not been data-driven", meaning that just the use of traditional financial data is not considered data-driven but the inclusion of human resources, marketing, social media, and others are all critical to Big Data (Morrison, 2015, p. 8). "Companies will need a power shift in their structures if they are to capitalize on Big Data Analytics capability" (Galbraith, 2014b, p. 5). Specifically, organizational design needs to focus on speed of decision-making (real-time), which BDA makes possible. In the Big Data era, DME brings into consideration the analytical interpretations that have occurred, and the boundaries in which these could be actioned or further deliberated upon. DME helps to rationalise the decision at hand through considerations of decision-making structures and quality of decision-making. DME facilitates decisional action.

Table 6: Definitions of major selective (actor) categories

Technology Infrastructure (TI) as a standalone actor does not democratise the decision-maker in data-driven decision-making. The collaboration within the DIP system, through the collective contribution of some type of value by actors based on information, results in the transformation of information into knowledge and IS artefacts that cause the realisation or breakdown of the democratisation of the decision-maker in DDD. The IS artefact is the basis on which democratisation of decision-makers in DDD processes are assessed within the DIP. The possible outcomes of the DIP are realisation or breakdown of democratisation of decision-makers in DDD, which is dependent on actors contributing DMI that include financial, governance, cultural, and expertise parameters. DMI and information, which arises from BDA/TI, is specific to the decision at hand, and form an IS artefact. A complete IS artefact results in the realisation of democratisation of the decision-maker in DDD, whereas an incomplete IS artefact results in breakdown. When an IS artefact requires further processing, it is returned to the DIP system. All three outcomes—realisation, breakdown, and further processing—contribute to organisational learning.

4.3.1. An example of a DIP system IS artefact

An example of an IS artefact from the study is as follows (see Figure 13 for a graphical representation). A KW wants to transform the current customer call analysis from manual listening to using speech (voice) analytics technology. This will allow searching for patterns across multiple calls, conduct trend analysis, and enhance the customer experience through better equipped agents. More advanced tools exist, such as emotional analytics or incorporation of AI into the call centre to automate responses or assist agents. The KW extracts information—via a question—through BDA (**TI)** techniques to show call centre volumes, customer satisfaction, and agent success rates. The Habitus (TH) enhances the information through deeper analysis and adds the motivation, which is based on upskilling KWs and advancing the customer experience through personalised, proactive, and better-informed interaction. The Organisation (TO) decline the request due to limited budget. The decision-making entity (**DME)** requests regulatory and compliance clarity with respect to the use of customer information. Each of the contributions by the actors mentioned above are termed DMI, and is conceptualised as an IS artefact, together with the information. The IS artefact in this example is complete, as all four actors have contributed. In this example, even though the KW request is declined for budget and compliance reasons, the democratisation of the decision-maker (KW) is realised. Had an actor (TI, TH, TO or DME) failed to contribute value, there would have been a breakdown. Further processing—for instance escalation to management, budget approval, and request for more information—is a realised status, as four actors have contributed. However, further processing is necessary.

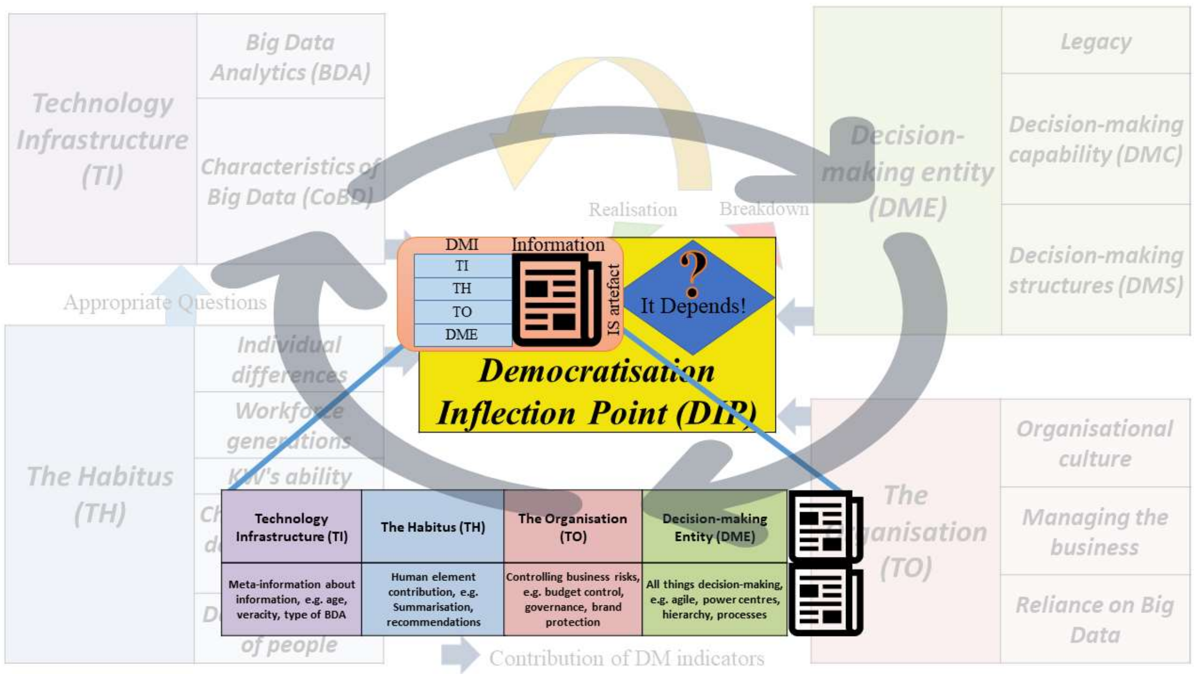

Figure 13: Representation of an IS artefact

The IS artefact is the outcome of the DIP processes. It is shaped by value contributions of the four actors—TI, TH, TO, and DME. Some value that could be contained in an IS artefact, based on the information, is the type of analytics, the decision type, context, authorisations, regulatory affairs, limits of authority, access control, assumptions, and interpretations. These values are considered as DMI. It is important to note that the contributions by the four actors are not sequential, meaning that each actor does not contribute in a specific order. Instead, the contributions are made as required, meaning that a new DMI contribution is made if it is needed; alternatively, standing DMI contributions apply. For example, limits of authority do not change frequently; therefore, if this type of DMI contribution is necessary, then the standing limits of authority are contributed by the DME to the DIP.

Although the IS artefact is not visible or tangible, it is present in every decision-making process, whether or not it comprises information based on Big Data information.

4.4. THE CODING AND CATEGORISATION PROCESS AND RESULTS

This section demonstrates the outcome of different stages of data synthesis that have produced meaningful codes, concepts, and categories, which are the building blocks of theory. The extracted codes, concepts, and categories are based on participants' contributions, with pertinent quotes provided to substantiate and support the interpreted findings.

Table 7 and Table 8 summarise the gradual reduction from open codes to the core category, each of which is discussed throughout this chapter.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***Technology Infrastructure (TI)***	***Big Data Analytics (BDA)***	Insight begins with appropriate questions
			Types of analytics
			Big Data Analytics (BDA) needs to be relevant
			The future of Big Data is the availability of analytical skills, not technology
			Wasted opportunity to gain insight from Big Data
		Characteristics of Big Data (CoBD)	Availability of, and access to, Big Data
			Big Data is a headache
			Vast amounts of knowledge are derived from Big Data
			Data silos
			Multiple data sources
			Time Value of Big Data - velocity
			Variety is key to completing the picture
			Veracity of Big Data
			Volume
	The Habitus (TH)	***Individual differences***	Education
			Experience
			Historical implications
			Individual's culture
		Workforce generations	Generational issues
			Newer generations forcing change
		KW's ability	Skills
			Power lies in the skill to analyse and interpret Big Data
			Decision-making abilities
		Characteristics of decision-makers (CoDM)	Decision-makers and empowerment
			Effective decision-makers communicate
			Decision-makers rely on competent people
			Risk-averseness
			Power centres rely on summary of information
			Participation of people: Perceived enablers and constraints

Table 7: Part A - Emergence of the Core Category

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***The Organisation (TO)***	***Organisational culture***	Collaboration is key to producing insight
			Transparency
			Freedom to contribute
			Communication
			Values
		Managing the business	Business processes
			Controlling risks
			Financial constraints
			Resource constraints
		Reliance on Big Data	Access to Big Data improves productivity
			Big Data is critical to CSA's decision-making
			Big Data use leads to competitive advantage
	Decision-making entity (DME)	***Legacy***	Big Data influences the transformation of traditional DM processes
			Pace of transformation
			New technologies not as reliable as legacy systems
		Decision-making capability (DMC)	Big Data Analytics (BDA) supports decision-making
			Big Data Analytics (BDA) supports agile decision-making
			Decision-making based on trends and best practices
			Quality of Big Data-driven decision-making
			Decision-making is context-driven
			Trust is vital to DDD
			Insights-driven decision-making
			Decision-making based on intuition
		Decision-making structures (DMS)	Death by consensus
			Evolution of decision-making processes
			Organisational configuration and decision-making processes
			Big Data promotes accountability
			Decision-making is authoritarian
			Governance and compliance policies affect power centres
			Evolution of power centres

Table 8: Part B - Emergence of the Core Category

From the study, there are four selective codes (actors) that play a role in the decision-making process. These actors have emerged from the coding steps shown in Table 7 and Table 8. Selective coding is the grouping together of codes based on overt and underlying relationships that contribute to answering the research questions.

After each interview was transcribed, all handwritten memos and data to find interesting quotes, keywords, and emotions were reviewed. These were tagged in Nvivo[15] and eventually copied into a spreadsheet. The excerpts formed the basis for the open codes, and are relevant as they relate directly to why codes and categories were selected.

In the following sections and subsections, explanations of the coding processes are provided, with the empirical findings following thereafter. A few pieces of evidence are provided *in situ* to maintain a storyline, with additional supporting evidence located in Section 9. Keeping the method and the empirical findings together builds a cohesive and easier-to-follow storyline.

4.5. Open Coding

4.5.1. Open coding process

The open coding process—discussed in Section 3.7.4.1—produced a large number of codes, as codes were applied without trying to find prior matching codes. This allowed for liberal coding. The process of consolidation supported the constant comparative analysis method. Each open code and the associated interview text were reviewed several times, and either left as a standalone code or consolidated with closely related codes.

The assignment of codes to data based on asking the question "what is happening here?" was grounded in interpretation of the discussions, descriptive text in the transcriptions, and In-Vivo coding (Corbin & Strauss, 2014). As can be seen in Figure 14, the number of open codes increased consistently until participant 16 was interviewed. Thereafter, the number of codes did not increase significantly, thus indicating possible saturation in the open coding process (Corbin & Strauss, 2014). CSA#01 for example is the codename for a participant, and was assigned randomly to further anonymise the contributions—see Table 52 in Appendix 8.3 for more detail.

[15] Qualitative analysis computer application by QSR International - https://www.qsrinternational.com/nvivo/home

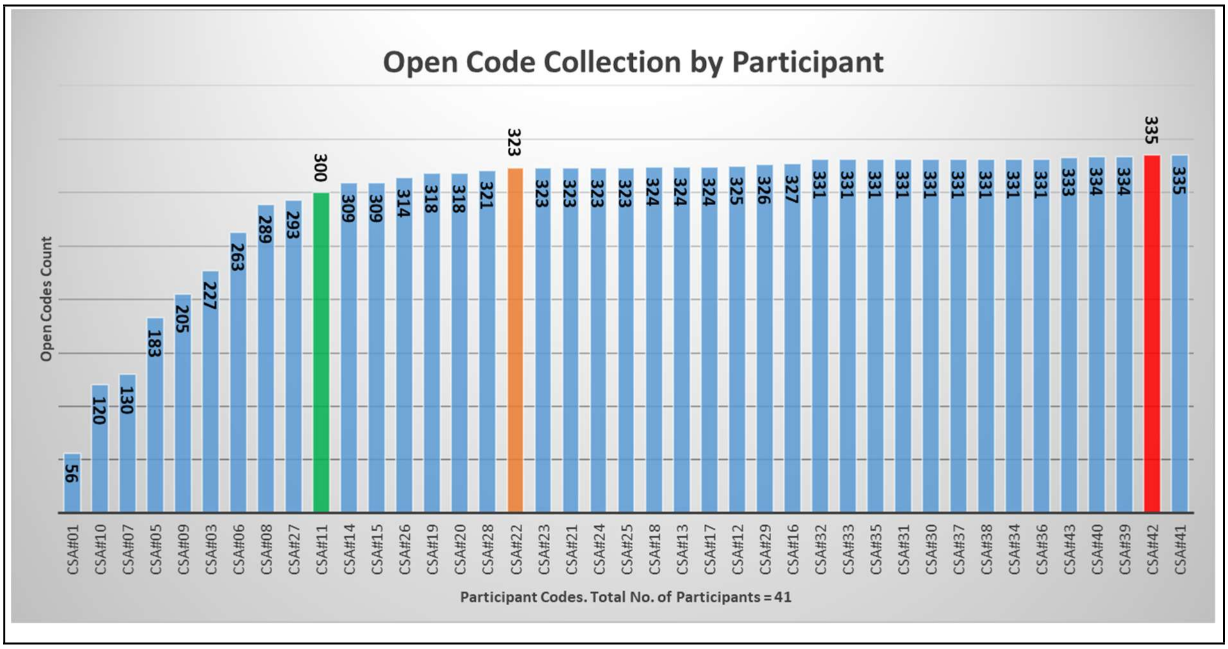

Figure 14: Number of codes collected by participant

A total of 300 open codes were created after 10 interviews. This increased to 323 open codes after 16 interviews, which was a moderate increase compared to the first 10 interviews. Although the open code count did not increase beyond 335, coding was more conservative after analysis of the 10th interview, with several codes collapsed into related codes based on similarities and duplication (Corbin & Strauss, 2014). Hence, new codes were generated through a refining process. Interesting codes that appeared to resonate with multiple candidates, and codes that helped to answer the research questions, were chosen over codes that at first review did not seem as if it could add value. The assigned tags (phrases) consistently increased throughout the analysis process. Approximately 1120 phrases were tagged, which are referred to as 'references' within Nvivo. References were assigned to more than one open code when multiple meanings were discovered; the decision of which open code to assign was based on the underlying meanings, which are hidden due to participants assumptions that the researcher is well-versed in their areas of expertise.

When consolidating codes into broader categories, open codes were studied together with the associated interview text, after which the open, axial, and selective codes were assessed against the research questions and captured in a spreadsheet (see Section 8.2), which is similar to Table 9. Both the main research question and sub research questions were tested against each open code and, if the open code answered or contributed to answering the research questions, the open code was assigned a checkmark. The main research questions and sub-questions were linked to some key open codes to demonstrate that the research questions have been answered. An example is shown below, with the remainder of open codes captured in Section 8.2[16]. Supporting evidence in the form of participant quotes is provided with each open code discussion and additional participants' quotes could be found in Section 9.

Technology Infrastructure (TI)							
Research Questions				Coding and categorisation process			
MRQ	SQ1	SQ2	SQ3	Core Category	Selective Codes	Axial Codes	Open Codes
√	√		√	Democratisation Inflection Point (DIP)	Technology Infrastructure (TI)	Big Data Analytics (BDA)	Insight begins with appropriate questions

Table 9: An example of participant phrases (evidence), coding, categorisation, and mapping of main/sub research questions

Table 9 demonstrates several aspects. The participant key phrases are the outcomes of minimising the collected data while following GTM core principles. Using the Nvivo software application, interesting phrases and keywords were tagged with an open code, which in this case is "Insight begins with appropriate questions". In most cases, the open code is long, as the intention was to make it immediately recognisable through descriptive text and in-vivo snippets. After 41 interviews were completed, all the open codes were exported to a spreadsheet, together with sub-code properties and participant key phrases.

Although open code findings are discussed in isolation of the other coding stages, open codes are linked with other coding stages through descriptive section headings and graphical table illustrations for storytelling purposes. This helps to mitigate the abstract appearance that would have resulted from discussing each of the coding paradigms in isolation of each other. The other coding stages are discussed separately, but the headings and tables provide an attempt to demystify the thesis progression.

With respect to the naming conventions used in headings and captions, the rationale is to highlight GTM coding and categorisation outcomes; hence, between the [brackets], starting from the left is the [core category-selective code-axial code] and open codes. As the empirical findings based on the GTM open, axial, selective, and core category coding progressed, the coding within the [brackets] were reduced up to the point of the core category discussion.

4.5.2. Open codes related to Big Data Analytics (BDA)

BDA is one example where concepts such as trends, root cause, and historical data are synonymous with descriptive analytics, which is discussed in Section 2.2.3. The open codes on the right of Table 10 capture the meaning and functionality of BDA from laymen's perspectives and real-world situations.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***Technology Infrastructure (TI)***	***Big Data Analytics (BDA)***	**Insight begins with appropriate questions**
			Types of analytics
			Big Data Analytics (BDA) needs to be relevant
			The future of Big Data is the availability of analytical skills, not technology
			Wasted opportunity to gain insight from Big Data

Table 10: [DIP-TI-BDA]-Open codes

Table 10 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

4.5.2.1. [DIP[17]-TI-BDA[18]] Insight begins with appropriate questions

a) The importance of questions

The questions asked by the KW are based on something that the KW (investigator) wants to answer. It could be based on descriptive, prescriptive, or predictive analytical enquiries. Appropriate questions are those that lead to output and insights that are of value. Even if the right question is initially asked, resulting in data output, further value-type questions are necessary to turn the output into insights such as 'What happened?' or 'Why did it happen'?. These qualifying questions help to expand the picture around the phenomena, thereby contributing to richness and insight. Extrapolating actions and tasks require further questions such as "What needs to be done?" or "What is the competitive advantage?" or "What is the opportunity or risk?".

[17] DIP - Democratisation Inflection Point

[18] BDA - Big Data Analytics

The quality of the question helps to determine the output from BDA systems.

EFQ1. "The first question is what do you want to achieve?" CSA#03.

Throughout the engagement with participants, the evidence suggests that, if KWs wanted information that was targeted at solving a problem, asking appropriate questions was key.

EFQ2. "Okay, normally you get a [data] dump if you don't have a question. But if you have a question, you'll get value" CSA#28.

EFQ3. "What I'm learning, and understanding is that BI folk and folk that are producing outputs[reports], if the person requesting the output can understand the question or has a good question that they understand, then everybody's lives become easy" CSA#03.

b) Assumptions

Assumptions came up several times, but meant completely different things to each participant.

The appropriateness (and hence, quality) of the questions is shaped by assumptions.

EFQ4. "I just think that we only know what we know. We'll only find answers to that question that we think we need to ask. Where Big Data comes in is, they will provide answers to questions that we haven't even thought of, but we need to open our minds to discovering" CSA#28.

KWs make assumptions which, in turn, guide their interpretation of the data.

EFQ5. "I take all my information and I hand it over. They [management] would need to assess whether the information I gave them is correct and true because I applied my mind, my assumptions, to it. They would need to know that in order to make a decision. So, they are actually dependent on what I provide in terms of data to make a decision" CSA#22.

Assumptions prevail when there is a lack of evidence.

EFQ6. *"Without a lot of data, you make more assumptions than decisions, to be honest. Well, you make more decisions based on assumptions and you want to make more decisions based on thorough analytics than assumptions" CSA#03.*

c) BDA output – what next?

The potential of BDA is not well understood by KWs, as they are used to standardised reports. The information in the reports does not require a large number of KWs to delve deeper into reports to find underlying insight; instead, the information that is visible is sufficient to achieve a task.

EFQ7. "So, data to me were always numbers and statistics. Whereas there was never even a thought in terms of the resources that are made available to one that can be used to turn this into knowledge, lasting knowledge" CSA#23.

In attempting to explain this statement, CSA#23 indicates that, when considering processed data (information), KWs do not realise what they have in front of them, how they are going to analyse it, how they are going to apply it, and how they are going to use it to repudiate or defend something—KWs become overwhelmed by the possibilities. KWs have characteristics that inform how they consume processed data. Two of these characteristics arise from the analysis of the data.

One cohort of KWs are satisfied to follow processes without adding any value to the information produced from their Big Data analytical tools and data warehouse. KWs configure reports into an agreed format and pass it on to other KWs and management.

Another cohort of KWs are restless, as the information before them does not reflect the whole story, and there are insights that are left untouched. They ask questions and examine the information from many angles to find underlying meaning, ideas, and answers.

Both cohorts are discussed in Subsections d) and e).

d) Information – reports and reporting

Information is mostly provided through standardised and process-driven reporting. These reports contain overtly mundane task-oriented data for day-to-day work activities.

EFQ8. "I get reports from our suppliers and then I just basically convert all of that into our own set of reports in Excel. I circulate this as management reports" CSA#15.

For standard reports, there is some synthesis and summarisation of the information by the KW, which is then shared with other KWs and/or management.

EFQ9. "Because I do dashboards and the reporting, and I extract all the information from the system. Maybe if [manager] got that view of what was coming ahead, [manager] wouldn't need to approve. [Manager] could give me approval six months up ahead and say 'these are your big-ticket items. I'm happy. What is your estimated contract value for it?' I give it to you. Sign off. That's my approval. You know what you're doing. Maybe it's a trust thing. You know what you're doing, you carry on but trust prevents that from happening" CSA#22.

Business Intelligence (BI) Analysts assist KWs with extracting customised reports. However, there is frustration between BI analysts and KWs, as KWs find that the requirements as determined by BI analysts are very often not clear. If these are not clear, then the output will likely not be what is expected or required.

EFQ10. "What I'm learning, and understanding is that BI folk and folk that are producing outputs[reports], if the person requesting the output can understand the question or has a good question that they understand, then everybody's lives become easy" CSA#03.

Asking appropriate questions is the first step to drawing insight from Big Data. As mentioned above by CSA#28 (EFQ2), without a question, the data output could represent a significant amount of information that could prove to be overwhelming and possibly irrelevant. Analysis of Big Data follows on from asking appropriate questions, for therein lies the path to extracting insight.

BDA has the capability to expose insights from Big Data to help decision-makers make better, evidence-based decisions rather than decisions based on intuition, including assumptions. Appropriate questions, in combination with BDA, facilitate effective decision-making.

Participants also raised the issue of the distribution and effectiveness of standardised reports, both in terms of being actioned and the participant circulation list that is used. The issues with circulation lists, according to CSA#05, is that participants subscribe to circulate lists so that they are seen to be interested, for management visibility and for 'just-in-case' reasons. For these reasons, ownership, as related to tasks/actions emanating from the reports, is blurred.

EFQ11. "You circulate this to everybody. All the team members are involved in it. I actually communicate the information and I feel that the right people need to be involved. I think there's this culture in the business also where people are too scared to tramp on people's toes, so they include others just in case they get into trouble. Now you see, it takes forever to make a decision" CSA#05.

e) Adding insight to information

Information and insight are different concepts. KWs add value to information that is extracted from BDA. Value could take many forms, such as analysis of information and making recommendations based on previous knowledge as well as on the new information. A common practice within CSA is for KWs to extract reports on behalf of mainly more senior people, synthesise the information, and add summaries that include recommendations. Power centres prefer summary reporting—see Section 4.5.7.5.

EFQ12. "It gives us the ability to see from many angles the different things that are happening and then we can use whatever is available to us to take advantage or mitigate risks" CSA#14.

4.5.2.2. [DIP-TI-BDA] Types of analytics

BDA is adopted to answer questions and produce insights. The types of BDA are defined as descriptive, predictive, and prescriptive analytics. Although these specific terms were not present in the interview conversations, apart from conversations with ICT participants, they came across strongly in connotations, explanations, and inferences.

a) A snapshot summary of BDA activities at CSA

Although this subsection should be located within the case study description, the evidence is relevant to the open code and enhances the storyline. CSA largely applies descriptive analytical tools to some datasets. With the vast amounts of data across the organisation, CSA faces several challenges; the most important one at this point in time is the prioritisation of resources for ongoing competitiveness. The business has deemed that deploying descriptive analytical tools are prioritised over predictive and prescriptive analysis. The collected data attributed this to resource constraints, which are discussed later in Sections 4.5.9.3 and 4.5.9.4. Additionally, the industry segment that CSA operates within, namely, financial services, supports this approach—at least in the short term.

EFQ13. "If I had to quantify our BDA utilisation, I would say 80% of the focus is on descriptive analytical tools producing mainly standard business reports. About 20% of BDA time is spent on predictive type analytics, so we play around with things like propensity to buy and lapse predictions which is valuable to the business. We have not engaged actively with prescriptive analytics yet" CSA#43.

See Figure 21 in Appendix 8.1.1 for the memo taken during a conversation with CSA#43.

b) Descriptive analytics describes what happened

Several participants indicated that a key benefit of descriptive analytics is the analysis of historical data, which is largely used to determine trends and provide benchmarks for the state of the business in relation to goals set by the organisation. From a decision-making perspective, historical data acts as evidence and justification in the decision-making process. Another use of historical analysis is to determine root cause analysis in problem-solving—for ICT systems as well as for call centre management. Call centres are critical to customer relationship management and communications.

EFQ14. "I think from the first step is to obviously analyse. To analyse your problem or issue and take a step back and obviously look at what went wrong, how it went wrong. I mean basically asking yourself questions" CSA#23.

c) BDA Operational Activities

Within CSA, Big Data analysis is divided into two different operational activities. The first activity is the use of Big Data analytical tools, such as data mining and business intelligence, to interrogate raw and complex datasets in order to produce data that is structured and in user-friendly formats such as spreadsheets and business reports. In the context of the thesis, these data outputs are not yet considered to represent insight, as some value must be added to turn the outputs into something meaningful and actionable.

EFQ15. "What it means is basically it's all about having a lot of information out there. But information is not really the right word. I'd like to say a lot of data that is not yet being turned into information like, raw data. And a lot of raw data and you could call it unstructured or whatever it is that still needs to be put together to become information. And then we examine that information from all sides to find things we don't know or didn't see" CSA#03.

The second operational activity is the interrogation and interpretation of processed data—that is, information—that is made available to KWs in the form of spreadsheets and business reports. While some activities to interrogate the data appear to be process-driven—for instance, predefined, automated business reports—there is little further value added. Value is added by finding root causes, examining the information from more than one angle, and painting a more holistic picture that contributes value to information, which in turns becomes knowledge and actionable insight. In order to understand business trends, KWs are required to interrogate and interpret the information before them. Information, without applying insight and referral knowledge, very often remains just information. Analytics (questioning) is the key to insight.

EFQ16. "A priority for us I think is analysing [the information]. It's kind of also creating and obtaining new knowledge because you learn every day from the data. I mean we live in a world that is fast-paced and changing, so analysing and then obviously creating that knowledge" CSA#26

d) Predictive Analytics facilitates operationalisation of historical learnings

While predictive analytics represents only 20% of BDA at CSA, as indicated earlier (see EFQ13 in Section 4.5.2.2), people are extrapolating predictive knowledge to manage their businesses at the department level. Work schedules are tailored to maximise productivity, based on call volumes that have been recorded over long periods. As such, predictive analytics is having a significant business impact.

EFQ17. "We could not actually predict as much as we can now, so it really improved a lot. Like I said it can forecast what our volumes can be, so we know exactly how many people we need in certain areas, we need to get these resources from another area... back in the day when it was the old school you were not able to predict those kinds of things. So, technology and Big Data plays a huge role, it has really changed things around immensely" CSA#35.

e) Prescriptive analytics facilitates proactive steps

Although prescriptive analytics seems to be less commonly used, based on CSA's prioritisation of the use of descriptive and to a lesser extent predictive analytics, there are pockets of use cases within CSA. Below is an example from the ICT department of their use of prescriptive analytics to mitigate unusual situations. Another sophisticated but extremely important example that was mentioned is the management of call centre resource based on service demand, which is primarily about optimising resources against customer demand.

EFQ18. "My role in managing the computing performance management means I need to see what happened to build trends, predict when it will happen, and then I put rules in place to manage what happens" CSA#11.

f) Multidimensional Analysis – looking at data from many angles

With data warehousing tools, interpreting data from multiple perspectives is beneficial to developing insights. A significant characteristic of Big Data is the multitude of sources of data. However, looking at a piece of data from a variety of angles and perspectives lends to expanding the insight so that more is uncovered.

EFQ19. "I think data has become more than just one dimensional. I think that it has evolved into a multifaceted sort of organism in the sense that there is data about data" CSA#32.

4.5.2.3. [DIP-TI-BDA] Big Data Analytics (BDA) needs to be relevant

BDA reporting has grown with time, which could be attributed to changing strategy, business processes, and leadership. However, most participants felt that reporting is broad-based and not granular enough, thereby affecting the relevance of BDA. The reports that are generated require further time-consuming analysis, but cost-cutting measures have led to the discontinuance of some preferred analytical tools. The limited relevance of the information that reports provide to KWs emerged as a significant consideration. Time and financial constraints are discussed in Subsections 4.5.9.3 and 4.5.9.4.

EFQ20. "Obviously, Big [Data] is a problem. But, relevance is a bigger problem to make decision-making quicker" CSA#16.

EFQ21. "I mean the data needs to be fit for purpose and for use" CSA#09.

4.5.2.4. [DIP-TI-BDA] The Future of Big Data is the availability of analytical skills, not technology

With the declining cost of storage, communication, and computing technologies over the years, the challenge for companies is not technology per se, but extracting insights from Big Data. This is especially from a people skills' perspective, as the demand for data analysis specialists (data scientist, data analyst) continues to rise.

EFQ22. "Companies are scaling down the technical resources and scaling up on the analytical resources because as far as they're concerned, their technical systems are up to scratch. It's now understanding what's being produced by these systems. Like now a lot of data are in these companies, but no one's able to be able to decipher what's coming out of this. So they are scaling up on the analysts, scaling down on the technical resources" CSA#03.

4.5.2.5. [DIP-TI-BDA] Wasted opportunity to gain insight from Big Data

The contents of Big Data[sets] that are homegrown or acquired is largely known; the extent thereof is well established and not a source of unique competitive advantage, as the marketplace appears to be well defined in South Africa. On the other hand, unsolicited Big Data content is unknown and risky. However, it has the possibilities of newness and uniqueness. Synthesising voice calls and social media are examples of unsolicited data that have possibilities for competitive advantage.

EFQ23. "Focus on unsolicited data as opposed to solicited data because therein lies competitive advantage" CSA#28.

In a highly competitive field that is vying for the attention of a limited customer base, it is difficult to elevate CSA's unique value proposition when the same or similar customer data is interrogated for a new business or expanding an existing business. CSA#28 believes that more of the company's resources—time, effort, money—must be dedicated to interrogating unsolicited data. Unsolicited data (see Memo 12)is, according to CSA#28, the data that is offered voluntarily by customers, partners, competitors, and employees. Two examples were offered to support this premise.

EFQ24. "Do we back the funding to analyse the Big Data, No. We can put in biometrics or voice biometrics. We can put in voice analytics in terms of our call data, and we have all the data. But do we spend the money on doing that, no? So, it's untapped. Then you have to take a physical person that has to read or go and listen to every single call. The data is there but we are not using it effectively" CSA#28

The first example revolves around understanding conversations between CSA employees and customers. Limited analysis does take place through analysis of transcripts and voice recordings when customers complain about agents, and for training purposes. However, CSA#28 believes that voice analytical tools, voice analysis experts, and behavioural analysts could uncover the deeper meaning and hidden value in conversations.

EFQ25. "At CSA, we are tapping into the same customer data that every competitor is tapping into, so we are all chasing the same customer. We need to tap into the unknown, the unsolicited or the accidental customer. CSA own tons of property that has tons of shoppers. We must apply [customer] analytics to those people to understand them, their needs" CSA#28.

The second example indicates that, while competing companies are focused on trying to win customers, albeit using obvious and common knowledge, they continue to position their offerings despite a misfit between products and customer requirements. Having a customised offering per customer is unrealistic; but then, having limited tools [customer analytics] to collate insight from unsolicited data contributes to wasted opportunity. It seems that listening to unsolicited data is not necessarily ignored, but not prioritised either.

The variety of Big Data, which CSA#28 referred to as unsolicited data, holds possibilities for new customers and new market identification. It could be the game-changer in highly competitive markets. The focus for companies is largely on tapping into solicited feedback, which is deterministic, predictable, and emanates from known sources such as customers, agents, and employees. However, unsolicited data by its very nature is voluntarily shared, and the sources thereof could be known or unknown. The dilemma with unsolicited data and the analysis thereof for CSA is that it will consume limited resources—money, time, expertise—in qualifying the data; the yield could be insignificant and/or irrelevant to the business. The advantage to analysing unsolicited data is that the feedback could be a valuable insight into potential customers and/or markets, and a competitive advantage.

EFQ26. "But I am ignoring the fact that there is a whole lot of complaints relating to an issue. So, my constant hidden, sort of niggling feeling in my head with regards to the reality that there is Big Data out there. Or the data exist, lots of it. And that I am not tapping into it" CSA#32.

Although there are missed opportunities at CSA with respect to customer analytics, the organization is successful and very big. The latter characteristic has some implications, such as being agile, at the forefront of technological innovation, and being data-driven. Being data-driven suggests that an organisation configures its business and responds to market conditions based on data. CSA is not wholly data-driven. As mentioned previously, the company generates most data from internal sources rather than from the marketplace. Two examples are rich data from social media and voice calls, which are not digitally harvested for analysis purposes or for actioning insight. These are lost opportunities.

4.5.3. Open codes related to Characteristics of Big Data

Table 11 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***Technology Infrastructure (TI)***	***Characteristics of Big Data (CoBD)***	**Availability of, and access to, Big Data**
			Big Data is a headache
			Vast amounts of knowledge are derived from Big Data
			Data silos
			Multiple data sources
			Time Value of Big Data - velocity
			Variety is key to completing the picture
			Veracity of Big Data
			Volume

Table 11: [DIP-TI-CoBD]-Open Codes

4.5.3.1. [DIP-TI-CoBD[19]] Availability of, and access to, Big Data

The availability of Big Data and access to Big Data are two different conundrums that have emanated from the case study.

a) Availability of Big Data

There is no doubt that the prolific nature of Big Data has the advantage of being widely available to the masses. The advent of the internet has been instrumental in this occurrence. At times, the internet (and education) have been evangelised, especially in practitioner literature, as the ‘great equaliser’ (Chambers & Brady, 2018). The basis for this is that people could connect to the internet to instantly avail themselves of an immense amount of data. This was not the case in past decades, because of inadequate electronic communication networks, especially in developing nations, and the limited accessibility of knowledge such as books, teaching aids (online learning and syllabi), and journals in digital format.

EFQ27. “My experience with Big Data is that it is the numerous [amounts of] information that we as people and organisations are exposed to, which unfortunately we cannot control how it happens, what happens, you just need to respond” CSA#13.

[19] CoBD - Characteristics of Big Data

b) Access to Big Data

The second conundrum is access to data, which is in abundance. It creates problems though for how data is stored securely, accessed securely and used.

EFQ28. "It's [Big Data] just giving me an incredible amount of access to information what I never had before" CSA#08.

However, it also introduces the issue of the relevance of Big Data as it relates to fulfilling a job requirement. A minority of participants felt that, although Big Data has afforded them access to an unprecedented amount of data, their concerns revolved around the relevance of data and difficulties (blocking) in accessing data. A reported practise demonstrates this, where a senior call centre agent (CSA#39) cannot execute customer requests without having to go through persons in different departments that have access to the required data.

EFQ29. At this point in time if I think of blockages I think from an interdepartmental perspective there are still blockages. If I think of the call centre and the more administrative side of things, both work hand in hand to solve problems, but currently there is still a block to the flow of information and it's not as it should be" CSA#39.

This causes delays in solving customer-related issues, and favours are often traded to overcome these hurdles. CSA#39 called this blocking behaviour, and attributed it to people silos and data silos. Customer information in a company such as CSA is one of the most precious and protected assets of the company. For those that have this data, limiting access also serves to safeguard their place in the organisation.

EFQ30. "There are pockets of excellence and there are those that still hold on to relevance, which hampers progress. Constrains the speed at which you actually want to go because they have not latched on to the bigger world, the bigger data, the bigger availability" CSA#23.

The historical evolution of CSA makes data silos an understandable reality (see Section 4.5.3.4 for more detail). However, blocking access to data places undue strain on inter-departmental relationships, as competition for customers' attention is paramount to survival.

EFQ31. "Clear barriers to access to data. Get rid of silos. Nothing will happen if it's not a top-down directive. We are held hostage" CSA#32.

In summary, access to the right information is a basic decision-making aid. There are hoarders and sharers of information. Hoarders, according to some participants, are mainly managers that hold onto information in spite of the value that it could add to subordinates and others. Hoarders want KWs to ask for information, rather than to openly share it.

Although the availability of, and access to, Big Data are significant steps towards democratisation, the relevance of data is critical (see Section 4.5.2.3). This is especially true when dealing with resource limitations such as money, time, and skills (see Sections 4.5.9.3 and 4.5.9.4 for supporting evidence).

c) Availability and access: the influence of organisational silos

Organisational silos are normal, and result from the organisational configuration (commonly referred to as departments, sections, and business units). However, these silos are also barriers to effective workplace practices, as there appear to be coordination and communication challenges between people. This directly hinders the availability of, and access to, data.

EFQ32. "I don't know whether people are aligned, or the data is. I would like to say that they both are. But I have sneaking suspicion that people up the line [management] are not aware of what sorts of data are available, or what the relevance of that data would be. I think if some important data finally lapses, they wouldn't know. They wouldn't recognise its value. They wouldn't have the line of sight of it because of the silo-driven business that we are in. There's such an interconnectedness nowadays in the world, which I think we are missing out on because we are compartmentalized in most respects" CSA#32.

4.5.3.2. [DIP-TI-CoBD] Big Data is a headache

As established earlier, Big Data by its nature has no prescribed structure; it could consist of voice, video, and data, and originates from a multitude of sources— hence, it is not as uncomplicated as traditional datasets. In the context of CSA, this is further compounded by the many data silos and large organisational challenges such as interdepartmental relationships (see above).

a) Big Data is a headache

Below is a powerful in-vivo statement.

EFQ33. "Big Data is a headache" CSA#08.

This necessitated a revisit to the handwritten memos of the actual interview to refresh the researcher's memory about the participant. The memo taken during the interview contains the following side note:

Memo 1 "Likes structure", describes Big Data as "cluttered, unorganised data", "talks passionately about technologies like IoT and AI".

CSA#08 is a millennial. It is interesting to note that CSA#08 fulfils an ICT role and is involved with consolidation, specifically from a cost-containment perspective. Hence, retiring assets, auditing software licenses, and terminating contractual agreements are key to cost-containment measures. CSA#08's statement makes sense, as finding the interrelationships and linkages of ICT data assets is daunting, especially in a Big Data world.

EFQ34. "I like technology but then also like the comfort of things in the way they are structured" CSA#08.

b) Big Data is causing distress in people.

[Big] Data is purported to be a new economic asset class, similar to precious metals and currencies. However, because of its size, complexity, and chaotic nature, it has had implications for KWs (Lohr, 2012). KWs are experiencing mental fatigue and hopelessness that is directly attributed to this technology phenomenon.

EFQ35. "As a person, your mind becomes very crowded and overwhelmed. It affects people mentally in terms of the fact that there is just too much on their plate" CSA#24.

Those who can manage the Big Data onslaught, minimise it as follows:

EFQ36. "I see it as a lot of noise in the background" CSA#18.

There is an acknowledgement that Big Data is causing mental distress.

EFQ37. "I feel I can't keep up with technology. Maybe I can get a bit of counselling or help or something. With the stresses of the world today, as well as with family life and the political and everything, it's overwhelming" CSA#21.

CSA#21 is a baby-boomer and challenged by the amount of data that needs to be synthesised and operationalised. CSA#21 works in a department that was in the past not known to be technologically advanced. Now every department is computerised and connected to communication networks. IoT is playing a significant role in facilities management. Physical ICT assets are no longer just on the premises, but also reside in the cloud. Very little is as it used to be.

4.5.3.3. [DIP-TI-CoBD] Vast amounts of knowledge are derived from Big Data

This subsection is closely related to the discussion in Section 2.2, wherein the key concepts of Data-Information-Knowledge-Wisdom (DIKW) are established. The well-known DIKW pyramid describes the progression from random symbols and objects (data) to organised information, knowledge (insight), and wisdom (foresight) (Rowley, 2007). The empirical work is provided the following supporting evidence:

EFQ38. "If they are not looking for ways and means to better the company to number one and to improve our systems by using the knowledge from Big Data then we are going to stay in the past. We are never going to evolve" CSA#33.

Participants consistently highlighted that Big Data is just more data that has very little meaning unless it could be turned into something useful, such as knowledge—useful in the sense that some actionable meaning is derived. For most people, reading binary data, hexadecimal data, and abstract objects/symbols, as if they are reading newspapers, is not a normal occurrence. The raw data needs to be passed through processes for it to be turned into purposeful and useful alphanumeric values (information) that are easier to read. The reading of raw data is an exaggeration that aims to make a point about the uselessness of data in its raw form, even when turned into numbers and statistics.

EFQ39. I don't think at this point in time from a data perspective that one can use it in any way, shape or form. It doesn't make sense. Like gibberish" CSA#23.

Information exists in an organised form, from which it is easier to derive some value since it is contextualised and enough to answer some questions. While there is more value to unearth, this requires money, time, skills, and organisational support to scrape away the layers and uncover how information, knowledge, and insight came about to be this way and what its current and future potential is. While these limitations are frustrating, some find it unacceptable to abandon their curiosity to follow standard processes. Instead, they are creatively overcoming obstacles.

EFQ40. I'm one person who likes to follow in a procedure, yes but at the same time, I need to address a problem that I'm facing. I know how CSA operates, what you can and can't do for a customer but, at the end of the day, it doesn't mean I can't push the envelope a little bit, as long as I'm not *breaking rules. I look at the other side of my decision and then, if I am not breaking any law internally, I come up with a creative solution and represent it as a report. Look, this what I'm sitting with and how the customer can be assisted. If there is no financial challenge to the organisation, why can't we explore? I follow that because, while we want to say we got figures [reporting] to do, everything we don't do is frustrating because we're limited to the rules. We have to operate within a process but yes, at the very same time, we are given that leeway to be creative" CSA#13.*

4.5.3.4. [DIP-TI-CoBD] Data silos

CSA has vast amounts of data, albeit everywhere. As mentioned previously, the extent of this is not clearly documented and therefore not well understood.

This could be attributed to the company's growth over the years, with some implications being organisation reconfiguration and shifting roles and responsibilities. For instance, at some point in time, ICT management was a horizontal function that provided services to the various vertical business functions such as HR, Sales, Supply Chain Management, and Operations (see Memo 3). However, over time, these functional groups have become autonomous through organisational redesign and structural changes. What resulted was that the ICT function transformed into decentralised auxiliary functions that were attached to the autonomous functional groups. These structural changes resulted in the deployment of autonomous and often parallel ICT systems, resources, and human capital. However, this not the only change that caused the shift in traditional ICT; 'cloud' computing was instrumental as well. With cloud computing, ICT infrastructure, and services (i.e., hardware and software) were now easily available 'as a service'. It required very little in terms of in-house infrastructure or knowledge. CSA is currently undergoing consolidation of ICT assets and human capital under one shared ICT department.

The most challenging of activities at CSA in dealing with the Big Data evolution, which has been compounded by some organisational changes, are the efforts to consolidate the many instances of data warehouses. The most arduous is not only discovering ICT assets, but trying to unbundle intricate linkages and dependencies with other ICT assets.

EFQ41. "So every department there's so many silos that are creating their own data but unless you come and put this data together you're not going to get an end-to-end picture" CSA#10.

Memo 2 19/05/19. Discussion with a data scientist. Each business unit has its own data warehouse (DW)—CSA is trying to centralise. Alteryx and Tableau are in use. People structures *(silos) are exacerbating consolidation of DW. Identifying the end-of-life ICT assets is not simple. Reports/reporting cost money – trying to pinpoint ways to estimate value contribution to the business. Insight is challenging – drowning in data.*

Memo 3 26/04/19. Discussed infrastructure architecture. The organisation has reconfigured ICT structures a few times. The ICT department is now consolidated under one horizontal ICT department.

4.5.3.5. [DIP-TI-CoBD] Multiple data sources

As already established from the literature review, the sources of Big Data are numerous. This is further corroborated by the case study.

EFQ42. "I suppose it's comprehensive data within the business that encompasses every division. So, whatever you are doing, there are data sources everywhere" CSA#16.

Although data silos, including data warehouses, have been discussed earlier (Section 4.5.3.4), the lack of a single source of truth is a debilitating factor to CSA. Multiple sources, which are characteristic of Big Data, are exacerbated in CSA's case, as a consequence of organisational changes. There are external data sources that are yet to be taken into consideration, controlled, and contained.

EFQ43. "It could be from anywhere, social media, call centres, video, sensors, cloud, partners, suppliers, Cherwell [software application]" CSA#05.

The interviews reflect that the older generations reminisce about the simple days where data sources were based on paper records, face-to-face meetings, simple transaction records, and unsophisticated, manageable in-house applications. However, there is a realisation that modern data sources are essential in modern-day business.

EFQ44. "If I think of when I started back twenty odd yes twenty years ago, If I look at it from company point of view, the infrastructural changes that's happened, all the different processes CSA gone through over the past twenty years, new products that's been launched, changes in administration, processes that's been implemented, so that we can maybe you know remain in business at the end of the day as the market changes" CSA#39.

EFQ45. "Everything's got to be faster, quicker and everything's got to be recorded so that somebody else can walk in and kind of take over your job, I mean, if I should die tomorrow. People *move jobs very quickly and you've got to be able to step into a role without losing too much time. It's that sort of situation where data is important, that everything is recorded" CSA#21.*

Nowadays, apart from traditional data sources, Big Data sources are immensely diverse, with machines and social media data contributions continuing unabated. The next few paragraphs capture some CSA Big Data sources from a single person's perspective.

Sensor (machine) data is particularly important for CSA, because of the size of their offices, real estate portfolio, and commitment to eco-friendly office buildings. Sensor data is generated by nearly all facility-related devices such as air-conditioning, lighting, elevators, security appliances, water, and electricity, to name just a few. Managing the huge and geographically dispersed ICT infrastructure of CSA generates volumes of network-related data, including system and device log information, device management protocols, and alerts.

EFQ46. My world works on Big Data if I can say that. As an engineer operating a facility that everything is on a feedback system. Whether we are working with systems like air-conditioning, mechanical systems or electrical systems, we need data to come back to us to tell us we are managing the building efficiently or not. Our business operates from these facilities so keeping it running requires data" CSA#16.

CSA#16 is also a manager. He has budgets and manages a team of people. All of this contributes to his Big Data world.

EFQ47. "On the HR side of things, managing a team. If you look at psychological behavioural issues as well. You have your sessions with your staff, whether it's one-on-one or team sessions as well. Then gauge what the mood in the camp is. You know that is in itself data. Everything ties in together to managing a particular space" CSA#16.

Social media streams from a variety of platforms that, knowingly and unknowingly, generate volumes of unstructured data that constantly flows through CSA's infrastructure, either for corporate or private use. Cognitive computing and dynamic learning algorithms are built into social media applications, specifically cloud-based free-to-use applications—Google search engine, Google Mail, LinkedIn, Facebook and Twitter. These are running continuously to mine all data, mainly for marketing purposes. These activities generate more content that contributes to Big Data.

EFQ48. I work in the complaints space and we as the company get lots of reports. We have got social media monitoring like your Facebook, Twitter, and then our normal websites. Then we have got *traditional media like newspapers, radio, etc. All places to complain. We respond to customers through social media as well, so we are on the same platform as the complainers. Whatever they're saying on social media we try to make sure we acknowledge, and we try to engage with them on that level. If one of them don't care for a phone call, then we'll DM [direct message] them or enter a means of contact but as long as it is on social media. We use a lot of DMs to amend to our customers who come through that platform" CSA#13.*

Memo 4 09/12/18 - CSA are not using all the unstructured data. CSA using a combination of structured and unstructured data. Very old processes in place.

4.5.3.6. [DIP-TI-CoBD] Time value of Big Data – velocity

There are several points to consider with regard to the velocity of Big Data. Speed and time are important factors.

a) Timeliness – performance

As the data comes in fast and voluminous, there must be technology in place that is capable of processing large portions of data in speeds that are conducive to the context of the inquiry and situation—for instance, the time it takes to run a query on a dataset should be appropriate.

EFQ49. We use Tableau, Microsoft tools and we're currently exploring other BI tools to gather more insights which we could basically solve one of our biggest problems, which are performance issues. So, we're trying to explore different reporting tools and seeing how we can actually get the performance better" CSA#43.

b) Timeliness - age

Timeliness, from an ageing perspective, is the period after which the relevance of data has passed. An example of this is financial instrument trading, which is a real-time or near real-time activity. Failing to transact within the opportune period results in outdated information and a missed opportunity. Timeliness from a Big Data ageing perspective is not always critical for CSA as most departments work with data that has aged, such as customer data, marketing data, and administrative data (HR).

EFQ50. "The ageing of the data is critical. It is still the relevance of it that counts in some of our business" CSA#10.

c) Timeliness – achieving workplace objectives

The “time value of Big Data” is the continual worry that KWs contend with, primarily the fear that data may become obsolete or stale and lose its efficacy before they could do their work. KWs, especially those mentioned previously who have a desire to see what is beneath the information, tend to be in a frequent state of unease.

EFQ51. “But we need to move with the times also and do it a bit faster to keep up. I think we need different methods, maybe tools, to deal with this” CSA#09.

Another example of the challenges of achieving job objectives within a reasonable time is reflected here:

EFQ52. “I mean you're talking about actually going through a huge amount of data and analysing this thing manually and trying to come up with stuff, it just a nightmare, it takes so much time that I end up ignoring it because by the time I’m finished new stuff has arrived” CSA#05.

From the memos taken for the CSA#05 interview, it is clear that the concerns expressed largely relate to the lack of tools. For instance, BDA will enable much more rapid production of insight.

Social media and voice events have characteristics that necessitate quicker responses to negate negativity and capitalise on opportunities, but timing is important.

4.5.3.7. [DIP-TI-CoBD] Variety is key to completing the picture

Multiple sources are synonymous with Big Data. However, variety of data is more important to CSA, in order to paint a more comprehensive picture of customers, for example. Taking this example further, third-party data sources, such as government data, ensures accuracy of birth and death records, which is extremely important for insurance claims. Other third-party data emanates from social media, suppliers, resale channels, and stock market trading systems. Participants felt that access to many sources of data, whilst debilitating in some respects as discussed previously, provides a more complete picture of customers and the marketplace.

EFQ53. “It gives you access to a lot of platforms, information and obviously enables you to think further in a certain scenario” CSA#14.

EFQ54. "Definitely volume and variety help with a better understanding of what's going on" CSA#04.

The sharing of data, by CSA and third parties is associated with regulatory responsibilities. For instance, customer information is protected by the laws of the country. Within the financial services industry, the attention to detail is of paramount importance due to risks of malfeasance, nonfeasance, and misfeasance.

EFQ55. "I would say your legislation, your regulatory compliance shape how we do things. I mean, to get access to the data is already a nightmare and you need permissions for every single thing" CSA#28.

While CSA has access to third party information repositories to assess biographical data and credit information for a more complete picture, this access comes with the various responsibilities outlined above. Social media (such as LinkedIn, Facebook) and search engines are further data sources that play a role in assessing customers. However, in the internet age where information is everywhere, so is disinformation. Therefore, having multiple sources of truth minimises the risks mentioned and provides a richer view of customers, suppliers, and employees.

4.5.3.8. [DIP-TI-CoBD] Veracity of Big Data

Big Data veracity addresses the precision, accuracy, and trustworthiness of Big Data. The quality of Big Data and BDA output directly shapes the value contribution to insight and ultimately decision-making (Cai & Zhu, 2015). Several factors contribute to the veracity of Big Data, including diverse data types, the volume of Big Data, timeliness of dealing with Big Data, relevance/fit for purpose, usability, and data security (Saha & Srivastava, 2014). Some of these factors have been addressed already, while others will be addressed in forthcoming sections.

The other important veracity related issues, for instance, quality of data for decision-making, and trust as related to people and data, are addressed later (Sections 4.5.12.4 and 4.5.12.6). Data security is a significant contributing factor to the veracity of Big Data, and is discussed separately in Section 4.5.9.2.

It is reasonable to conclude that veracity of Big Data is concerning for CSA. CSA, as a large organisation and participant in the financial services industry, does not have unique challenges. However, challenges nonetheless exist in terms of managing fraudulent insurance claims, dealing with social media—positive and negative—and managing vast estates of data warehouses and ICT assets.

Few areas have a direct bearing on Big Data veracity, such as a single source of truth, having an understanding of ICT assets, and KWs' awareness of veracity aspects. These are explored further below.

a) Single source of truth

CSA generates most operational data from internal sources, the quality of which should be less doubtful. However, the discussions about the many data silos, a trusted source of truth, is work in progress and strategically important, and therefore driven by the leadership team. CSA is not unique in this regard, as firms globally are challenged with the same dilemma (Sweetwood, 2014). *Ceteris paribus*, this would be less troublesome if internal information was used solely for customer operational aspects, such as financial planning and insurance management, as the likelihood of familiarity with customers' information is well-founded. However, information is not only about customers, but pertains to a myriad of other mission-critical operational aspects such as sensory data, license management, asset management, and corporate financial information.

The internal consolidation of the many data silos is a big task, and is a strategically driven event, since this was mentioned by a number of participants. Apart from the internal data quality issues, CSA, being part of the financial services industry, cannot trust data from the many unknown sources without proper governance and vetting processes. Quality of data, in terms of its accuracy, was of paramount importance to KWs.

EFQ56. "If I look at the strategy from our CEO and our MD that data is playing is a pivotal role in our transformational journey. That's why there's such a lot of resources invested in getting our data correct. And that we're getting relevant data to help us through this change" CSA#28.

Decision-making quality depends on data quality, and these cannot be separated.

b) Asset Management

Asset management at CSA is important to the veracity of Big Data—not only for tracking assets, but also for building in-depth relationships between people, licensing, and ICT assets. This is critical to validating sources and destinations of Big Data, and is a significant challenge for CSA. Asset management-related issues extend to ICT assets within data centres and standalone devices such as desktops, laptops, and mobile devices.

EFQ57. "Linking of data [ICT assets, applications, user accounts] from one to another becomes difficult because this data is linked to everything and creating that link becomes a hassle *even with different unique identifiers creating relationships is difficult and then understanding the discrepancies between data which opens up room [need] for checking and validating because everything has to be accounted for. Even I have a list of 1,000 people and those 1000 people I know but then you look at every other thing that relates back to people and you discover I have 1300 people now so where did this three hundred people come from. So validation and actually cleaning is constant" CSA#10.*

The conundrum is that ICT assets that are not in use, redundant, and unmanaged need to be shut down as consolidation of the data silos occurs. However, there are active application links, users, and services that make it difficult and risky to power down. Apart from the costs of licensing and maintenance contracts, other cost contributors include utilities, human resources, and asset management licensing.

EFQ58. "Mapping of assets seems like an impossible task. If we could just take things offline or isolate groups, we could create linkages and relationships [assets, people, services] but we need to keep the business running" CSA#10.

EFQ59. "We've got the service desk tools that we use. The service desk tool is a mechanism to either report that something is not working, or it is a mechanism to request a new service catalogue. So, at the end of the day, basically, it has a view of all the assets that we have in the organization, which is quite key if we're trying to manage everything" CSA#08.

EFQ60. "What's your asset number? I'm not sure everybody necessarily understands that but for you, it's your mark [starting point] to interact with me. So, I think we need to evolve to where everybody knows a little about the assets they use and [are] around them" CSA#06.

The tracking of ICT assets, appear from the above statements (EFQ59, EFQ60) to be within CSA's control. However, the challenges that CSA face is defining relationships between ICT assets, people, and services (see EFQ58), which is much more difficult because of the size of the organisations and the many data silos.

c) Awareness of veracity aspects of Big Data

Data silos, the internet, and regulations have contributed to trust issues that are related to data quality and integrity. The evidence also suggests that trust concerns are extended to trust between people.

A scenario was put to participants in which they receive a "box" of data anonymously, and the question put to each of them was "what do you do next?" Most participants immediately started to test the relevance of the content to their job. This implies that basic steps were overlooked, such as challenging the veracity of the 'box' before exploring the content. A few others asked questions to determine the veracity of the 'box'. Questions centred around determining the source of the data, ensuring that the data is 'safe', establishing the veracity of the data, and then moving on to interrogating the data. Admittedly, the participants largely work with internal datasets that are deemed to have passed the relevant assurance tests. However, with Big Data being pervasive in every aspect, processes anchored in veracity are critical to ensure that internal compliance and governance rules are maintained. Equally, adherence to regulatory requirements is critical to business survival and success.

EFQ61. "I would need to ascertain if it comes from a reliable source and, in reliable, I mean a source that's firstly allowed to have solicited the data. That it's not corrupt, that it's not been messed around with" CSA#28.

Trust, as related to people and data, emerged as an aspect by which participants are conflicted. There were no clear winners or losers in the discussions around whether people or data could be trusted. There were credible arguments for and against.

Memo 5 12/02/19 – In discussing trust as related to people and data, CSA#33 took a position of trusting neither.

EFQ62. "I don't trust either of the two [people, data] because people manipulate data to get answers they want" CSA#33.

EFQ63. "That's a very difficult one for me. I do trust people as we said before based on their experiences. So, I trust what comes from them, but I would trust a system more because to me a system is supposed to be audited. It's supposed to be checked. So yeah. And even so I know sometimes systems can lie, I still will trust the system more" CSA#22.

An important concept, namely, 'unsolicited' data, emerged from the interviews. Unsolicited data is all the data that the firm receives involuntarily, which mainly stems from social media and through call centres. Social media mainly comprise the complaints, brand recognition mentions, third party website clicks-through, and related sponsored events. Call centre logs are enquiries, complaints, and administration that is entering the firm. Ideally, these may appear to be solicited and valuable, but organisations may not be geared, technologically and strategically, to take advantage of the underlying insight through data and voice analysis. Unsolicited data is untouched, and is stored or discarded.

EFQ64. "I think Big Data can help us as unsolicited feedback is often the truth. People are emotional beings and their feelings could be positive or negative towards CSA and in the service industry that is an opportunity for innovation. But the company needs to believe first and then invest" CSA#28

CSA#28 gave examples of customers calling CSA to log service requests, which are unsolicited and untapped sources of competitive advantage. CSA#28 believes that if CSA had customer analytical tools to digitize the volumes of recorded call-centre phone calls, they could conduct deeper analysis, for example on trends, operational impact, financial implications, resource planning and, importantly, identify real customer needs. CSA#28 believes these are hidden and unique competitive advantages, as customers are calling into CSA and sharing openly, rather than CSA cold calling customers.

In summary, trust in data and security of data, specifically from a home-grown perspective, were manageable prior to Big Data. However, Big Data, especially its unstructured nature and variety, pose challenges to organisations. Resources are stretched in trying to achieve and maintain the veracity of Big Data. One option that is being practised, at least for the short term, is to focus on CSA's ever-expanding crown jewels, namely, customer data, and forego that which is unsolicited, even though the potential could be significant. CSA is cautious when it comes to Big Data.

4.5.3.9. [DIP-TI-CoBD] Volume

In a mixed participant cohort such as that interviewed at CSA, the divergence in perspective is rich and mostly unexpected. The divergence comes from generational differences, job roles within the organisation, and levels of authority/responsibility. Workplace dynamics are shaped and affected by generational issues and individual cultural differences—these are discussed throughout the rest of Section 4, but specifically in Sections 4.5.4 and 4.5.5.

Most participants are not oblivious to the data storm that is happening around them. They choose to treat it as noise and ignore it, explore the data, or become overwhelmed.

EFQ65. "There is so much data around us at the moment that it's overwhelming. Sometimes I think this data that's not really needed. So not all the data that's thrown at us actually adds value" CSA#05.

4.5.4. Open codes related to Individual differences

Individual differences are the unique characteristics that are ascribed to a person and have an impact on their behaviour. Table 12 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***The Habitus (TH)***	***Individual differences***	**Education**
			Experience
			Historical implications
			Individual's culture

Table 12: [DIP-TH-Individual differences]-Open codes

4.5.4.1. [DIP-TH-INDIVIDUAL DIFFERENCES] Education

CSA has a highly diverse workforce in every respect. Most of the younger generations (Y Gen) have some tertiary education, while the older generations have a mix of high school and tertiary education. Below are two opposing viewpoints from a Gen X (EFQ66) and a millennial (EFQ67) participant.

EFQ66. "I don't want to say that for instance if one individual is more educated than the other, that in essence leads to an individual who'll make better decisions or will be successful versus somebody who doesn't have an education because that's not true because there's education on different levels" CSA#37.

EFQ67. "If you didn't study, there's no decision that you going to make. Obviously studying, reading up the books I think, this opening your mind to what you need in the future, what are your plans? Being uneducated doesn't open anything for you. So, studying and study further, I think it gives you more of the information that you want before you make a decision or better decisions" CSA#34.

4.5.4.2. [DIP-TH-INDIVIDUAL DIFFERENCES] Experience

Experience is the accumulated knowledge gained from participation in historical events and activities. Experience cannot be taught; instead, it is about involvement and exposure to a situation (Lewis, 1999). Experience plays a significant role in decision-making, both when evidence is available for decision-making and when evidence is not. Participants often spoke about tapping into stored knowledge and past experiences to help them make situational decisions.

EFQ68. *"Why kids aren't afraid, and they just jump in? I mean, it's because they haven't built that subconscious of experience. Sort of, they don't know yet. Your experience is largely based on your learning, your exposure over the years" CSA#28.*

4.5.4.3. [DIP-TH-INDIVIDUAL DIFFERENCES] Historical implications

South Africa's new democracy has been realised as recently as 1994 (Garcia-Rivero et al., 2002). Prior to this, there have been serious human rights violations through apartheid government-sanctioned "deprivation" laws, "adversarial labour relations", and significant economic disparities (Naidoo & Kongolo, 2004). These include gross inequality among people, racial categorisation, and racial segregation, which were manifested in unequal and significantly disproportionate opportunities in education, jobs, wealth, health, and social upliftment. Since 1994, the workforce is becoming more representative of the society through employment equity legislation[20], which is more commonly known as affirmative action in the workplace. Historical implications include cultural differences, stereotyping, prejudice, lack of understanding, communication problems, and the forcing of diversity on employees (Joubert, 2017).

EFQ69. *"I will say I'm extremely excited at the calibre of especially black professionals coming through whereas a few years I would still have said that they're employing the people [black], they're not really giving them decision-making [responsibility], they're just there in the background. They maybe just signed off things and whatever but behind the scenes, the real power is sitting in the white hands but now I'm definitely encouraged by the credibility of people that they're employing now" CSA#19.*

4.5.4.4. [DIP-TH-INDIVIDUAL DIFFERENCES] Individual's culture

Education, experience, and historical implications influence KWs, and that influence plays out in their role in the workplace. However, cultural background has the most influence on the individual. Given its apartheid history, and efforts aimed at redress in the workplace, racial identities[21] are still prominent considerations. From the case study, Black employees cited culture as having the most significant

[20] Employment Equity Act, 55 of 1998

[21] Black, White, Coloured and Indian/Asian are ethnic (racial/race) groupings based on similar physical characteristics. https://www.sahistory.org.za/article/race-and-ethnicity-south-africa, https://en.wikipedia.org/wiki/Ethnic_groups_in_South_Africa

influence on them. Other races—Coloured, Indian, White—did not bring their cultural background into the discussions. Christian and Islamic beliefs were credited for some participants' value system. Language is a minor issue. At CSA, culture is not a concern and individual cultures, although aggregated, is hugely celebrated.

EFQ70. "Culture is within us; it shapes the person to a certain way of living and thinking" CSA#40.

EFQ71. "The different cultures are celebrated by CSA" CSA#35.

EFQ72. "You have a big variety in culture and so, for example, there are language barriers. So, we need people that can speak the different languages" CSA#35.

a) Decision-making and culture connection

Cultural backgrounds influence in profound ways. One of these is manifested in decision-making processes, which serve as evidence of cultural ties, including background and tradition, in the workplace. Cultural decision-making processes appear, in some instances, to be consultative and hierarchical.

EFQ73. "So traditionally if you sit down with your mother or father or the uncle, I think that's only people who could tell you this what needs to be done in your culture before you can do this before you can make a decision. This tradition is important to business decisions also. [The] Decision process is same" CSA#34.

The quote below serves as evidence that the views of CSA#38, a millennial, are completely different from others with similar demographic characteristics.

EFQ74. "Can I use my personal life as an example? I have a father who's a traditionalist, so he understands Christianity, he read the Bible for our purposes, he'll pray for us, but he also prays to his ancestors. I have a mom who is super Christian, who won't hear anything but Jesus. Because of all of that, you know I've been exposed to all that different churches, different religions and in there, our culture and our tradition is sort of embedded because my father's such a strong traditionalist. But I'm not going to actively be engaged in any kind of culture-driven things, tradition-driven things or religion-driven things. That was pushed even further by my ability to have vast conversations with people all over the world, to get these ideas and to have these conversations" CSA#38.

4.5.5. Open codes related to Workforce generations

Table 13 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point	***The Habitus (TH)***	***Workforce generations***	**Generational issues**
			Newer generations forcing change

Table 13: [DIP-TH-WORKFORCE GENERATIONS]-Open codes

4.5.5.1. [DIP-TH-WORKFORCE GENERATIONS] Generational issues

Throughout the data collection phase, generational differences and conflicts were evident. Unbeknown to the participants (whose contributions were confidential), there appeared to be attacks and counter-attacks, which are evident in the quotes. If the researcher was to keep count of the attacks between Gen X and millennials, the score would be even. Areas of conflict include workplace behaviour, ways of work, decision-making style, data-driven approaches, managing style, and perceived cultural differences.

EFQ75. "My younger colleagues who are on average 30-35 years younger than me, like taking off all the time, [they are] sick all the time. They don't have the same passion or drive, level of integrity that I have and funny enough I work with a lot of them" CSA#19 (Gen X).

EFQ76. "If I look at how the older managers managed, it's a very set structure of doing things a certain way. Whereas I see myself looking at okay what is the data telling me? What are the trends? What is the customer's behaviour? What is the staff behaviour? And using data to understand those avenues to make decisions and how to run operations" CSA#12 (Gen Y).

4.5.5.2. [DIP-TH-WORKFORCE GENERATIONS] Newer generations forcing change

In the age of Big Data, which is complementary to the internet era, newer generations are driving the need for change. Newer generations are younger Gen X and millennials. Change is happening or being pushed to happen in areas such as adopting technology that facilitates quicker decision-making, data, and action. Data-driven decision-making is normal to newer generations, but older generations tend to bring experience, human touch, and consensus into decision-making discussions.

Memo 6 16/01/19. Interesting contrast between different generations. Generational differences in decision-making – speed versus accuracy.

EFQ77. "Sometimes it's difficult to work with people that are from a different generation but it's not a general thing because you get some people that are in the older generation that is open to technology and open to change and open to digital platforms" CSA#25.

EFQ78. "I would find that the younger generation's production is a lot better, they produce higher volumes, where the older generation produces lower volumes with better quality" CSA#35.

The generational aspects within the study environment came across as a key shaping factor with respect to Big Data acceptance, adoption, and use. It was evident that, while older generations were agreeable—albeit with reservations—, the younger generations were discontented in that they wanted more from the organisation in terms of BDA, especially along the lines of deriving actionable insight. With three to four generations currently occupying the workplace, there is a higher propensity for conflict, and this was reflected in the perceived drawn-out processes in decision-making.

Younger generation KWs—millennials—wanted instant gratification by getting decision-making done. The older generation was content with adhering to the process—the ways it has always been. Some older generation KWs did not care either way, as retirement was looming and/or they were uncomfortable venturing outside of job roles and responsibilities.

EFQ79. "I want to move with the times. I want to use it to my advantage. I want to be more competitive. Sometimes a hindrance can be, you know what, I've got xx years to go and then I retire. I'm done with that. To be quite honest I think I might be in that sort of group now. If I go and learn more about technology where's it going to get me. I'm going to stop working" CSA#21.

Big Data came across as overwhelming to all generations, but this was markedly more apparent with older generations, to the point that possible mental breakdowns were mentioned (see Section 4.5.3.2). This unexpected finding is a cause for concern; Baby-boomers and more senior Gen Xers appear to be caught in a whirlwind of change that is beyond their control.

EFQ80. "I'm adapting. It's a bit of a paradigm shift, I've got to go with it because I don't have a choice, but I am adapting" CSA#21.

Note that, in contrast to the prevailing trend, the evidence indicates that some managers within the older generation spectrum appeared to embrace Big Data.

EFQ81. [Researcher] What does Big Data mean to you? [CSA#20] Power. It can be a brilliant tool for getting away from assumptions. It is decision-making that you have evidence for. So, for me, it will be a brilliant [form of] power to support you because people believe in data, not assumptions.

4.5.6. Open codes related to KW's ability

Table 14 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***The Habitus (TH)***	***KW's ability***	**Skills**
			Power lies in the skill to analyse and interpret Big Data
			Decision-making abilities

Table 14: [DIP-TH-KW's Ability]-Open codes

4.5.6.1. [DIP-TH-KW's ABILITY] Skills

Education and experience are factors that contribute to skills. However, BDA skills require different analytical, technical, and managerial abilities (Gupta & George, 2016). In a survey, South African retail organisations highlighted the difficulty in finding not only analytically minded people, but also of finding people with complementary skillsets, meaning that a cohort of skills are supportive of each other, which include grounding in business understanding, technology, analysis, and attention to detail (Mneney & Van Belle, 2016). A concluding remark in the paper is that skills shortage, especially the combination of skills, is a challenge for harnessing Big Data (Mneney & Van Belle, 2016). Older generations are overwhelmed by BDA, and younger generations demonstrate a keenness to learn new skills; CSA is investing in upskilling employees.

EFQ82. "That is essentially what I understand by the ability to extract all of that information to make sense. And to do that as an individual, a person without the proper tools and without the proper training is often where that limitation comes. Given the right training and the right makeup of a person changes that" CSA#32.

EFQ83. "As I said they send us out for training and outsource people that can help us to gain some info or knowledge. The last time I went to Tableau training so that I can up my skills and understanding" CSA#30.

4.5.6.2. [DIP-TH-KW's ABILITY] Power lies in the skill to analyse and interpret Big Data

As CSA#20 said, Big Data is power. However, the power lies in extracting insight; this requires skills, foresight, and patience. There is a cohort that thrives on extracting hidden insights and extrapolating that which is unique. In addition, they are curious and ask questions of the data and not just accept the face value, as is presented in reports. They consider the same data from many perspectives, and at times draw different conclusions. Others fulfil their job requirements with standard reports, as discussed in open code 'Insight begins with appropriate questions', see Section 4.5.2.1.

EFQ84. So, it's [Big Data] meaty. It's really detailed, and you have to sit with it. It's more understanding the data because you will have all this information at your fingertips, but now the interpretation of that data and then obviously applying it. So now what action must be taken based on what I see" CSA#08.

EFQ85. "Data whispers. Does not shout. You must listen attentively, or you will miss it" CSA#30.

The power lies in Big Data analysis and interpretation. It is evident that grasping key metrics from business reports is critical for a person not only to survive, but to thrive. There are differences between KWs who engage with information and those who do not. KWs who appreciate the information are keen to find insight and are comfortable in their roles as they engage Big Data. These KWs are consistently included in collaboration sessions and sought after. On the other hand, there are KWs who dislike the amount of information that is traversing around them and openly share this disdain. Finding underlying meaning is not within their comfort zone, to the point that having access to Big Data is frowned upon. Most of the KWs who reflected these feelings are content with the status quo.

EFQ86. It's very important to have segregation of duties so that I do not do tasks that I'm not skilled to do [analytics] or I don't have access to stuff that I'm not supposed to have access to because I won't know what to do with that stuff or I wouldn't know what to do with the access" CSA#29.

Older Gen Xs and Baby Boomers struggle with the vast amounts of information and tend to avoid Big Data completely, where possible. Some Gen Xs and millennials tend to skim the surface of information, looking for instant gratification, that is, scouring for the bare minimum in Big Data to achieve tasks.

EFQ87. "I am purely focused on finding the data that relates to that new business enquiry. Putting it all together and delivering a report. I am contracted to deliver a report on new business at month-end. We are just interested in the number. Did we hit our target or not?" CSA#32.

There is a group of participants, who fall in the middle of older and younger employees, that appear to be insight-hungry and actively speak about descriptive, predictive, and prescriptive analytics, albeit not using these technical terms. They are frustrated at not being able to analyse more, due to resource constraints—time and money.

EFQ88. We are moving from an environment where you just pushing numbers to an environment where you actually using your brain to think and to analyse and use that to influence the way you do things" CSA#12.

EFQ89. "Because it [data] doesn't scream all the time but you must be the one who must go search. What is that key point? What are you looking for?" CSA#30.

a) Reliable analysis and interpretation of Big Data is essential to value creation

Analysing and interpreting data is not easy for many of the people interviewed. Some find data analytics in its simplest forms daunting (see EFQ93). However, for those that have an appreciation for BDA, there is value that could be provided, as well as gained.

EFQ90. "Remember the more you work with data, the more you gain and the more you understand things better, but it needs you to very conscious, digging and thinking out of the box. Because the problem, sometimes data only whispers, it doesn't shout so you must be very, very able to listen to it attentively" CSA#30.

b) Big Data analysis unmerciful, especially to older generations

EFQ91. "Some people are moving with it a lot easier because they might have that technical inclination. I'm unfortunately not one of those people. I'm technically challenged. I see myself as technically challenged so I stick with what I know. But a lot of people have got those inquiring minds and fall into the technical stuff a lot quicker than what I do" CSA#21.

CSA#21 has a long work history with the firm and has occupied several roles over the years. However, recent roles have been challenging to CSA#21, as technology has become a significant part of the operation that is under CSA #21's responsibility. CSA#21 is not alone in this regard, as several other participants in the study have expressed a similar sentiment. Some are close to retirement and are waiting out the remaining period, while some are challenged because of limitations around education, exposure to similar situations, and experience in dealing with this.

EFQ92. "The fact that it is not structured, it is raw, you sometimes doubt your own decisions because you don't know if you interpreted the data correctly. Sometimes I feel that I might have missed something. I haven't checked all the angles because of the vastness of the data. Sometimes I feel I need somebody else to look at it. Maybe there is another perspective because I expose this decision-making only from my own personality, my own values, there might be a different angle and that is why I say if the data is somehow filtered in a way it is not only myself that is adding my flavour to this decision-making" CSA#20.

EFQ93. It is overwhelming, it is normally in a format that you need to apply a lot of IT skills before you can do anything about it like pivot tables. It is raw" CSA#21.

There are concerns across the workforce with respect to Big Data. The more recent generation, that is, millennials, are more familiar with BDA than the older workforce. However, millennials appear frustrated since they want quicker decision-making; they believe that the evidence is in the data, and therefore have the expectation that this is sufficient to make decisions. They do not understand the delays that result from time-consuming analysis, establishing an understanding, and escalation to decision-making bodies. The older workforce, for many years, had less home-grown data to work with, owing to the state of technology of the time. Older generations had a vastly more intimate relationship with data. Today, data for decision-making is everywhere and comes from everywhere.

4.5.6.3. [DIP-TH-KW's ABILITY] Decision-making abilities

Big Data is daunting, as the evidence suggests. The ability of KWs to make decisions in the context of Big Data is further exacerbated by the fact that insight has to be found among vast quantities of data to guide decisions. The ability to make decisions has nothing to do with the firm's decision-making capabilities and structure, which is attended to later (Sections 4.5.12 and 4.5.13). KWs' interpretation of information leads to decision-making. KWs' interpretation is shaped by experience, adeptness with BDA, and background.

EFQ94. "My decision-making has evolved. I think it comes with experience and the way you make certain decisions. I was a manager for nearly 6 years. You definitely evolved in terms of how you see certain things or say something different than what you think, respond in a certain way, act a certain *way in terms of how your decision-making processes were. So firstly, for me, I think as an individual, I think I've matured over the years. I hear things better. I can figure out the situation better based on my experience" CSA#06.*

4.5.7. Open codes related to Characteristics of decision-makers

Table 15 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***The Habitus (TH)***	***Characteristics of decision-makers (CoDM)***	**Decision-makers and empowerment**
			Effective decision-makers communicate
			Decision-makers rely on competent people
			Risk-averseness
			Power centres rely on summary of information
			Participation of people: Perceived enablers and constraints

Table 15: [DIP-TH-CoDM]-Open codes

Although the open codes and the CHARACTERISTICS OF DECISION-MAKERS axial code could be placed within Decision-making Entity (DME), the rationale is that it resonates closer with the characteristics of people as opposed to the organisational design, processes, and hierarchy of the organisation.

4.5.7.1. [DIP-TH-CoDM[22]] Decision-makers and empowerment

Although empowerment as a liberating concept is debatable (see 2.6.2), participants have embraced the concept and made references to it in discussions around the delegation of duty. This understandable, as empowerment is well known in organisations and implies autonomy and self-determination (Maynard et al., 2012). There are opposing views to empowerment insofar as ability to act independently and under own authority. Management that empower people share information, operate transparently, promote accountability and responsibility, and emancipate. However, these privileges are afforded within thought through guidelines and measured business risks. From the KW (non-manager) perspective, empowerment at times comes across as a checklist item and disingenuous, as the ability to effect decisions does not transpire and recognition does not emerge.

[22] Characteristics of Decision-makers

EFQ95. "I can have all this data and I can hold it to myself because I want to frustrate you. Or I can use it and I can empower you with that information and then you flourish. So, it also depends on management, whether you're holding on to it or whether you're sharing" CSA#23.

EFQ96. "The ability to question from different perspectives makes a good decision. The ability to empower other people makes a good decision-maker" CSA#10.

EFQ97. "I'm not the type that will check with 15 people to get their buy-in. That's an awful way to operate because I think that is just not efficient and I'm about, you need to make quick decisions and I also like to enable my staff to make decisions for themselves" CSA#06.

EFQ98. "It sorts of makes them [management] feel more empowered where they basically sort of micromanage you because there is this Big Data that they utilise. You know so it is a case of even though you have come up with your ideas, you give your opinion, but it is not actually taken into account. It is a case of "yes, thank you for your opinion, but you are going to have to do it like this". You just feel so disempowered, it does not make sense" CSA#35.

4.5.7.2. [DIP-TH-CoDM] Effective Decision-makers communicate

Communication comprises active listening, clarification by asking questions, and exchanging responsibly without recourse.

EFQ99. "I find that it's one of the main downfalls with some companies is that the executive layer doesn't necessarily listen to the people at the bottom" CSA#37.

EFQ100. "So good decision-makers ask the good questions from a different perspective. So not just listening to what you're saying and saying yes or no. Questioning it from a different perspective. These are the best decision-makers" CSA#10.

4.5.7.3. [DIP-TH-CoDM] Decision-makers rely on competent people

Although processed data (information) is available to decision-makers, more so at times than KWs, decision-makers rely on KWs to support them. KWs appear to be focused on specific areas of the business, while management type decision-makers have a broader scope of work and typically report on multiple different areas of the business. For these reasons, decision-makers rely on the analysis of reports by competent KWs.

EFQ101. "Data is available. It is available in people. It's available on the internet and as a good executive, I would surround myself with those kinds of people to be able to get the knowledge to make the right decision" CSA#32.

4.5.7.4. [DIP-TH-CoDM] Risk-averseness

Risk averse implies that risk is avoided and/or contemplated with due consideration for the sacrifice, rewards and benefits before a deciding. Empowerment is a calculated risk that managers take when imparting responsibility to KWs. From the KW perspective, the knowledge that the empowerment with which they have been bestowed is calculated causes them to learn to be risk-averse or frustrated at not being able to contribute through riskier encounters. Intuition, ownership, and innovation are characteristics of risk-based decision-making.

In terms of being innovative and having the insight to support innovation, CSA tends to follow best practices rather than being innovative. While this frustrates employees as they want to be more innovative than smaller competitors, CSA prefers to be risk averse. Such risk-averseness could be reflected by the KW, the organisation, and/or DME

EFQ102. "Empowering someone else to own it counts as being able to take a risk. I'm just taking calculated risks and that also makes a good decision-maker. Good decision-makers are able to back someone" CSA#10.

4.5.7.5. [DIP-TH-CoDM] Power Centres rely on the summary of information

Power centres are in decision-making roles that are more impactful, in that their decisions very seldom have minor implications. Therefore, having a big-picture view informs the decision-making process. However, the details are lost, which could be intentional. It's a case of information without essence. Power centres operate in abstract, that is, they use summaries of data and second-hand information, as the focus is on the big picture. This open code is complementary to open code 4.5.7.3 (Decision-makers rely on competent people).

KWs (experts) are in effect the real decision-makers, while power centres fulfil senior administrative duties, but take ownership for decisions. From a management perspective, managers (CSA#10, CSA#16, CSA#20) that were interviewed appeared to be comfortable with not having detailed knowledge of operational matters, and were comfortable with having high-level understandings of the business at large.

EFQ103. "Executives don't have the detailed data so decision-making is largely based on a summary of data" CSA#12.

EFQ104. "Experts are decision-makers, power centres are administrative approvers" CSA#12.

4.5.7.6. [DIP-TH-CoDM] Participation of people: Perceived enablers and constraints

An enabler facilitates making something possible. Enablers provide guiding mechanisms such as processes, rules, authority levels, and a set of best practices that help achieve outcomes that are good for KWs and the organisation. Enablers do not appear to address specific issues, guide behaviour of KWs towards harmful conduct, and engender ineffective organisational behaviour that result in outcomes that are detrimental to individuals and the organisation. Clear and consistent guidance facilitates less risky employee participation in the workplace. Employers tend to encourage worker participation; however, if the environment is not conducive to KWs participation, it will be constrained, and employee involvement will be limited. A constraint hinders making something possible. Constraints arise externally to the individual and from within the individual. Constraints arising externally include inconsistent and unclear policies and processes, while constraints from within the individual include issues that are based on experience, exposure, and education. The participation of people takes into consideration the effective involvement in workplace activities, decision-making included, that facilitate outcomes that, in turn, have positive outcomes for KWs and the organisation.

At the heart of this thesis is satisfying the curiosity around Big Data's possible influence on the democratisation of decision-makers in DDD, which relates directly to this open code. The positioning of an aspect as an enabler or constraint is subjective. It is closely related to the KW's perspective, interpretation, role, and responsibility, amongst others. Therefore, the words enabler and constraint are prefixed with 'perceived'. For instance, compliance within the financial services industry is perceivably restrictive to business undertakings, which could be perceived as a constraint. However, given that the boundaries are known and assured through policing, compliance is perceived as an enabler, as there is flexibility to operate within predetermined boundaries. Another example is collaborative decision-making; while it is an enabler, on the one hand, it could be perceived as death by consensus on the other hand. This conundrum is applicable to most other discovered enablers and constraints of democratisation—it is a case of perception and interpretation.

KWs' perception of enablers and constraints of realising democratisation are dependent on the following:

- KWs attitude, skills, and ability to decide;

- Collaborative decision-making;
- Consideration for others;
- Access to Big Data;
- Access to necessary resources (tools);
- Organisational backing;
- A business strategy; and
- Adherence to policies and regulations.

a) Perceived enablers

Some perceived enablers are the following.

EFQ105. "Democratisation is achieving similar outcomes or better outcomes without following the same processes" CSA#12

EFQ106. "When a question is posed [by a customer], being able to access the resources that you require to make those decisions to get the information that you need. So reliability of systems that is key to assisting in solving a problem or providing the advice that's required" CSA#39.

EFQ107. "I think what makes me feel democratised is knowing the business strategy for instance. So, if your business strategy says we are moving into 2020 and this what's going to be happening in 2020 that should be enabling factor" CSA#38.

b) Perceived constraints

Perceived constraints are evidenced by the following.

EFQ108. "Start with the individual's attitude, if that's not geared toward being successful and doing the right thing then no amount of democracy is going to work because they are trapped" CSA#38.

EFQ109. "All for one [democracy] cannot happen because in this company I can make a recommendation and I can trust all the facts in front of me, but my superior can overrule my decision. And even though all the facts are pointing in the right direction for my decision, they can overrule my decision to say, "No, you will go with this". Done. Then I've got to go with that" CSA#22.

EFQ110. "I think again that security, that ambiguous space you know, the legalities of it, what do we share, how much of it, who do we share it too, what would the implications be? And so I think *that unsafe, sort of unsure space that we play in. That's a constraint because we haven't found a sweet spot yet" CSA#38.*

4.5.8. Open codes related to Organisational culture

Organisational culture is the unique identity of the organisation that is shaped over time through the people, beliefs, assumptions and values. Table 16 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***The Organisation (TO)***	***Organisational culture***	**Collaboration is key to producing insight**
			Transparency
			Freedom to contribute
			Communication
			Values

Table 16: [DIP-TO-Organisational Culture]-Open codes

4.5.8.1. [DIP-TO-ORGANISATIONAL CULTURE] Collaboration is key to producing insight

Throughout data collection and analyses, KWs consistently described workplace situations that involved two and more people being involved in problem resolution and decisional-action sessions. Manifestations of collaboration included consultation and consensus approaches. From a consultation perspective, it appeared that experts were consulted to help analyse information and solve problems. Management's need for KWs to provide summarised information required frequent collaboration between management and KWs. This was by far the most spoken about method of collaboration.

Collaboration also came across strongly when discussing individual cultural makeup, where examples were given about consulting with elders in decision-making processes in a tribal setting. Consultation also came across when deploying or considering new technologies, where best practice advice was solicited from external organisations that had deployed a technology of interest and under consideration. Consensus appeared to be the preferred method when tasked with group or individual decisional action, as it helps share risks (and rewards).

Collaborative sessions produced clearer and less complicated outcomes that result in action and tasks. For the purposes of this thesis, collaborative discussions are considered as valuable contributions without which the information continues to be just information rather than insight.

EFQ111. "You'll find that we are unnaturally required to be more democratic in our decision-making. Pulling in experts in various fields to actually dissect data reports to make sure that we're actually making the appropriate decisions" CSA#16.

These reports contain a significant amount of underlying insight. However, to extract the underlying insight requires the ability to interpret the data which, in turn, requires a firm understanding of the subject matter and the necessary data interrogation skills; the KWs appeared to lack these. This could be due to a lack of training, experience, job role/process, motivation, exposure, or education. To overcome these limitations, more knowledgeable workers or subject matter experts are consulted to help debunk seemingly complex reports. Collaborative discussions appear to be a normal and well-established occurrence within CSA. The access to expertise and the inclusion of expertise leads to effective collaboration conditions, be it for decision-making purposes or consultations; it is important to democratisation, as expressed above by CSA#16.

The evidence for this open code has been considerable, and are provided in Sections 4.5.7.3, 4.5.7.5, and 4.5.7.6.

4.5.8.2. [DIP-TO-ORGANISATIONAL CULTURE] Transparency

Transparency, within organisational compliance guidelines, is necessary for KWs to carry out their duties. It promotes a sense of well-being and inclusion. Factors that inhibit data transparency, such as blocking (4.5.3.1) and data silos (4.5.3.4), have been sufficiently evidenced. Transparency, as related to business operational information, is consistently transparent across the organisation.

EFQ112. "So, what would make it all fit together? So, I would say access to data, security, analysis, and transparency from CSA. I'm saying transparency because, in all of this, you ultimately want to get to one source of truth that will then influence your decision-making. You have to tie all of it together" CSA#38.

EFQ113. "Everything's got to be faster, quicker, and everything's got to be recorded so that somebody else can walk in and kind of take over your job, almost. So, transparency is not negotiable" CSA#21.

EFQ114. "Now that information is shared at the top level and it actually filters down whereas before it stopped at a certain level then it was kind of like on a need to know basis whereas now everybody knows the direction the organisation is going" CSA#19.

Transparency is critical to effective decision-making and while CSA appear to fair amount of transparency, there appears the sentiment that it is insufficient.

EFQ115. "I think there's a frustration at CSA. So, there's not like the most transparency. I mean making sure that everybody's transparent and making sure that everybody understands that we have the same set of rules that apply to everybody, and I know that it's very easy to say the same sort of rules applies to everybody, but it's not" CSA#06.

EFQ116. "They must create an environment where there's openness and transparency, and there must be a firm commitment to growing the talent pool among non-white managerial staff" CSA#19.

4.5.8.3. [DIP-TO-ORGANISATIONAL CULTURE] Freedom to contribute

In a competitive marketplace, especially for jobs, it often falls on the KW to make strides toward achieving better outcomes in the workplace through value contribution. This can be achieved by stepping outside the constraints of roles and responsibilities and do something extraordinary, such as to apply thinking to a piece of information so that it becomes knowledge, and eventually turning that into actionable insight. Big Data is complex, and resources are constrained, but seeing beyond the obvious is what elevates one KW from another. Freedom to contribute is an open code that collates KWs' desire to contribute to the organisation.

Some participants felt that the freedom to contribute is hampered by a lack of effective feedback mechanisms.

EFQ117. "Nowadays the decision-making is so authoritative that it stumps innovation. It stumps people wanting to give ideas because there isn't really an appetite for your idea to work" CSA#28.

EFQ118. "Because not one person is going to know everything even though some people think that. It was just about listening to people and maybe I'm coming from my old school you must listen to people to win people and sometimes you can learn from a better experience" CSA#11.

4.5.8.4. [DIP-TO-ORGANISATIONAL CULTURE] Communication

Communication is interrelated with several other open codes, for instance, freedom to contribute, transparency, and collaboration. Communication stands on its own, as it is the voice of KWs and an essential component in collaboration, which has been highlighted as a key enabler in the democratisation of decision-makers in DDD.

Effective communication bridges the generational divide, contributes to firm competitive advantage, and acknowledges the valuable contribution of KWs.

EFQ119. "People think listening to people is old school. But you must listen to people to win people" CSA#11.

EFQ120. "I'm not saying that we don't have a strategy around Big Data, because we've got a whole digital thing that's working with data. I think from a communication point view it's not filtering down to everybody and Big Data should become a concept or a term that everybody can identify with and not only the people sitting on top or working with data or in the digital space" CSA#28.

4.5.8.5. [DIP-TO-ORGANISATIONAL CULTURE] Values

The values of an organisation are the fundamental beliefs and principles from which all business-related aspects are derived (Schein, 2017). For instance, decision-making, strategy making, and persona of the firm—that is, how the company is seen by internal and external stakeholders—are based on organisational values. In an industry such as that of CSA's, values are interlinked, meaning that they span the entire organisation, to ensure consistency in ethical practices, safeguarding against regulatory infringements through enforcement, and keeping good governance through rigorous checks and balances. Values are reflected across the organisation's departmental boundaries—finance, human resources, and customers.

It is found that:

- organisational values are instrumental in driving workplace behaviour and outcomes;
- there are generational differences in how organisational values are embraced; and
- conflicts arise when there are inconsistencies in the adoption of organisational values.

EFQ121. "Mostly the decisions that I make in terms of business are based on what I've learnt at school and then in terms of how I conduct myself with customers and people is based on how I grew up and how I was raised. From a company point of view, it's based on following the processes, the values and the vision of the company" CSA#29.

EFQ122. "Sometimes they [management] say they're going to listen, but you can say the same thing over and over and that falls on deaf ears, so I think it's them that's needing to align with the vision" CSA#17.

EFQ123. "I think in terms of the decision-making, Big Data has sort of desensitised the newer generation to your morals and values versus the older generation where I do think that the principle in terms of the formula is the same but because the new generation has more access to so many of society's issues that we face today, it's become a norm for them. [What issues?]. Corruption, violence, company theft, leadership issues. Even there's a distinction between white corruption and black corruption" CSA#37.

4.5.9. Open codes related to Managing the business

Table 17 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***The Organisation (TO)***	***Managing the business***	**Business processes**
			Controlling risks
			Financial constraints
			Resource constraints

Table 17: [DIP-TO-Managing the Business]-Open codes

4.5.9.1. [DIP-TO-MANAGING THE BUSINESS] Business processes

An organisation consists of people and things that fundamentally are supposed to deliver value. Value is realised through the coordination of people and things, meaning that achieving common valuable outcomes is the goal of the resources (people and things). Business processes are a set of activities that focuses on optimising organisational processes (workflows, decision models, data management) which, after implementation, is meant to deliver on better processes that "contributes to meeting the strategic objectives of an organisation" (Van Der Aalst et al., 2016, p. 3). The impact thereof is on the organisation, collectively, but more immediately on the KWs and departments. Automation of routine tasks is referred to as business process automation.

The evidence suggests that:

- Automation of routine tasks are hampered by the complexity of ICT;
- There is an awareness, across participants, of the need for continuous improvement;
- Some business processes are not aligned to corporate culture; and
- Business processes reduce human interaction.

ICT complexity: CSA is an old establishment that has legacy systems in place, which is difficult to replace due to deep integration across business functions. There appears to be an alignment issue between business and ICT function within the organisation, meaning that at times it appears that synchronisation and harmonisation is lacking. For example, multiple data silos and deployment of BOTs have been mentioned.

(see EFQ185 for supporting evidence).

Continuous improvement: Given the deluge of data, the challenge for CSA is prioritising data consolidation from data silos, data accuracy, KW training, and deploying automated processes.

EFQ124. "So, we've got all this data coming in but how can we actually use it to make processes simpler and eliminate waste and automate" CSA#09.

EFQ125. "Continuous improvement is always required. Because people have been doing things a certain way for the last ten years doesn't mean it's the best way of doing it" CSA#16.

Aligned business processes: Having business processes in place are considered to be good for the organisation as they provide uniformity and consistency. However, they appear to be restrictive for KWs who want to apply themselves beyond what the process entails.

EFQ126. "So, for each and every single thing that we do, there's a set process. I always need to ensure that I follow those processes" CSA#14.

Alignment of business processes to organisational culture: There appears to be a mismatch between business processes and organisational design and characteristics.

EFQ127. "We did a [organisational] culture shift and the culture shift says, "we need to be agile, we need to make risk-based decisions, we need to own our decisions, so we need to do all these things". But I don't think our processes are aligned to that. We're not allowed to do that. So, our processes are not aligned to our culture" CSA#22.

EFQ128. "We've been able to streamline a lot of our processes, meaning that we don't have a lot of human interaction. That's been reduced to a minimum".

4.5.9.2. [DIP-TO-MANAGING THE BUSINESS] Controlling risks

CSA is in the highly visible and regulated financial services sector. Therefore, CSA are focused on controlling risks, which is incorporated in every decision-making type. An example of this could be a CSA strategy, which is to grow revenue and reduce cost. What underlies this strategy could include deploying counter-risk measures to protect the existing revenue stream, optimise business functions to reduce operational costs, and target new customers to offset end-of-life revenue streams. Underlying these are supporting operational, tactical, and administrative risk mitigation measures—for instance, improving the customer experience through robot (BOT) deployments, managing CSA-concerned social media content, safeguarding data integrity, and having governance processes in place to bolster the integrity of the organisation.

a) The internet, social media and other media outlets

Managing the discourse in the public sphere is an important activity at CSA. This entails being continuously aware of all contributions—negative and positive—that are made on CSA-owned (websites) and controlled (Facebook pages and Twitter accounts) platforms. Although it is currently a manual process, CSA proactively monitors and responds on the same platform to ensure customer satisfaction and avert negative consequences. Teams monitor other media outlets, such as print and electronic media.

In a recent attack on financial institutions in South Africa, cybercriminals demanded ransom and subsequently caused service disruption through distributed denial of service attacks on websites (Quintal, 2019).

The evidence suggests that participants considered the internet as the great equaliser, and also as something that has to be treated with a healthy paranoia in order to be proactive against brand attacks.

EFQ129. "Too much history and too much of a digital footprint that's left on the internet. This is scary" CSA#14.

b) Data Security

It may seem prudent to place this open code within TI, but data security matters are pervasive and affect the entire organisation, including people and assets. The boundaries of the organisation have become fluid in that there are multitudes of data sources—both internal and external—and the security perimeters of the organisation extend beyond the traditional network firewalls to now include mobile devices and the cloud.

The evidence suggests that:

- Data security concerns around Big Data are not unwarranted, due to the impact the 4Vs have on the business;
- KWs are concerned with preserving data privacy;
- KWs with ICT-related roles are concerned with securing data integrity; and
- Every KW has a role to play in protecting the organisation's data.

Participants' conversations around data security tended to take different paths, which seemed to be based on the role of the particular KW.

KWs were concerned about data privacy as related to legislation, source of the data, and authenticity of the data, which is very strictly based on current regulations around the protection of personal information (PoPI[23]) act. These concerns centred on the use of the data for customer marketing and sales-related activities, and the implications thereof in terms of the veracity of their customer information and custodianship of home-grown and acquired third-party data. In light of legislation around the protection of personal information (PoPI) Act, there was awareness of the restrictions and implications related to personal information. In most cases, KWs did not feel comfortable with how people-related information is disseminated.

EFQ130. *"The notion that data needs to be obviously at the right grain [relevance, depth] and available, causes us problems as business analysts as restrictions in terms of the protection of information in peoples' personal lives [PoPI]. I think that making that data available to everybody is not my call but a governance one, but it is a concern so much so that we feel restricted" CSA#32.*

EFQ131. *"Everything is connected; my phone is a threat [...]. I can unknowingly or unwillingly leak information, leak customer service information firstly or leak information that I use, about me. So that is quite concerning for me" CSA#33.*

[23] Protection of Personal Information act - http://www.justice.gov.za/inforeg/docs/InfoRegSA-POPIA-act2013-004.pdf

EFQ132. "I think again that security, that ambiguous space in the legalities of it, what do we share, how much of it, who do we share it to and what would the implications be? I think that unsafe, sort of unsure space that we play in; we have not found a sweet spot yet. I think that's probably one of the constraints for me is that there's just no security around it" CSA#38.

For KWs who were in an ICT-related role, the concern was an operational dilemma of how to secure Big Data, given its volume and unstructured nature. Both put substantial strain on ICT resources as performance, in terms of response times, become noticeable for user experiences that require real-time or near real-time responses. For non-real-time requirements and for data within structured environments (for example, relational databases), securing the data with respect to performance is less of a concern.

EFQ133. "How do we encrypt Big Data in motion and at rest, so that the end-user experience appears seamless? We wrestle with this" CSA#43.

With respect to EFQ133, there are decisions that need to be made that would satisfy some and not others, as advanced technology is required to provide Big Data security in-motion and at-rest, while providing a somewhat seamless user experience. Although corporate Big Data, that is, datasets that are home-grown, are unencrypted in rest and seldom encrypted in motion when used internally, this is not the case for cloud-based data repositories and external Big Data. For CSA, home-grown and business-critical data resides within internal data warehouses, and are therefore already protected by some form of security mechanism, for example, firewalls, access control, and authentication services.

c) Managing Access

CSA has a complex ICT environment. The organisational changes over the years have resulted in complex ICT systems and stresses on support functions.

Organisational change and staff turnover have a direct bearing on the ability to maintain and secure ICT assets.

EFQ134. "When we first started and wanted to do [software license audit] to tell how many you have. And then we found these people have left the company, but they still have access to our systems. Obviously, that's a breach of security with those things. So, it'd be a major impact in terms of HR data, but the same could be for a PC. So, if you found, for example, a piece of software that has been installed on a PC that's known to our system as being reconditioned, stolen, what's the implication? Because it's a license cost attached to that" CSA#08.

Memo 7 *18.12.18 – discussion with CSA#08. Similar activities have been reported with respect to other access control systems. These will be not be shared and they were attended to before the interview.*

d) Corporate Governance

Good governance is about ensuring that checks and balances are in place to safeguard the organisation's integrity and protect its brand. Corporate governance seeks to ensure that the behaviour of the people within an organisation is in accordance with laws, in line with shared objectives and upholds shareholder value. Governance could be considered restrictive but also liberating, as the boundaries are known.

The evidence suggests that:

- Big Data has influenced corporate governance because of its uncontrolled nature, which arises from the multitude of sources;
- Corporate governance is under pressure from the external environment to ensure regulatory compliance; and
- Corporate governance checks and balances extend across departments, or are interdepartmental rather than contained within departments.

EFQ135. "I think the data has changed everything so there are a lot more policies in place, there's a lot more structure. There's a lot more rules and regulations you need to follow, and the company is a lot stricter than it used to be" CSA#24.

CSA has put in place stringent policies due to external regulatory requirements and to manage the deluge of data that resides internally and externally.

EFQ136. We [CSA] are ruled by fear because compliance has to uphold all of these compliance and regulatory forces in the market and it is because companies like ourselves in the past have been that bad to customers. You know because of the lack of information and we had all of these little hidden clauses in what we do, particularly in the financial services industry. We burnt our fingers with the ombudsman and so the government has come in and implemented all of these sweeping changes across the industry. That has really put limitations on the way we operate" CSA#32.

CSA have put in place interdepartmental scrutiny as an additional governance level. The rationale behind this is to vet data and compliance adherence across departments.

EFQ137. "I think if you look at how we do things, in how we structure the business, Big Data helps. Because I use data to manage the operations, but I also use it to manage areas where I am not directly managing, but I have to have a certain level of control. So, let's just say compliance, I need to have data from compliance in order for me to make sure that they [other departments] are doing their job, even though they don't report directly to me" CSA#12.

e) External Influencing Factors

External factors, such as political stability, economic stability, labour stability as well as adherence to regulatory requirements (such as employment equity (affirmative action), black economic empowerment, labour regulations, data privacy (PoPI), and financial intelligence (FICA[24])) influence decision-making processes. However, the implications are more difficult to establish at the individual KW level, as the impact is largely at the organisational level. The extent to which these factors influence the processes and results of decision-making is also difficult. From the wider corporate perspective, the influence is visible through regulatory and legal statutory laws. The economic influence is visible as organisations deploy measures to counter and advance their positions in the marketplace, depending on the situation and organisational strategy. The socio-economic influences are visible through strike action and economic empowerment policies that address previously disadvantaged citizens[25] (see Section 4.5.4). While initial thoughts were that external influencing factors affected TO and DME only, TI and TH are affected as well through the mentioned data privacy and affirmative action policies, respectively.

External influencing factors affect all DIP actors in some way or another. However, TO and DME are most affected, as they are seen to be the guardians of the business. It is within these two actors' purview to ensure that everything related to ensuring stakeholder value is upheld. A few of these include delivering on profitability goals, running a law-abiding business, and attracting the best talent. CSA is in the financial services industry, which is highly regulated as it is in the business of managing people's finances.

[24] FICA – Financial Intelligence Centre Act - 2001 (Act 38 of 2001) (FIC Act) https://www.fic.gov.za/Resources/Pages/Legislation.aspx

[25] Prior to 1994, South Africa employed apartheid to segregate citizens into ethnic groups and afforded benefits based on ranking of these groups. Whites were the most privileged and Blacks were the most disadvantaged.

Although CSA are largely autonomous and self-governing, external influencing factors play a significant role in how the business conducts itself in most respects. Furthermore, external influencing factors affect internal employee relationships.

EFQ138. Governance and compliance are there to protect our customers. But it also made us cautious in everything especially in terms of our decision processes. We need compliance you know… money laundering and all this sort of thing that is external forces in the outside world, which have forced us to become formal and certainly controlled" CSA#32.

4.5.9.3. [DIP-TO-MANAGING THE BUSINESS] Financial constraints

Financial constraints appear to be a key limitation to expanding BDA. The expectations of Big Data is different for each KW. Some KWs are interested in understanding history through descriptive analytics, while others are interested in predictive analytics to understand future events based on past occurrences. Some KWs want the ability to proactively prescribe solutions based on the nature of the event. As established in Section 4.5.2, the latter two analytical types are not as widely deployed as descriptive analytics. There are hurdles to overcome in the analysis of Big Data, such as the financial capability of the firm, specifically in terms of procurement of analytical tools and continuing with licensing of popular tools.

Financial constraints are a limitation to extracting insight from Big Data for decision-making purposes.

EFQ139. "If we use Big Data and we bring in analytics, I would say yes, we are creating knowledge. Because I would have the necessary at my disposal to make ground-breaking or not ground-breaking, [or] significantly change the service experience of our customers which would contribute to brand loyalty. But you need to invest the money and you need to invest the time" CSA#28.

Since CSA engages with customers through call centres, it could be beneficial to turn call centre audio conversations (recordings) into data that could be analysed. The extracted insight could be used to increase sales, improve the customer experience, and facilitate compliance requirements more easily. However, the financial investment is lacking. This seems like a strategy and business investment prioritisation decision for CSA.

The three departments face similar issues with respect to limitations in enhancing the call centre experience for both internal and external customers.

EFQ140. "I listened to voice recordings of the call and I was like why we don't have software to actually put that into your [data] warehouse so that we can start doing word trends and see what is the common knowledge that is coming through this data. My problem there was that there was no budget and there was no interest from the rest of the business to start understanding the customers" CSA#01.

4.5.9.4. [DIP-TO-MANAGING THE BUSINESS] Resource constraints

From the case study environment, standardised BDA extractions were the main form of business reporting. Even these standardised reports were underutilised—the information provided was either insufficient to perform work-related tasks, or deeper analysis was required. Further interpretation to extract underlying insight through trend, causality, and relationship analyses were seldom undertaken because of time constraints, or constraints around the availability of data specialists.

Apart from financial constraints that were discussed in the previous section, lack of data specialists and time limitations are generally significant hindrances to extracting value from Big Data at CSA.

a) People constraints

The abundance of Big Data has been acknowledged already; however, the limited data specialists are problematic for CSA, as information without knowledge remains as such, meaning that extracting insight is hampered.

The study data suggests that:

- Data specialist resources are scarce and, when they are available, they are constrained because of the lack of business knowledge;
- Some millennials are not inclined to spend time with data to grasp underlying insights due to a lack of interest; and
- Big Data facilitates better usage of human resources.

The scarcity of data specialist resources is influencing the ability to understand the business, given the complexity of not only BDA but also of the highly competitive industry within which CSA operates.

EFQ141. "I think CSA could improve by getting all stakeholders, let me say multi-generational resources, into one room to really unpack what it is that Big Data can do for us and what we need, what we can get out of it. Then give it to the [data] specialists to run with it. CSA's way currently is we have a niche of [data] specialists that will talk their language but have no idea of the business impact. You need a multi-dimensional view of a problem that you're trying to solve. I feel that we're working in *specialist pockets. IT will sit with an IT problem whereas you can have a non-IT person that can see that blind spot that you can't" CSA#28.*

Apart from the requirements for more KWs to alleviate the workload, there is also the perception that generational issues are constraints. As mentioned in Section 4.5.6.2, older generations (Baby Boomers and older Gen Xers) find BDA and in-depth information analysis overwhelming. However, there are behavioural characteristics of millennials that suggest a lack of interest in finding underlying meaning in information.

EFQ142. "If we look also at the millennials and how they do business. They do not have time for bureaucracy, they do not have time for reading endless pages of documentation, they have short concentration spans, and they are restless. They want answers instantly, quickly, and not prepared to look" CSA#19.

Resource constraints are well established. However, Big Data has been complementary to the optimisation of human resources.

EFQ143. So now, with all the data that we have been provided with, it has made my job a lot easier. In fact, it is a lot quicker to extract information, because I manage people, I can see immediately if the consultant has made an error. At the end of the day, I can extract a report to see where somebody has made errors or where they failed on something and address it immediately. Previously it was always after the fact you know, so now you can actually remedy it immediately and change that behaviour.

b) Time Constraints

Although constraints such as financial and human resources were shown to be important contributors to the better use of BDA and, more specifically, the deeper analysis of data/information, time constraints were the most spoken about constraint.

BDA is time-consuming and, although the insight is known to be beneficial, allocating focused BDA time into KWs' workday is not practised.

EFQ144. "But I just don't find the time to analyse the stuff. You want to actually analyse and look and kind of build some trends. But, there's just not enough time to do that stuff" CSA#05.

Spending additional time with BDA is taken to be an optional task. However, this risky as job expectations may not be met and the added effort may not be recognised by the organisation.

Several KWs demonstrated a willingness to engage with BDA, as they are keen to uncover the insight behind the information presented. However, they are constrained in terms of time and access to data specialists. Most participants acknowledged these as constraints to the democratisation of decision-makers in DDD.

4.5.10. Open codes related to Reliance on Big Data

Table 18 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***The Organisation (TO)***	***Reliance on Big Data***	**Access to Big Data improves productivity**
			Big Data is critical to CSA's decision-making
			Big Data use leads to competitive advantage

Table 18: [DIP-TO-Reliance on Big Data]-Open codes

Although the below open codes and RELIANCE ON BIG DATA axial code could be placed within Technology Infrastructure (TI), the rationale is that it resonates closely with the characteristics of the organisation.

4.5.10.1. [DIP-TO-RELIANCE ON BIG DATA] Access to Big Data improves productivity

Big Data is not without its challenges—as mentioned throughout this thesis. However, the benefits of BDA are also evident in the study.

Big Data facilitates innovation and improves KWs' productivity. However, access to Big Data is critical to achieving this.

EFQ145. "If I didn't have this data then I wouldn't be able to come up with ideas, of new ways to do things, better ways to do things" CSA#05.

EFQ146. "I think that we starting now to see more of the benefit because people are more productive with access to Big Data. I am able to get plans up, I'm able to get work done. If there was more access to certain things, I would be able to do my job even better. Certain things are obviously restricted for security reasons, but it inhibits me from doing more in my *day-to-day because I've got to find another avenue to do it so that I can get that information" CSA#18.*

4.5.10.2. [DIP-TO-RELIANCE ON BIG DATA] Big Data is critical to CSA's decision-making

Big Data is critical to CSA in every decision-making sphere—strategic, tactical, operational, and administrative—of the organisation.

EFQ147. It [Big Data] shows how can we improve our company because that is the only way that you can find out how are we doing out there, what are the things that we are missing? What are the things that we can improve? Is our client happy? Without data, we cannot say anything because whatever we might assume might be useless or might be pointless" CSA#30.

EFQ148. "We use it [Big Data] in every aspect of every single thing that we do in the business. It's powerful for continuous improvement, for benchmarking, for upgrades, for system analysing, everything" CSA#27.

EFQ149. I also think it [Big Data] gives us the ability of being strategic. To look at where you actually want to go, are you just going to follow every trend. Over the last 5 years for example we did this so let's keep doing it because it worked or do you say okay at some point we need to maybe change over to try something new, to try something different so it's more the risk taking in that aspect.

4.5.10.3. [DIP-TO-RELIANCE ON BIG DATA] Big Data use leads to competitive advantage

To survive and thrive in the highly competitive financial services industry, CSA employs Big Data resources in a manner that facilitates the best competitive advantage.

Big Data is essential to CSA's competitive strategy in the marketplace because of the vastness of underlying insight that arises from, among other things, social media, unsolicited data, third-party provided data, and competitor data that is publicly available.

EFQ150. "I think decision-making processes are becoming quicker. So, if I think about just in our space, one company does something and there's always another way to try to improve it. I think that is what's making decisions happen quicker. It's the competitiveness of the market" CSA#21.

4.5.11. Open codes related to Legacy

Table 19 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***Decision-making entity (DME)***	***Legacy***	**Big Data influences the transformation of traditional DM processes**
			Pace of transformation
			New technologies not as reliable as legacy systems

Table 19: [DIP-DME-Legacy]-Open codes

4.5.11.1. [DIP-DME-LEGACY] Big Data influences the transformation of traditional DM processes

Traditionally, business processes were largely time delayed. Examples are reports that were requested and delivered several days later, business information to manage the business was limited, and decision-making was manually progressed based on limits of authority. Big Data allows for ease of access to vast amounts of information, insight to manage the business is readily available, and decision-making tools are available to facilitate quicker decision-making. KWs, both managers and non-managers, could enable or inhibit the transformation.

The evidence suggests that, although Big Data is widely available for business management purposes and decision-making processes are evolving, people appear to constrain the progress.

EFQ151. "Decision-making is evolving. I think it's evolved a lot already because people are more demanding because they see everything, they know what's going on" CSA#18.

EFQ152. "So, having this data available now changes the manner in which we do things, the manner in which we run this business, the way that we see ourselves in the market differently because we are actually using these platforms to build better processes" CSA#23.

EFQ153. "People are still reluctant to make that call. It's still a very old school type of thinking where I can't do this, I need to first talk to this person, or I need to do this" CSA#18.

EFQ154. We now see there's a change. You don't have to go through so many people to have decisions made and approved in those kinds of things" CSA#05.

Transparency, because of insights derived from Big Data, is key to transformation.

EFQ155. "To improve processes by collecting volumes of data, I can understand things and basically make things better in my space" CSA#26.

Big Data expands the evidence base to support decision-making.

EFQ156. "The data that we would look at obviously, everything that I do because there's such a large financial implication or investment required to do these things, a business case needs to be built. A business case is built on data. Now days you look at what's happening in the industry, case studies, success stories, failures and how to build from there" CSA#16.

Transformation of essential business processes, such as customer engagement and customer experience management, is enhanced in the Big Data era.

EFQ157. "To basically help us streamline our processes and make it easier for our clients to engage with us and to also let customer behaviour drive how we run our operations" CSA#12.

4.5.11.2. [DIP-DME-LEGACY] Accelerated pace of digital transformation

In the context of the study, digital transformation is centred on the evolution of the traditionally separate business and IT strategies to digital business strategy, which is the fusing of business and ICT strategy; the latter is manifested through "leveraging of digital resources to create differential value" (Bharadwaj et al., 2013, p. 472). Fundamentally, it is about identifying and utilising all the digital resources within and outside the organisation (for example supply chain participants). A key aspect of transformation is to identify and transition non-digital resources to digital. The digital resources are sources of Big Data.

The rapid pace of transformation, considering Big Data use, is essential to competitiveness.

EFQ158. "We always need to remain current at all times and if possible think ahead, try to be one or two steps ahead [of the competition], because at the end of the day we want to be number one in the industry so change is vital and its change that is taking place on a daily basis" CSA#39.

EFQ159. "We're a massive organisation, and to try and change a massive boat and steer it in a different course takes time. I do not know what we need to do to improve specifically in the industry, but how we can ensure that we are always relevant in the industry is that change is required much *quicker. We must be accelerating our IT modernization, link things together so it's easier for us and our customers" CSA#16.*

4.5.11.3. [DIP-DME-LEGACY] New technologies are not as reliable as legacy systems

While newer technologies bring additional benefits and features, there is the perception that legacy systems are more stable and reliable.

EFQ160. "The load of users and data on the different platforms, sometimes it has an effect on the reliability of systems; so, if a system shuts down you are affected here in the building trying to assist clients. These impacts on our credibility. From a systems point of view, the old systems didn't go down" CSA#39.

EFQ161. "We've got new technology; you know sometimes it's not as reliable and robust as what our legacy systems are" CSA#06.

4.5.12. Open codes related to Decision-making capability (DMC[26])

Table 20 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***Decision-making entity (DME)***	***Decision-making capability (DMC)***	**Big Data Analytics (BDA) supports decision-making**
			Big Data Analytics (BDA) supports agile decision-making
			Decision-making based on trends and best practices
			Quality of Big Data-driven decision-making
			Decision-making is context-driven
			Trust is vital to DDD
			Insights-driven decision-making
			Decision-making based on intuition

Table 20: [DIP-DME-DMC]-Open codes

Although some of the open codes within this axial code are Big Data-centric and could be placed within Technology Infrastructure (TI), the rationale is that it resonates closer with the decision-making characteristics of the organisation.

[26] DMC – Decision-making Capability

4.5.12.1. [DIP-DME-DMC] Big Data Analytics (BDA) supports decision-making

There is consensus that BDA is essential to data-driven decision-making. The benefits of BDA are well known to KWs, such producing better insights and making smarter and effective decisions as the data is interrogated from multiple angles. The cost-benefits associated with analysing and automating processes are good for CSA. However, realising these benefits have challenges that mainly involve the data analytical skills that are required but in limited supply, and the perception of KWs that machines are making decisions in their stead.

EFQ162. "Definitely everybody looks to Big Data to make decisions. I mean you can't make these decisions without data, but you need to delve into the data first" CSA#26.

EFQ163. "When it comes to Big Data and decision-making, I think one of the main issues we have is not actually analysing the data properly" CSA#09.

EFQ164. "We're working reactively, because we struggle with analysing data. And, we definitely need to change that decision-making process. It is too long, and it is too cumbersome" CSA#22.

EFQ165. "On the negative side is that you know Big Data does have an element that you rely on it so much so that you override and oversee the people that are actually working there. That you making decisions purely based on numbers, figures, the surface" CSA#37.

EFQ166. "With Big Data, if they need information, they can look for it themselves on the internet or get it from robots. I think it's going to have a big influence going forward because of its time and money saving" CSA#24.

4.5.12.2. [DIP-DME-DMC] Big Data Analytics (BDA) supports agile decision-making

There is consensus among all participants that decision-making is slow, despite the organisation's agile approach to the messaging of decision outcomes. There is the belief that Big Data has enabled quicker decision-making, specifically for social media events that have the potential to affect the business, either negatively or positively. Social media specialists monitor and curtail fallouts before they develop momentum and become uncontrollable.

Big Data is forcing CSA decision-making processes to be more rapid and more responsive to stimuli.

EFQ167. "Top management, they are forced to respond to those that are out there and the data they have to incorporate in the report. Meaning in any business, gone are the days that your strategy is going to be this rigid. It must be a work in progress. So, you change your business strategy every day depending on the data that is available out there" CSA#13.

4.5.12.3. [DIP-DME-DMC] Decision-making based on trends and best practices

Descriptive analytics facilitates decision-making that considers trends and best practices.

EFQ168. "So, it's a measurable unit, being able to spot trends from it, being able to use it for analysis to run your business, being able to understand customer needs" CSA#12.

4.5.12.4. [DIP-DME-DMC] Quality of Big Data-driven decision-making

As established, Big Data supports decision-making through evidence-led decision-making, rather than through intuition and assumptions. However, for decision-making to be credible and effective, the quality of the data is important.

The quality of decision-making is enhanced by good quality Big Data. Quality, among others, relates to the data's recency, source, relevance, and compliance with organisational guidelines.

EFQ169. "Decision-making is based on the quality of the data and how up to date it is. I would say also how consistent it is, because if you notice like major irregularities in specific data, that is going to be your concern and to definitely impact decisions. I mean that again it would be dependent on where it is actually being used, where the data is coming out of [source]. I mean the data needs to be fit for purpose and for use actually. It needs to provide the information that's needed" CSA#09.

EFQ170. "I also need to mention the risk of having this data available, there is a massive risk because the data can also go the wrong way and the decision we make based on that. And that is a bit scary, so Big Data is also bad data" CSA#20.

EFQ171. "I feel extremely positive and extremely scared about it simultaneously, so I love the idea of Big Data because I can make decisions. It is empowering me, it is giving me the facts, it is supporting me, and it is giving me a foundation to work on. But at the same time, it is a scary portion because the freewill portion of that is, if you haven't got integrity and your values are not in place, what will happen to decisions?" CSA#20.

4.5.12.5. [DIP-DME-DMC] Decision-making is context-driven

In decision-making, situational context is key. Context here includes the type of decision-making, time, place, and consideration for people. Strategic, tactical, operational, administrative, time, place, spontaneous vs. calculated, and human situational factors are all contextual considerations in decision-making.

Context is key in decision-making situations.

EFQ172. "So, it's always situation-driven – context. It is always key to how I make decisions. People, things, situation shape my decision-making approach" CSA#10.

4.5.12.6. [DIP-DME-DMC] Trust is vital to DDD

The veracity of the data has been addressed, which is the foundation upon which DDD hinges. This open code is related to trust in people in data-driven decision-making processes. Trust begins with trustworthiness of the data. However, trust factors extend beyond this to KWs involved in producing the information and trust between people. So, trust in people is an important consideration, beyond the trust in data.

Trust in people and trust in data, especially in the financial services industry, is not *fait accompli*, hence CSA has strict governance processes and people in place to verify and validate data. A case in point is CSA's access to the Department of Home Affairs—mentioned in Section 4.5.3.7—to verify personal information.

Apart from data trust issues, trust in the people that handle data and information is a consideration. Some participants indicated that they trust data more than they trust people, while others trust people more than they trust data.

Both trust in data and trust in people are vital to data-driven decision-making.

EFQ173. "Systems can be manipulated. I trust people more than I would trust data from a machine" CSA#21.

EFQ174. "A bit of both [people and data]. But I would say more data, provided that the data is accurate" CSA#12.

EFQ175. I trust data more than people, because data will never lie to me, but people might tell me their opinion, their insight, what they think. If I have to make a decision and there is somebody and there is data. I will rather take data and try to find out if it will give me that which I am looking for. Because somebody might tell me their belief. Everybody has their own different beliefs so data will never do that on me" CSA#30.

4.5.12.7. [DIP-DME-DMC] Insights-driven decision-making

From discussions with data scientists at CSA, it emerged that, although the organisation is data-driven, it is not yet insight-driven. From a data perspective, the company is overwhelmed by data that is everywhere. However, insight as a decision-making aid is less prevalent than one would expect.

KWs are provided with standard information reports that contain answers to frequently asked questions. Custom reporting is possible, but the data scientist finds it challenging to satisfy requirements, as basic questions cannot be answered. For instance, what is the purpose of the report, what exactly is needed, and what are the expectations from the data? While these appear to be basic questions, the answers are lacking. The reason seems to be a realisation by the firm that, with the vast amounts of data, the decision-making entity is lacking insight-driven decision-making because of skills and resource limitations, as discussed previously.

The evidence supports the notion that CSA is data-driven, but not yet insights-driven as the firm is in its infancy when it comes to better utilisation of BDA. Importantly, the firm is largely engaged with descriptive analytical tools and even with descriptive analytics; the analysis is at a high-level.

EFQ176. "We are a business that is governed by rules; we have stakeholders we answer to, so we use data to make decisions. What we lack is digging into the data to find less obvious things that can make us more innovative, more competitive. We are pushing digital aggressively and maybe that will change things, but we are just playing on the surface" CSA#43.

4.5.12.8. [DIP-DME-DMC] Decision-making based on intuition

Within the data collection phase, evidence and intuition—both key concepts—were put forward without regard for the underlying meanings or implications. Some respondents appeared to suggest that evidence and being data-driven are the major contributors to the decision-making process, while others seemed to support intuition and gut-instinct as the major influencing factors of decision-making processes. Deeper discussions highlighted that these two seemingly opposing decision-making factors are largely contextually driven, as opposed to an ‘either-or’ decision, meaning it depended on the actual conundrum at that point in time. In addition, they (evidence and intuition) are complementary at times as The Habitus, meaning that they bring experience, cultural influences, and education, which shape the interpretation of information/evidence.

CSA indicated that evidence-based decision-making processes are dominant, since routine work is based on use and re-use of system data (reports). However, it came across convincingly that intuition played a significant role in people-centric decisions, such as in management and relationships. Management of people and relationships with people appeared to be influenced by culture, experience, and exposure—not forgetting the role generational differences played.

Evidence is the use of data to support the decision-making process. From an organisational data perspective, although in-house controls are in place, all the evidence [or data] is not necessarily factual or truthful. This statement could place organisations on the defensive. However, as mentioned in Section 2.2 (specifically Section 2.2.1), the quality (i.e., truthfulness and accuracy) of the data within big datasets are not wholly within the organisation’s control for obvious Big Data-related reasons. Further, CSA themselves do not trust the data completely, which warrants further verification through South Africa’s Department of Home Affairs to verify customers’ personal details such as birth and deaths, and medical and financial credit information through third-party providers. Unstructured Big Data is huge and varied, and the sources are multiple. This challenges the veracity from many angles, the most important being the understanding of the dataset in its entirety, which requires resources (time, money, and skilled people). For Big Data that is within the organisation's control, data silos, organisational strategy, and business processes have a direct bearing on the accuracy, truthfulness, and authenticity of the data. A simple example relates to the crown jewels of the company, that is, customer information, that resides in multiple data warehouses that are autonomously managed. There is evidence from the case study that the differences in customer information repositories have grown over time. While the effort to reconcile this not impossible, it is time-consuming and expensive. Based on the above argument, it holds that ‘evidence’ is rather data and, subsequently, information that are made available through company ICT systems such as customer relationship management (CRM), enterprise resource planning (ERP), and supply chain management (SCM).

On the explanation of intuition from their own perspective, CSA#18 expressed it as follows –

EFQ177. “That is your internal monologue that knows how you think and how you function. So, it knows that answer for you before you even get to all of that” CSA#18.

Nineteen research participants distinctly mentioned the approaches that they take when making people, financial, and business decisions: all participants relied on intuition when dealing with emotive and people-driven situations; for financial and business decisions, evidence, insight, and judgement were used. In the absence of data, intuition was used.

EFQ178. "If you're sitting in life-type of decisions or emotive decisions then you are looking at gut feel. For business decisions, you would look at data and look at the evidence and look at those type of things to see what has happened" CSA#16.

EFQ179. "Instinct, I think most of the time comes from experience and knowledge" CSA#30.

4.5.13. Open codes related to Decision-making Structures (DMS[27])

Table 21 highlights the captured open codes, together with the resulting follow-on stages of coding. These open codes will be discussed below, with supporting empirical evidence provided.

Coding and categorisation results			
Core Category	**Selective codes**	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	***Decision-making entity (DME)***	***Decision-making structures (DMS)***	**Death by consensus**
			Evolution of decision-making processes
			Organisational configuration and decision-making processes
			Big Data promotes accountability
			Decision-making is authoritarian
			Governance and compliance policies affect power centres
			Evolution of power centres

Table 21: [DIP-DME-DMS]-Open codes

4.5.13.1. [DIP-DME-DMS] Death by consensus

Death by consensus is another way of capturing 'risk averse'. This was echoed a few times by many participants. The long chain of hierarchical (empowered) decision-makers supports the earlier notion that empowerment is a bestowed-upon privilege, as decision-making appears to be detached from the decision-making epicentre and cascaded up organisational structures. When decision-making is bestowed upon an individual, as is the case with empowerment, it appears to be partial that final

[27] DMS – Decision-making Structures

judgement lies elsewhere. This as opposed to decision-making that is based on democratisation, where decision-making is entrusted—with accountability and responsibility—to KWs at the epicentre.

In addition, there appears to be death by consensus at KWs' peer levels. KWs and managers tend to involve peers for decision-making purposes through inclusion in communications and meetings. This results in decision-making coming to a standstill, as everybody is relying on everybody else to make the decision.

The concept of consensus arose in two different scenarios: 1) Consensus appears to be the outcome of collaborative interactions, specifically the agreement to pursue a certain line of action. When collaboration within teams appears to be a performance measure of teams and individuals, consensus-seeking appears to fulfil this requirement and raises visibility to management. 2) Consensus, as an inclusion mechanism in order to share risks—meaning that when a decision is perceived to be a risk, it appears to be an approach in which the risk of making the decision is spread among the participants.

Risk-averse decision-makers introduce consensus measures that frustrate decision-making processes.

EFQ180. "Smaller, less impactful decisions or tactical decisions should not require consensus. Larger, more impactful decisions should undergo some consensus. In-depth analysis key to major decisions" CSA#03.

EFQ181. "Too many opinions, too many decision-makers, too many feelings not enough fact" CSA#22.

4.5.13.2. [DIP-DME-DMS] Evolution of Decision-making processes

CSA is continually undergoing changes. Some of these include organisational structural changes—technological, strategic, and operational. The inevitability of change has implications for the organisation, workers, and the workplace. Therefore, all the mentioned implications have an effect on the decision-making processes of the organisation. It stands to reason that, as the various organisational actors evolve, so too should the related processes.

a) Workflow automation

Experts will emerge from within teams to add human intellectual abilities to the decision under review, and for decision-making processes that are manually accomplished. If there is enough use of that exact piece of expert knowledge, it could be automated and operationalised as a "robotic" process. From discussions with KWs, AI is mentioned; however, in trying to understand the actions or activities behind the concept, it appears to comprise task automation and business process automation through workflows and robot deployments. Terms or phrases such as "mundane task automation" or business process automation more accurately describes the reality.

EFQ182. "So, your mundane task could be automated with AI and natural language. You are just there to actually improve and optimise the processes that are already in place" CSA#43.

EFQ183. "The more dependent we become on artificial intelligence the more we're handing over that ability to make a decision ourselves" CSA#16.

b) Real-time decision-making

Decision-making is real-time or near real-time for some aspects of the business, for example, financial instrument trading, business performance management, and customer retention.

EFQ184. So, I think currently a lot of processes are still on that monthly data feeds. But looking at the last month [activities], I can see that changing. People saying, "what happened now?". So, it is immediate data, immediate response, what happened in the last half an hour [...]. How do we move forward? What are we going to do for the next hour? I think it is going to become very fast-paced. A lot of your decision-making gets done sort of monthly at forums and executive meetings when they already changed. It is already on a weekly basis we are deciding this the monthly target. What data is available to make that decision to change, what is happening in the next three weeks? So, you can really see people are not waiting for the month-end and said okay this what went wrong, they are progressing weekly.

c) Automation of decision-making processes

Decision-making processes will be automated. There is concern about future job security due to the misnomer about AI replacing workers. There is a gap in participants' understanding of AI vs. the automation of mundane tasks. In discussions with an autonomous department that is driving the digital strategy for CSA, robot (BOT) deployments were a work in progress, with a small number having been deployed. CSA was behind its planned schedule of BOT deployments because of ICT complexities.

EFQ185. "Our systems are very complex and interrelated and it's not very straightforward. The one thing I think being in a big organisation like this, nothing is straightforward. We set a target for [xxx] BOTs this year [2018] but we only achieved 15%. It is challenging" CSA#06.

EFQ186. "To drive processes and to get efficiency done. That is basically having a dependency on technology to make certain types of decisions. Where does that stop? The more dependent we become on these artificial intelligent agents the more we're handing over that ability to make a decision ourselves" CSA#16.

Revisiting the gap in participants' understanding, it was clear that mundane tasks were being automated through BOT/robot deployments. However, these were limited to activities that address customers' interactions through digital channels. Over time, CSA planned to automate more mundane tasks and processes. The wider workforce is uninformed with respect to understanding AI and task automation, which they find confusing and intimidating.

Automation of processes/mundane tasks is an inhibitor, as people fear job losses. So, instead of trying to better decision-making with Big Data insight and automation tools, it is shunned because of job security concerns. Productivity is hampered, as job security is top-of-mind for most people. CSA understand that, for automation to be viewed positively, they would have to devise plans that reskill, upskill, and cross-skill their people. In parallel to the automation of perceived mundane tasks, CSA also—in advance—considered optimum organisational structures and the effectiveness thereof through organisational planning and effectiveness projects. It is well understood that the consequences of routinely and systematically changing processes and tasks without consideration for people could have a dire impact on the organisation in the form of an exodus and brain drain, which implies the loss of scarce resources. This could be because of people pre-empting the situation, which could be avoided if enough due consideration was demonstrated, if the process was inclusive, and if ample communication keeps people abreast of developments.

EFQ187. I see it basically as fast, quick decisions that will be made and I think it would be a case that little input from staff is needed because everything you need will be on data on machines. So, I think there will be very little input from staff" CSA#24.

Measures are actively taken to automate some decision-making processes. The intention is to streamline decision-making and make it less human dependent. This would improve the situation of CSA from a data-driven perspective, as decision-making will be quicker and automated. However, for insight-driven decision-making, the human factor is still essential at this point in time.

4.5.13.3. [DIP-DME-DMS] Organisational configuration and decision-making processes

Organisations could be as simple as owner-led with a few employees, to large complex organisations such as CSA that employs thousands of people. Large organisations are segmented into function-based departments—for example, marketing, sales, administration, human resources, ICT, and customer services. Organisations, as mentioned earlier (Section 2.3), centralise or decentralise decision-making; in the case of CSA, it is somewhat decentralised. However, there are limits of authority, so decision-making is cascaded through hierarchical management structures, depending on the level of impact for the decision at hand, which is tied to the limits of authority. The greater the impact on the organisation, the higher up the decision-making process extends. Further, there are governance and compliance processes and people that are responsible for upholding the rules. Two sub-codes were prominent in discussions with most participants, namely, tall hierarchical decision-making structures and the timeliness of decision-making. Both are complementary to each other.

a) Perceived tall hierarchical decision-making chains

Participants indicated that the decision-making chain is tall, which could be defined as several hierarchical decision-making layers. Tall decision-making chains do not necessarily mean that decision-making has to be slow. However, the problem of tall decision-making chains is compounded when there are bottlenecks within the chain that, for whatever reason, delay decision-making.

Tall hierarchical decision-making chains are perceived as wasteful.

EFQ188. There are all these unnecessary wasteful decision-makers in the process. Give authority to people on the ground that actually knows what is happening. Our processes have become too broad" CSA#22.

b) Timeliness of decision-making

The timeliness of decision-making affects the decision-making process, such that the decision is irrelevant.

EFQ189. We get people that take long; [we] get people that are quick thinkers. But in this organisation, it's always been this long flowchart of this person, then that person, then that person. It is a big stumbling block because, by the time the last person makes a decision, things have changed so *much already. So, we go back to starting over because whatever was sent is no longer relevant" CSA#18.*

4.5.13.4. [DIP-DME-DMS] Big Data promotes accountability

Accountability is a cornerstone of decision-making, in that the basis on which to make a decision has to be justified by evidence and/or a credible rationale and, accordingly, the decision-maker takes responsibility by way of defending the decision. Apart from evidence-led decision-making, intuition-based decision-making is another decision-making aid. Throughout data collection at CSA, intuition was mentioned several times, and no participant could cite an example of when intuition failed them. However, intuition is used sparingly and in situations where evidence is scarce and/or immediate decisions are necessary. As with governance and compliance practises, accountability contributes to the integrity of corporations.

Big Data promotes accountability.

EFQ190. "So, one of the reasons now that accountability is popular is because you can set up the correct data-driven decision-making via approval and authority processes. Driving authority with accountability via data has really improved" CSA#10.

EFQ191. If you want to become a better individual contributor at CSA, yes altogether it lies with you firstly, so I think there's some sort of accountability or responsibility the individual has to take" CSA#37.

4.5.13.5. [DIP-DME-DMS] Decision-making is authoritarian

In terms of the CSA organisational structure from a hierarchy perspective, CSA is multitiered with reporting continuums that comprise team leaders, line managers, senior managers, and executive management. The next piece of evidence appears to be conflictual, as the organisation is deemed to be synonymous with a decentralised decision-making model. However, an organisation as large as CSA warrants roles/responsibilities that have limits of authority mechanisms in place to enhance compliance and governance protocols. Decision-making is perceived to be tightly controlled, considering the potential risks of Big Data.

EFQ192. "Before, the culture within CSA was one of where you felt empowered and you were allowed to make mistakes, provided that you can learn from that. Nowadays, there is no appetite and *there are many things that influence it. We have the economy; we have the fact that CSA is listed [publicly traded]. We need to keep the reigns quite tight because we cannot afford mistakes for us to lose face in the market. Big Data is forcing our hand in this regard" CSA#28.*

4.5.13.6. [DIP-DME-DMS] Governance and compliance policies affect power centres

Most open codes, to varying extents, have governance and compliance policies that facilitate the behaviour of persons within CSA. Power centres are held to stricter guidelines and required to be transparent in decision-making. However, power centres could opportunistically invoke governance and compliance policies when faced with decision-making.

Big Data appears to be a reason for the more recent governance and compliance policy updates, with power centres affected in the process.

EFQ193. "There is always corporate governance…And because of that, there are bodies that get formed to assist and drive decisions in an appropriate way. They don't necessarily influence the core of the decision, but they guide the process to make sure that it was considered fairly" CSA#16.

4.5.13.7. [DIP-DME-DMS] Evolution of power centres

Big Data is forcing power centres to evolve and adapt to new ways of thinking and working. The evolving workforce, meaning the entrance of new generations and younger management, is causing a shift in power centres and the style of leading at CSA.

EFQ194. "I think they [management] are forced to evolve because of data. I do not think anybody had a choice. You're forced to be either informed with what is happening, the latest ways of thinking and working, then to stick to the old ways" CSA#18.

EFQ195. "But I do see in the future that it will change. We are bringing in more millennials. They are not going to accept directive management. They are going to challenge, and if we want to retain them, we'll have to change" CSA#28.

EFQ196. "In the past like I said a decision was made on what your gut feeling was and yes I'm sure there was data there. But I don't think the way they collated data and the way they analyzed it is like how we are doing it currently. We respond to data" CSA#05.

EFQ197. "I still think it's all the same. I do not think anything has changed. They're in the same positions, same people making the same decisions" CSA#07.

EFQ198. "Decision-makers are getting younger all the time" CSA#03.

EFQ199. "The decision-making is also different. Again, it is headed by a different CEO that is much younger, which had probably a greater exposure to the private sector out there in different industries, and he brought a lot with him. Injected a lot of new DNA into it. So, there is a feeling of speed nowadays" CSA#23.

4.5.14. Reflections on the open codes

BDA applied to Big Data leads to information and insights. Some value contribution is necessary to turn data into information, for insight to be realised. Value forms a key part of the IS artefact. Value contribution could take many forms. For instance, the application of skills to interrogate data, the collaboration with others to build consensus with the intention of creating actionable activities, and asking profound questions to engage deeper with the data to realise a better understanding.

For many within CSA, the information is skimmed over without any additional value contributed—for instance, asking why the information presents in a certain way and looking at the information from different perspectives. For example, call centre-related activity logs are collated on a regular basis, which is transferred as feeder data to other systems and information reports for management and subject matter experts. In the example, interrogating the call centre logs falls outside of that particular KW's responsibility. Therefore, no further value is applied, which is a missed opportunity to gain knowledge and thereby contribute to democratisation—at least in this instance. Others interrogate the call centre reports to determine, among other things, staffing requirements, training, and customer satisfaction. This a simple example that demonstrates the passing of information without value addition—representing a missed opportunity.

'Reports' or 'reporting' is a common culmination of mundane task automation processes that have become routine occurrences, the benefit of which may have been lost over time. Alternatively, it may have unknowingly become unnecessary. A large number of the participants thrive on reports and reporting to fulfil their roles and responsibilities. Three points arose from the 'reporting' phenomenon.

- First, the reports are produced as part of an automated process and managed through routine operational activities. The question that appears valid and persistent is the value contribution of the reports in achieving and exceeding role expectations.

- Second, reports are generally available to CSA employees. However, there are discussions as to the relevance of the reports to KWs, as it relates to fulfilling a job role and aspects of governance such as information security. In addition, reports that could be of value—relevance—are not reaching the employees that could benefit from these reports. This could be partially attributed to the many data silos and organisational structural issues that segment people by functions and business units.
- Third, the workplace comprises people that are very different in terms of age, culture, skills, knowledge, position, and tenure within the company. This has a bearing on how appropriate questions are formulated, how information processing occurs, the conclusions derived from new knowledge, and the decision-making outcome. Detail and summaries of textual material resonate with different KWs. If this not taken into consideration, then the reports represent not only wasted efforts, but also a lost opportunity to engage KWs.

In summary, CSA has adopted BDA. What is evident is that human intelligence, from a questioning ability, is still key to producing value-laden and relevant reports. Descriptive analytics are tools that extract insight from historical data, which is the most-used analysis approach. Trend analyses are important activities that participants spoke about frequently. An ICT analytical specialist mentioned that predictive analytics, using predictive modelling tools such as statistical analysis, machine learning, and data mining, are sparsely deployed. KWs frequently used 'predictive' in conversations, but based that on trend analysis and more logical extrapolation based on historical evidence, rather than on any sophisticated modelling tools. Even 'prescriptive' was used by KWs, albeit sparsely; but again, the term did not have a grounding in prescriptive computer-related optimisation and simulation techniques.

The case study consisted of CSA as an organisation, and three departments were part of the study (see Section 3.6.2). Study data from the empirical situation—did not reveal significant differences in the perceived benefits of Big Data across departments. On the contrary, there was agreement on the benefits and possibilities that Big Data presented to their organisation, such as competitive advantages and knowledge. Below is a closer analysis of the departments.

a) Areas of consensus across the three departments

- With respect to Big Data, there is consensus that it is a reality, overwhelming, intimidating, and has immense potential value that is waiting to be uncovered. However, CSA requires a radical paradigm shift in how the business entity adopts and uses Big Data.
- From the business perspective, the following emerged:

    - Competitive advantage is waiting to be uncovered, possibly by seeing the unseen and embracing unsolicited data.
    - Resource constraints—financial, people, and time—are factors that prevent Big Data from being broken down and reassembled into meaningful insight.
- The different generations across the departments shared their feelings about the generation gap. Across departments, there appears to be consensus amongst similar generations about other generations' shortcomings and strengths. The discussions at times resonated in a *déjà vu* manner. For instance, while older generations are slower at decision-making, they are perceived to deliver better quality outcomes. On the other hand, while younger generations are deemed to be more agile decision-makers, their decision-making outcomes are sometimes perceived as questionable.
- The speed in decision-making is lengthy and drawn out because of the processes within the organisation, even though data (evidence) is pervasive.
- Tall hierarchical decision-making chains frustrate participants, especially younger generations.
- Most participants believe that decision-making would be more automated in future.
- Customer analytics is underutilised for both internal and external customers.

b) Across the three departments, these areas of differences were observed.

- The automation of tasks is a concern for most KW participants, as it is inaccurately thought to be AI and machine learning implementations. There appears to be a gap in knowledge and communication. Participants that were within the ICT department had a fair understanding of automation, and were therefore not concerned.
- With respect to BDA, Data Analysts that provide BDA support across multiple departments expressed concerns that the foundation for getting information begins with asking appropriate questions; however, this was often not the case. It makes sense then that reports were generic, irrelevant, or insufficient to fulfil tasks.

c) Within departments, these areas of consensus were observed.

- There is consensus that Big Data is important to gaining insight.
- Tall hierarchical decision-making chains are problematic and counter the organisations' goals of being agile.

d) Areas of difference within departments

- Similar generations banded together and expressed similar opinions about the imperfections, shortcomings, and strengths of other generations.
- There are generational differences in extracting insight. The following traits were observed: Younger generations are impatient, and this evident in the lack of time spent in understanding and manipulating data; older generations feel overwhelmed by Big Data and avoid Big Data when possible; and, for those that have interests in extracting Big Data insights, resource constraints were inhibiting factors.

In closing, the value of Big Data is recognised by all participants. Appropriate questions lead to relevant information.

4.6. AXIAL CODING

The next step in GTM is the axial coding process. First, the axial coding process is briefly introduced, after which the axial codes are presented. For readability and flow of logic, the axial codes are grouped by higher-level selective codes with section headers acting as signposts and quick reference guides. This is illustrated here as an example: 4.6.2.1. [DIP-TI] BIG DATA ANALYTICS (BDA). DIP is the core category; TI is the selective code; and Big Data Analytics (BDA) is the axial code. The selective codes (see Section 4.7) and core category (see Section 4.8) are discussed later.

4.6.1. Axial coding process

Axial coding, discussed in Section 3.7.4.2, is the next coding step in SGTM, with the objective to identify relationships between categories, sub-categories, and codes (Matavire & Brown, 2013; Seidel & Urquhart, 2013). Table 22 illustrates the coding and categorisation process and the outcomes that contributed towards answering the research questions. Each of the axial codes is discussed in more detail. behind the open codes in the above table are sub-codes and supporting evidence that have been explained previously (Section 4.5), but that are not shown. The rationale for each of the axial codes is explained below.

4.6.2. Axial Codes related to Technology Infrastructure (TI)

Technology Infrastructure (TI) is a selective code, with BDA and Characteristics of Big Data as related and supporting axial codes.

EFQ200. We have multidimensional analysis cubes and one of our biggest cubes got thousands of measures so our insight can be deep and wide also" CSA#41.

EFQ201. "Our greatest challenge is trying to consolidate so many data warehouses, a lot we don't know of. Data is everywhere" CSA#43.

4.6.2.1. [DIP-TI] Big Data Analytics (BDA)

Big Data refers to the raw data that makes no sense to most people. The only way for Big Data to make sense, is for BDA to be applied to the raw data to extract information, and thereafter insight and wisdom, based on KWs' interpretations. To demonstrate the relatedness of the open codes (see Table 22) to the BDA axial code, the open codes will be discussed holistically.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*Technology Infrastructure (TI)*	***Big Data Analytics (BDA)***	Insight begins with appropriate questions
			Types of analytics
			Big Data Analytics (BDA) needs to be relevant
			The future of Big Data is the availability of analytical skills, not technology
			Wasted opportunity to gain insight from Big Data

Table 22: [DIP-TI] Big Data Analytics (BDA)

BDA is initiated with a question (or puzzle) that needs to be solved (see Section 4.5.2.1). This question is put to datasets through BDA tools, and the output is information that is organised and contextualised. The new information is interrogated based on previous knowledge, resulting in new knowledge and insight. It makes sense that, if questions are poor and limited, the output will reflect this. Should the question be insightful, the information output is richer, provided that the data is of good quality. The current constraint is not technology, but the ability of KWs to interrogate datasets. CSA spends most of its time and resources on descriptive analytics.

EFQ202. "Our priority is to harvest what we have to learn from it [Big Data] because that is what the business demands and slowly do other things" CSA#43.

EFQ203. "It's just too much information that it doesn't make any sense until you start to analyse" CSA#30.

4.6.2.2. [DIP-TI] Characteristics of Big Data

Big Data is a key concept in this research; therefore, the concept has been defined extensively within Section 2.2 and throughout this study, from both academic and practitioner perspectives. It is encouraging that the language extracted from participants' keywords and phrases stands out in support of earlier writings (Section 2.2). These are captured as open codes in non-technical language (see Table 23). It also indicated that the conversations were on the right path to understanding the phenomenon. The 4Vs come across strongly.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*Technology Infrastructure (TI)*	***Characteristics of Big Data (CoBD)***	Availability of, and access to, Big Data
			Big Data is a headache
			Vast amounts of knowledge are derived from Big Data
			Data silos
			Multiple data sources
			Time Value of Big Data - velocity
			Variety is key to completing the picture
			Veracity of Big Data
			Volume

Table 23: [DIP-TI] Characteristics of Big Data

As mentioned previously (Section 2.2), Big Data within the case study continues to be characterised by the most prominent 'Vs' of volume, variety, velocity, and veracity. There are several other 'Vs' in academic and practitioner literature, but these four are consistently mentioned. In discussions with participants, there appears to be a fair amount of understanding of Big Data, from personal experiences on social media and in using Big Data in their jobs, rather than from ICT perspectives. Although the characteristics of Big Data, as stated by non-ICT KWs, do not directly include the 'Vs' as expressed in academic and practitioner literature, the descriptions appear to relate very closely and translate easily to current literature. In addition, the characterisations provided were richer and more meaningful, for example, vast (volume), big-picture (variety), fast (velocity), and truth (veracity).

Owing to the size and history of CSA, data growth has mostly been exponential and uncontrollable. Apart from data growth, the organisation has structurally been reconfigured several times over the many decades of operations; these reorganisations could be attributed to business growth, change in strategy, and driven by market forces. These changes have had a profound impact on the ICT function.

As mentioned in Section 4.5.3.4, organisational changes resulted in the establishment and/or retention of data repositories across the organisation. Over the years, autonomous business units have rolled out purposeful data systems and procured ICT assets that addressed their needs. In a single market of operation, data—especially that which pertains to customers—are duplicated across several databases. There are projects underway to consolidate the data into a master data repository. However, this is challenging, as there are many unaccounted data assets, and some duplicated data assets are still in operation. Exceptions include data assets that are managed and controlled by departments because of operational (financial trading) and regulatory requirements.

"Messy", "overwhelming", "complex", and "confusing" are some of the words that participants used to characterise Big Data. These non-technical terms capture the characteristics of Big Data.

EFQ204. "You use the resources that the company provides to you so that you can report or give the information in a suitable way that everybody can understand. So, you create knowledge" CSA#30.

EFQ205. "Is it [a] reliable source? Is there any other data to support this because it's useless just having this data in front of you? The age of the data. The relevance of it. Can it be substantiated? Can it be repeated? This really what I need - truth and understanding. If I don't have an understanding of the data, I cannot make a decision with the data" CSA#10.

4.6.3. Axial Codes related to The Habitus (TH)

The Habitus (TH) is a selective code, with Individual differences, Workforce generations, KW's ability, Characteristics of decision-makers, and participation of people as related axial codes.

Memo 8 20/12/2018. In discussing Big Data, CSA#11 mentions that Big Data is overriding people, but within people, there is data that comes from education, experience, and exposure over many years. The key is how to operationalise Big Data insight and tap into the person's intellectual capabilities, so one is not lost because of another.

EFQ206. "People are data [The Habitus]" CSA#11.

4.6.3.1. [DIP-TH] Individual differences

The demographics of the participants are representative of the South African population, as indicated in Section 4.5.4.4 and 8.3. Like most countries, South Africa is shaped by its history—a history that practiced a gross violation of human rights. Although people fulfil similar job roles, the constitution of KWs are different in a lot of respects, as depicted in the open codes in Table 24. It was observed from the case study that education, experience, historical background, and culture uniquely shaped each KW. It was observed that no two persons were the same—hence the interpretation: individual differences.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*The Habitus (TH)*	***Individual differences***	Education
			Experience
			Historical implications
			Individual's culture

Table 24: [DIP-TH] Individual differences

EFQ207. "Education is huge. I operate on a one-liner that says: "You are only as good as what you know." You don't know what you don't know and so all of those things will influence what you know and therefore what decisions you can make" CSA#38.

EFQ208. In terms of experiences that people go through whether some go through extremely traumatic experiences, some have you know that sort of silver spoon type of life. So, I think yes it has a massive influence; I think it plays a huge part in you being that or the type of individual you will be and also influences the types of decisions you will make" CSA#37.

EFQ209. "[Politics, work relationships, economics and society...] it plays a big role. When it comes to politics, you are aware of everything that is happening around you. And in order for you and me to engage, obviously, there are certain factors that I am looking at. I mean we come from different backgrounds; we are not the same. If I may put it that way. And obviously what impacts other people and what impacts me will be different when it comes to politics and when it comes to society" CSA#36.

4.6.3.2. [DIP-TH] Workforce generations

Within departments and across departments, it was observed from body language and dialogue that generations do not recognise the unique value in people. Behaviours across generations are perceived by other generations to be lacking in professionalism, ethics, and good conduct. Each generation and individual KW are motivated differently; this manifests in attention and respect deficits, and tardiness. Table 25 captures the open codes that contributed to the workforce generations axial code.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*The Habitus (TH)*	***Workforce generations***	Generational issues
			Newer generations forcing change

Table 25: [DIP-TH] Workforce generations

All participants recognise the value of Big Data. A group of people that fits between the older and younger generations have an affinity for Big Data and the possibilities it holds. However, there are resource constraints. The perceived characteristic of 'instant gratification', as ascribed to younger generations, is not necessarily bad, as this could be one way in which AI and machine learning is utilised to produce information quicker through Natural Language Processing. The negative implications of organisations that are not paying attention to the perceived attention deficit is that KWs, especially younger KWs, are not beholden to the firm by loyalty.

Generational differences are having an impact on Big Data use and adoption at CSA.

EFQ210. "I think there's a lot of conflicts because the younger and older generations obviously work completely different. They don't understand each other. It becomes frustrating. I can't understand why you work this way. And I can't understand why you're being so impatient and demanding on me. Obviously, you'd clash because you think completely different. You grew up in different ages, so it definitely causes conflict" CSA#18.

EFQ211. "Older generations are being forced to think like younger generations so that they can stay relevant. We're forcing them to get out of their comfort zone" CSA#18

4.6.3.3. [DIP-TH] KW's ability

This axial code deals with the abilities of the KW rather than the organisation—abilities such as analysing information, having decision-making capabilities, and being able to engage with information to produce the insights that the organisation appreciates. The open codes in Table 26 are supporting of this axial code.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*The Habitus (TH)*	***KW's ability***	Skills
			Power lies in the skill to analyse and interpret Big Data
			Decision-making abilities

Table 26: [DIP-TH] KW'S ability

DIP progression (see Figure 12) starts and ends with the KW's ability. Big Data is a block of raw data that has no personality, is largely unstructured and, in simple terms, appears complex and messy to most people. Somewhere in this data are answers to questions, and insights that are descriptive in nature and value. To expose anything meaningful, the data must be interrogated to find patterns and relationships that come together as information. However, without asking appropriate questions, the chances of good outcomes are minimised.

Appropriate questions indicate that the KW has an inherent ability. They may not necessarily have the technical ICT skills to conduct the actual query through Big Data analytical tools, but they have a phenomenon in mind that they would like to address—a question.

Within CSA, there are BI analysts that help KWs to produce meaningful reports. This helps to negate the requirement for the KW to have data warehousing skills to interrogate large datasets, as the information will be created based on the question. Deriving knowledge and insight requires skills that could be the result of experience, exposure, and education. KWs who are able to see information from many angles are in demand at CSA and add value to information, which eventually becomes an IS artefact. It was evident that there are KWs who are able to produce decision-making knowledge, but who could not make a decision. They were either fearful of making decisions, risk averse, or the firm's decision-making entity (DME) did not align insofar as that particular decision by that KW was concerned.

EFQ212. "I think it's really difficult also to try and see things from a user perspective. I was saying this morning I try to school people; I try and teach them the process via the tools, but it may just be too much for them. We don't actually need to be giving them all that information" CSA#09.

EFQ213. "The quality of the information, that's important. Also, how the information gets interpreted also affects the decision-making because two individuals can receive the same data but because of factors like their own backgrounds, they interpret information differently and as a result, the decisions that come from that can steer in different directions" CSA#39.

4.6.3.4. [DIP-TH] Characteristics of decision-makers

Leading on from the previous axial code, there are key characteristics that the KW needs to possess to be a decision-maker, as show in Table 27. The most prominent characteristic is that decision-makers allow others to make decisions and hold them accountable. The sense that the researcher got from this discussion is one of liberation—the manager moves on to other priorities. In other cases, managers merely hold on to decision-making knowledge.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*The Habitus (TH)*	***Characteristics of decision-makers (CoDM)***	Decision-makers and empowerment
			Effective decision-makers communicate
			Decision-makers rely on competent people
			Risk-averseness
			Power centres rely on summary of information
			Participation of people: Perceived enablers and constraints

Table 27: [DIP-TH] Characteristics of decision-makers

Other key characteristics that participants used to describe effective decision-makers are superior listening and questioning skills. Decision-makers are not necessarily experts. However, they are good at listening and at internalising the sound advice that they get from subject matter experts and KWs in general. They question from different perspectives to get a firm grasp on the different options available. Decision-makers see the decision that need to be made and makes them. Finally, good decision-makers recruit talent that is better than them.

EFQ214. "The biggest fear in my space is fundamentally risk-based decisions. What that really means is evaluating anything that we are going to do against probability and impact. What's the probability of something bad happening and what's the impact if that bad thing does happen? How do you know that if you don' t have experience? You look at the data" CSA#16.

a) Participation of people in decision-making processes

In terms of Big Data, the participation of people is not as simple as taking data and transforming it into decision-making knowledge. The identified enablers and constraints are perceived, meaning that it depends on the person—as discussed in Section 4.5.7.6. As discovered, the participation of people begins with the person and their ability to make decisions. The complexities of Big Data, particularly in terms of the deluge of information that is possible, makes it in most instances difficult for a single person to interrogate information and make a decision. Therefore, collaboration has come across strongly as an important enabler or constraint, after access to data, availability of tools, and organisational support. The evidence is clear regarding this.

In terms of elevating collaboration as a possible open code, axial or selective, collaboration is consistent across open codes as ways to arrive at decision-making by using experts to help firstly to extract information from BDA, secondly, to make sense of the information and, thirdly, to derive actions that lead to decisions.

4.6.4. Axial Coding related to The Organisation (TO)

4.6.4.1. [DIP-TO] Organisational culture

Table 28 shows the open codes that led to organisational culture as an axial code. The evolution of organisational culture is similar to that of individual culture, in that it is a culmination of background structures, social interactions, and experiences that are learnt over time. It manifests in ways of thinking, "social behaviour", and interactions (Schein, 2010, p. 3). However, clashes between individual and organisational cultures do occur when these do not align or are diametrically opposite.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*The Organisation (TO)*	***Organisational culture***	Collaboration is key to producing insight
			Transparency
			Freedom to contribute
			Communication
			Values

Table 28: [DIP-TO] Organisational culture

Some individuals have deep traditional beliefs regarding consultative decision-making processes, meaning that elders are consulted before any major decision is taken. In the corporate world, empowerment in decision-making processes is bestowed upon people—largely thought of as a privilege. This creates unease, as individuals are forced into decision-making situations and compelled to make decisions.

Generational differences expose seemingly disrespectful behaviour by younger-generation managers as they fulfil leadership roles and enact those responsibilities (see Section 4.5.5 for related open codes). Older KWs expect some form of hierarchy based on age. For instance, older people are to be addressed with respect and, ideally, in the third person. However, younger leaders in the workplace are evidence-led (data-driven) and short on conversation and pleasantries. This raises the concern and questions whether or not the behaviour is bad-mannered/disrespectful. Regardless of the answer, this behaviour disturbs the "social order", which oversees the harmonisation of individuals into a cohesive and stable workforce (Schein, 2010, pp. 3–4). What is bewildering from this example is the behaviour of the younger generation in relation to how elders are addressed. Should there be a continuity of culture, or has cultured been shocked into a new era?

Organisational culture is broad, and therefore has the inherent range to influence decision-making at the strategic, tactical, operational, and administrative levels. Considering the pervasive nature of Big Data, decision-making—which was once hierarchical because of the scarcity of data—is not necessarily hindered by this any longer, but by organisational culture instead. From the case research, DDD is a normal occurrence, albeit still in the hands of managers. KWs extract, analyse, and summarise the evidence in support of DDD by managers. The reasons for this could be attributed to governance, accountability, or reluctance to forego decisional power.

EFQ215. So, I think it's aligning with the vision. If they [management] can be on a strategic, executive and corporate level clear on the vision and mission, I think then it's easier to follow. Because then I know what I need to do in my job to be able to achieve that goal, to set that goal, to be able to grow with that. But if you aren't clear where you're going as an organisation, it makes me unclear of where I'm going as a person. Because at some point we go in different directions or we're going to align and drive it to succeed together" CSA#17.

EFQ216. "Be consistent in applying rules" CSA#06.

4.6.4.2. [DIP-TO] Managing the business

Table 29 shows the open codes that contributed to managing the business axial code. The fundamental premise of a business is to sustain itself by selling a product for a profit and deploying the necessary measures to achieve this, including building competitive advantage, hiring competent people, and managing the business within acceptable stakeholder, regulatory, and compliance parameters. Failing to achieve acceptable scores within managing the business parameters has potential socio-economic, political, and legal ramifications, not only for management but for employees as well. Managing the business entails putting in place processes, checks, and balances to protect the business against competitors, poor performance, and unsavoury elements that could tarnish the brand and reputation. Managing the business as a set of underlying open codes emanated from discussions with KWs, who are adversely aware of the limits of their authority and impositions on the organisation from a regulatory perspective. Adversely is used because it causes innovation to be stunted, or leads to risk-aversion in decision-making. Mostly, managing the business is about operating within guidelines that keep the business in operation.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*The Organisation (TO)*	***Managing the business***	Business processes
			Controlling risks
			Financial constraints
			Resource constraints

Table 29: [DIP-TO] Managing the business

In the current business environment, effectively managing the business is a priority for firms globally, especially considering Big Data and the multiple sources and destinations of data. With respect to CSA, two regulations were of significant concern to most participants in the research, due to the implications for the person and the firm. First, the Protection of Personal Information Act (2013)[28] was enacted largely to enhance the right to privacy through the protection of personal information and the use thereof by public and private institutions. Multiple data warehouses, access policies and processes, and disappearing ICT boundaries led to this concern, because of the difficulties to maintain control. Second, the Financial Services Conduct Authority (FSCA[29]) is the single body that is meant to regulate the entire sector's conduct. Included in this act are regulations to protect the integrity of financial markets and the customers of financial institutions, to name just a few. However, the mandate is much more complex and broader than this. In addition, there are oversight bodies within CSA that have the responsibilities of governance and risk mitigation. Big Data is both beneficial (in its ability to facilitate improved decision-making and enable strategic advantage) and frightening (in that it poses security and privacy risks that need to be managed).

The discussions pertaining to not getting more out of Big Data highlight the presence of resource constraints. However, this is part of CSA managing the business, and of prioritisation based on business drivers.

EFQ217. *Looking back to last year, I think about the security [···] and I think that has determined a lot in terms of how we tighten in terms of governance and how we protect that data access and*

[28] http://www.justice.gov.za/inforeg/docs/InfoRegSA-POPIA-act2013-004.pdf

[29] Financial Sector Regulation Act 9 of 2017 (the FSR Act) - https://www.fsca.co.za/Pages/Default.aspx

all of that. How do we educate our staff? So, it's not about just data uses but it's everything else in terms of you know somebody speaks to you and ask you certain things. Everyone could share data; you send the email with all peoples' information and attachments and how is that not a breach? So, it's about educating and I think understanding that the people in your organisation is key to your organisation and you need to make sure that they are equipped to understand not only their role but things like cybercrime and things like that" CSA#06.

EFQ218. "For me, Big Data means that we are no longer in a controlled environment. Everything that was controlled in the past is now boom, in your face and you as a person now need to control yourself, control how you react to that so that you know what is right and wrong for yourself and our company. We need to take governance up several notches" CSA#13.

4.6.4.3. [DIP-TO] Reliance on Big Data

CSA relies on Big Data, and evidence has been presented throughout this chapter to support this statement. CSA's crown jewels are its customers. Therefore, it holds true that anything related to customers is of importance. In this case, it is the information and knowledge about customers that the company treasures. For this reason, the ownership of customer data took on a life of its own over decades, through replication and duplication that resulted in islands of data warehouses that are painstakingly tedious to consolidate. To this day, holding on to and blocking access to customer data is practised; this is a debilitating factor in inter-departmental collaboration.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*The Organisation (TO)*	***Reliance on Big Data***	Access to Big Data improves productivity
			Big Data is critical to CSA's decision-making
			Big Data use leads to competitive advantage

Table 30: [DIP-TO] Reliance on Big Data

Tying customer data to Big Data demonstrates the immense relevance and importance to CSA, without which the organisation is handicapped. The open codes in Table 30 demonstrate the importance of, and reliance on, Big Data at CSA.

Throughout the interviews, it was expressed repeatedly that Big Data has had profound implications for CSA and for the three departments that were included in the research. The general need for Big Data in performing against job roles seems to be equally essential across departments. From a use case perspective, servicing customers, literally keeping the lights and water supply on, and managing ICT assets keep CSA afloat and competitive.

EFQ219. "I think Big Data has helped us look at what do we sell? How do we market ourselves? To whom do we appeal? So, target markets and looking at individuals and saying, "how do you structure certain products for certain people?" How do we appeal to certain markets?" So, it helps, not only to run your operations but also run your sales" CSA#12.

4.6.5. Axial Coding Related to Decision-Making Entity (DME)

4.6.5.1. [DIP-DME] legacy

In attempting to understand the acceptance of emerging technologies and the transition from old to new, it was important to understand how the organisation has transformed. It was evident that CSA has transformed over the years mainly because of technology. However, in trying to understand the chasms crossed in the transformation, it became apparent that CSA is conservative. This conservative stance is manifested in the awareness of the possibilities of Big Data insight, while the lack of complete pursuit is unclear. There are digital transformation strategies afoot within the organisation, and an autonomous division driving digital initiatives. One initiative is around automation of processes, commonly referred to as BOT or robot. While this one initiative attempts to make customer interactions more responsive, the other views, due to a clear misunderstanding of AI, is that these are designed to make jobs redundant.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*Decision-making entity (DME)*	***Legacy***	Big Data influences the transformation of traditional DM processes
			Pace of transformation
			New technologies not as reliable as legacy systems

Table 31: [DIP-DME] Legacy

Table 31 captures the open codes that contributed to the legacy axial code. Legacy is important; the discussions not only covered technology, but business processes, firm strategy, governance, transparency, and risk pivoted towards how the firm is changing. There was sentiment expressed around the pace of change and, as can be expected, there are proponents and opponents, with some believing it to be too slow and others believing it to be too fast, respectively. Proponents are newer generations, while opponents are largely the older generation; some from across the generational spectrum were represented.

EFQ220. "If they are looking for ways and means to better the company, number one is to improve our systems and improve our processes. If we don't, we are going to stay in the past. We never going to evolve" CSA#33.

4.6.5.2. [DIP-DME] Decision-making capability

Decision-making capability is the collation of open codes (see Table 32) that pivot around the organisation's willingness to make decisions and share decision-making responsibilities. This willingness is accompanied by establishing the necessary processes and tools to facilitate effective decision-making. Sharing of decision-making responsibility is deemed to be a form of democratisation.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*Decision-making entity (DME)*	***Decision-making capability (DMC)***	Big Data Analytics (BDA) supports decision-making
			Big Data Analytics (BDA) supports agile decision-making
			Decision-making based on trends and best practices
			Quality of Big Data-driven decision-making
			Decision-making is context-driven
			Trust is vital to DDD
			Insights-driven decision-making
			Decision-making based on intuition

Table 32: [DIP-DME] Decision-making capability

'Agile' is core to CSA's culture and strategy. However, DMC is hampered by tall decision-making chains, and by trust issues that are related to people and data.

Big Data facilitates decision-making and is instrumental in helping the organisation build historical pictures. However, insight that is forward-looking and proactive is not yet a reality. Again, CSA is juggling priorities that the interviewed KWs and the researcher may not be aware of.

EFQ221. What is the impact? What am I forgetting because, when you make a decision on an impulse and at that moment, you will never look at the big picture? That is why it is important to situate yourself around people who can actually think fast as well and can actually tell you. On the other hand, thinks from a different perspective. It's a different perspective which actually builds quick decision-making" CSA#10.

EFQ222. "So, you need to change your decision based on different data that we are given. You have to respond accordingly, or risk being late or being beaten or being outfoxed" CSA#15.

4.6.5.3. [DIP-DME] Decision-making structures (DMS)

DMS, as shown in Table 33, primarily captures participants' thoughts around governance, accountability, authority, decision-making continuum, and power centres.

Coding and categorisation results			
Core Category	Selective codes	**Axial codes**	**Open codes**
Democratisation Inflection Point (DIP)	*Decision-making entity (DME)*	***Decision-making structures (DMS)***	Death by consensus
			Evolution of decision-making processes
			Organisational configuration and decision-making processes
			Big Data promotes accountability
			Decision-making is authoritarian
			Governance and compliance policies affect power centres
			Evolution of power centres

Table 33: [DIP-DME] Decision-making structures (DMS)

There are contrasts between the governance of old and new. In the past, where there was significant amounts of information, evidence, and judgement in paper and legacy systems; it was easy to hide information for reasons of selfishness, malfeasance, or management style. Nowadays, information is mostly in digital format and is closely governed through legislation, policies, and processes. Therefore, it is less easy to hide or evade scrutiny. In a company such as CSA, checks and balances are conducted through several different types of audits, which are managed by autonomous internal departments and external entities.

Leading on from the previous discussions, the 'tolerance for mistakes' appears to be complementary to the accountability and governance discussions. In a learning environment, mistakes are expected, provided that learning has taken place and that there is no repetition of the same mistake. However, the intolerance levels seem to be high, which goes against organisational cultures that want to be, or are seen to be, innovative and employee-driven. The perceived excessive authority that stifles ideas and participation also counter innovation.

Based on the discussion in Section 2.3, CSA *appears* to have a decentralised decision-making structure, in that decision-making is largely bestowed upon managers through 'levels of work' guidelines. Given this, decision-making should be effected easily and timeously. However, decision-making seems to be semi-decentralised or semi-centralised in reality, which implies that decision-making still rolls up to power centres. This adds time to decision-making turnaround, which often causes frustration.

This long chain escalation also negates the decision requirements, as some decisions are time sensitive. Another notable concern with this type of decision-making process is that knowledge is lost in translation, that is, the information is inadvertently reshaped as it goes through the minds of different people, each with their own shaping mechanisms. Reporting has already been discussed, wherein KWs apply thought to information to create knowledge, which is in turn passed on to other KWs for decision-making purposes. If these are simple summarisations, then KWs are not notably perturbed. However, in the case of storytelling, it becomes a constraint to the person's democratisation, as they feel that the imperfections and passion that they possess are not carried with the information—an incomplete storybook. A widening gap between the story and the storyteller is significant in corporations when selling an idea or attempting to obtain management support.

Organisational structures, as the outcome of organisational configuration, can be manifested as organisational hierarchy—for instance, based on lines of business, function-based departments, and geographic location. This, inadvertently, comes across as people silos. When the organisational culture and leadership anchor key performance metrics and results in the performance of hierarchical entities, the potential for winners and losers become a reality. This is evident in the empirical environment in which data silos and ring-fencing, based on authority-centric boundaries, promote barriers; it should instead be based on collaboration and sharing for the greater good of the company. However, this not the case, as participants indicated that they are being hampered by blocking when trying to solve customer-related problems. Solving these problems required inter-departmental participation. Barriers were encountered not only based on data silos, but also on people silos.

EFQ223. "Why do we sometimes need all the sign-off just to make a small change? It is not necessary as long as you have someone take accountability. You are making the change, you are going to own it and [if] things go wrong, you are accountable. So much easier to do things but we do not always have that" CSA#10.

EFQ224. "Let's start with the process of decision-making. It is important to have consensus depending on the impact it could have in the vast sense. So, for example, if I had to change the whole strategy of CSA, I'd want full consensus with everyone agreeing that this the way to go" CSA#10.

4.6.6. Reflections on realising the axial codes

The benefit of conducting research using GTM is that the evidence leads the researcher. In following axial coding reduction techniques, a story emerges from what was once abstract—a story that explains the phenomenon. All the axial codes have become what they are, as they are representative of the hundreds of open codes.

The various axial codes contribute some value to the eventual IS artefact upon which a decision is taken. While not every axial code is necessary in every IS artefact, axial codes are integral to the actors and eventually to the IS artefact.

In summary, axial coding processes have contributed to streamlining many important but disconnected open codes. This process helped to focus the attention on the phenomenon at hand.

4.7. Selective coding – The Main Actors

In following SGTM, selective coding "allows for more abstract theorising", which implies that it is the penultimate step to realising theory from the empirical data (Urquhart et al., 2010, p. 362). The benefit, although slow and methodical, is the gradual build-up to theory emanating from the empirical data. Four codes were selected, namely, Technology Infrastructure (TI), The Habitus (TH), The Organisation (TO), and Decision-Making Entity (DME); these contribute to the core category, and are discussed in more detail below.

4.7.1. Selective coding process

Conversations with participants are rich, emotional, based on their interpretations of real-life situations, and therefore complex for the researcher to interpret and derive further meanings. GTM is suitable, as conversations are broken down and rebuilt in a methodical way to get to the crux of the phenomenon and provide an explanation. The selective category process resulted in four categories—the main actors—which are TI, TH, TO, and DME. Each of these actors have a rich and deep underlying story that justifies their selection.

Coding and categorisation results	
Core Category	**Selective codes**
Democratisation Inflection Point (DIP)	***Technology Infrastructure (TI)***
	The Habitus (TH)
	The Organisation (TO)
	Decision-making entity (DME)

Table 34: Selective codes and core category

Table 34 illustrates the selective codes that resulted from the prior two coding stages, namely, open and axial coding. Selective codes are discussed below, together with the justifications and relationships that resulted in the emergence of the codes.

The final step to the selective coding process is to elevate theory that emerges from the empirical evidence and develop theoretical propositions, which are presented in Sections 4.9 and 5.1, respectively (Creswell, 2007).

4.7.2. [DIP] Technology Infrastructure (TI)

TI has been discussed in Section 4.3. Table 35 illustrates the open and axial codes that led to TI as a selective code. The concept of the Technology Infrastructure (TI) is centred predominantly on Big Data as related to ICT assets, such as the databases and analytical applications that a firm possesses. Within the TI, Big Data Analytics (BDA) activities occur that fundamentally turn a question into answers by producing information in the form of business reports. It is critical to appreciate that the quality of questions asked has a direct relation to the output from BDA. From CSA, it is apparent that standard reporting processes dominate the output of TI. However, as BDA becomes easier to use and more pervasive in CSA, some anticipate a shift in their current roles, meaning that they move from performing menial tasks to tasks that are intellectually more challenging.

Coding and categorisation results			
Core Category	**Selective codes**	Axial codes	**Open codes**
Democratisation Inflection Point (DIP)	***Technology Infrastructure (TI)***	*Big Data Analytics (BDA)*	Insight begins with appropriate questions
			Types of analytics
			Big Data Analytics (BDA) needs to be relevant
			The future of Big Data is the availability of analytical skills, not technology
			Wasted opportunity to gain insight from Big Data
		Characteristics of Big Data (CoBD)	Availability of, and access to, Big Data
			Big Data is a headache
			Vast amounts of knowledge are derived from Big Data
			Data silos
			Multiple data sources
			Time Value of Big Data - velocity
			Variety is key to completing the picture
			Veracity of Big Data
			Volume

Table 35: [DIP] Technology Infrastructure

As indicated in Section 4.5.3.1, the basic condition for democratisation of decision-makers in DDD is to have access to needed and relevant (fit for purpose) information. The information needs to be delivered timeously and in a suitable format (spreadsheets, visualisation tools, dashboards), failing which decision-making is hampered (Horita et al., 2017).

Several findings emerged from the empirical evidence that supported TI and was captured throughout Sections 4.5.2 and 4.5.3. A few of these are shown below.

EFQ225. "I can't really speak about the past to be honest, but what I can see more and more is the emphasis on analysis of data because the people want to make the decisions. They want to make good decisions, better decisions, even the board [of directors], they are needy in terms of this data analysis. They are always requesting these packs [reports] that are refined analysis of this history so that they can now make a decision" CSA#32.

EFQ226. Big Data is just a lot of information that doesn't mean anything until you can use a specific tool to clean it and then you can report or analyse it in such a way that it can give somebody clarity on what they're looking for. For instance, you might be looking at how the customer experience is doing by recording the number of calls that they call in everyday, but remember you must have the characteristics on what are you looking for. Calls that were successful, calls that failed, calls that were rejected and why was that so" CSA#30.

4.7.3. [DIP] The Habitus (TH)

TH has been discussed in Section 4.3. TH is applicable to all human beings, as they are rich sources of data that require much further analysis and context to gain the slightest understanding and appreciation for the vastness and complexity of their makeup. In the context of the study, people (are data) refers to KWs, who include managers and non-managers. Table 36 illustrates the open and axial codes that led to TH as a selective code. If we follow the GTM premise that all is data, then The Habitus, who are generating more data. Understanding human behaviour is complex, especially in a work environment, because of the many different influencing and environmental factors. One of the most profound revelations, mentioned by several participants, ignited different thinking—thinking that no longer considered data as just business or machine-generated data.

Coding and categorisation results			
Core Category	**Selective codes**	Axial codes	**Open codes**
Democratisation Inflection Point (DIP)	***The Habitus (TH)***	*Individual differences*	Education
			Experience
			Historical implications
			Individual's culture
		Workforce generations	Generational issues
			Newer generations forcing change
		KW's ability	Skills
			Power lies in the skill to analyse and interpret Big Data
			Decision-making abilities
		Characteristics of decision-makers (CoDM)	Decision-makers and empowerment
			Effective decision-makers communicate
			Decision-makers rely on competent people
			Risk-averseness
			Power centres rely on summary of information
			Participation of people: Perceived enablers and constraints

Table 36: [DIP] THE HABITUS (TH)

EFQ227. *"People are forms of data" CSA#31* (see Figure 22)

Memo 9 During discussions with CSA#31, the above phrase arose. Although culture, traditions, and values had been mentioned previously as components that shape the human being, the explanation by CSA#31 is that everything around us is data. We look at people, and they have embedded in them a data network that machines are trying to emulate (neural networks). Within the person is Big Data, most of which is untapped and unknown.

EFQ228. *"Devices that are creating data themselves or through people. But you forget people can be data. There is so much depth in them that we just don't know. So Big Data can be and can mean many things" CSA#32.*

EFQ229. "I think sometimes it [evidence] leaves out the human factor because that's ultimately the drive. You can have all the technology in the world, you can have all the data in the world. However, the consumers of that are human beings. And so, I think often that those factors get left out, right to the end. I think that's what's probably bad about it, but what's good about it is that it advances humans you know, we just kind of morphing into new beings and we learning new ways, we learning all the time. So that's one of the good things about it, I would say" CSA#38.

Memo 10 [Interview with CSA#22 23/01/19] When discussing the concepts of intuition and evidence, the participant drew a picture of an iceberg to illustrate how they perceived intuition versus evidence. Another candidate—CSA#32—elucidated the iceberg analogy in terms of implicit and explicit knowledge, while yet another candidate—CSA#28—spoke of tacit knowledge as opposed to 'stated' knowledge to explain the iceberg analogy.

EFQ230. "My feeling. It's based on my feeling. It's based on who you are. What you've built up… I don't know if you ever seen an iceberg. You see the spot on the surface, but you don't know what has built up underneath. So, I think it's that build up. So, it's your feelings, knowledge, it's everything about you" CSA#22.

The iceberg analogy is premised on two parts. One part is visible above the water surface line, and the other is below the surface, hence unseen. The unseen part is exponentially larger (90%) than the seen part (10%). The size of the seen portion of the iceberg, which is above the surface, could easily be deduced through various measurement methods. The extent of the unseen part is very difficult to gauge. The iceberg analogy demonstrates similarities to the human decision-making essence. Evidentiary (or seen) information, such as insight that is extrapolated from Big Data, is largely tangible and measurable. The unseen aspect of the human decision-making process includes influences that are immeasurable or difficult to measure, such as societal culture, religion, value systems, background, financial status, well-being, and tradition.

Human beings are both enablers and inhibitors in the democratisation of decision-makers in DDD. This has come across in conversation around data silos and the blocking of access to data. This ignites the interest around collaboration; not necessarily only from the human-to-human perspective, but from the human-to-machine perspective as well. It is evident from participant discussions that there are underlying and overt competition between human intellectual capabilities and machine capabilities.

EFQ231. "I think the negative bit that I see is the fact that, when it comes to Big Data, for instance, it is relied on I think most of the time, but that sort of overrides the people that are sitting there" CSA#37.

While this sentiment appears to resonate with a few participants, especially the older generation, a mix of generations see the value in Big Data insight as being a supporting resource in fulfilling their job roles. In either case, the need for interaction and collaboration between people and data is implied. Further evidence, provided in earlier sections, deal with the evolution of decision-making processes (Section 4.5.13.2).

The KW requires "extended knowledge or experience" to extract insight from data (Horita et al., 2017, p. 12). From the study, it is evident that consultations occur between team members and subject matter experts to discuss data processing and information retrieval. Apart from process-oriented tasks, which require no further knowledge due to the routineness of activities associated with the data, there is data that requires expertise to interpret. For instance, extrapolating trends from data are relatively simple. However, the implications and consequences associated with the identified trends require further knowledge and wider engagement to develop actions. This requires people to engage with the data and each other, share ideas, and add value through the collaborative development of new insights.

4.7.4. [DIP] The Organisation (TO)

TO has been discussed in Section 4.3. Table 37 captures the open and axial codes that led to TO as a selective code. The evidence has suggested that TO play an enabling or inhibiting role in decision-making. TO largely deal with factors that safeguard the organisation's reputation, integrity, profitability, and culture. These are achieved through policies, creating an inclusive culture, and using the firm's resources to benefit stakeholders. TO are critical, as without a KW who understands organisational culture, strategy, mission, objectives, the boundaries of managing the business within acceptable parameters, and the risk/reward of relying on Big Data, an incomplete decision-making platform exists, meaning that key decisional information is missing or misunderstood, which puts the KW and the organisation at risk.

Coding and categorisation results			
Core Category	Selective codes	Axial codes	Open codes
Democratisation Inflection Point (DIP)	***The Organisation (TO)***	*Organisational culture*	Collaboration is key to producing insight
			Transparency
			Freedom to contribute
			Communication
			Values
		Managing the business	Business processes
			Controlling risks
			Financial constraints
			Resource constraints
		Reliance on Big Data	Access to Big Data improves productivity
			Big Data is critical to CSA's decision-making
			Big Data use leads to competitive advantage

Table 37: [DIP] THE ORGANISATION (TO)

EFQ232. "The fact that you work with raw data, there is no tool that can filter the stuff for me and make a decision on the data. You still need to apply your mind. You still need to do what is good for this business. A simple thing, the values of this business, the culture of this business is going into a certain direction, so I need to take that culture, the values, what are we standing for, what are our people values in this business, we are going for agile management so apply that principles over this data, is this data taking me there or not? So, if I take this data and this data, and I say this policy or product is no good, is that where we are going or do we take this data and make it work in another way so I still need to apply my gut by taking my company values and my company direction into account" CSA#20.

4.7.5. [DIP] Decision-making entity (DME)

DME has been discussed in Section 4.3. 'Entity' is used to draw similarities to a single, self-contained unit that delivers decision-making value that is unique to decision-making processes. DME takes into consideration legacy aspects and the organisation's decision-making capabilities and structures. These have been discussed in previous sections. Table 38 illustrates the stages of coding, from open to axial to selective codes, which include DME.

Coding and categorisation results			
Core Category	**Selective codes**	Axial codes	**Open codes**
Democratisation Inflection Point (DIP)	***Decision-making entity (DME)***	*Legacy*	Big Data influences the transformation of traditional DM processes
			Pace of transformation
			New technologies not as reliable as legacy systems
		Decision-making capability (DMC)	Big Data Analytics (BDA) supports decision-making
			Big Data Analytics (BDA) supports agile decision-making
			Decision-making based on trends and best practices
			Quality of Big Data-driven decision-making
			Decision-making is context-driven
			Trust is vital to DDD
			Insights-driven decision-making
			Decision-making based on intuition
		Decision-making structures (DMS)	Death by consensus
			Evolution of decision-making processes
			Organisational configuration and decision-making processes
			Big Data promotes accountability
			Decision-making is authoritarian
			Governance and compliance policies affect power centres
			Evolution of power centres

Table 38: [DIP] Decision-making entity (DME)

DME brings into consideration the analysis and interpretation that have occurred, and the boundaries within which these could be actioned or further deliberated upon. DME helps rationalise the decision at hand through considerations for quick decision-making, quality of decision-making in light of the information at hand, consideration of the information through interrogating the information from multiple perspectives, the awareness of personal bias (intuition) in shaping the direction of the decision, and structures that are in place to enable or inhibit the actual decision, such as being compliant, having the authority to execute a decision, and being accountable. DME facilitates decisional action.

EFQ233. We operate on 'levels of work' for authority purposes. So, if it is decision-making that is impacting my business for the next year to three years, I feel comfortable to make the decisions based on the data. If it is impacting the strategy, it goes higher level to my boss. If it is impacting the way we have decided we are going, I obviously need to check in with my boss. If it is data that will impact customers or our brand it must go to a higher level. I can identify a brand to flag it up so brand, the customer, and anything to do with our values and strategy I will escalate" CSA#17.

4.7.6. Reflections on realising the selective codes

The rationale behind the selective codes was explained in Section 4.3. As the selective codes emerged, they reflected individual and combined aspects that resembled information, and social and technological artefacts that come together as an IS artefact (Lee et al., 2015). As standalone selective codes, the value contributions could be deduced for each of the selective codes or actors. However, the collective contributions of value by each of the actors, based on information that has been extracted through BDA, represents a value-laden IS artefact. The IS artefact contains all contributions made by the actors and the information under review, and is the IS artefact upon which decisions are based.

The decision-making point is where the IS artefact is interrogated by the KW for completeness and quality. An incomplete and/or inferior IS artefact does not afford the KW assurance as related to participatory and co-determination privileges in DDD. It is at this inflection point that the KW is democratised or not in that particular instance of DDD. It is this measure, namely, the democratisation inflection point (DIP), that has emerged as the core category. The core—central—category is discussed in Section 4.8.

4.8. Outline of Core category findings

After the selective codes emerged, questions arose as to what their relevance were, what differences do they make, whether they contribute uniqueness, and whether they added profound enlightenment of the phenomenon. Most importantly, if the selective codes are removed, could the phenomenon still be explained? The value co-creation and contribution of selective codes (actors) come across consistently. Selective codes are value-laden actors in terms of the value contributions to DDD, without which DDD appears to lack the necessary elements that wholly support data-based decision-making. Data underpins DDD; however, it is the collective contributions by all actors that facilitate effective DDD, which could be realised by KWs with confidence.

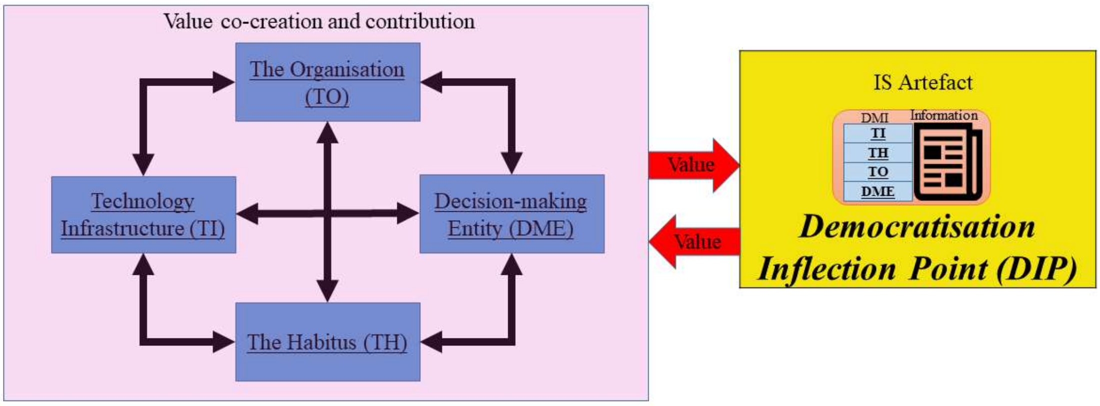

Figure 15: Value contribution and co-creation

Herewith follows an explanation of Figure 15, which is based on Memo 32 . For each of the actors, value appears to be both a constituent and an outcome. An example of this is the transformation of data into information into knowledge that entails several different value contributions, such as the knowledge (value) of a KW who begins the process by asking a question of TI and BDA. BDA is value-laden through analytical tools and applications that come together to interrogate Big Datasets to produce contextual information. The application of knowledge (value) by the KW to new information leads to newer knowledge and possibly insight (value). Having knowledge alone is insufficient for DDD purposes, as there are The Organisation's characteristics such as financial and resource constraints and adherence to the organisations decision-making processes, which must be considered prior to deciding. This demonstrates the value-laden nature of actors, both in terms of makeup and output, and their importance in DDD as they contribute key DMI to the decision-making process. In sum, an actor is a sum of values that is constituent of the actor itself, and co-created with other actors and contributions from other actors. The point where the assessment of value contributions (DMI) by actors to the decision-making process takes place is referred to as the Democratisation Inflection Point (DIP), which is part of a greater system—the DIP system.

4.8.1. Why 'Democratisation'?

Democratisation within the DIP is important to the core category. However, the basis for concluding democratisation as the core category, which is facilitated through the DIP, requires explanation. The rationale for 'democratisation' is based on definitions within literature, extrapolation from empirical data, and employment of latent techniques. These are expanded upon below.

4.8.1.1. Definitions and The Organisation of democratisation in literature

Within Section 2.6, definitions were provided for 'democratisation'. Below are additional definitions and characteristics of workplace democracy. The idea is to develop a list of keywords and characteristics of democratisation to support the selection.

Definitions	Keywords	Reference
"Common definitions of workplace democracy contain characteristics of **equality**, **decision-making**, and **participation**".	equality, decision-making, participation.	(Hatcher, 2007, p. 2)
"Industrial democracy (also referred to as '**co-determination**' […]) is concerned with the **structure** and **institutional**	co-determination, structure, institutional mechanisms, power, decisions.	(Humborstad, 2014, p. 395)

mechanisms that provide workers […] with **power** over **decisions** within their places of employment".		
"The main issues in workplace democracy are employee **participation** in **decision-making**, inclusion of employees in corporate **governance processes**, and **co-determination** of organizational strategy".	participation, decision-making, inclusion, governance, processes, co-determination, strategy.	(Matten & Crane, 2005, p. 8)
Characteristics of democratised organisations include; "Devolved **power** and **responsibility** for many more organizational **decisions**, leading to smaller, **self-organizing** units. Acceptance of diverse internal and external interests based on power as a function of successful **relationships** rather than **structure**. High levels of psychological **ownership** of organizational activities that depend on **individual contribution**, **knowledge** and **leadership**".	devolved power, responsibility, decisions, self-organising, relationships, structure, ownership, individual contribution, knowledge, leadership.	(Butcher & Clarke, 2002, p. 36)
Workplace democracy "are aimed at creating work environments where employees have more **control** over their jobs and somewhat expanded **decision-making authority**".	control, decision-making authority.	(Potterfield, 1999, p. 104)

"Workplace democracy is associated with the application of democratic practices to the workplace. Such practices include **voting**, **discussions** and **deliberative** or **participatory decision-making**".	voting, discussions, deliberative, participatory, decision-making.	(Pausch, 2014, p. 3)
Table 39 provides a summary of characteristics of workplace democracy.	open communication, underrepresented groups, open governance, freedom of expression, meaningful work, gender and ethnic equity, tolerance, respect, inclusion, competence, solidarity community, general good of community, self-interest, trust, less fear, question control, organisational commitment, ability to change, quality, privy to strategy, worker group decisions, flatter, team-based organisation structure.	(Hatcher, 2007, p. 5)

Open communication internally and externally	Fuller participation of women and underrepresented groups
Open governance	Devolved power and responsibility for decisions
Individual freedom of expression and choice	Power is related to relationships versus structure
Meaningful work	Workplace democracy is not possible without "unalienated and meaningful work" (Mason, 1982, p. 102).
Gender and ethnic equity	Tolerance, respect, inclusion of women and underrepresented groups
Less managerialism	Psychological ownership of activities depends on worker contributions, knowledge and competence.
More worker control over the functions that impact them	"Reduce alienation, create a solidarity community based on work, strengthen attachments to the general good of the community, weaken the pull of self-interest…[and], stimulate citizenship in the government of the state itself (Dahl, 1985, p. 95). Individuals have control over their work tasks (Luhman, 2006)
Improved trust and less fear	Legitimacy for workers to question control (Markowitz, 1996)
Enhanced flow of information	Increase in organizational commitment, personal responsibility, ability to change (Harrison & Freeman, 2004)
Worker voice in job design, work requirements and quality	Because worker groups may not be privy to organizational strategies or have the required skills and knowledge they may make incorrect or less than advantageous decisions. Worker group decisions may take an inordinate amount of time and may disrupt normal operations (Harrison & Freeman, 2004).
Flatter, team-based organization structures Non-hierarchical controls (Luhman, 2006)	Educate through participation thus inculcating democratic values in the citizens of the workplace (Grady, 1990)

Table 39: "Characteristics and Outcomes of the Practice of Workplace Democracy" (Hatcher, 2007, p. 5)

Literature is rich with definitions and characterisations of democratisation (and related concepts) from many perspectives, including political, social, and workplace. The above definitions and characteristics are drawn from literature and are workplace-specific. The keywords are used within the next section (4.8.1.2) to create a link between literature and the empirical data.

4.8.1.2. Democratisation: An extrapolation from empirical data

Table 40 contains keywords and characteristics that have been drawn from the various definitions and explanations of workplace democratisation (see 4.8.1.1). The keywords are grouped based on similar meanings. The selection of 'democratisation' as the core category is supported, alongside the keywords with supporting empirical evidence. Examining the empirical data, certain keywords have guided the selection of the concept of democratisation, which are compared to literature (see 4.8.1.1). A sample of the supporting empirical data and the associated reference is provided.

Grouping of similar and related keywords	Sample of supporting empirical data	References to empirical data
Co-determination, voting, participation, participatory, consensus.	***Collaborative*** *information, your* ***collaborative decision-making*** *basically. What's that saying, are you* ***autocratic*** *or* ***democratic*** *in the way you make a*	EFQ317, EFQ306.

	decision*. You sit around the table with your* ***team*** *and discuss it. Leverage off everybody's experiences and make a much more* ***informed decision*** *because one person who's looking at a set of data will not necessarily absorb everything. You sit in a room and you* ***workshop*** *it if I could say so" CSA#16.*	
Open communications, privy to strategy,	*"I'm not saying that we don't have a* ***strategy*** *around Big Data, because we've got a whole digital thing that's working with data. I think from a* ***communication*** *point view it's not* ***filtering*** *down to* ***everybody*** *and Big Data should become a concept or a term that* ***everybody*** *can identify with and not only the people sitting on* ***top*** *or working with data or in the digital space" CSA#28.*	EFQ120, EFQ112.
Control, question control	*"****Governance*** *and* ***compliance*** *are there to protect our customers. But it also made us* ***cautious*** *in everything especially in terms of our* ***decision processes****. We need* ***compliance*** *you know… money laundering and all this sort of thing that is* ***external forces*** *in the outside world, which have forced us to become* ***formal*** *and certainly* ***controlled****" CSA#32.*	EFQ138, EFQ136.
Discussions, cooperation, worker group decisions, team-based organisation structure, relationships, solidarity community, general good of community,	*"You'll find that we are* ***unnaturally*** *required to be more* ***democratic*** *in our* ***decision-making****. Pulling in* ***experts*** *in various fields to actually* ***dissect*** *data reports to make sure that we're actually making the appropriate* ***decisions****" CSA#16.*	EFQ111, EFQ306.
Power, authority, leadership,	*"****All for one*** *[democracy] cannot happen because in this company I can make a recommendation and I can trust all the facts in front of me, but my superior*	EFQ109, EFQ104.

	*can **overrule** my **decision**. And even though all the **facts** are pointing in the right direction for my **decision**, they can **overrule** my decision to say, "No, you will go with this". Done. Then I've got to go with that" CSA#22.*	
Deliberative decision-making [agile]	*"We did a [organisational] **culture shift** and the culture shift says we need to be **agile**, we need to make **risk-based decisions**, **we** need to **own** our **decisions**, so we need to do all these things. But I don't think our **processes** are **aligned** to that. We're **not allowed** to do that. So, our **processes** are not **aligned** to our **culture**" CSA#22.*	EFQ127, EFQ356.
Organisational commitment, tolerance, ability to change,	*"I think they [management] are **forced** to **evolve** because of data. I do not think anybody had a **choice**. You're **forced** to be either **informed** with what is happening, the **latest** ways of thinking and working, than to stick to the **old** ways" CSA#18.*	EFQ194, EFQ151, EFQ154.
Underrepresented groups, equality, gender and ethnic equity, inclusion, freedom of expression,	*"I will say I'm extremely excited at the **calibre** of especially black **professionals** coming through whereas a few years I would still have said that they're employing the people [black], they're not really giving them **decision-making** [**responsibility**], they're just there in the **background**. They maybe just signed off things and whatever but **behind the scenes**, the **real power** is sitting in the white hands but now I'm definitely encouraged by the **credibility of people** that they're employing now" CSA#19.*	EFQ69, EFQ116.
Structure, flatter, institutional mechanisms, devolved, non-hierarchical control,	*There are all these **unnecessary wasteful decision-makers** in the **process**. Give **authority** to people on the ground that actually **knows** what is happening. Our **processes** have become too **broad**" CSA#22.*	EFQ188, EFQ189.

Responsibility, ownership, trust,	*"If you want to become a better **individual contributor** at CSA, yes altogether it lies with **you** firstly, so I think there's some sort of **accountability** or **responsibility** the **individual** has to take" CSA#37.*	EFQ191, EFQ173, EFQ174, EFQ175.
Open governance, governance,	*"There is always corporate **governance**...And because of that, there are bodies that get formed to assist and **drive decisions** in an **appropriate** way. They don't necessarily influence the core of the **decision**, but they guide the **process** to make sure that it was considered **fairly**" CSA#16.*	EFQ193, EFQ135, EFQ136.
Individual contribution, knowledge, meaningful work, competence, respect, less fear, quality work design,	*"I don't want to say that for instance if one **individual** is **more educated** than the other, that in essence leads to an **individual** who'll make **better decisions** or will be successful versus somebody who doesn't have an education because that's not true because there's **education on different levels**" CSA#37.*	EFQ66, EFQ82, EFQ83, EFQ84.
Processes	*"Our systems are very **complex** and **interrelated** and it's not very straightforward. The one thing I think being in a big organisation like this, **nothing is straightforward**. We set a target for [xxx] BOTs this year [2018] but we only achieved 15%. It is **challenging**" CSA#06.*	EFQ185, EFQ124, EFQ125, EFQ126.
Self-organising, self-interest, less managerialism,	*"I'm not the type that will check with 15 people to get their **buy-in**. That's an awful way to operate because I think that is just **not efficient** and I'm about, you need to make **quick decisions** and I also like to **enable** my staff to make **decisions** for **themselves**" CSA#06*	EFQ97, EFQ98.

Table 40: Keywords and characteristics of democratisation

4.8.1.3. Democratisation is the product of the whole: latent content thread

Within the prior two sections (4.8.1.1 and 4.8.1.2), literature and empirical data have provided the chosen basis for democratisation. However, an important aspect at "higher levels of abstraction" in qualitative research is the interpretation of the underlying meaning, which is known as latent content analysis (Erlingsson & Brysiewicz, 2017, p. 94). Another perspective of latent content is analysing the "'red thread' between the lines in the text", meaning that as data follows GTM processes, threads persist and give rise to core categories and themes, which in this case is democratisation (Graneheim et al., 2017, p. 30).

From earlier interaction with the data, the keywords, concepts and characteristics of democratisation began to emerge. At one point, 'collaboration' was thought to be the concept that could emerge as the core category. 'Empowerment' did not appear to fit, as Big Data as technology artefact in the thesis is more than just organisational data, and principles of empowerment came across as a value contribution to DMI within the IS artefact. When the open codes are taken together, the conversations with participants are played back repeatedly and, reading between the lines or searching below the surface of what's being said, 'democratisation' is the product of the whole. 'Democratisation' captures the essence and implications of Big Data that is unfolding within organisations. Big Data is generated everywhere, intentionally and unintentionally, and there is very little that organisations can do to minimise or stop the impact it is having on KWs and the workplace. 'Democratisation' espouses good faith in terms of the use of resources that result in good outcomes for the KW and the firm. 'Democratisation' provides boundaries, encourages participation, recognises specialists, and promotes conducive organisational design.

Democratic workplace	Industrial workplace
Decisions are made at all levels and the organizational structure is flat	Decisions are made at management or high levels of authority and the organizational structure is rigid and hierarchical
Leaders are evaluated by different stakeholders	Leaders are not evaluated by others
All levels are encouraged to participate and give feedback	Employees are expected to comply with directive
Diversity is encouraged	Norms, behaviors, and activities are prescribed and closely scrutinized
Information is readily available to all and knowledge sharing is encouraged	Information held by management

Source: Adapted from Nightingale (1982, p. 11)

Table 41: "Differences between democratic and industrial workplace" (Safari et al., 2018, p. 76)

Table 41 draws attention to two different workplaces, namely, democratic and industrial. The table highlights the principles that democratisation promotes, such as availability of data, sharing of knowledge, decentralisation of decision-making, accountability of leadership, and co-determination, inclusion, and recognition of diversity. These formed the 'red thread' that consistently and persistently appeared during GTM processes. Therefore, democratisation [inflection point] is relevant and fitting as the core category.

Below is a synopsis of the core category (DIP), with detailed explanations provided in Section 5.1.

4.9. Emergent theory

The crescendo to this thesis, following the path of data collection, data analysis, and proposition extrapolation, whilst adhering to GTM, is the formulation of theory. The theory, which is required to stand on its own, is the interpretation of more than 41 people's thoughts, ideas, fears, and worldviews. The theory cannot capture participants' real emotions, sentiments, and feelings that were expressed through anxiety, euphoria, frustration and, at times, nonchalance. This thesis is an injustice to the genuine contributions made by the case study participants. However, it is hoped that the theory goes toward representing their worldviews, and explains this phenomenon and other phenomena.

4.9.1. The theory emanating from the case study

Theory generation is central to the chosen research method, GTM (Urquhart et al., 2010). The key premise behind theory is not only to explain the phenomenon identified in this thesis, but also to develop emergent theory that could be applied to similar phenomena that are experienced elsewhere (Matavire & Brown, 2013). Furthermore, it is important to be 'faithful' to the participants, the case, and the context (Matavire & Brown, 2013, p. 120).

Selective coding had revealed four major codes or actors, which are TI, TH, TO, and DME. As described in Section 4.7.6, these contribute value in the form of DMI based on the information at hand. DMI and information are an IS artefact. The influence of Big Data on the democratisation of decision-makers in DDD is dependent on the completeness and quality of the IS artefact that originates from within the DIP system and is used for decision-making within the DIP—the core category. The democratisation of decision-makers in DDD in a Big Data environment is about having choices that are adequately supported by the main actors, through contribution of DMI. Without DMI, decision-making is constrained and risky, which compromises the KW as related to that instance of DDD.

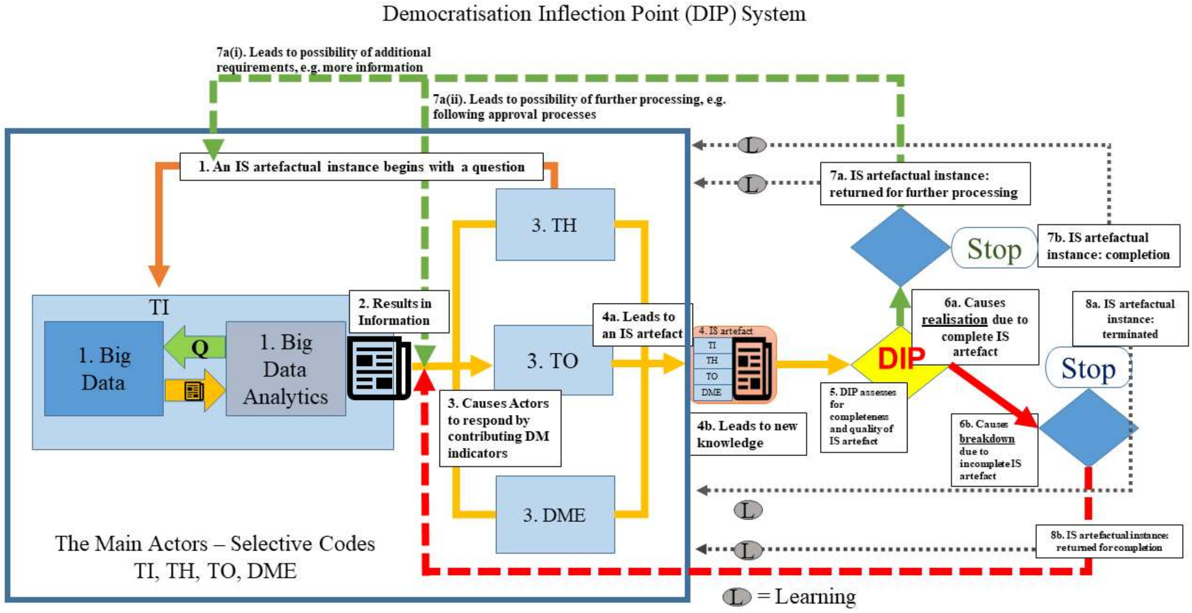

Figure 16: Emergent Theory - The democratisation of decision-makers in DDD in a Big Data Environment

Herewith follows an explanation of Figure 16.

1) An IS artefactual instance—Democratisation Inflection Point (DIP)—within the DIP system, begins when a question is posed to Technology Infrastructure (TI). (2) Big Data Analytics (BDA) processes the question, which results in information. (3) The resulting information causes the remaining actors, which are The Habitus (TH), The Organisation (TO), and Decision-making Entity (DME), to collaborate by contributing knowledge, in the form of decision-making indicators (DMI). (4a, 4b) The information (processed data) and DMI (knowledge) results in the creation of a value-laden IS artefact and new knowledge. (5) Within the DIP, the IS artefact is assessed for completeness by the decision-maker (KW). The completeness of an IS artefact is determined by the contributions of DMI by actors. (6a) A complete IS artefact contains DMI from each of the four actors, causing the **realisation** of the democratisation of decision-makers in data-driven decision-making (DDD) in a Big Data environment. (6b) An incomplete IS artefact implies that DMI are missing due to lack of contribution by one or more actors, causing the **breakdown** of democratisation of decision-makers in data-driven decision-making (DDD) in a Big Data environment. (7a, b) A **realisation** results in further processing of an IS artefact, or termination of the IS artefactual instance as a decision is realised. (8a, b). A **breakdown** results in the return of the IS artefact to the DIP system to address the incomplete IS artefact, or termination prior to the completion of data-driven decision-making process. An assured outcome of the DIP system is always **learning,** as new knowledge is created despite **realisation** or **breakdown** and is distributed to actors.

4.10. THEORETICAL SATURATION

At the risk of labouring a point, the foundation of GTM is constant comparative analysis and theoretical sampling, which implies that rigour in extracting value from every participant's contribution is certain (Corbin & Strauss, 2014). Most importantly, theoretical saturation entails teasing out every ounce of meaning before the next participant is chosen, based on something interesting; alternatively, a gap in understanding arises. Although, Figure 14 demonstrates that the number of new open codes did not increase greatly after 27 interviews; however, it does not suggest theoretical saturation (Corbin & Strauss, 2014). Theoretical saturation is achieved when "each category is well defined and developed in terms of its properties and dimensions" (Corbin & Strauss, 2014, p. 203). In addition, "nothing substantially new emerges" (Matavire & Brown, 2008, p. 140). Based on this, theoretical saturation has been achieved and is reflective in the developed and cohesive open, axial, and selective codes.

4.11. SUMMARY OF FINDINGS CHAPTER

The use of GTM to guide this study has been rewarding in that participants' voices within a case study environment have resulted in novel perspectives and credible theory that answer the research questions.

The thesis journey began with a question. After reviewing the current literature, the question remained unanswered. In investigating current IS theories that could explain the phenomenon, it became apparent that use of an existing IS theory would at best entail retrofitting an existing IS theory to explain something novel. This would have been an injustice, as the fresh perspectives obtained from participants within the case study would have meant forcing emergent outcomes to fit the chosen IS theoretical lens. GTM guided the thesis from case study selection, to data collection and analysis, to seeing a theory emerge that could explain the phenomenon. The idea is to take a complex discussion with participants, deconstruct it into meaningful codes, and ensure that every bit of data is taken into consideration. The consolidation of codes into higher level categories helps to demonstrate consensus among participants in terms of their interpretation. Concluding the empirical investigation is based on completeness and well-developed categories, and not on the number of codes collected or participants interviewed (Corbin & Strauss, 2014). Theoretical saturation is achieved when nothing novel arises, indicating that nothing of further interest is identified or gaps in the understanding comes to the fore (Bryant & Charmaz, 2007). Theory emerges that is validated by the collected data from the case study (Eisenhardt & Graebner, 2007).

Despite the possibility that existing literature attempts to creep into the interpretations and shape the findings, theoretical sensitivity has been top of mind throughout thesis development (Seidel & Urquhart, 2013). However, with adequate focus on coding and constant comparative analysis during data collection and analysis, it is less daunting due the mentioned preoccupation activities (Seidel & Urquhart, 2013). The empirical findings, with supporting evidence, are credible as the researcher's unintentional but preconceived ideas have been challenged by the empirical findings on several occasions, which provides relief in that what was unavoidable, was proven wrong by evidence (Glaser & Strauss, 1967).

5. DISCUSSION AND THEORETICAL ELABORATION OF THE CORE CATEGORY: DEMOCRATISATION INFLECTION POINT (DIP)

The purpose of this discussion chapter is to expand on the core category that was briefly presented in Section 4.8, and to discuss and situate the emergent theory that emanated from the empirical situation in extant literature and practice (Urquhart et al., 2010).

Theoretical integration is approached from a sociomaterial practice perspective, which takes into consideration the importance of sociotechnical systems, actor networks, and Practice Theory (Cecez-Kecmanovic et al., 2014). Sociomaterial is a portmanteau for social and material (Leonardi, 2013; Orlikowski & Scott, 2008). Selecting sociomaterial theory is relevant, as the DIP is essentially the place where both human and non-human actors of varying natures and characteristics come together to collaborate in a real-world context. A key concept of the thesis is democratisation, which has been discussed from the open coding phase through to selective coding and is based on the completeness and quality of the IS artefact, which comprises DMI and decision-making information.

The rest of this chapter is structured as follows.

Section 5.1 builds upon the findings in Section 4, particularly the core category, which was the culmination of continuous data collection and analysis, following grounded theory methods (Corbin & Strauss, 2014). In addition, the emergent theory is expanded upon.

Section 5.2 focuses on situating the emergent theory in relation to extant literature, and on highlighting practice contributions. It addresses theoretical integration aspects such as comparison to relevant theories to find similarities, differences, and extensions of extant literature (Urquhart et al., 2010). The findings have similarities as well as profound differences with the works of other theorists, which will be explored further. The intention is to demonstrate that contributions of this thesis is original, novel, and add to both academic and practitioner knowledge.

Section 5.3 provides a summary of the chapter.

5.1. THE CORE CATEGORY:[DIP] DEMOCRATISATION INFLECTION POINT

"Ultimately, a company's value is just the sum of the decisions it makes and executes" (Blenko et al., 2010, p. 3).

Section 4.8 indicated that a core category and complementary findings, related to knowledge and people, emerged from the study. The core category is discussed here, while the complementary findings are discussed in Sections 5.2.3.2 and 5.2.4.

The DIP is the point at which the actors' (Technology Infrastructure (TI), The Habitus (TH), The Organisation (TO), and Decision-making Entity (DME)) DMI contributions and the information extracted through BDA are assessed for completeness. Prior to the DIP, the data is formatted for consumption, and merely represents processed data or information. The information has taken on no further meaning or insight, be it actionable or not.

5.1.1. The emergence of the core category

For the final step of GTM, two approaches to theory validation are suggested, namely, "comparing it to raw data or by presenting it to respondents for their reactions" (Corbin & Strauss, 2008, p. 161). The former suggestion of comparing the theory to raw data was chosen and is presented in Section 5.2.1 as part of theoretical propositions.

In following the SGTM processes, the aim is to narrow down open, axial, and selective codes to categories, and finally to a core—central—category (Corbin & Strauss, 2014). Arriving at a core category is largely based on following an iterative process that is grounded in field data, and applying interpretations to derive meaning from the field data (Walsham, 1995). Preconceptions are minimised and managed through theoretical sensitivity awareness, which have been covered within Section 3 (Matavire & Brown, 2013). The codes and categories that are not chosen as selective codes, and finally as the core category, are still valuable for further research undertakings, as "An imaginative interpretation sparks new views and leads other scholars to new vistas. Grounded theory methods can provide a route to see beyond the obvious and a path to reach imaginative interpretations" (Bryant & Charmaz, 2007, p. 13).

Coding and categorisation results	
Core Category	**Selective codes**
Democratisation Inflection Point (DIP)	***Technology Infrastructure (TI)***
	The Habitus (TH)
	The Organisation (TO)
	Decision-making entity (DME)

Table 42: [DIP]

Table 42 illustrates the latter GTM processes—core and selective coding—that started with conversations, which were broken down into open codes. Thereafter, reduction and rebuilding resulted in axial codes. Selective codes emerged as interesting, persisting, and important to answering the research questions. These selective categories are instrumental and contribute to the core category of the thesis, which is the 'Democratisation Inflection Point (DIP)'.

KWs are value-laden beings who contribute varying levels of expertise, experience, exposure, and education to decisional processes. They also contribute biases and specific perspectives, from which they interrogate reality. In turn, these biases, perspectives, and value contributions fuel other collaborative efforts. An example of this is the 'volume' characteristic of Big Data, which is subjected to Big Data analytical processes by BI experts, for the vastness and messiness to be transformed into information that, in turn, has the possibility of being transformed into insight. While this insight may be understood by some, participants in the study indicated that they consult with subject matter experts and business partner resources who help them to understand the true meaning of the information through analysis and interpretation, thereby resulting in insight.

From these discussions, actions are formulated. Value is added to Big Data, whether through analytical processes, analysis, or discussions. The output from the discussions—be it actionable or otherwise—forms the basis of further discussions between KWs, for instance, for decisional purposes by power centres or other KWs. Power centres, as consistently established in the study, are interested in the summary of Big Data—that is, the big picture. KWs who are challenged through lack of skills, experience, and age also prefer summaries.

EFQ234. "If you have a love for data, you will grab it and do something with it" CSA#20.

EFQ235. "The amount of data sometimes I think is not really needed. So, not all the data that is thrown at us actually adds value. But I also think that comes to the fact maybe it is a question of having the right people or not having the right tools to actually look at this data and spit out something to analyse" CSA#05.

The effective collaboration between data, technology, people and organisation, which are synonymous with selective codes and referred to as actors (TI, TH, TO, and DME), results in value that could be further developed into actionable insight. As mentioned by CSA#05, individuals as well as the organisation as a whole are overwhelmed by data. On the one hand, Big Data may be too much; on the other hand, the right combination of knowledge (skills) and tools (BDA) applied to Big Data could result in value.

Collaboration and contribution—which was carried through the data collection and analysis phases, but which was initially building up to be a collaboration among people—was replaced by the better explanation of the collaboration between actors, which includes both animate and inanimate objects (i.e., TI, TH, TO, and DME). The IS artefact is the result of collaboration and contribution by the four human and non-human actors, that have agency in producing an IS artefact for the democratisation of decision-makers in DDD; without this, DDD results in breakdown. The IS artefact is not only the basis for decision-making, but also the gauge for determining democratisation of decision-makers in DDD.

As the empirical data began to unfold, it became evident that a direct (yes or no) or simple answer to the main research question was unlikely. However, as several of the open, axial, and selective codes were captured and analysed, they contributed collectively to the main research question. Answering the main research question depended on the impact of the question on the organisation, the type of decisions under consideration, the tactical or strategic nature of the questions, and the implications for the business. There were many dependencies to consider, such as the quality and appropriateness of questions put to BDA, the ability of the KW to interrogate and interpret the information, and the governance, financial, resourcing, and decision-making structures.

5.1.2. The DIP as a contributor to democratisation

Theory emanating from the study suggests that, while Big Data's characteristics have an impact on the democratisation of decision-makers in DDD, the researcher's preconceived notion was different to the reality in the case study setting. Democratisation could be thought of as organised labour or direct participation based on individualistic privilege (Laird, 1993). The study suggests that the democratisation of the decision-maker/KW in the workplace is achieved through the collective collaboration and value contribution by actors, human and non-human, based on specific information. This is achieved through an IS artefact, which is the contribution of DMI—value contribution by actors; the artefact is based on specific information which, in turn, is assessed at the DIP. This results in realisation or breakdown of outcomes of the democratisation of decision-maker/KW, as related to DDD.

An activity, such as asking BDA a question, initiates an IS artefactual instance within the DIP system, which results in an IS artefact that causes the possible democratisation or not of the individual as a KW/decision-maker in data-driven decision-making. As this research pertains to Big Data, the activities that are of relevance are those triggered by the Technology Infrastructure and by IS artefacts that are returned to the DIP system. While there is collaborative consensus and consultation, the final decision appears to be at the individual level, albeit with strong influence by the four actors and the contextual situation (Frisch, 2011). The Habitus also exposes the biases that KWs possess; this is manifested in the manner in which a completed IS artefact is enacted upon.

The key premise of democratisation is the fair participation of KWs in DDD; here, fair refers to having all DMI available prior to making a decision. The contextual situation mentioned previously refers to the decision-making impact, which is based on the type of decision—that is, strategic, tactical, or operational. An example of strategic decision-making impact is where the Chief Executive Officer (CEO) assumes complete responsibility for the direction and performance of the organisation—hence, single-person responsibility. This responsibility is supported by a slew of collaborative efforts that emanate from various factions inside and outside the organisation. Another example is the call centre environment, where customer satisfaction is important: an agent's democratisation (not ability, in this case) in decision-making is measured against The Organisation's capability and the decision-making entity. This illustrates the point that, although several collaborative cohorts, comprising many actors, have provided supporting documentation and evidence for decision-making, a single person is ultimately held accountable for a decision that is based on an IS artefact. In the case study, accountability usually does not extend to collaborating groups, but is at the designated responsible-person level, which could be management or an individual contributor. Even when team-based decisions are taken through consensus, the team leader or responsible authority figure is ultimately held responsible. Unlike committees where the consensus of the group implies that the decision and risk is shared equally and the reward and consequences are distributed across the group, there was no indication that such a situation occurred at CSA.

The DIP is the point at which actors' contributions (DMI), and the information extracted from BDA come together to add value to KW decision-making. This value could be in the form of a business report (information), skills, experience, governance, processes, or the capability to make decisions. The essence of the DIP system is co-creation of value through the Technology Infrastructure, people, The Organisation, and a decision-making entity. This results in value-laden DMI that, together with specific information, culminate in an IS artefact. The IS artefact remains as is until it is utilised to effect decision-making, or passed back into the DIP system for further processing. For the latter, the IS artefact is no longer relevant, as DMI contributions will change and the IS artefactual instance begins again with different DMI contributions, albeit based on the same information. It is important to note that the IS artefact is not the evidence upon which data-driven or evidence-based decision-making is based, as information continues to be the evidence for DDD. The IS artefact facilitates democratisation by affording KWs participation in data-driven decision-making based on the transparency of DMI, thereby mitigating or minimising KWs' risks, insecurities, and possible negative outcomes based on an incomplete decision-making picture. The concept of the IS artefact is to enable self-confidence through DDD that is based on a more complete picture.

The contribution by actors are neither sequential nor a step-through model, which implies that no specific sequence is followed for DMI contributions. The DMI contributions by actors are not dependent on what other actors contribute, but is based on the information and decision at hand. If a DMI contribution is absent or insufficient, the IS artefact is returned for further processing.

5.1.3. The Democratisation Inflection Point (DIP) causes an "It Depends!" outcome

Given the focus of this thesis on Big Data, the initial expectations were that Big Data characteristics would be central in answering the research questions. However, this is only partly the case, as Big Data is enabled through a "large nexus of associations" (Mikalef et al., 2018). In support of this, the entire cycle within the DIP system begins and ends with Big Data, and it was discovered that there is not only an interplay between Big Data and other factors or actors, as they are known, but also a mandatory reliance on the realisation of knowledge, insight, and effective decision-making (Mikalef et al., 2018). In the context of this thesis, the extent of contributions (DMI) by actors either causes a realisation or a breakdown outcome for democratisation of decision-makers in DDD. What in hindsight may seem to be common sense in decision-making processes, the contribution of DMI to an IS artefact was not initially evident from discussions with participants. Furthermore, after extensive searches of the literature, little has been found on this phenomenon.

The DIP has emerged to explain the phenomenon and answer the research questions. It has evoked several concepts such as collaboration, participation, decision-making, and value co-creation. These concepts are significant in that they are tied to the major theoretical frameworks such as sociotechnical systems, Actor Network Theory, and Practice Theory, which are encapsulated in sociomaterial practice (Cecez-Kecmanovic et al., 2014). The DIP resonates with these theories and sociomaterial practice to explain the phenomenon.

The literature that either supports, complements, or conflicts with the empirical findings are discussed in Section 5.2.

5.1.3.1. An IS artefactual instance within the DIP system

Figure 17 illustrates an IS artefactual instance within the DIP system. An IS artefact's initiation is typically based on a question that is put to BDA, which results in processed data or information. Based on the information, actors contribute valuable DMI, which results in an IS artefact—information and DMI— and is presented to the KW within the DIP as a valuable decision-making aid. An IS artefact could also be initiated when information is presented back to the DIP system for further processing, for example, by following an approval process. Within the DIP, the KW assesses the IS artefact for completeness and quality. The process for the realisation of an IS artefactual instance is outlined in Figure 17.

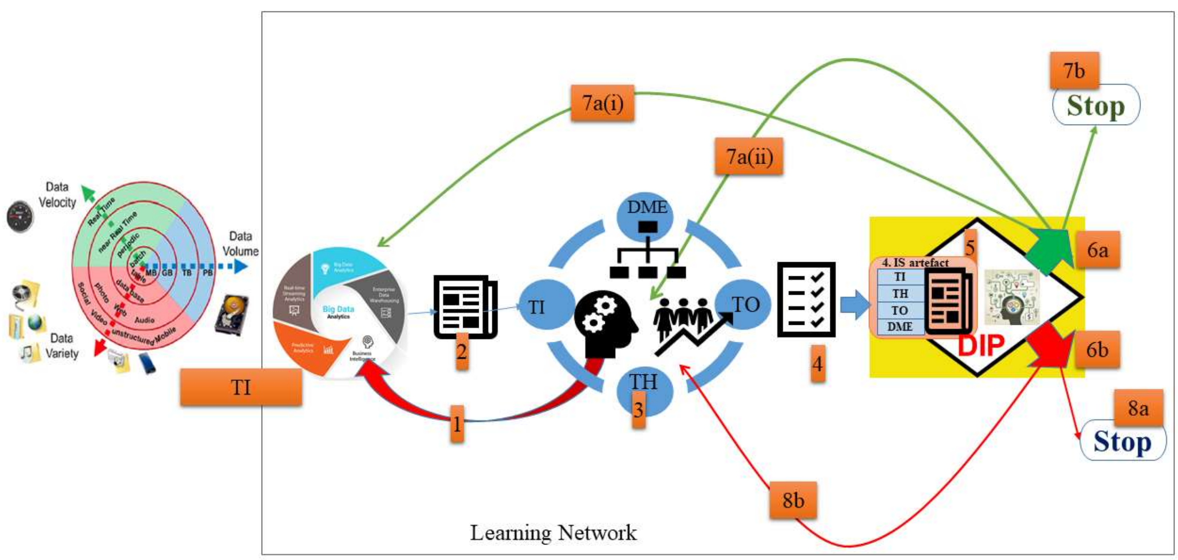

Figure 17: An IS artefactual instance within the DIP

TI - Big Data is housed in CSA data warehouses, machines, the cloud, and the internet. BDA interrogates datasets.

1 – An IS artefactual instance is initiated by a question that is put to Big Data Analytics. The question could be descriptive, prescriptive, or predictive in nature.

2 – The output of BDA work is an information repository, such as a report, document, or spreadsheet. In addition, information about information (metadata), such as the time and date of creation, file size, quality of data, and source of data, are contributed as DMI.

3 – The remaining actors—TH, TO, and DME—contribute DMI to the IS artefact. With DMI contributions, the information transforms into knowledge. TI also contributes DMI in the form of information about information (metadata).

4 – The knowledge, together with the value contributions (DMI) by the actors, are conceptualised as an IS artefact.

5 – The IS artefact is assessed at the DIP for completeness and quality.

6a – IS artefacts that are deemed as complete, i.e., they contain DMI/s from each of the actors, results in democratisation of decision-makers in DDD being **realised** in a Big Data environment.

6b – IS artefacts that are deemed as incomplete, i.e., they do not contain DMI/s from each of the actors, causes the democratisation of decision-makers in DDD to **break down** in a Big Data environment.

7 – As a result of **realisation**: a decision occurs (6a), the IS artefact is passed back to the DIP system for further processing such as the requirement for more information (7a(i)), or the information is sufficient but decision-making processes require escalation of the decision (7a(ii)). Once a decision occurs, the IS artefactual instance is concluded (7(b).

8 – As a result of **breakdown**: a decision does not occur and the IS artefactual instance terminates (8a), or the IS artefact is sent back for further processing (8b), specifically to the actor that had failed to contribute DMI.

Learning network – In spite of realisation or breakdown, the IS artefact becomes new knowledge that is distributed to all actors.

When an IS artefact is returned to earlier steps in the DIP system, as in Steps 7 and 8, the actors remain the same but could play different roles; for instance, when following a workflow approval process, the DMI contributions may be different because executive judgement may need to be exercised, compliance may need to evaluate the risks, or a better option may be suggested from prior knowledge.

The steps outlined above are not mechanistic, since there are no automated processes behind the activities within the DIP system. The steps follow the DIKW approach, that is, incremental value is added to data and the steps are largely sequential. This becomes challenging at Step 3 (and conflicts with the prior sentence), as an actor or actors may not have contributed to the DMI, which are only realised in the DIP. While this appears as a fault within the DIP system, it is the basis upon which the DIP rests: the DIP (Step 5) is the place where the IS artefact is assessed for completeness, which causes a realisation or breakdown in democratisation of decision-makers in DDD.

In an organisation as large as CSA, simultaneous instances of DIP systems are taking place across the organisation for every DDD. In an organisation as hierarchical and well-governed as CSA, some DIP systems feed into other DIP systems. The following reporting-based example explains the DIP systems' interrelationships. Reporting is a common workplace activity that is discussed several times by participants. KWs are part of a value chain, meaning that they add incremental value to information that results from BDA—in this case, reports. However, prior to a report being produced, BDA experts sit with KWs to scope out the requirements. Once the requirements are agreed to, the reports are produced. These reports are then synthesised and summarised by the KWs for executive management consumption. Executive management decision-making also requires that all actors (TI, TH, TO, and DME) play a role. This example demonstrates at least three DIP systems and spans several decision-making types (see Section 5.1.3.2 for how this example is mapped to the DIP system).

If the IS artefact, specifically the information, is still relevant, the DIP system cycle starts again with the previously processed information, but with **different enactments** by the same actors, for example: management (KW) versus individual KW involvement when following approval processes; specialist versus management involvement when expert input is needed; and the strategic importance and impact of the decision. The following reasons for restarting the DIP systems cycle have been identified from the study:

- The nature of the decision, that is, tactical or strategic.
- The context of the decision, that is, time, place.
- The power structures in place, that is, supportive or blocking.
- The risks involved.
- The business benefits, including financial implications.

In the above example, TI did not contribute new information, as there was no need; however, information about information (metadata) is relevant and important, and TI continues to be a relevant actor.

DIP systems impact all actors in some manner. If we consider the DIKW, covered in Section 2.2.1, information has been transformed into awareness and know-how, which is knowledge. Regardless of the outcome of DIP systems and the DIP, whether realised or broken down, the actors in the network are influenced to varying degrees through a change in their knowledge, based on the DIP and the DIP system.

5.1.3.2. Use cases to illustrate the DIP system

The DIP system concept is a culmination of empirical data from CSA—more specifically collecting and analysing participants' interpretation of real-world situations. Below are two use cases to demonstrate the DIP system.

a) Decision-making chain

The scenario is that CSA#22 produces reports around service contracts, which are escalated through management structures to arrive at a decision. While the exact number of service contracts in CSA is unknown, these are estimated to be several hundred; their importance and impact on the business are considered critical.

1 – KWs, management, and non-management staff need to fulfil a data-driven task. Therefore, a question is put to BDA, which could be as follows: Extract all services contracts that will terminate within three to six months.

2 – BDA responds with a report that lists all the services contracts that will terminate in 3, 4, 5, and 6 months.

3 – Actors' DMI contributions:

TI: Although TI produced the report, the DMI contribution is information about information (metadata), such as report date, authentication of CSA#22, history of each service contract, compliance status, source data, and report revision in the case of a standard report.

TH: CSA#22 synthesises the information by applying past knowledge (experience) and skills to the new information, thus yielding newer knowledge. CSA#22 produces a summarised report indicating service contracts that are to be renewed, renegotiated, and concluded. CSA#22 adds recommendations and suggests service contract priorities.

TO: It is key to the business that risks are controlled. Therefore, the shared knowledge is evaluated against organisational culture, vision, internal and external risks, resource constraints (which could be financial or people-related), and the benefit to the organisation. TO contributes DMI, which indicate that compliance checks and balances are in order and that the service contracting parties meet regulatory requirements, such as preference for the previously disadvantaged.

DME: The decision-making capabilities of the organisation are evaluated against trust among people, machines, and data; expediency of decisions; and the decision-making continuum. DME contributes DMI that mandate changes in service providers.

4 – The new knowledge (which is the DMI contributions by the actors in point 3 above) and the information are conceptualised as an IS artefact.

5 – The IS artefact is assessed at the DIP for completeness. Based on the contribution of DMI by all actors, the IS artefact is deemed complete.

6a – The completeness of the IS artefact has caused the realisation of the democratisation of decision-makers in DDD. Decisional choice is possible.

6b - N/A.

7a(i) – N/A.

7a (ii) - Based on the DMI contained in the IS artefact, a decision is deferred back to the DIP system for further consideration, which comprises further collaboration with respect to service providers before the approval process can start again.

8a – N/A.

8b – N/A.

Learning network – The IS artefact becomes new knowledge that is learnt by the actors.

b) Facilities monitoring

Managing mega real-estate campuses require real-time, near real-time, and non-real-time information to ensure that the facilities function consistently and safely. Facilities monitoring includes monitoring of heating and cooling systems, lighting systems, water treatment plants, escalators, and lift systems, which produce large amounts of sensor data that is necessary for operations and management.

1 – Facilities management requires operational status reports of escalators and lifts for the previous 12 months.

2 – TI, through BDA, produces a report that shows the operational status of each escalator and lift over the last 12 months.

3 – Actors’ DMI contributions:

TI: Contributes information indicating the source of data, time, and detail of the KW requesting the report.

TH: Technical, administrative, and management skills are applied to the information to understand the current status. The collaboration determines that one escalator requires significant refurbishment. The rest of the escalators and lifts are operational when required, with routine maintenance and checks required.

TO: The Health and Safety department monitors the situation for any concerning alerts. Budget is identified for significant repairs.

DME: [left blank to indicate missing DMI contribution]

4 – The new knowledge, combined with DMI contributions by the actors, are conceptualised as an IS artefact.

5 – The IS artefact is assessed at the DIP for completeness. Based on the contribution of DMI by the actors, the IS artefact is deemed incomplete, as the DME did not contribute DMI.

6a – N/A.

6b - The incompleteness of the IS artefact has caused a breakdown of the democratisation of decision-makers in DDD. Decisional choice is not possible.

7a (i) and (ii) – N/A.

8a – N/A (not applicable at this point; however, it could be applicable, should the DMI not be complete and the decision-maker abandons the decision).

8b - The IS artefact is referred back to the DIP system for contribution of DMI by DME.

Learning network – The IS artefact becomes new knowledge that is learnt by the actors.

Examples of realisation and breakdown demonstrate democratisation of decision-makers in DDD in relation to Big Data. The DIP system, as a concept, is easily applied to other scenarios that arise from the business.

5.1.3.3. Key contributions (DMI) by the main actors to the Democratisation Inflection Point (DIP) system

The emergence of a theory is the outcome of inductive processes, which include reducing and selecting codes as GTM processes are followed. However, the DIP cannot be entirely considered as an outcome of the reduction of open, axial, and selective coding processes. Although the selective codes—TI, TH, TO, and DME—contribute to the DIP as the core category, the DIP is based on interpretation of the evidence, which has been explained in Section 4.8. The selective codes are more aptly considered as actors in the DIP system, and collaborate in IS artefactual instances by contributing to the creation of the IS artefact.

Some of the types of contribution by the actors are listed below (it is by no means comprehensive). These contributions are based largely on the different coding stages undertaken. The culmination of the core category followed processes of teardown, rebuild, and reduction, based on empirical data.

a) Technology Infrastructure (TI)

This comprises the repository for Big Data, computing technologies, Big Data Analytics Applications, data modelling tools, data management, data security, job tasks, job schedulers, dashboards, and user experience. Importantly, TI contributes information about information (metadata), which could be as simple as report date/time, or complex metadata such as data quality, geospatial, source of data, and schemata.

b) The Habitus (TH)

Human capital (skills and abilities), personalities, cultural background, historical background, risk propensity, human emotion, and interpersonal relationships.

c) The Organisation (TO)

Managing business metrics, controlling risks, business processes, organisational culture, vision, strategy, and deploying firm resources for betterment of the business.

d) Decision-making Entity (DME)

Evidence-based decision-making, organisational structures, transformation, and decision-making processes.

Each of the actors contribute DMI based on Big Data, which result in an IS artefact which, in turn, is used for decision-making.

5.1.3.4. DIP as learning network

The final deliverable of the DIP system is that it is a learning network, as is indicated by the grey arrows in Figure 16 and the grey rectangular box in Figure 17. This implies that learning occurs at each of the stages by which data becomes information and then knowledge as it traverses the DIP system. Knowledge plus the IS artefact is sent back to actors as incremental knowledge. For instance, a KW produces a report and recommends that an asset is replaced because of age. TO will assess the request based on budget availability. The DME does not approve, as there are competing priorities. This leads to a realisation within the DIP, even though the request was denied. The IS artefact now contains all the actor contributions—information, request for new asset, budget approval, and request denied; all of these amount to new knowledge.

5.1.3.5. Big Data without other actors

Assume that BDA output results in information, that is, a report that is organised in some way but in which the contributing actors' DMI are not present or are partially present. What happens next? It stands to reason that the information will be read and possibly understood, which implies knowledge is applied to the information. This knowledge emanates from the 'The Habitus' actor. Even if 'The Habitus' is a constant participant, actionable insight resulting from a DIP instance is still in an indeterminate state. Without The Organisation and DME contributions, democratisation as related to decision-making will not be sanctioned and possibly transgresses the firm's protocols.

Regardless of the combination of actors that is tested to see whether company support is possible, this always falls short of a sanctioned, democratically enabled DDD.

5.1.3.6. Contribution by all actors are necessary for DIP success

The use cases discussion (see Section 5.1.3.2) includes an example where TI is not engaged as an actor once a report is produced. When an information repository is produced and is fit for purpose, there is no need to produce another report, even if it is returned to the DIP system for further processing. However, TI continues to provide metadata, and learning takes place that could be used for a different analytical purpose (i.e., predictive and prescriptive analytics), namely, task automation (BOT) and machine learning.

Testing for DIP Achievement	TI	TH	TO	DME
DIP 1	√	√	√	√
DIP 2	X	√	√	√
DIP 3	√	X	√	√
DIP 4	√	√	X	√
DIP 5	√	√	√	X

Table 43: Testing for DIP Success

Table 43 demonstrates the importance of selective codes in achieving meaningful outcomes from the DIP. This thesis holds that the four selective categories are collectively necessary for the DIP to produce value-laden knowledge and an IS artefact that facilitates DDD. DIP 1 is highlighted in green to indicate that an IS artefact is successfully produced. DIPs 2, 3, 4, and 5 suggest that an IS artefact has not been successfully created, as at least one actor's DMI contribution is missing; hence, the IS artefact is incomplete.

In summary, the DIP captures Big Data decision-making processes from the perspective of participants at CSA. Actors are active contributors to the information repository, which transforms over time into knowledge. The contributions by the actors, together with the information repository, become a decision-making IS artefact that leads to the realisation of a decision-making need, or to breakdown.

5.2. Theoretical integration and practical contributions of the Democratisation Inflection Point (DIP)

The main premise of theoretical integration is to demonstrate how the particular findings fit with current knowledge, which new knowledge is contributed and, specifically, which consequences result from the findings for academic and practitioner knowledge (Urquhart et al., 2010). Practice-related contributions are also included and integrated into the discussion.

There are a few theoretical frameworks, such as Actor Network Theory and Structuration Theory, that could have guided this research and provide an appropriate research methodology. However, the hesitance to use existing theory was because such theories would not only guide the research, but also shape the outcomes of the empirical situation and the theoretical contribution (Ågerfalk, 2014; Grover & Lyytinen, 2015). Having chosen GTM and conducted case study research, new discoveries arose from portions of the emergent theory; these appeared to resemble existing theories such as Actor Network Theory, practice theories, and sociomaterial approaches to socio-technical phenomena (Cecez-Kecmanovic et al., 2014; Orlikowski, 2010). This is acceptable, as new theoretical contributions could support, expand, or refute existing theory, thus representing theoretical integration (Urquhart et al., 2010).

What follows are several theories that could be applied to the major findings that collectively support the emergent theory. The sections that follow are based on the core category findings (Section 4.8) and discussion (Section 5.1).

The use of sociomaterial practices for theoretical integration is largely based on the work of several contributors (Barad, 2003; Boell & Cecez-Kecmanovic, 2011; Cecez-Kecmanovic et al., 2014; Feldman & Orlikowski, 2011; Leonardi, 2013; Orlikowski, 2010; Orlikowski & Scott, 2008; Scott & Orlikowski, 2014). In a study by De Camargo Fiorini et al. (2018), dozens of organisational theories were assessed for applicability to Big Data research; of these, nineteen theories have been used to investigate Big Data issues, and some of these are included in the discussion. Reflecting on the key premises and characteristics of sociomaterial practices, the DIP resonates closely with sociomaterial practices (De Camargo Fiorini et al., 2018).

5.2.1. Theoretical Propositions

This section extrapolates the emergent theory-based theoretical propositions (TP) (see 4.9.1) that emerged from empirical data (Matavire & Brown, 2013). TP and sub-theoretical propositions (STP) contribute to explaining the empirical data and what is happening through observation and deep reflection (Tanner, 2013). While "some authors mistakenly use propositions to summarize a body of literature", theoretical propositions are statements that aim to elevate evidence from the case study (Whetten, 1989, p. 492).

Table 44 and Table 45 show the TPs, including supporting references to evidence. The TP and STP collectively contribute to the theory in Section 4.9, and answer the main research questions (MRQ) and sub research questions (SRQ) in Section 6.2. Some of the applicable theories in the tables are based on a recent study of organisational theories, which are pertinent and beneficial to past and future Big Data research (De Camargo Fiorini et al., 2018). Further, the aforementioned tables include other contributions that are related to sociomaterial practice theories (Cecez-Kecmanovic et al., 2014; Orlikowski & Scott, 2008). Knowledge contributions by academia and practitioners, specifically a comprehensive collection of IS-related theories, are available online in a single repository[30] of theories that could support the DIP.

TP1: The democratisation of decision-makers in DDD is dependent on the completeness of an IS artefact that results from the collaboration of, and contribution by, the following actors: the Technology Infrastructure (TI), The Habitus (TH), The Organisation (TO), and Decision-making Entity (DME), of value-laden decision-making indicators (DMI) that are based on specific information.				
RQ	**STP**	**Sub-theoretical proposition**	**Some applicable theories**	**Supporting empirical evidence**
MRQ **SRQ1** **SRQ2** **SRQ3**	**P1a**	An IS artefactual instance begins with a relevant question that is put to Big Data Analytics (BDA) within the Technology Infrastructure (TI).	Organisational Information Processing view (OIPV), Technology acceptance model (TAM),	Sections: 4.5.2.1, 4.5.2.2, 4.5.2.3 4.5.2.4.
OIPV posits that information is necessary to execute tasks (decision-making). When the task is complex or not understood, "more knowledge is acquired" during the execution to better support the task (Galbraith, 1974, p. 28). OIPV is relevant to P1a, as it suggests that BDA/BI, which are information processing tools, "are able to help reduce uncertainty and equivocality in different types of decision-making processes" (De Camargo Fiorini et al., 2018, p. 118). The DIP is focused on clarifying the basis for democratisation of decision-makers in DDD, based on information extracted through BDA. TAM addresses users' acceptance, rejection, and utilisation of information technology—in this case, Big Data (Davis, 1989). TAM is relevant to the discussion of the DIP as the starting point of the IS				

[30] https://is.theorizeit.org/wiki/Main_Page

<table>
<tr><td colspan="5">artefact, and the subsequent use thereof within decision-making is reliant on KWs decision to utilise BDA in the workplace.</td></tr>
<tr><td>MRQ

SRQ1

SRQ2

SRQ3</td><td>P1b</td><td>The basis for the democratisation of decision-makers in DDD is the completeness of the IS artefact, which is validated within the Democratisation Inflection Point (DIP).</td><td>Actor Network Theory (ANT), Sociomaterial theory (practice) (SMP), Knowledge-based View of the firm (KBV), OIPV, Theory of technology dominance (TTD),</td><td>Sections:

4.5.2.1, 4.5.2.3, 4.5.3.3, 4.5.3.6, 4.5.6.1, 4.5.6.2, 4.5.7.3, 4.5.7.1, 4.5.7.4, 4.5.7.6, 4.5.8.1, 4.5.8.2, 4.5.9.1, 4.5.9.2, 4.5.9.3, 4.5.10.2, 4.5.12.1, 4.5.12.5, 4.5.13.2, 4.5.13.4, 4.5.13.6.</td></tr>
<tr><td colspan="5">ANT is defined as “organization constituted by relationships that form ties with both human and non-human agencies” (Orlikowski & Scott, 2008, p. 458). ANT is discussed in Section 5.2.3.3.

SMP is discussed in Sections 5.2.2 and 5.2.3.

The premise of the KBV is to use all the firm’s resources, especially knowledge, to gain and sustain competitive advantage (Barney, 1991). “The one sure source of lasting competitive advantage is knowledge” (Nonaka, 1991, p. 162). Resources include human and non-human assets, capabilities, information, and knowledge. The KBV maps to P1b, mainly because of knowledge contributions (information-based DMI) that lead to the IS artefact. As indicated within the definitions table on page xviii, DMI is an aspect of knowledge management as it contains both the story behind the decision and the knowledge that was used to decide.

OIPV is relevant to the DIP, as providing clarity in DDD supports the democratisation of decision-makers.

TTD’s premise is that information from BDA has reliance and dominance consequences, which implies that information aids in decision-making judgements, or that information overrides the decision-maker, respectively (Arnold & Sutton, 1998). Overriding the decision-maker sacrifices important aspects such as intuition and knowledge. TTD has commonalities with the DIP, but the DIP is based on knowledge contributions by all actors in the decision-making process.</td></tr>
</table>

<table>
<tr><td>MRQ
SRQ1
SRQ2
SRQ3</td><td>P1c</td><td>The enablers, which facilitate democratisation of decision-makers in DDD in a Big Data environment, and the constraints, which hinder democratisation of decision-makers in DDD in a Big Data environment, extend beyond the technology artefact, Big Data.</td><td>ANT, SMP, TAM, OIPV, Contingency Theory (CT),</td><td>Sections:

4.5.4.1, 4.5.4.2, 4.5.5.1, 4.5.6.3, 4.5.7.1, 4.5.7.2, 4.5.7.3, 4.5.7.4, 4.5.7.6, 4.5.8.1, 4.5.8.2, 4.5.8.4, 4.5.8.5, 4.5.9.1, 4.5.9.2, 4.5.9.3, 4.5.9.4, 4.5.12.6, 4.5.13.2, 4.5.13.3, 4.5.13.7.</td></tr>
<tr><td colspan="5">CT theorises that organisations are susceptible to external pressures and adapt accordingly (De Camargo Fiorini et al., 2018). CT is relevant to the DIP, because the DIP provides clarity in determining the democratisation of the decision-maker in DDD, which is through the completeness of an IS artefact. The IS artefact provides the mechanisms for adapting.</td></tr>
</table>

Table 44: Theoretical Propositions: TP1

<table>
<tr><td colspan="5">TP2: Actors—TI, TH, TO, and DME—contribute value-laden decision-making indicators (DMI) that are based on specific information extracted through Big Data Analytics, within an IS artefactual instance called the Democratisation Inflection Point (DIP) system, to democratise decision-makers in data-driven decision-making.</td></tr>
<tr><th>RQ</th><th>STP</th><th>Sub-theoretical propositions</th><th>Some Applicable theories</th><th>Supporting empirical evidence</th></tr>
<tr><td>MRQ
SRQ1
SRQ2</td><td>P2a</td><td>The actor, Technology Infrastructure (TI), contributes to the democratisation of decisions-makers in DDD.</td><td>ANT, SMP, KBV, Technology-Organisation-</td><td>Sections:

4.5.2.1, 4.5.2.3, 4.5.2.5, 4.5.3.1, 4.5.3.2, 4.5.3.3, 4.5.3.7, 4.5.3.9.</td></tr>
</table>

SRQ3			Environment (TOE)	
The Technology-Organisation-Environment (TOE) framework addresses the adoption of technology innovation based on the influence of technological, organisational, and environmental contexts (DePietro et al., 1990). The TOE framework addresses decision-making as related to technology adoption and use, rather than the use of information from technological innovation as the basis for decision-making.				
MRQ **SRQ1** **SRQ2** **SRQ3**	**P2b**	The actor, People as Data (TH), contributes to the democratisation of decisions-makers in DDD.	ANT, SMP, KBV,	Sections: 4.5.4.1, 4.5.4.2, 4.5.4.4, 4.5.5.2, 4.5.6.1, 4.5.6.2, 4.5.7.2, 4.5.7.6.
Applicable theories have been mentioned earlier.				
MRQ **SRQ1** **SRQ2** **SRQ3**	**P2c**	The actor, The Organisation (TO), contributes to the democratisation of decision-makers in DDD.	ANT, SMP, KBV, Institutional Theory	Sections: 4.5.8.1, 4.5.8.2, 4.5.8.3, 4.5.8.4, 4.5.8.5, 4.5.9.1, 4.5.9.2, 4.5.9.3, 4.5.9.4, 4.5.10.2.
Institutional Theory explains that processes by which institutional structures come into being are a means to control social behaviour through governance, regulations, culture, and strategy. Managing the business is a critical DMI within the DIP IS artefact; therefore, commonality is plausible between IT and the DIP.				

MRQ **SRQ1** **SRQ2** **SRQ3**	**P2d**	The actor, Decision-making Entity (DME), contributes to the democratisation of decision-makers in DDD.	ANT, SMP, KBV, IT,	Sections: 4.5.11.1, 4.5.11.2, 4.5.12.1, 4.5.12.2, 4.5.12.5, 4.5.12.6, 4.5.12.7, 4.5.13.1, 4.5.13.2, 4.5.13.3, 4.5.13.4, 4.5.13.5, 4.5.13.6, 4.5.13.7.
Applicable theories have been mentioned earlier.				
MRQ **SRQ1** **SRQ2** **SRQ3**	**P2e**	The transformation of raw data into information and knowledge is dependent on value contributions by actors within the DIP system.	ANT, SMP, KBV,	Sections: 4.5.2.1, 4.5.2.2, 4.5.2.3, 4.5.2.4, 4.5.3.1, 4.5.3.3, 4.5.4.1, 4.5.4.2, 4.5.5.2, 4.5.6.1, 4.5.6.2, 4.5.7.6, 4.5.8.1, 4.5.9.1, 4.5.9.2, 4.5.10.2, 4.5.11.1, 4.5.11.2, 4.5.13.6.
Applicable theories have been mentioned earlier.				

Table 45: Theoretical Propositions: TP2

Based on TPs and STPs, and the applicable theories that are briefly discussed above, ANT, SMP, and the KBV of the firm have been selected for further discussion, as they consistently and closely relate to the emergent theory, theoretical propositions, and research questions. The main and sub research questions are addressed by TPs and STPs, which demonstrates the benefits in following GTM processes from open coding to realisation of theory.

5.2.2. Theoretical integration of the DIP with Sociomaterial Practice

This section is largely based on the premise that, while organisational scholars have studied technology in abundance, the disconnected nature of studying technology in isolation of social settings does not account for the interrelatedness of the social and the material, and for the entanglements that occur (Orlikowski, 2010). Supporting academic studies give credence to the unevenness—or lack thereof—of technology (material) discussions within social (practice) situations as an entanglement, rather than of technology being an aspect of practice (Orlikowski, 2007; Orlikowski & Scott, 2008; Scott & Orlikowski, 2014). The work of IS scholars that objectively considered this fairly new approach to IS research is also a cornerstone of this discussion (Cecez-Kecmanovic et al., 2014). Sociomaterial-based research is increasing in the field of Information Systems (IS) (Cecez-Kecmanovic et al., 2014; Orlikowski & Scott, 2008).

Sociomaterial is defined as the routine "constitutive entanglement" of the social and the material (Orlikowski, 2007, p. 1437). Constitutive entanglement neither favours human over non-human and vice-versa, nor is the interaction between social and material mutually reciprocal (Orlikowski, 2007). The relationship is "inextricably related", meaning that there is not one without the other (Orlikowski, 2007, p. 1438). The role of technology in organisational theories and practice has been an ongoing concern and expressed through duality of technology, based on Structuration Theory (Giddens, 1984)—wherein "the analytic decoupling of [technology] artefacts from human action allows the conceptualisation of material artefacts as the outcome of coordinated human action and hence as inherently social" (Orlikowski, 1992, p. 403). A key outcome of this decoupling is to frame the relationship between technology and agent as purposeful interaction that is an outcome of "structural and social constructions" (Orlikowski, 1992, p. 403). Sociomaterial simply means "that the phenomena in question are simultaneously social and material" (Leonardi, 2013, p. 60).

Three key concepts are pertinent to sociomaterial practice: (1) relational ontology and (2) performative understanding of (3) agential realism (Scott & Orlikowski, 2014, derived from Barad, 2007). Agential realism is fundamentally about constitutive entanglement and relationships that are inextricably linked (Barad, 2007). Performativity posits that it is "through intra-action that material-discursive practices reconfigure relations and thus delineate entities and enact their particular properties" (Cecez-Kecmanovic et al., 2014, p. 811). An example of performativity use is to "understand how financial models and economic theories produce the market conditions and effects that they attempt to represent and explain"[…]"economics creates the phenomenon it describes, rather than describing an already existing 'economy'" (Orlikowski & Scott, 2008, p. 461). This is consistent with relational ontology. The foundation for relational ontology is that relations are more important than entities, and that the world is constituted by relations. In other words, things are "not first self-contained entities and then interactive. Each thing, including each person, is first and always a nexus of relations (Slife 2004, p. 159)" (Scott & Orlikowski, 2014, p. 878). This leads to the concept of becoming ontology, which holds that "all things and events are in a constant state of emergence and that stability is achieved only temporarily if at all" (Cecez-Kecmanovic et al., 2014, p. 826). "Relational ontology is at the core of agential realism" (Barad, 2007, p. 93). It behoves a brief discussion on substantialist/representational ontology, which is dominant in IS research and assumes that the social and material are separate, while relational ontology, on the other hand, espouses that they are inseparable (Cecez-Kecmanovic et al., 2014; Kautz & Jensen, 2013). The DIP is deemed to be "strong relationality" as the reality is achieved through relationships within the DIP system, without which the reality is non-existent (Cecez-Kecmanovic et al., 2014, p. 811). For the purposes of integrating the DIP system into literature, sociomaterial practice is beneficial in positioning the actor-social relationships within practice. However, the researcher believes that the existence of materials, prior to the sociomaterial phenomenon, are real and therefore in agreement with substantialist thinking.

The limitations and weaknesses to sociomaterial practice are largely based on agential realism (Leonardi, 2013; Mutch, 2013). Leonardi (2013) cites several critiques, primarily by Mutch (2013), of sociomaterial practice, which are mainly around the concept of agential realism. A brief expose thereof is as follows: "the lack of unique explanatory power" suggests that theories such as ANT could have sufficed as a theoretical lens; analysis of empirical data is problematic as the tussle between social and material results in indeterminate states of phenomena; the absence of time as a contributing factor to explain the lifetime/lifecycle of a practice-based phenomenon; and the notion that "people and things only exist in relation to each other", thereby negating the existence of material prior to the sociomaterial phenomenon. The sociomaterial "practice lens has been criticized for offering an overly socialized view of technology" (Leonardi, 2013, p. 64). Another criticism relates to the voice or elevation given to the sociomaterial phenomenon, which is a uniquely human action/activity, the absence of which silences the sociomaterial assemblage (Hultin, 2019).

The proponents of situating technology in relation to social practices begin with earlier work, namely, the duality of technology (Feldman & Orlikowski, 2011; Orlikowski, 1992, 2010; Orlikowski & Scott, 2008; Scott & Orlikowski, 2014). Duality of technology and sociomaterial approaches are largely based on Structuration Theory (Giddens, 1984), but also on Barad (1998, 2003, 2007) and Latour (1987, 2005), who have provided "philosophical inspiration" (Leonardi, 2013, pp. 60–61).

Table 46 is a synthesis of the different perspectives within management research that are related to sociomaterial practice and the positioning of the DIP (Orlikowski, 2010). The DIP perspectives in Table 46 are provided from the case study viewpoint, which is the basis for the DIP. Technology is acknowledged, but the acceptance varies as the workforce is diverse in many respects.

Conceptual Positions	**Explanation**	**Democratisation inflection Point (DIP)**

"Absent Present"	"Technology is essentially unacknowledged by organisational researchers and thus unaccounted for in their studies" (Orlikowski, 2010).	Technology matters within the DIP, unlike the 'absent present' concept that is reminiscent of the past and elevates social and human agency alone. Technology participation and implications in social practices are acknowledged within the DIP.
"Exogenous force"	Technology is positioned as an external and autonomous occurrence that had historical implications for businesses (Orlikowski, 2010).	Social and human have enjoyed agency in the production of technology. Technology is central to the DIP and is considered as critical to sociomaterial practices. The IS artefact is grounded in technology, but also brings in social and human agency, as is the case in social practice. From a practice perspective, the DIP resonates—differently—with 'exogenous force' from the perspectives of participants. ICT KWs are understandably deeply rooted in ICT, and therefore see technology as integral to business operations. With respect to non-ICT participants, some older generation participants view technology as an add-on to social practice, implying that technology is not critical to business operations. Younger generations view technology as an integral part of social practice and as critical to business operations.
"Emergent process"	"Technology is positioned as a product of ongoing human interpretations and interactions", implying that it is social and grounded in historical and cultural contexts (Orlikowski, 2010).	Technology is afforded agency in sociomaterial practice, and Big Data (technology) has elevated the technology hype because its impact on society is undeniable. From an academic perspective, technology within the DIP resonates with the characterisations within 'emergent process', in that Big Data research is growing. From the practice perspective, technology (Big Data) is

		overwhelming for all participants, including ICT KWs. Due to the diversity of the workforce, technology adoption and acceptance varies based on age, education, experience, imbalances of the past, and cultural differences. Technology within social practices is subject to interpretations that are based on the assumptions and worldviews of people.
Sociomaterial: Entanglement in practice	"The technological and social are inextricably entangled in multiple ways" (Cecez-Kecmanovic et al., 2014, p. 810). "The inseparability of meaning and matter" (Scott & Orlikowski, 2014, p. 873).	From an academic perspective, entanglement and the ensemble view of technology within social practice resonates closely with the DIP, as is demonstrated through the agency afforded to all actors (social and material) within the DIP system. Decision-making in the Big Data era is not just about technology, but also about contributions by people, organisations and processes. Although the explanation of 'Sociomaterial: Entanglement in practice' is plausible for the case study, all participants are not at the same level of realisation when it comes to the intertwining of social and material. For example, some continue to advocate for less automation and less ICT, that is, to revert to the old ways of more social and human agency, and more human involvement in business processes, thereby promoting higher human agency in sociomaterial practices.

Table 46: Perspectives on technology in management research with DIP perspectives (Orlikowski, 2010)

The DIP as an emergent theory could be compared to several theories. However, the comparison would not be verbatim, but on portions of the emergent theory. Therefore, based on its underpinnings (see Table 46), The DIP resonates closely with sociomaterial practice, but earlier conceptual positions are present within the case study. The DIP system is a social practice that comprises social and material relational ontologies, which lacks ontological substance prior to relational adherences. Therefore, the DIP system and the IS artefact are in a constant state of becoming and being ontological. Based on Table 46, the DIP system represents iterations of entanglements in practice.

5.2.3. Theories within the Sociomaterial Practice umbrella

This section discusses scholarly contributions that are considered within the ambit of sociomaterial practice theories. Sociomaterial is the fusion of social and material, implying that "(a) materiality is social in that it was created through social processes and it is interpreted and used in social contexts and (b) that all social action is possible because of some materiality" (Leonardi, 2012, p. 32). Sociotechnical systems (STS), ANT, and Practice Theory have been suggested as "the roots of sociomaterial practice" (Cecez-Kecmanovic et al., 2014, p. 813). These theories are summarised within Table 47, and are explored further within this section.

Theory	**Focus of theory**	**Theoretical integration of the DIP**
Sociotechnical Systems (STS)	Interrelatedness of social and technical components in the workplace.	The DIP is based on the fact that social systems such as the workplace, working, and organisational structures, and technical systems such as BDA, are co-created by actors. The social creates the technological artefact which, in turn, co-creates decision-making processes. The DIP resonates closely with STS, in that KWs participate in producing an (IS) artefact.
Actor Network Theory (ANT)	ANT considers people, technology, objects, and organisations as part of a heterogeneous network, and recognises the contributions made by human and non-human actors within the network (Latour, 2005).	The DIP is based on the contribution of valuable decision-making indicators (DMI) by human and non-human actors. Agency in the DIP system is extended to the heterogeneous network, because collaboration and contributions by actors are critical to the social practice of decision-making. The realisation or

		breakdown of democratisation of decision-makers is attributed to the co-created IS artefact (the DIP). The lack of participation by an actor leads to breakdown.
Practice Theory	"Practice [theory] is central to understanding human conduct because practices constitute horizons of intelligibility, and allow us to respond to different matters in different ways. In so doing, practices constitute conditions of life and worlds" (Nicolini, 2013, p. 164)	The DIP relates to Practice Theory from the central notion of democratisation of the decision-maker in DDD. Unbeknown to the KW, the democratisation inflection point is the culmination of actions and interactions in social practice between actors that are human and non-human. Practice Theory is the study of real world occurrences (Tanner, 2013), which is consistent with the DIP in that the latter draws attention to decision-making practices that occur transparently to KWs, and without the realisation of the underlying interactions that are occurring. The DIP is synonymous with Practice Theory, as real-world practices are elevated beyond the abstract.
Knowledge-based view of the firm	See Section 5.2.1	Knowledge is an inherent characteristic of every object, including actors. Based on prior knowledge, participants offered interpretations of their world and knowledge guided GTM processes to arrive at the DIP. Knowledge is the most valuable contribution by actors (human and non-human) to decision-making processes in the DIP IS artefact within the DIP system. Without knowledge

		contributions, democratisation of the decision-maker breaks down.
Data-Information-Knowledge-Wisdom (DIKW)	See Section 2.2.1	DIKW is not a theory, but uses hierarchy, framework, and model as some of the suffixes when discussing DIKW. The latter offers a logical way to explain the transformation from raw data to wisdom. The DIP system and DIP IS artefact identify very well with DIKW. The latter is evident when BDA provides processed data, called information, but BDA output is based on a knowledge-based query or question. This begins the cycle of knowledge contribution by actors, which results in an IS artefact that is used by the DIP. It does not end here, as new learning (i.e., knowledge) is fed back to actors.

Table 47: Summary of theoretical integration of the DIP

For the purposes of theoretical integration of the DIP, the following will be addressed in more detail in this section: Sociotechnical Systems, ANT, and Structuration Theory. Other theories that are suggested as part of Practice Theory, namely, the work of Bourdieu and Foucault, will be discussed briefly (Cecez-Kecmanovic et al., 2014). In addition, the emergent theory is hinged on knowledge from transformation and value contribution perspectives, as discussed in Section 5.2.4.

5.2.3.1. Sociotechnical systems

Sociotechnical systems are based on the 1950s work of the Tavistock Institute, which revolved around an approach that sought to balance what that they believed was a work environment that was unfairly in favour of technology ("covered both machines and the associated work organization"), at the sacrifice of quality and satisfying workplace and worker conditions (Mumford, 2006, p. 318). A key premise of sociotechnical systems (design) is that equal credence be given to technical and social components, such that one is not dominant over the other, but rather that the interrelatedness is emphasised (Cecez-Kecmanovic et al., 2014). Sociotechnical systems foster democratic and participatory principles that involve the inclusion of employees in sociotechnical design of workplace systems; the belief is that employees will be using the systems, therefore their voice is necessary from the beginning (Mumford, 2006; Trist et al., 2016). Inclusion of the workforce in decision-making processes have resulted in fewer failures. In order to understand the contributions of the workforce or technology, the whole must be investigated, which includes technical, social, and environmental, as these elements mutually shape each other (Trist & Bamforth, 1951).

Sociotechnical systems, from the substantialist ontological paradigm, hold that each component within the cohort is an entity with associated ontological properties (Cecez-Kecmanovic et al., 2014). Social and technical ontologies are considered separately, but should be considered together (Orlikowski, 2010). As opposed to substantialist ontology, relational ontology "rejects the notion that the world is composed of individuals and objects with separately attributable properties that 'exist in and of themselves' (Law, 2004, p. 42). Such an ontology privileges neither humans nor technologies" (Orlikowski, 2010).

From the DIP system perspective, the sociotechnical premise partly resonates with the emergent theory, as a number of aspects appear to be common to both paradigms, namely, giving weight to material and social aspects, the design of processes to achieve better outcomes for workers, and for workers to be accountable and take responsibility for tasks. An important difference is the ontological thinking in which the DIP embodies relational ontology (versus substantialist ontology), as the DIP attributes results from the entanglement of social and technical/material practice.

Additional principles of STS, as related to the DIP, are highlighted below (Leonardi, 2012; Orlikowski, 2010; Trist & Bamforth, 1951):

- Responsible autonomy relates to treating the social practice, in this case the DIP system, as a unit of measure (Tanner, 2013, p. 52), thereby having complete decisional responsibility within the unit. Actors within the DIP system contribute DMI to an IS artefact, which is assessed for completeness within the DIP by the KW. Based on this, the KW decides whether the IS artefact is complete (accept/realise) or not (deny/breakdown). The entire decision-making process, although involving multiple actors, is decided by the KW within the unit of measure. "A primary work-organization [DIP System] of this type has the advantage of placing responsibility for the complete [decision-making] task squarely on the shoulders of a single, small, face-to-face group [KW/actors] which experiences the entire cycle of operations within the compass of its membership" (Trist & Bamforth, 1951, p. 6).

- Adaptability refers to the ability to adjust task outputs based on the prevailing conditions. Adaptability within the DIP system is the acceptance or rejection of an IS artefact. As mentioned previously, Big Data is overwhelming to the entire organisation, and extracting insights requires skills and experience, which is not easy given the newness of the technology. The DIP affords the KW the ability to slow down the process through assessment of the IS artefact and, by doing this, the KW can systematically approach DDD with the necessary supporting decision-making indicators. The KW is "able to vary the work pace with changing conditions, [which] would appear to be the type of social structure ideally suited to the underground situation" (Trist & Bamforth, 1951, p. 7).

STS elevates the interrelatedness of social and technical actors within social practice. The principles of STS are relevant to the DIP, as has been shown.

5.2.3.2. Practice Theory

"Practice theories are a set of conceptual tools and methodologies for investigating, analysing, and representing everyday practice through written text, language, images, and behaviour" (Nicolini, 2013, p. 214). Practice Theory relates primarily to the "practice" aspect of social affairs; hence, it is the study of social beings in social structures that interact with heterogenous actors—human and non-human—in order to coexist, transform, and organise within the practice (Cecez-Kecmanovic et al., 2014, p. 815). Practice Theory is a collection of scholarly contributions that study work and organisations, rather than being a standalone theory (Cecez-Kecmanovic et al., 2014; Nicolini, 2013; Schatzki et al., 2001). Social occurrences are manifestations of heterogeneous interactions that take place within practice. "Thinkers once spoke of 'structures', 'systems', 'meaning', 'life world', 'events, 'and 'actions' when naming the primary generic social thing. Today, many theorists would accord 'practices' a comparable honor" (Schatzki et al., 2001, p. 10). Practice Theory is a family of theories that is attributed to the seminal and well-regarded contributions by Bourdieu, Giddens, Foucault, and Latour (Reckwitz, 2002). Reckwitz (2002, p. 244) surmises that the commonality between these esteemed contributors is based on their interest in the "everyday and life-world", meaning that agents/entities/components of social practice are a product of the world (social practice), with inherent characteristics and perceptions shaped by the world. Practices are dynamic and composed of, and contribute to, other practices; similarly, agents within practice are also agents within other practices (Schatzki et al., 2001).

Practice Theory is a family of theories with significant contributions that discuss Theory of Practice, power relations, duality of structure, and interactions within practice (Bourdieu, 1990, 2013; Foucault, 1995; Giddens, 1979, 1984; Orlikowski, 1992; Schatzki et al., 2001). For the purposes of theoretical integration of the DIP within Practice Theory, the focus will be Structuration Theory. However, an important complementary finding—The Habitus—will be discussed briefly through the Theory of Practice (Bourdieu, 1990, 2013).

a) Giddens: Structuration Theory (ST)

Giddens, a sociologist, investigated human interaction and the rules and structures that emanate/d from the interaction (Giddens, 1979, 1984). These rules and structures then became the measure by which people themselves evaluated societal behaviour. The focus of Structuration Theory is on the structures that are created within systems. Structuration Theory (ST) is imperative to DIP theoretical integration, because it helps to explain the notion of the DIP (structuration) as the point at which an actor—KW or decision-maker—meets structure, which is the DIP IS artefact. The democratisation inflection point (DIP), which connects human action with structural explanation, is termed structuration in social analysis. The DIP maps closely to ST, which is elaborated on below, after ST has been further defined.

Giddens' Structuration Theory is useful to explain real-world social practices by showing the connected relationships between human action and the structure that occur within social systems (Giddens, 1979, 1983, 1984, 2007). There are two main concepts within the theory that, when combined, evoke structuration—these are agency and structure. Agency is the "continuous flow of conduct", meaning not at a given moment but continuously (Giddens, 1984, p. 9). Agency is "one who exerts power or produces an effect" (Giddens, 1984, p. 9). An agent is defined as a social unit that is capable of making a difference; agents can be either human or non-human. Structures are rules, resources, and relations that contribute to the properties of the social or practice. Structuration Theory forwards the thinking that agents and structure are not independent (dualism) of each other, but mutually dependent (duality) on each other (Giddens, 1979). Structuration Theory posits the duality of structure, meaning that social structures create an environment for enactment of action, and that social structures result from enactment of action—"By the *duality of structure* I mean that social structure is both constituted *by* human agency and yet is at the same time the very *medium* of this constitution" (Giddens, 2007, pp. 128–129).

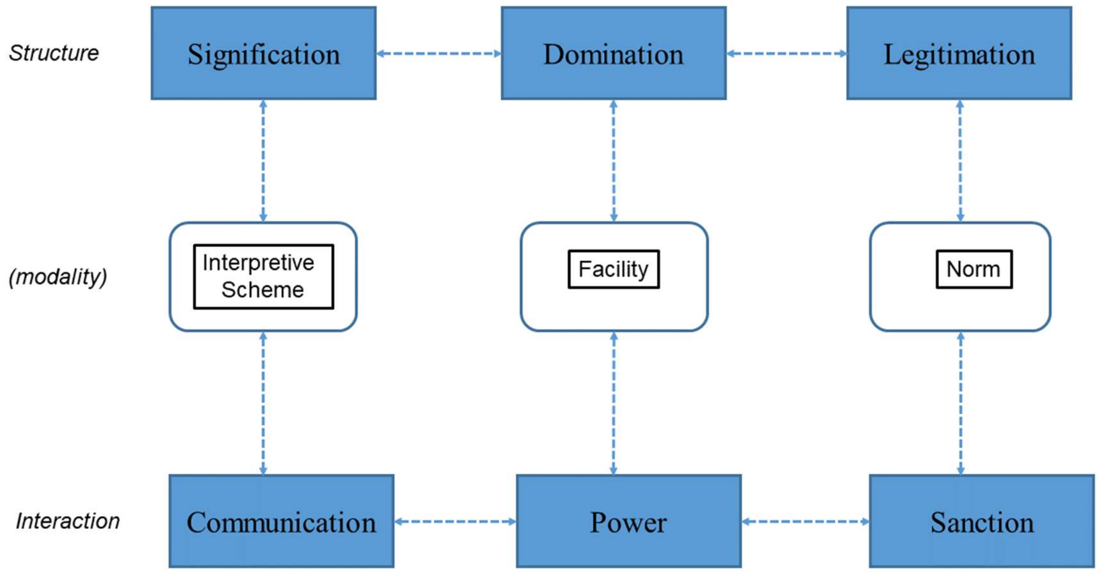

Figure 18: Giddens' Structuration Theory (Giddens, 1984, p. 29)

Figure 18 depicts three layers, each with three dimensions. Table 48 provides a brief explanation of each of the dimensions from the bottom up.

[Social] Structure	3: Structures of meaning. How should an event be interpreted? Signification refers to the production of meaning.	3: Domination. What means should be used to accomplish goals? Domination refers to degrees of power.	3: Legitimation. What should happen in each situation? Legitimation refers to the societal (organisational) norms.
(Modality)	2: Of human knowledge, the basis for interpretation, which leads to [3 above]	2: Command allocation of resources, which leads to [3 above]	2: Use of norms and standards, which leads to [3 above]

[Human] Interaction	1: Human communication involves interpretation [2 above]	1: Humans use power in interaction to [2 above]	1: Humans sanction their action through [2 above]

Table 48: Definitions of key concepts (Walsham & Han, 1991, p. 54)

Structuration is defined as the “conditions governing the continuity or transformation of structures, and therefore the reproduction of systems” (Giddens, 1979, p. 66). In terms of mapping to the DIP system, ‘structuration’ is similar to the democratisation inflection point (DIP). An explanation of this is as follows: the DIP system is a social system that facilitates the democratisation of decision-makers in DDD; it is synonymous with ST’s system, because systems are “reproduced relations between actors or collectivities, organised as regular social practices” (Giddens, 1984, p. 25). The actors—TI, TH, TO, and DME—(or agents as defined above) contribute key DMI as “every social actor knows a great deal about the conditions of reproduction of the society of which he or she is a member” (Giddens, 1979, p. 5). DIP and structuration are (respectively) points at which structural (the DIP IS artefact) analysis is undertaken in social analysis, and upon which a decision (human action) is taken (Giddens, 1979, p. 49).

In the context of the DIP system, KWs—individuals, according to Giddens (1984)—initiate an IS artefactual instance (agency) by asking questions of BDA. The actions include contribution of DMI by actors, based on information that results in an IS artefact. The rules (DMI), resources (information), and transformation—applying knowledge to new information—result in the IS artefact. Rules and resources are fitting to the DIP, as “rules have two aspects to them, […as they] relate on the one hand to the constitution of *meaning* [DMI], and on the other to the *sanctioning* of modes of social conduct”, which is the mandatory contribution of DMI and democratisation of decision-makers in DDD (Giddens, 1984, p. 18). Democratisation of decision-makers in DDD is that the “awareness of social rules, expressed first and foremost in practical consciousness, is the very core of that 'knowledgeability' which specifically characterizes human agents” (Giddens, 1984, pp. 21–22). Further to this, ST promotes flexibility within the DIP system from a democratisation perspective and, in particular, the completeness of the IS artefact through employment of the “typified scheme”; this is taken to mean that democratisation is possible most of the time, as prior knowledge suffices in constructing an IS artefact, specifically DMI, because social activities are produced and reproduced (Giddens, 1984, p. 22). The

DIP system is synonymous with Giddens' definition of system, which is "reproduced relations between actors or collectivities, organised as regular social practices" (Giddens, 1984, p. 25).

[Social] Structure	3: Signification: Information (processed data) and knowledge	3: Domination: The DIP IS artefact	3: Legitimation: Democratisation: realised or breakdown
(Modality)	2: BDA is a tool	2: Contribution of DMI by actors.	2: Organisation policy, processes, and culture. Individual culture and ethics. Veracity of information.
[Human] Interaction	1: KW asks a question of Big Data	1: KW requires relevant decision-making parameters	1: KW assesses IS artefact

Table 49: Overlaying the DIP system onto Giddens' Structuration Theory framework (Giddens, 1984)

An explanation of Table 49 follows:

Signification: (1) Communication involves a question put to BDA; (2) BDA processes the question based on knowledge of data scientists; and (3) processed data (information) becomes the structure. Structures of social systems such as rules and resources enable social practices such as decision-making. These structures are produced and reproduced by agents, meaning that Big Data is created by agents and thus also result from social practices.

Domination: (1) The KWs require a complete picture before making a decision; (2) actors, who know the social practice well, contribute DMI; and (3) the completeness of the DIP IS artefact determines the levels of power (democratisation) that a KW has in DDD.

Legitimation: (1) The KW assesses the IS artefact; (2) norms and standards for each actor is assessed; and (3) the democratisation of the decision-maker in DDD is realised or breakdown occurs.

It is important to highlight that, as the DIP is an emergent theory, the "structure is regarded as rules and resources which exist only as memory traces in human minds and are made manifest only in the instances when they are drawn on in action and interaction" (Walsham & Han, 1991, p. 54). ST and the DIP emphasise that human agents have capability, that is, they have the power to intervene and influence outcomes. Further, human agents can act in a knowledgeable way, meaning that choices could be rationalised discursively, practically, or unconsciously (Giddens, 1979). Similar to ST, in which there are always unintended consequences, the unintended consequences of the DIP always comprise learning that takes place for all actors.

In summary, "the principal issue with which I shall be concerned in this paper is that of connecting a notion of human action with structural explanation [DIP IS artefact] in social analysis. The making of such a connection, I shall argue, demands the following: a theory of the human agent [decision-maker], or of the subject [democratisation of decision-maker in DDD]; an account of the conditions [DMI] and consequences of action [democratisation realisation/breakdown and learning]; and an interpretation of 'structure' [DIP/IS artefact] as somehow embroiled in both those conditions and consequences" (Giddens, 1979, p. 49).

b) Bourdieu's Theory of Practice: An integration of The Habitus (TH)

Theory of Practice, specifically Bourdieu's contribution, explains the use of the firm's resources, that is, the people, to construct the social reality. The theory that emerges from the case study has similarities with Theory of Practice, in that The Habitus elevates the complex nature of people and, in particular, the knowledge worker. KWs are complex due to the diversification associated with their varying cultural backgrounds, different levels of education, different eras of birth, and economic status.

Bourdieu (1992, 2013), a social thinker, developed the Theory of Practice, which theorises that individuals are participants of/ located within a multidimensional social structure that is manifested in, or appears to be based on, social classes. Class or social class is a means of hierarchically structuring society so that we can compare how much influence (power) an individual or group of people have, as opposed to another individual or group within the same society (social practice). Social classes are based on the different types and levels of capital (that is, social, cultural, economic, and symbolic) that an individual possesses—all of which represent forms of power and domination. The more capital you possess, the more power (position) you have in society. "According to my empirical investigations, these fundamental powers are economic capital (in its different forms), cultural capital, social capital, and symbolic capital, which is the form that the various species of capital assume when they are perceived and recognized as legitimate" (Bourdieu, 1989, p. 17). **Social** capital is related to an individual's standing and relationships within social structures or networks. **Cultural** capital comprises attributes related to education, skills, interpersonal traits, lifestyle, and linguistic/dialect/language style. **Economic** capital is measured by the possession of wealth (amongst others, assets, and salary), which is in essence the extent of individuals' prosperity. **Symbolic** capital is the recognition of the other forms of capital; "is nothing other than economic or cultural capital when it is known and recognized" (Bourdieu, 1989, p. 21). Each of these capital attributes are weighted, with privileges afforded based on instances of social practices that amount to distinction. Bourdieu encapsulates individuals' interpretations, value judgements, perception of the world, and guidelines to deal with the world in a central concept of **habitus** (Bourdieu, 2013). **Habitus** is shaped by upbringing, education, and experiences which, in turn, are manifested in how agents think and act within social practice (Allbright et al., 2018). **Habitus** connects agency with structure. Distinctions, according to Bourdieu, are key to social structures (Bourdieu, 2013).

From the DIP system perspective, all forms of capital were evident in the discussions. However, social and cultural capital were more pronounced. Social capital reverberated mainly from the perspectives of generational issues, power distribution, and the effectiveness of power structures. Cultural capital was evident in traditional values, especially when related to decision-making processes, and in differences in skills, education, and knowledge—specifically in terms of BDA. Since the case study is situated in South Africa, language and linguistic style demonstrated divisions in the workforce, specifically related to interpersonal relationships, fulfilment of job requirements, and inclusivity. The theoretical integration was mainly situated within sociomaterial practices, which draws attention to equal agency when dealing with human and non-human actors. While this has positioned the importance of the four actors that emerged from the empirical findings that led to the core category, the importance of the KW needs to be elevated.

Emanating from the case study, Big Data is but a small part of the decision-making process, while a large part thereof is tied to the vastness of the human being. According to Freud (1900, 1905), the human mind is mostly beneath the surface (Heller, 2005). The conscious mind is what we see, and is very small (10%) compared to the unconscious mind (90%) that we do not see (Mcleod, 2015). **The Habitus** attempts to highlight the critical role that both the unconscious and conscious mind play in decision-making. **Habitus** supports the notion of the conscious and unconscious, which is relevant here as the KW enters the social practice (work) with resources known as **capital** (discussed earlier) (Bourdieu, 2013). "The habitus [TH] consists of deeply internalized dispositions, schemas, and forms of know-how and competence, both mental and corporeal, first acquired by the individual through early childhood socialization" (Swartz, 2002, p. 62S). Throughout the empirical journey, participants spoke about the profound effect that traditions and traditional culture, upbringing (background), and experience (different forms of habitus) have on decision-making within the workplace (field). An example that comes to mind relates to consensus-driven decision-making, in that consensus by senior figures or elders in a tribe are paramount to decision-making processes; this is difficult to abandon in the workplace and personal situations. As organisations in South Africa continually transform to be more representative of the society in which they operate, factors inherent in decision-making processes exist that stem from individual and tribal cultural practices (Mangaliso, 2001). “A decision that is supported is considered superior to the “right” decision that is resented or resisted by many”—an Ubuntu belief (Mangaliso, 2001, p. 27). It is clear from the example given that **habitus** plays a critical role in shaping decision-making within the workplace insofar as the conditioned cultural and structural dispositions shape the participation of individuals in social practice. Collaboration and knowledge are two important forms of capital that facilitate the realisation of the IS artefact for decision-making purposes that puts ‘The Habitus’ at the core of the democratisation of decision-makers in Big Data-driven decision-making. Fundamentally, the DIP is the regulation (guide) of behaviour without being the product of rules; given the pervasiveness, newness, and lack of controllability of Big Data, this is fitting as organisations grapple to overlay traditional business processes while trying to navigate the vastness and hype of Big Data (Bourdieu, 2013).

While the notion of generational differences in dealing with Big Data is relevant and persisting, as suggested by the evidence, the issues arising from different generations’ acceptance, adoption, and use of Big Data within this thesis require further study. Generational issues could be attributed to KWs vying for power, which is normal within a field (Bourdieu, 1990). Habitus (capital) determines power, since it “involves an unconscious calculation of what is possible, impossible, and probable for people” within a social setting (Swartz, 2002, p. 64S). The evidence suggests that all generations (agents) believe that Big Data (social tools within the field) is overwhelming: older generations try their best to avoid BDA, including interrogating information and relying on experience (capital), while younger generations tend to skim for answers and rely on familiarity with technology (capital) (Sterne, 2003). There is a midpoint of generational workers—a band between older and younger KWs—who feel that they do not have enough information, and want more from BDA and better BDA tools. However, there are also midpoint generational KWs who are nonchalant when it comes to Big Data. “According to Bourdieu, as an individual moves between fields their ability to succeed is determined by the congruence of their habitus and capital with that of the dominant within the field, and their ability to utilise or gain capital in the field” (Beckman et al., 2014, p. 358).

It is evident that generational clashes, from a behavioural and interpersonal perspective, occur within and across departments. One could argue that there are different people with different perspectives, interests, and skills in the workplace, and that the generation is simply incidental; however, the evidence supports the notion that conflict is generation-specific. Generational issues/clashes draw attention to symbolic power, which is "invisible power which can only be exercised only with the complicity of those who do not want to know that they are subject to it or even they themselves exercise it" (Bourdieu, 1991, p. 164). Therefore, this indicates that there is an awareness across generations of their differences, which knowingly is manifested through conflict.

The Habitus: knowledge and power

Human knowledge is tightly integrated or interrelated with power: "there is no power relation without the correlative constitution of a field of knowledge, nor any knowledge that does not presuppose and constitute at the same time power relations" (Foucault, 1995, p. 27). This is interpreted as implying that knowledge occurs within social, economic, and political power relations, rather than external to these realms, and Foucault argues that they are inextricably linked. The knowledge that is produced is directly related to power relations. Power, in Foucault's writing (Foucault, 1995, 1996; Rabinow, 1984), is rarely about politics, as in the nation-state or the economy; the researcher's interpretation is that it is more about the possibilities for self-determination, meaning that the knowledge obtained from the era in which KWs live affords them agency, which implies creating identities according to their own design and avoiding standard, normalised behaviour.

Foucault puts forward thinking that describes the shift, within societies, from juridical to disciplinary power (Rabinow, 1984). Juridical power refers to the power that rulers, monarchies, dynasties, and aristocrats wielded over common people. Disciplinary power, on the other hand, has similar characteristics in that power and privilege is not only reinforced, but is profoundly more in that meanings and value are associated with individuals for the sole purpose of controlling them. Rabinow (1984) explains the principles of disciplinary power as follows. S*pacialisation* holds that each individual has a specific place, which is in relation to, and relevant for, power enforcement. *Minute control* ensures that every detail of organisational life is planned completely. *Repetition* fosters standardisation and repetition of actions that become routine. *Detailed hierarchies* ensure the deployment of complex and authoritative hierarchies that enforce privilege and power of one over another. *Normalising judgments* is intended to draw on the first four principles to build a baseline matrix, with associated meanings, that describes normal and abnormal behaviours (Foucault, 1995).

With respect to the DIP, Foucault's work is relevant and further supported by the findings from the case study. Within these five ideologies or principles, the entire organisational and interpersonal relationship is mapped succinctly. KWs have roles and responsibilities that are specific and targeted; business processes and automated robots are deployed continuously to optimise interactions/exchanges; management structures are in place that enforce organisational control from the top down; governance ensures checks and balances; and employee management systems are in place not only to reward and recognise, but also to manage performance.

5.2.3.3. Actor network theory (ANT)

Actor Network Theory (ANT) (Latour, 2005) defines and describes relationships between the technological and social aspects—human and non-human objects or actors—that form the network. "ANT decenters the human subject and considers heterogeneous actors—people, natural phenomena, technologies, documents, knowledge, social structures—as being equally engaged in, and responsible for, reassembling the social" (Cecez-Kecmanovic et al., 2014, p. 814). The social network is the sum of the actors. ANT advocates the equality of technological and social aspects through equal value and agency. ANT addresses the somewhat flawed technological and social determinisms that purport that technological and social changes are explained through technological and social accounts, respectively, thereby downplaying the importance of the other. In other words, both social and technological occurrences result in sociotechnical/sociomaterial outcomes, rather than in separate social and technological outcomes. ANT gives preference and privilege to neither technological nor social aspects that participate in the same network. "For ANT, as we now understand, the definition of the term is different: it doesn't designate a domain of reality or some particular item, but rather is the name of a movement, a displacement, a transformation, a translation, an enrolment. It is an association between entities which are in no way recognizable as being social in the ordinary manner, except during the brief moment when they are reshuffled together" (Latour, 2005, pp. 64–65).

"Actor network theory treats the social and the technical as inseparable, and indeed argues that people and artefacts should be analyzed with the same conceptual apparatus" (Walsham, 1997, p. 467). DIP theory is similar to ANT in a few areas. The DIP system takes into consideration human and non-human actors (concepts in this case—TI, TH, TO, and DME), which are heterogeneous in that both animate and inanimate objects such as information, knowledge, skills, decision-making, and governance are given agency. Actors make contributions to the IS artefact through DMI, but it is the human being (KW) who makes the decision that leads to democratisation when all actors contribute DMI. The DIP, like ANT, considers contributions of animate and inanimate objects, but the DIP holds that the human being, through knowledge, education, and cultural background, is the main actor in the decision-making process. With respect to the actual democratisation of the decision-maker, the stand is based on substantialist/representational ontology, which recognises the separatedness of entities (actors) with associated properties—in this case, the human decision-maker. The development of the IS artefact from inception to completion is consistent with relational ontological prescriptions. The ANT lens explains the DIP system almost completely, except for the fact that the actual decision-making, as the human intellect, reasoning capacity, and rationality, are incomparable to inanimate objects (Walsham, 1997). While the characteristics of ANT are comparable to the DIP as it affords Big Data—the technological artefact—centrality, the fundamental importance of social aspects such as knowledge, gender, race, and power cannot be given equal credence. Latour's Actor Network Theory (ANT) has had profound implications for our understanding of social structures and human agency—particularly their coexistence and mutual dependencies. The similarities between ANT and the DIP supports the earlier work of ANT through empirical evidence, and contributes/extends ANT in terms of the IS artefact.

5.2.3.4. Summary

DIP and Practice Theory are similar in that the foundational idea is to explore the complex roles and contributions of actors within a network which, in the case of DIP theory, is the transformation of raw data into decision-making knowledge that is adequately supported by the main actors within the network (Tanner, 2013).

The entanglement of actors (material)—that is, human and non-human having equal credence within relationships that occur within the DIP system (the social practice)—jointly produces an IS artefact (an ontological entity) that lacked ontological properties prior to the occurrence of the sociomaterial phenomenon. The IS artefact is an example of a relational ontology that results from a performative encounter. The entire DIP system and its components are jointly and separately sociomaterial, as all organisational practices are sociomaterial practices (Orlikowski, 2007). Each of the mentioned theories and families of theories are similar to the DIP, and/or the DIP extends the theory, or the DIP contributes novelty.

5.2.4. Theoretical integration with knowledge-based view (KBV) and DIKW

Within the theoretical propositions (TP) (Section 5.2.1), knowledge is consistently underlying the TPs and sub-TPs within Table 44 and Table 45. Knowledge contributions in the form of DMI have resulted in the transformation of raw data into information into new knowledge (based on old knowledge and new information), which is the cornerstone for democratisation of the decision-maker.

The basis for data-driven decision-making is access to, and visibility of, Big Data through BDA, which may be problematic for organisations that currently and/or traditionally housed data warehouses in highly restricted silos (Mikalef et al., 2018). Access to Big Data facilitates “transformative opportunities” for business (Wamba et al., 2015, p. 244) through value creation, which is “the extent to which Big Data generates economically worthy insights and/ or benefits through extraction and transformation” (Wamba et al., 2015, p. 236). Although knowledge is realised through transformation processes and value contributions, the veracity of the transformations based on the DIKW model, as shown in Figure 19, could be problematic as the creation (and extraction) of data begins with a KW that is laden with perfections, imperfections (e.g., lack of skills), assumptions, and interpretations that could lead to information and knowledge that is based on poor data to begin with (Boell, 2017). *Ceteris paribus*, Data-Information-Knowledge is the basis for DDD. Knowledge is critical to decision-making, as was demonstrated throughout the empirical findings, and specifically within the emergent theory.

Knowledge was defined in Section 2.2.1. Situating the DIP within theory necessitates a literature discussion of the Knowledge-based View (KBV) of the firm, which follows, as the DIP IS artefact is largely based on knowledge. The KBV of the Firm has its origins in the Resource-Based View (RBV) (Grant, 1996). The RBV’s main premise is to leverage all the firm’s resources in a non-specific manner to gain and sustain competitive advantage (Barney, 1991). Resources, similar to ANT, include human and non-human assets, capabilities, information, and knowledge. The KBV differs from the RBV with respect to the knowledge aspect and its importance, such that knowledge in the KBV is considered as the most strategic asset that a firm possesses (Grant, 1996). Knowledge, according to KBV, is central to a firm’s competitive advantage and superior performance, because knowledge is difficult to replicate, socially complex, and heterogeneous. Knowledge is embedded in everything (human and non-human); the interpretation or how the knowledge is perceived is based on "justified true belief" or “knowledge as a dynamic human process of justifying personal beliefs as part of an aspiration for the 'truth' ” (Nonaka, 1994, p. 15). Although KBV theory is limited in terms of definition and foundation, and the concepts and relationships are inconsistent, the prevalence of knowledge within the DIP IS artefact warrants a mention (Kaplan et al., 2001, p. 146).

The crux of the emergent theory, the DIP IS artefact, relates closely to the DIKW (Data-Information-Knowledge-Wisdom) model, as illustrated in Figure 19. Iterations of DIKW appears to be linear (and a one-way direction) in several illustrations, implying that the starting point is always data, with information, knowledge, and wisdom realised as incremental steps (Rowley, 2007). DIKW-based models begin with [raw] data and end with knowledge and wisdom. Value is added in order to transform raw data into something meaningful, thereby causing a transition from

Data→Information→Knowledge→Wisdom (Abbasi et al., 2016). BDA is necessary for studying stored data to extract patterns and insight. The output of BDA is information, which is contextualised based on an appropriate question, and arranged in a format that is easier to read (Frické, 2019). This output of BDA could be in the form of standard and custom reports, spreadsheets, or formats that are compatible for third party application support. Value contributions (DMI) are added as data and are transformed into information through questions; information transforms into knowledge through the application of prior knowledge and experience; and existing knowledge transforms into new knowledge as new information is interrogated. Actionable insight from knowledge facilitates DDD.

Although the DIP emerges from empirical data, the concept relates to the DIKW model and embraces the transitions from meaningless data to wisdom, with information and knowledge as progressive layers of value creation and contribution (Abbasi et al., 2016). The evidence suggests that the DIP highlights the fact that CSA is overwhelmed by Big Data, and that BDA is the ultimate tool for extracting insight. However, the manipulation of data and the outcomes of BDA are determined by the content of the data, the questions asked of the data, and the ability to interpret the results. Therefore, the transitions are complex in terms of the value contributions made by actors within the network. The DIP expands on DIKW, based on empirical evidence, in two key areas: 1) The DIP enhances DIKW by contributing the IS artefact that comprises DMI and information. In addition, prior knowledge is the mainstay of the generation of new knowledge/insights, as it is the application of old knowledge (experience, exposure, and education) to new information. The generation of new knowledge or insights could mean absolutely nothing or be significant. However, it depends on the KW who interacts with the insight. 2) As established from the literature, iterations of DIKW models appear to be linear and on a confusing trajectory. The evidence suggests that the DIP system is a learning network that contributes knowledge back into the system at every step of DIKW. Even at the Democratisation Inflection Point, realisation and breakdown of democratisation leads to learning which, in turn, becomes knowledge (experience, exposure, and education) that, together with new information, contribute to new knowledge. The learning network is anything but linear, as feedback loops occur throughout the DIKW continuum.

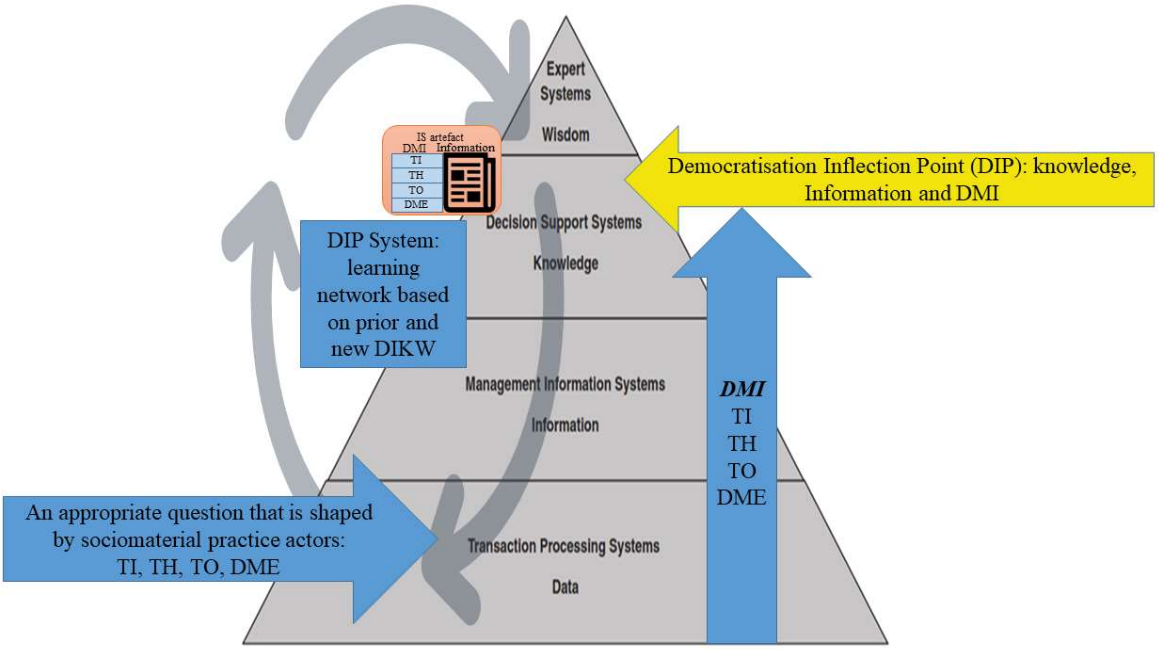

Figure 19: Mapping the DIP to DIKW to types of Information Systems (Rowley, 2007)

The blue box and arrows illustrate the enhancements to DIKW, based on the emergent theory and empirical evidence. An anticlockwise explanation of the arrows is as follows: An appropriate question initiates the DIKW continuum from a Big Data perspective. Actors contribute to DMI. At the DIP, the IS artefact at completion comprises of DMI and information, which are interrogated based on prior and new knowledge. The blue box and grey arrow draw attention to DIKW (DIP) as a learning network. The grey cyclical arrows also draw attention to the fact that knowledge is returned for further processing, which includes subsequent business processes, and requests DMI from actors.

A different approach to articulating DIKW is illustrated in Figure 20 (Abbasi et al., 2016). The premise of the original work is to highlight the disruption of traditional information value chains by Big Data and, in light of this, to highlight areas of research within IS. There are fundamental differences in people, processes, and technology in terms of value contributors. However, the mapping from the traditional to the Big Data era does not appear to be different in terms of the DIKW model.

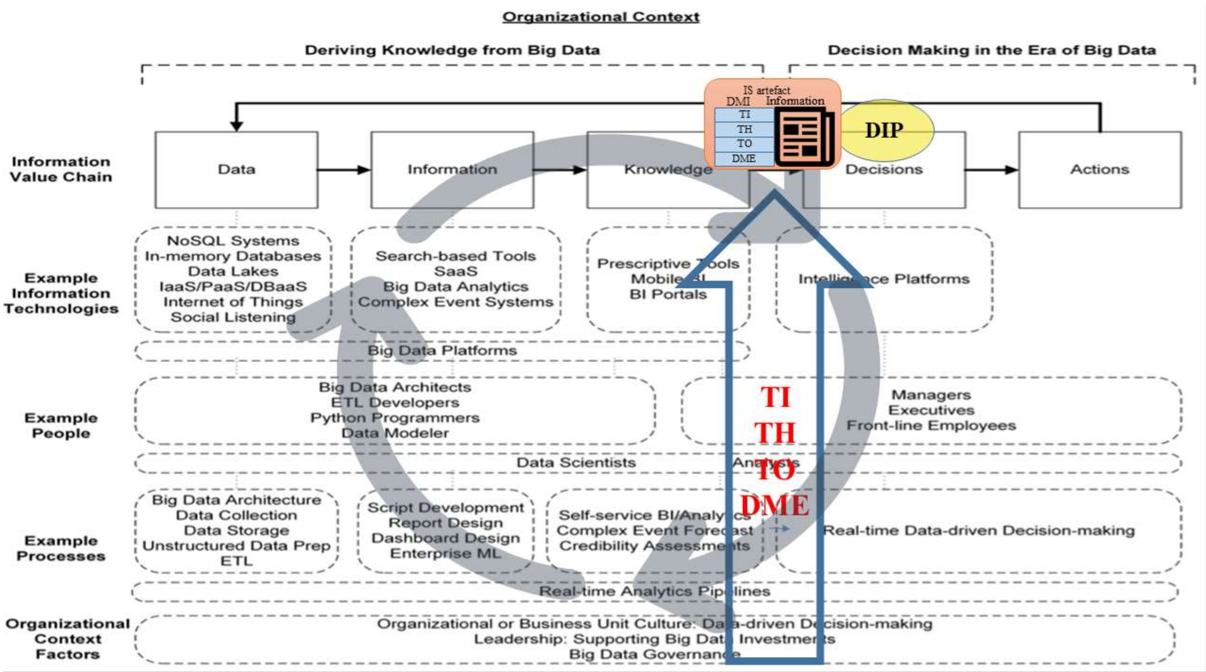

Figure 20: Mapping the DIP to the Big Data Information Value Chain (Abbasi et al., 2016)

It is appreciated that the original illustration (Figure 20) depicts a Big Data value chain, and that the components resonate closely with the DIP System and the DIP IS artefact. The enhancements to Figure 20 draw attention to the importance of DMI as a value contributor by actors, and the use thereof within the DIP. The illustration demonstrates that all the components across the horizontal layers, namely, Organisational Context Factors, People, Processes, and IT, contribute valuable decision-making indicators to decisions. The enhancements draw attention thereto that the DIP IS artefact is an important decision-making aid. The basis for how ‘decisions’ take place within the decision box is clearer with the DIP, in that a realisation or breakdown occurs based on the IS artefact.

Several studies have suggested different models for the flow of data from its raw state to realising wisdom (Abbasi et al., 2016; Rowley, 2007). The contribution of value that causes an escalation at each of the different stages in the DIKW model appears to be lacking. The theoretical contribution of this thesis partially addresses this gap by contributing an IS artefact that could better explain the contributing factors to transformation at each level of the DIKW model.

5.3. SUMMARY OF THE DISCUSSION CHAPTER

The contributions of participants during the interviews led to the emergent theory. It is completely attributed to the participants, and emerged from interpretation of their thoughts, opinions, worldviews, as well as the subsequent processes of breaking this down into abstract symbolling meanings and then rebuilding them into something (theory) that could explain the phenomenon (Corbin & Strauss, 2014). Unbeknown to the participants, the emergent theory provides a different, yet consolidated, explanation of their daily work practices, specifically from a democratisation of decision-makers in DDD perspective. The DIP exposes the multidimensional nature of decision-making to which actors, social and material, contribute (Wamba et al., 2016).

The DIP exposes the steps that lead to the democratisation of decision-makers in DDD. While the DIP is not concerned with the actual decisional outcome per se, it is concerned with the factors that inhibit or enable the democratisation of decision-makers in DDD—that is, the ability to make a decision while having a more complete picture (DMI) of the decisional situation.

The DIP system is a sociomaterial practice. It affords agency to actors that are non-human and human, each with relational properties that arise from other social practices in which they are engaged and are products of. Several theories that are IS- and management-related have been explored for theoretical integration purposes. A few of the theories, based largely on the sociomaterial practice family, have been used; these include Sociotechnical systems, Actor Network Theory, Structuration Theory, and Bourdieu's Theory of Practice. It is evident that knowledge is critical to the emergent theory; therefore, the Knowledge-based View of the firm and the DIKW model are used as well.

The DIP is happening—knowingly or unknowingly—within CSA; the explanation provided above is the culmination of learnings that took place at CSA. However, the explanation and emergent theory is unique in that an IS artefact, itself a non-human actor and an outcome of iterations of social practice, has not been articulated in this manner. The emergent theory is novel to literature and practice.

6. CONCLUSION

This chapter concludes the thesis by reviewing the research and the findings from the empirical study, demonstrating that the work has a place within extant literature and practice, reflecting on the research questions, and suggesting areas for further research, debate, and discourse.

Big Data has caused in a shift in organisational approaches to the business decision-making processes, especially from the perspective of Big Data Analytics (McAfee & Brynjolfsson, 2012). The approach to decision-making is no longer purely based on intuition or authority, but rather on evidence and insight.

Selecting GTM, and specifically the Straussian (SGTM) approach, is fitting, as the existing knowledge around the interrelatedness of Big Data, decision-making, and democratisation is limited. Situating novel empirical inquiries within existing theoretical frameworks has the potential to distort and minimise the richness that is anticipated from the empirical study (Grover & Lyytinen, 2015). SGTM is relevant as it provides an opportunity to explore the phenomenon and research questions through methodological guidelines such as coding, conceptualisation, and categorisation in an iterative process called constant comparative analysis. Rigour is one benefit of the constant comparative method (Stol et al., 2016). Another benefit of SGTM rigour is the theoretical sampling process that guides towards the next recommended sample, which is ultimately a journey from data to theory production after reaching saturation (Corbin & Strauss, 2014)—that is, the point at which nothing new is uncovered.

This research intended to explain the democratisation of the decision-maker in DDD as related to Big Data (the phenomenon) within a case study and, in the process, to produce theory that explains the phenomenon in general. It also intended to contribute to knowledge by minimising the gap/s identified, so that practitioners and academia could benefit through agreement, expansion, and debate. It is hoped that the theory would also be applicable to the explanation of other phenomena that are researched (Corbin & Strauss, 2014).

The rest of this chapter outlines the research objectives (Section 6.1), answer the research questions (Section 6.2), summarises the research contribution (Section 6.3), and highlights the limitations (Section 6.4) and directions for future research (Section 6.5). Closing remarks are provided in Section 6.6.

6.1. RESEARCH OBJECTIVES

This study aimed to understand, through exploration, whether Big Data characteristics have influenced decision-making, specifically from the perspective of workplace democratisation of decision-makers in DDD.

The objectives of the study were to gather the most prominent of Big Data characteristics that affect data-driven decision-making, explore the changes that organisational data-driven decision-making policies, processes, and procedures have undergone in the light of Big Data, better understand the internal and external environmental factors that influence workplace democracy from a data-driven decision-making perspective, and develop a theory that explains the phenomenon in question.

The above objectives where achieved, and are expanded upon in Section 6.2. The findings are also summarised against the research questions.

6.2. ANSWERING THE RESEARCH QUESTIONS

Big Data is topical and relevant to practitioners and academics alike, because of the insight that can be generated (Akter et al., 2016; Lavalle et al., 2011; Russom, 2011; Watson, 2014). There is immense value to be found in the torrents of data that flow through the internet and organisations (McAfee & Brynjolfsson, 2012). Big Data has the potential to inform and transform societies, businesses, and nations if analysed from appropriate perspectives (Gerard George et al., 2014). Foremost, it will require acceptance at the various organisational authority levels, and a pronouncement that Big Data outcomes improve evidence-based decision-making. Thereafter, for Big Data to be insightful, investments are necessary for skills development of not only the data analyst/scientist, but for all KWs who have relevant questions (Lavalle et al., 2010). In an age where data is created by human beings and machines alike, it is not unrealistic to be considered as overwhelming (Sivarajah et al., 2017). Anything written, spoken, and viewed is easily digitised. With so much data being produced, it is a challenge to extract value to aid in decision-making (Mayer-Schönberger & Cukier, 2013).

The democratisation of decision-makers in DDD is dependent on the completeness of an IS artefact that results from the collaboration of, and contribution by, social actors of value-laden decision-making indicators (DMI) that are based on specific information, which is extracted from Big Data through BDA. The democratisation of decision-makers in DDD, considering the prevalence of Big Data, largely comprises the addition of value to data and information through BDA. Without BDA, the data reflects an uninteresting, meaningless, and wasted opportunity. Value is realised through key contributions by

Big Data, people, the organisation, and the decision-making entity. Value cocreation and contribution lead to democratisation of decision-makers in DDD. People within the organisation are laden with hidden and visible influences, such as culture and experience, that have a direct bearing on the transition of data into insight through value contributions.

6.2.1. Main Research Question (MRQ)

MRQ. Does Big Data influence the democratisation of decision-makers in data-driven decision-making in organisations?

The answer to the MRQ is not a YES/NO response, but **it depends.** Big Data is an enabler, a key contributor, and is strategically important to the organisation's DDD processes (McAfee & Brynjolfsson, 2012). However, reflecting briefly on the emergent theory (see Section 4.9), Big Data by itself does not influence the democratisation of the decision-maker in DDD, but is one part of a whole. The whole consists of complementary actors who contribute critical decision-making parameters to the decision-making process, without which decision-making is risky and is contrary to democratisation principles. Therefore, the sum of the whole (an IS artefact), which includes Big Data, influences the democratisation of the decision-maker in DDD.

"Doing first" posits that, in the absence of the decision-making artefact, the decision maker has to decide—make the call—based on judgement or intuition, regardless of the outcome; however, experiential learning has taken place (Mintzberg & Westley, 2001, p. 91). While there is a place for 'doing first', the implications of decision-making, and the associated consequences for the decision-maker, vary. "Seeing first" affords the decision-maker the ability to use all resources—tangible and intangible, visible and invisible—from within and outside the organisation, and within-self, to conceptualise the decision at hand, see what others do not see, and visualise the possibilities (Mintzberg & Westley, 2001, p. 90). This frames the essence of the democratisation of the individual from a decision-making perspective in a Big Data environment.

In decision-making research, key factors of focus are important considerations: "action-taking approach, context, content (kinds of decisions), and outcome" (Nutt, 2008, p. 426). In following GTM processes, the factor that emerged as overwhelmingly important to addressing the research question is **context**. Context takes into consideration, among others, "individual differences", The Organisation, "risk", and "industry", which are not subject to change at the decisional level and time, meaning that internal and external environmental conditions (influences) are considered at face value when a decision is under consideration (Bell et al., 1998, p. 168). "**Context** documents the environment in which a decision is made. Both the internal and external environment are believed to influence what is decided and how the decision is made" (Nutt, 2008, p. 429). Decision-making is dynamic as contexts varies, supporting the notion of the IS artefact, which is context-driven (Bell et al., 1998). **Context** is what makes the answer to the research question indeterminable.

'It depends' results in two possible outcomes, realisation or breakdown, which is based on the completeness of the IS artefact, specifically the DMI (context) within the IS artefact; the latter enables choices for the decision-maker, thereby inferring or not the democratisation of the decision-maker in DDD. Big Data and the completeness of contextual parameters (DMI) equal the IS artefact, which influences the democratisation of the decision-maker (KW) in DDD.

The following SRQs contribute to answering the MRQ. SRQs complement each other, and some aspects may therefore come across duplications; however, they are relevant to the storyline and reinforce addressing the phenomenon.

6.2.2. Sub Research Questions (SRQ)

SRQ1. In data-driven decision-making (DDD), what characteristics of Big Data affect decision-making processes and policies?

Enterprises, in varying degrees, have relied on data for decision-making, and continue to do so with Big Data (Fredriksson, 2018). Management accounting, production planning/forecasting, supply chain management, marketing, and sales have used data to plan, predict, and execute the firm's business strategy through abstraction—that is, through business models, plans, and goals (Mayer-Schönberger & Cukier, 2013). However, decision-making was based on latent, structured, and organised data (Mayer-Schönberger & Cukier, 2013). This is unlike Big Data, which lacks structure, is messy, and includes a plethora of information sources, such as machines, social media, mobile data, video, and audio.

Based on key and well-known characteristics of Big Data, namely, volume, variety, veracity, and velocity (Mikalef et al., 2018) (but not forgetting the lesser known value, variability, and visualisation (Seddon & Currie, 2017)), the research question appears to be sufficiently addressed (see Chapter 4). However, it is important to note that: 1) Big Data, through BDA, on its own does not entirely influence the democratisation of decision-makers in DDD—it depends on the completeness of the IS artefact, which considers other unavoidable but necessary influences (Mikalef et al., 2018); and 2) the transformation of raw data into information into knowledge into insight, through the application of knowledge at each level, leads to DDD (Boell, 2017), which enhances firm performance (Brynjolfsson et al., 2017).

The well-known characteristics of Big Data (i.e., the 4Vs) contribute, in varying degrees of importance, to decision-making (Mikalef et al., 2018). This is a realistic assessment: while the requirements of Big Data are vastly different across users based on their roles, all KWs have Big Data needs in fulfilling a job and business requirement. At the typical KW level, the 4Vs are impactful but, at the same time, organisations have ICT and job roles/responsibilities in place to help minimise the effect of the 4Vs on KWs.

The ***volume*** of Big Data is overwhelming, because it is voluminous, complex, and messy as it incorporates all things that are digitally enabled (De Mauro et al., 2016, 2015). From a volume perspective, less than 10% of Big Data datasets are worked on, and much less are analysed for insight; this is not that different for firms around the world (Krisifoe, 2018). This aspect is attributed to the cost of ICT (BDA included), time and resource constraints, and lack of data analytical skills. There is an unequivocal acknowledgement that Big Data volume is beneficial, but the conundrum revolves around what is needed of Big Data (the question), finding answers through BDA, and applying an analytical mind to extract underlying insight—standard and custom reports alleviate some of this burden. Less than 0.5% of a firm's data repository is analysed for insight (Krisifoe, 2018). For some firms, analysis of Big Data is more descriptive rather than predictive and prescriptive in nature, which is tantamount to wasted opportunity. However, given the resource limitations—skills, finances, time—the priority is to achieve immediate and impactful results that are sufficient for business operations (Lavalle et al., 2011; Tsai et al., 2015). Volume generally appears to be less important (but still a concern and stressful) to users, but it is critical in artificial intelligence projects, as it contributes to machine learning and automation of processes. What is important to users in general is the availability and access to relevant data for DDD to fulfil job requirements; however, organisational bureaucracy (blocking) and multiple data silos are inhibitors, which appears to be a global phenomenon (Sweetwood, 2014).

Variety appears to be important, as searching for a more complete picture supports data-driven decision-making and contributes to better insight; multiple sources and types (voice, video, mobile, IoT) of data help achieve these objectives (Janssen et al., 2017). The variety embedded in Big Data is a key element of success, with insight being sourced from many repositories, including homegrown datasets, third party datasets, and social media and instrumentation sensors (IoT), to manage most of the property utilities (Baesens et al., 2016; Qiu et al., 2019). Because of the variety mentioned, Big Data is difficult to manage. Digital disruption, specifically social media as a communication/interaction tool, provides organisations with new ways of reaching customers (Prevost et al., 2018). However, social media also poses a significant challenge to organisations, as maintaining control of external sentiments are difficult given the widespread nature of the internet, the unknown acceleration capabilities of negative/positive sentiments ("fake news", dissatisfaction, satisfaction), cybercrime, and the lack/disregard of emotive control and respect for intellectual property (Geeling & Brown, 2020, p. 1). Variety appears to be key to organisations, as it is believed to be the critical gateway to better customer interactions, retention, and outcomes. Having an end-to-end view of the business and customers is not credible with a single source of data. However, having multiple data sources that contribute to Big Data, including data warehouses, data silos and cloud, and varying types of data (structures) and content, contributes to the challenges of establishing a single source of truth—a critical requirement for veracity (Malaka & Brown, 2015).

Veracity can be defined as data consistency and "trustworthiness that is defined by a number of factors including data origin, collection and processing methods, including trusted infrastructure and facility" (Demchenko et al., 2013, p. 3). Several factors contribute to the veracity of Big Data, including diverse data types, volume, timeliness of dealing with Big Data, relevance/fit for purpose, usability, and data security (Saha & Srivastava, 2014). Data security is critical to veracity, as it encompasses the authentication and protection of Big Data, which is difficult given the myriad of sources (Demchenko et al., 2013) This elevates the dilemma with which organisations deal around access to a single source of truth (Sweetwood, 2014). Veracity within organisations comes across as non-negotiable and enforced through business processes, specifically role-based access control, compliance, and governance. However, with Big Data, ensuring veracity across internal ICT resources are routine; it is the veracity of external sources of Big Data that is challenging because of the impact of the remaining Vs on veracity (Venkatraman & Venkatraman, 2019). Given the pervasiveness of Big Data, data security and integrity management necessitate a more holistic approach in that the focus must shift from ICT governance to information governance (Mikalef et al., 2020). The current global challenges that organisations face, such as data integrity because of cybercrime and disinformation/misinformation, lead to distrust of Big Data; however, BDA is also instrumental in fighting cybercrime (Hutchings et al., 2019; Shalaginov et al., 2017). The quality of Big Data and BDA output directly shape the value contribution to insight and ultimately decision-making (Cai & Zhu, 2015). Data quality in decision-making is an extremely important concern and priority for organisations (Walker & Brown, 2019). This is certainly true for organisations within the Financial Services and Insurance industry, which is highly regulated (Godwin, 2017). The consequences for failing to adhere could be detrimental. Therefore, veracity is tantamount to not only thriving, but also surviving scrutiny from customers, regulators, shareholders, and competitors. Maintaining veracity could be problematic, as: 1) KWs lack education, awareness, and understanding the consequences of non-compliance, and 2) it is difficult to secure ICT assets, which are critical to data security, as it is the window into the organisation's data repositories (Demchenko et al., 2013; Moreno et al., 2016).

Velocity is the speed at which data is collected, processed, and analysed; it varies from non-real-time, near-real-time to real-time, and has implications for different business requirements (Abbasi et al., 2016; Kitchin & McArdle, 2016). Targeted ICT deployments enable real-time data for specific requirements rather than for general use due to the cost of facilitating data at real-time and near real-time speeds (George et al., 2016). Therefore, the importance of velocity is dependent on the job at hand and the organisational function, for example, financial and stock trading (Trelewicz, 2017). For most KWs who were interviewed, data-driven decision-making is based on non-real-time, aged data/information in the form of reports. However, there are consumption requirements such as trading in financial markets, where real-time data/information is critical to decision-making (Trelewicz, 2017). This type of data is procured through real-time service providers, thus contributing an element of variety. Near-real-time data/information (sensor) is largely used for the management of utilities across the various campuses (Williams et al., 2014). The implications of velocity on ICT is significant, specifically for applying data security such as encryption in motion and at rest for large datasets, so that the user experience is seamless (Benjelloun & Lahcen, 2019; Dupré & Demchenko, 2016). Furthermore, ICT resources to achieve this is available but expensive, and the investment therefore has to be based on cost-benefit analysis.

SRQ2. What internal and external environmental conditions inhibit or promote DDD in a Big Data environment?

As stated in answering SRQ1, the quality of data used in decision-making has consequences for the outcome, such as the value of insights extracted, and the actual decision realised. When answering the MRQ (Section 6.2.1), it was mentioned that internal and external environmental conditions have a profound impact on decision-making (Nutt, 2008). Businesses do not operate in isolation; therefore, consideration for the context within which the decision is made is critical to the outcome thereof, and is the crux for this SRQ. A few key considerations are always given the highest attention in organisational decision-making, DDD included, namely: the culture of the organisation (its mission, vision, values, culture), ethical considerations, and availability and optimum use of the organisation's resources (Warrick, 2017). However, risk management in decision-making is of paramount importance to the organisation, as the consequences could be severe (Buchanan & O'Connell, 2006).

Risk management—controlling risks—is incorporated in every decision-making type, because risk is the “chance of an undesirable outcome” (Yoe, 2019, p. 1). Even though profitability (success) is the main driver for businesses, managing associated risks are equally important, as “the content of the term 'risk' is hidden in the uncertainty of the future process”, which has a direct bearing on profitability (Lu et al., 2012, p. 92). Risk management is about the establishment of expectations, shaping organisational culture to accept risk, and facilitating risk assessments when performing business activities such as strategic investment or project decision-making (Yoe, 2019). Examples of risk management interventions include deploying organisational strategy based on growing revenue and reducing cost through process automation (e.g., workflow, decision-making, and improving customer experiences), deciding which assets are necessary in expense management, expanding into newer markets, organisational design, and consolidation of ICT assets, such as data silos. Risk management intervention includes deployment of counter-risk measures to protect the existing revenue stream, optimisation of business functions to reduce operational costs, and targeting of new customers to offset end-of-life revenue streams. These interventions are supported by operational, tactical, and administrative risk mitigation measures, such as improving the customer experience through business process automation (BOT) deployments, managing social media content, safeguarding data integrity, and having governance processes in place to bolster the integrity of the organisation. Risk management activities are generally based on data, and therefore have an impact on DDD. The latter is ineffective when the extraction of insight is based on inadequate BDA tools, given the implications of the Big Data Vs.

As mentioned in the MRQ, context is key to decision-making, which is shaped by internal and external environmental factors (Nutt, 2008). “The [external] environment is infinite and includes everything outside the organization” (Daft, 2010, p. 140). The external environment includes influences that are oriented toward competition, political, economic, social, technological, legal, and environmental context (Daft, 2010; Nutt, 2008; Yoe, 2019). Although external environmental factors, which have an impact on the business but are outside its direct control, are vast, controlling risks are limited to that which affects organisations and to that which organisations have to respond to—context (Daft, 2010). External factors, such as those mentioned, and adherence to regulatory requirements—such as employment equity (affirmative action), black economic empowerment, labour regulations, data privacy (PoPI), and financial intelligence (FICA[31])—influence decision-making processes. However, the implications, although impactful, are more difficult to establish at the individual KW level, as the

[31] FICA – Financial Intelligence Centre Act - 2001 (Act 38 of 2001) (FIC Act) https://www.fic.gov.za/Resources/Pages/Legislation.aspx

consequences are largely at the organisational level. The influence is visible through regulatory and legal statutory laws. The economic influence is visible as organisations deploy measures to counter and advance their positions in the marketplace, depending on the situation and organisational strategy. The socio-economic influences are visible through strike action and economic empowerment policies that address previously disadvantaged citizens.

The internal environment is within the organisations' control, and includes aspects related to the deployment of strategy, vision, and mission, which in turn is enabled through alignment of the firm's resource (Nutt, 2008). "Firm's resources include all the assets, capabilities, organizational processes, firm attributes, information, knowledge, etc." (Barney, 1991, p. 101). The workforce, discussed further in SRQ3, is a critical and complex firm resource, and its management holds challenges for organisations.

SRQ3. How does data-driven decision-making (DDD) democratise decision-makers?

To answer SRQ3, the enablers and constraints of DDD in a Big Data environment is taken into consideration. Simplistically, an enabler facilitates the realisation of an intent of the KWs, while the constraints hinder the intent of the KW. Enablers, which facilitate democratisation of decision-makers in DDD in a Big Data environment, and the constraints, which hinder democratisation of decision-makers in DDD in a Big Data environment, extend beyond the technology artefact, Big Data (Mikalef et al., 2018). The fact that Big Data is pervasive is important, as it relates to earlier discussions (Section 1.2) around the characteristics of democratisation and empowerment and its relationship to the control and reach of information in the Big Data era as compared to the past (Berner et al., 2014). The discussions above (answering SRQ1 and SRQ2) is relevant and supports the notion that answering SRQ3 extends beyond the Big Data technology artefact. The empirical evidence suggests apart from technology infrastructure (TI), TH, TO and DME are contributors to democratisation of DDD in a Big Data environment.

At the heart of this thesis is satisfying the curiosity around Big Data's influence on the democratisation of decision-makers in DDD, which relates directly to this SRQ. The labelling of a factor, either as an enabler or constraint, is subjective as it is based on the perceptions, interpretations, roles, and responsibilities of the respective KWs. Therefore, the words enabler and constraint are prefixed with 'perceived'. For instance, compliance within the financial services industry is perceivably restrictive to business undertakings, which could be perceived as a constraint. However, given that the boundaries are known and assured through policing, this could be perceived as an enabler, as there is flexibility to operate within predetermined boundaries. Another example is collaborative decision-making; while it is a perceived enabler on the one hand because it is a consultative approach involving subject matter experts, it could be perceived as death by consensus on the other hand. This conundrum is applicable to most other discovered enablers and constraints of democratisation of DDD—it is a case of perception and interpretation by the respective KWs.

Some of the perceived enablers and constraints to realising democratisation in DDD in a Big Data environment are dependent on:

- KWs attitude, skills, and ability to decide;
- Collaborative decision-making;
- Consideration for others;
- Access to Big Data;
- Access to necessary resources (BDA tools);
- Organisational backing;
- A business strategy; and
- Adherence to policies and regulations.

Although the KW is managed as a firm's resource (Barney, 1991), uniformity in behaviour across the workforce is unlikely, given the many influencing factors that contribute to the KW's persona (TH), even as a member of the workforce. The workforce, when taking into consideration generational, cultural, and social differences, are diverse in their approaches to achieving work objectives and contributing to organisational performance through effective decision-making (Larson, 2018). KWs are influenced by culture, traditional practices, religion, value systems, and education (Humpisch, 2018; Mangaliso, 2001; Schein, 2010). Apart from these, external stimuli arising from social, political, technological, and economic situations have impacted workplace behaviour, interpersonal relationships, and productivity (Hatch & Schultz, 1997). Some situations are more impactful on DDD than others in the South African context, such as those stemming from historical inequalities, varied social circumstances, and the strong influence of traditional practices (Humpisch, 2018; Michie & Padayachee, 2019). In the workplace, what works for some may not necessarily work for the others; this has a direct bearing on the individual's ability to effect DDD, which has consequences for productivity and the firm's competitiveness (Potterfield, 1999).

The workforce is continually evolving in terms of age, ability, and cultural composition (Bencsik et al., 2016). New entrants into the workforce, as compared to an older workforce, use technologies that are social in nature, and that appear to be less secure and difficult to control from a governance and regulations perspective (Bolton, 2013). Social media is available on most computing platforms and the adoption of social media in emerging economies, South Africa included, is over 64% (Silver et al., 2019). This raises several firm-related issues that has a bearing on the KW, such as privacy, security, and governance. Data security matters are pervasive and affect the entire organisation, including people and assets, and have a significant impact on DDD. Data security is influenced by: 1) internal factors such as role-based access control, limits of authority, source of data, protection of data, and secure storage (Demchenko et al., 2013), and 2) external factors such as authenticity of the data, relevance, impact on the business, and age. The digital boundaries of the organisation have become fluid, in that there are multiple data sources, both internal and external, and the security perimeters of the organisation extend beyond the traditional network firewalls to include mobile devices and the cloud (Benjelloun & Lahcen, 2019; Watson, 2014). KWs with ICT-related roles are concerned with securing data integrity and protecting the organisation's data. KWs are concerned about data privacy as related to legislation, source, and authenticity of the data, which is strictly based on current regulations around the Protection of Personal Information (PoPI[32]) Act. Data security is critical to organisations. However, its effect on KWs shapes how DDD is conducted, insofar as KWs' reluctance to engage in DDD for fear of breaching data security. A suggested solution to this problem is to transparently and comprehensively disclose the parameters (DMI) that could be used in DDD, so that the KW understands the boundaries in advance. This in essence is the democratisation of decision-makers in DDD.

Approaching the KWs behaviour toward DDD begins with an understanding of the historical and cultural nature of the person as the seen and unseen contributing factors (Mangaliso, 2001). Assumptions, perceptions, and interpretations play a significant role in the determining enablers and constraints of democratisation; even the availability of Big Data has different connotations. It is reasonable to surmise that, as the firm becomes more representative of the society in which it operates, the persona of the firm is shaped by the collective workforce, who are influenced by these internal and external conditions (Mangaliso, 2001).

6.3. THE RESEARCH STUDY'S CONTRIBUTIONS TO INFORMATION SYSTEMS

As established in earlier chapters, Big Data is a hype that continues to gain momentum in terms of acceptance, adoption, and use. However, empirical studies with a business perspective are limited (Mikalef et al., 2018). Hence, the intended contribution was to expand the existing body of knowledge, produce a theory, and enable organisations to better understand the phenomenon. The practical

[32] Protection of Personal Information act - http://www.justice.gov.za/inforeg/docs/InfoRegSA-POPIA-act2013-004.pdf

contribution intended to explain the phenomenon through the theory that was produced from the empirical situation, and to encourage discourse by academia and practitioners alike (Gregor, 2006). This thesis makes several contributions to literature and practitioner knowledge, which follow below.

6.3.1. Theoretical contributions

"Good theory is produced by a fortunate combination—an inquiring mind, rich experience, and stimulating data" (Glaser & Strauss, 1967) (page). The evaluation of the contribution of this thesis and emergent theory is based on the work of Whetten (1989). The Subsection headings 6.3.1.1 to 6.3.1.7 are verbatim (Whetten, 1989), each addressing one of the criteria that Whetten proposes for the evaluation of a research contribution.

6.3.1.1. What's new? Does the paper make a significant, value-added contribution to current thinking?

The Democratisation Inflection Point (DIP) assimilates with many theories, such as Actor Network Theory, Practice Theory, and sociotechnical systems—to name just a few—to produce a theory that explains how human and non-human actors, who are afforded agency, contribute specialised indicators, based on a piece of information that is a result of BDA, to produce an IS artefact. The IS artefact is the key to whether a KW is democratised or not in data-driven decision-making.

The main contribution centres on the DIP system, DIP, DMI, and IS artefact that are put forward as new concepts to explain how democratisation of decision-makers in DDD in a Big Data environment is realised or breaks down. The newness is that democratisation of decision-makers in DDD, specifically in a Big Data environment, has not been explored, to the best of the researcher's knowledge. Big Data is new and gaining momentum, both within academia and practitioner circles; this theory contributes to the Big Data phenomenon by explaining the realisation, or lack, of democratisation. The theory also supports the notion that Big Data in DDD is but one of four, or possibly many, actors that are given agency to facilitate democratisation.

DIP is applicable beyond answering the phenomenon in this thesis, based on the case study, as the IS artefact is relevant across DDD in organisations. The newness is the evidence-based notion that information, together with specific knowledge (DMI), facilitate better and more informed decisional choices for the decision-maker.

6.3.1.2. So what? Will the theory likely change the practice of organizational science (information systems) in this area?

Knowledge has not been found that explains how DDD in the age of Big Data facilitates democratisation of the decision-maker. The position taken within this thesis is that empowerment is relevant and applicable to traditional data eras in which organisations were in complete control of data, as it largely emanated from internal sources and was internally managed. Empowerment entails a bestowed authority in decision-making, but is accompanied by well-defined control mechanisms such as access control and limits of authority. Again, it is not the intention of this thesis to discard empowerment completely, as there remain in most organisations massive datasets that are completely within the organisations' control and empowerment is included as a DMI. Big Data is pervasive, and the sources are many, which necessitates a different approach to DDD.

The contribution to practice is that democratisation, as opposed to just empowerment, addresses DDD in the Big Data era from the perspective that the decision-maker, when armed with all decisional criteria (context) (empowerment included), is able to make decisions confidently, quickly, and in the best interest of the organisation. After all, democratisation is the co-determination and participation of the individual in decision-making, which builds loyalty and commitment that, in turn, has direct goodwill implications for the organisation. It is the belief that, as KWs grow in confidence, it has a direct bearing on their productivity and contributes to organisational success.

In terms of whether the theory will change organisations, Big Data is going to get bigger, the digital boundaries of the organisations are continually blurring, and deploying ICT to mitigate the many risks is impractical and possibly insufficient. Therefore, based on the DIP, organisations could create social, technological and information artefacts, such as business processes, applications, and training, to implement DIP. While this may be hopeful, DIP is clear and concise in how to facilitate actors' contribution to the co-determination and participation of KWs in DDD.

6.3.1.3. Why so? Are the underlying logic and supporting evidence compelling?

DIP is a theory that is based on empirical evidence, which has been gathered from a case study. The selected case study was ideal to answer the research question, as the workforce was diverse in most respects, the organisation is large and within a visible industry, and ICT deployment is complex, which is representative of continually evolving organisations. Although the theory is novel and unique, it is based on interpretation of participants' worldviews.

Throughout Chapter 4 and parts of Chapter 5, the adherence to Straussian Grounded Theory Methods were followed, which entailed constant comparative analysis and theoretical sampling approaches. The rigour in the methodology ensures that the breakdown of conversations into meaning codes, relationship building of codes, and then the selection of interesting codes come to fruition when a theory emerges from the evidence. The coding processes (open, axial, and selective coding), together with empirical evidence, are provided. The emergent theory is grounded in empirical data that was acquired within a case study environment. Throughout the data gathering and analysis phases, memos were recorded, some of which have been provided *in situ* and within the appendices. The evidence has also contributed to the researcher's knowledge and, in fact, changed some of the preconceived notions about empowerment, democracy, and collaboration. All the findings are novel, as the case study setting, the phenomenon, and the researcher's paradigm are unique; therefore, the theory is unique in many respects.

6.3.1.4. Well done? Does the paper reflect seasoned thinking, conveying completeness and thoroughness?

Big Data is topical, and the literature suggests that it is not well understood, both from an academic and practitioner perspective (Akter et al., 2016; Lavalle et al., 2011; Russom, 2011; Watson, 2014). The literature review identified current gaps (see Section 2.7) that serve to justify this research project. The discussion chapter (see Chapter 5), apart from expanding on the core category that was briefly presented in Section 4.8, also discusses the theory that emanated from the empirical situation, and situates the emergent theory in extant literature and practice (Urquhart et al., 2010). The idea was to demonstrate the novelty of the theory and to contextualise it in current literature.

Theoretical integration was approached from a sociomaterial practice perspective, which takes into consideration the importance of sociotechnical systems, actor networks, and Practice Theory (Cecez-Kecmanovic et al., 2014). The term 'sociomaterial' is a portmanteau for social and material (Leonardi, 2013; Orlikowski & Scott, 2008). Selecting sociomaterial theory is relevant, as the DIP is essentially the place where actors of varying natures and characteristics come together to collaborate in a real-world context. A core concept of the thesis is democratisation, which has been discussed throughout, and it is based on the completeness and quality of the IS artefact that comprises DMI and decision-making information. This demonstrates that the emergent theory was taken through a theoretical elaboration process to evaluate it against theoretical contributions by peers and distinguished scholars. The DIP is credible, well grounded in empirical data, and fulfils a gap in knowledge.

6.3.1.5. Done well? Is the paper well written?

From a researcher's perspective, every effort has been made to follow extant literature on the technological concepts and methodological aspects. In considering adherence to Straussian GTM, it should be noted that Glaser, the GTM founding member, has criticised this method for its rigidity (Heath & Cowley, 2004). However, it is precisely the rigidity of this particular GTM method that allows for the paper to be well written. It is hoped that debate and disagreement around the theory will lead to betterment of the theory over time.

6.3.1.6. Why now? Is this topic of contemporary interest to scholars in this area?

Big Data is growing exponentially and is a reality for most large firms, as data is continuously generated, from both internal and external sources to the organisation (Baesens et al., 2016). Despite the possibilities of Big Data in aiding better decision-making, the limitations do not lie solely with the technology (Davenport, 2012). Data analytics, which are the tools for extracting value, always start with people-driven questions. From the literature, it is not possible to gauge the capabilities of organisations in South Africa for producing usable DDD knowledge. This appears to be a global phenomenon, as further research is suggested to understand the interrelationships between analytics, organisational decision-making processes, and firm performance (Akter & Wamba, 2016; Braganza et al., 2017). Top-performing firms use analytics five times more than lower-performing firms (Lavalle et al., 2011). However, the benefits of BDA are not fully realised, as the complete decision-making picture does not appear to be known to academics and practitioners alike. Therefore, without this understanding, the importance of Big Data and BDA continues to be less known.

6.3.1.7. Who cares? What percentage of academic readers are interested in this topic?

An answer to this question is not possible, as the information is unknown. However, an attempt at providing an answer is important; therefore, Table 50 is presented to demonstrate the interest among academics in topics of a similar nature. It summarises the research question, objectives, gaps, and contribution to demonstrate areas of study that are warranted.

Research Question/s	**Research Objectives**	**Problematising the Literature**	**Contribution**

Main Research Question: Does Big Data influence the democratisation of decision-makers in data-driven decision-making (DDD) in organisations?	Main Objective: The aim of the study is to ascertain the factors of Big Data that enable or constrain democratisation of decision-makers in DDD in an organisation.	DDD, as related to Big Data, is hampered because of organisational configuration (Malaka & Brown, 2015).	Knowledge. Theory. Practice.
In data-driven decision-making (DDD), what characteristics of Big Data affect decision-making processes and policies?	Establish the most prominent of Big Data characteristics that affect DDD.	Further research to establish the gravity of intuition versus evidence-based decision-making (Elbanna, 2006).	Knowledge. Theory. Practice.
What internal and external environmental conditions inhibit or promote DDD in a Big Data environment?	Better identify and understand the internal and external environmental factors that influence workplace democracy from a DDD perspective.	The effect of DDD and organisational alignment—taking into consideration culture, politics, regulatory, economic, social, legal, and competitive matters (Sheng et al., 2017).	Knowledge. Theory. Practice.
How does data-driven decision-making (DDD) democratise decision-makers?	Ascertain how Big Data use is changing and/or influencing organisational DDD.	The dynamic capabilities of the firm and its adaptation to a Big Data environment (Braganza, Brooks,	Knowledge. Theory. Practice.

		Nepelski, Ali, & Moro, 2017).	

Table 50: Summary of key research topics

The key contributions are as follows:

As ascertained, current IS theory frameworks limit and potentially distort the expected empirical results; hence, undertaking a GTM approach allowed the study data to morph into a theory that explains the phenomenon (Glaser & Strauss, 1967). A new theory firstly explains the phenomenon and, secondly, it is hoped that it stands on its own as a novel theory contribution that could be debated, extended, and used to explain other phenomena (Grover & Lyytinen, 2015).

"Huge opportunities exist for collaboration in big data", therefore "it is a great time to be in IS doing IS research" (Goes, 2014, p. viii) Big Data is topical and intriguing; therefore, research opportunities are plentiful (Abbasi et al., 2016). IS research, an interdisciplinary approach (Guha & Kumar, 2018), is well suited to Big Data research, as the call for understanding Big Data is not just from technological perspectives but from legal and economic disciplines, among others (Schermann et al., 2014). The popularity of Big Data as an IS research opportunity was evident in an overwhelming response to a call for papers (MIS Quarterly special issue: Transformational issues of Big Data and analytics in networked business), as Big Data is considered transformational in many respects, of which the impact on businesses is one (Baesens et al., 2016). "Leveraging big data and analytics comes with a host of challenges, many of which are fertile ground for future research" (Baesens et al., 2016, p. 813). This call has been heeded within this thesis, insofar as providing a unique perspective of Big Data as it relates to the democratisation of the decision-maker in DDD.

From a knowledge perspective, the interrelationships between the key concepts, namely, Big Data, Democratisation, and DDD, are novel to IS research (Ågerfalk, 2014; Grover & Lyytinen, 2015). The extant literature is scant, and this thesis contributes to knowledge by showing the influence of each concept on the other.

From a practice perspective, the workforce is changing and their use of productivity tools are based on transparency and "instant gratification" (Bolton, 2013). What once were silos of data (voice, video, data), which were easier to manage, are now lumped into complex datasets, called Big Data (Lavalle et al., 2011). Organisations have to contend with internal and external influencing factors that could enable or inhibit democratisation processes, as organisations contend intuition and DDD as decision-making aids (Harrison & Freeman, 2004). The knowledge will help organisations to identify characteristics of Big Data that could facilitate a balance between these extremes (Abbasi et al., 2016). Balance facilitates optimisation of decision-making and risk mitigation, as the best of both decision-making aids continue to be relevant and valuable.

Addressing this dearth of knowledge will help firms to better understand the tools at their disposal for enabling their businesses to evolve. Big Data has an influence on traditional business models through the need for these models to be updated or developed entirely from anew (Woerner & Wixom, 2015). By addressing the phenomenon, the firm and workforce will be enabled to transform business models to take advantage of the "new ways of working, communicating, and interacting" (Carillo, 2017). Having a complete IS artefact could be operationalised as an organisational level decision-making requirement, with supporting processes in place.

6.3.1.8. Generalisation of the Theory

"Theory building, not theory verification, is the main and only aim of grounded theory" (Urquhart et al., 2010, p. 360).

Generalisation of theory "refers to validity of a theory in a setting different from the one where it was empirically tested and confirmed" (Lee & Baskerville, 2003, p. 221). In conducting interpretive and qualitative studies, the main premise is to gain an understanding of some phenomenon by identifying concepts and relationships that are specific to the case, the replication of which is doubtful (Corbin & Strauss, 2014). Instead of generalisation, the concept of applicability appears to be a more fitting approach; it is based on transferability of theory that, in turn, is based on the demonstration of rigour throughout the research and transparent disclosure of the details of the study, as contextuality is critical to replaying the theory (Tsang & Williams, 2012). The context (or "situated dynamics") from which theoretical concepts and relationships emerged may be unique, but remains useful for understanding other contexts, thus uncovering knowledge in other sociomaterial practices (Feldman & Orlikowski, 2011, p. 1249). From a case study perspective, it is flawed to think about cases as sampling units for generalisability; further, the cases are too few for generalisation. Instead, the idea is to focus on elevating the empirical findings, such as concepts and principles, that facilitate generalisation to theoretical propositions (Yin, 2018). Having situated the theory within sociomaterial practice, the theory is deemed to comprise "principles that can explain and guide action" and "articulate particular relationships or enactments (e.g., technologies in practice, resources in use) that offer insights for understanding other situations while being historically and contextually grounded" (Feldman & Orlikowski, 2011, p. 1249).

This research is based on Grounded Theory Methods, for the reasons explained in Chapters 3 and 4. Verification of the theory is not a requirement and is frowned upon, based on the risks that theory verification is given priority over theory generation (Glaser & Strauss, 1967; Urquhart & Fernandez, 2006). "Theory building, not theory verification, is the main and only aim of grounded theory" (Urquhart et al., 2010, p. 360). Two opposing weaknesses are presented, namely: 1) the risks in trying to include everything, thus resulting in complex theory; and 2) on the other hand, the theory may be too "narrow and idiosyncratic" to a particular case (Eisenhardt, 1989a, p. 547). Choosing to highlight GTM's primary objective of theory generation does not negate verification, but places it secondary to theory generation.

The findings section did not attempt to prove the relevance or validity of the core category, namely, DIP. Such an approach would defeat the GTM principles on which this study is based. Rather, the entire thesis project paved the way for the DIP to emerge on its own by following the core GTM principles of constant comparative analysis, theoretical sampling, and of consistently asking: "What is happening?".

Theory generation takes preference over generalisation of theory concerns (Corbin & Strauss, 2014). However, the theory could never be generalised verbatim, as the conditions in the case research are completely unique (Yin, 2018). Moreover, the case itself is continually evolving, with each of the actors undergoing some form of transformation.

6.3.2. Practical contribution

Although people understand the vastness and extent of Big Data, participants in the empirical situation described Big Data more in terms of utility, that is, the value that they derive and the relevance to them. Some participants brought into discussion the importance of sensors in managing the property utilities such as water purification, electricity, and air conditioning. Others focused the discussion around the marketplace and the need to manage customer satisfaction so that the business survives and thrives. Further, there are those who have the daunting tasks of controlling risks by addressing social media threats and always being vigilant in protecting the company brand. Big Data is employed as a tool to achieve well-defined objectives.

While definitions of BDA cover a wider spectrum of concepts that are essential in addressing Big Data, they do not include the organisational resources that are necessary to turn (raw) Big Data into information, knowledge, and actionable insight (Mikalef et al., 2018). The contribution of this thesis, through the DIP, exposes a layer that is integral to understanding the various components which, in turn, are necessary for transforming raw Big Data into useable/actionable knowledge. There is a shortage of empirical investigations that elevate the social and economic values of Big Data (Günther et al., 2017).

Competitors are consistently attempting to win market share from CSA; the reverse is also true, as CSA targets competitors' market share. CSA looks to Big Data for insights to derive competitive advantage. However, a consistent message from participants is that time, money, and skills are inhibiting factors. This is viewed as a quagmire, in that what lies beneath the obvious is the insight that is largely unknown, but that could be the key to industry domination. To mine these insights requires time, money, and skills that are in short supply; hence, these unsolicited, untouched, and unknown insights are left hidden. Further, the company continues to compete in the old-fashioned way, which is hard work, and competes for the same customers in the same industry. What if the extracted insight could tell the story of the latest generation's need for dynamic, flexible, and community-centric products that are elastic in nature? The researcher is not an expert in CSA's industry. However, the point under consideration is to push the boundaries to demonstrate what could be hidden. Further, the decision to uncover what is hidden may require hard decisions that sacrifice other things to make data insight a reality. Knowing how decision-making comes to fruition in the Big Data era could help organisations to transform the IS artefact into processes and tools. The IS artefact could be the basis upon which automation processes, evaluation of business performance, and workplace ways of work are operationalised. The IS artefact is based on empirical evidence which, in turn, is based on the voice of employees.

Big Data is different from traditional data, as is proven by the evidence from literature and the empirical findings of the case. Empowerment, as a workplace participatory approach, is fitting for data that is within the control of the organisation and is relevant even in the Big Data era as a decision-making guide. However, empowerment is limited as a participatory principle in the Big Data era as volume, variety, veracity, and velocity is to a large extent outside the organisations' control. The concept of democratisation, a co-determination and participatory principle, is better fitting in the Big Data era as it promotes responsibility with accountability. This does not imply that the firm relinquishes control of DDD. Rather the firm has the power through policies, processes, and tools to transparently and in advance of decision-making provide critical parameters and boundaries so that decision-making flows easily, and at the same time provides the decision-maker with reasonable assurances and confidence in DDD. This is the democratisation of the decision-maker in DDD in the Big Data era.

6.4. LIMITATIONS

As noted in Section 6.2, the measure of each actors' contribution to a DIP instance has not been established. While this does not minimise the contribution, it does support the notion of the profound impact that GTM's theory emergence could have on academia and practice, such as discovering how little is known and that the possibilities to discover more are insurmountable.

While the collaborating and contributing actors have been established based on the case research findings, each of the actors results from other DIP systems and social practice. Contributing actors to the main actors identified in this thesis have not been empirically established.

Single-case designs are vulnerable, only because the researcher will have put "all ... eggs in one basket". (Yin, 2018, p. 98). Although a multi-site case could have contributed to better generalisation of the theory, the lack of knowledge as related to the phenomenon would have resulted in massive amounts of data (Eisenhardt, 1989a). This could have resulted in less focus and attention to what participants were saying. The single case has yielded credible theory to explain the phenomenon, which now opens the way for the theory to be tested across multiple case studies.

There are limitations to choosing Straussian GTM. Constant comparative analysis, as related to large volumes of data, could lead to confusion, mistakes, and overlooking important pieces of information within the data (Corbin & Strauss, 2008). Although the data collection and analysis methods prescribed by SGTM minimise this, the concern remains that important data could have been overlooked.

The findings and subsequent theory that emanated are based on two sets of interpretations. First, participants' worldviews are based on their interpretations, which are influenced by their culture, education, experience, and exposure. Second, participants' worldviews have been passed through the researcher's interpretative lens and filters, which are possibly shaped by personal biases. While every effort has been taken to minimise personal bias, complete elimination thereof is not realistic.

6.5. FUTURE RESEARCH

Although theory emerged that could explain the phenomenon, there are limitations (see above) and opportunities for future research:

- Within section 2.3, decision-making is discussed. Although the empirical evidence and findings led the research to the decision-maker (KW) as the focal point for ascertaining democratisation in a Big Data environment, there is a research opportunity that appears to be persisting in establishing democratisation of data-driven decision-making processes.

- The extent of each actor's contribution to the DIP system has not been established, therefore equal agency, or extent thereof, has not been established. It would be interesting to understand the extent of, and impact by, each actor within sociomaterial practices.
- An interesting and open phenomenon to study is the relationship between Big Data, an individual's values, and organisational values, specifically from the perspective of the influence on workplace behaviour.
- A pertinent, yet persisting, problem pertains to the effect that digital transformation, as it relates to Big Data and DDD, will have on an organisations' ICT function, given that data for decision-making is everywhere (Gerster et al., 2020).
- There is some evidence that the acceptance, adoption, and use of Big Data vary by generation (see Section 4.5.5). However, the study has not focused sufficiently on this aspect to understand the extent thereof. Future research is recommended around a more in-depth study to understand the extent of differences in this regard.

6.6. IN CLOSING

A Big Data challenge lies not only in extracting value-laden insight but, importantly, in the use thereof to support the democratisation of decision-makers in DDD. It is apparent from the discussions that KWs struggle with Big Data, and with data in general that requires manipulation for the extraction of insight. Newer generations seem to be impatient, as the time-value of data is very short and decision-enabled knowledge is visible. However, the capability that supports unhindered decisions based on Big Data is not forthcoming, possibly due to one or more of: organisational support, the ability of the KW to make the decision, or it being outside the actor's job role.

The most fitting answer to the main research question is: 'it depends', which appears simple enough. However, achieving this simple answer entailed data collection, followed by rigorous analysis and constant comparative analysis. The core category that emerged from the research environment is the Democratisation Inflection Point (DIP). The DIP is the point at which several competing and complementary factors come together. What results from this is complex to pinpoint as, again, it depends: on the person, the problem, the organisation, power centres, and the data at hand that are captured as DMI. These separate but interrelated areas of influence come together to yield decision-making guidance. Having this guidance, in the form of DMI and combined with the relevant information, results in a decision-making artefact. This decision-making artefact causes the realisation or breakdown of the democratisation of decision-makers in DDD.

The use of Grounded Theory Methods (GTM) to guide this study has been rewarding, in that participants' voices within a case study environment has resulted in novel perspectives and credible theory that answers the research questions. In following Strauss' version of GTM, processes were followed that aligned completely with the suggested methods and outcomes. As the analysis through coding and constant comparison produced concepts that could explain the phenomenon, it became clear that—in reaching the core category and as a theory emerged— the subsequent open, axial, and selective codes formed an integral part of the story. These codes, achieved through analytical, synthetic, and reductive processes, exposed relationships and duplications that all became part of the story. The theory, although representing an injustice as the essence of human emotion cannot be expressed, succinctly attempts to capture CSA's and participants' contributions to understanding this phenomenon. The codes (conversations) are the foundation of the theory and complementary in every respect, without which the emergent theory fails.

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8. APPENDICES

8.1. MEMOS

8.1.1. Sample of handwritten memos

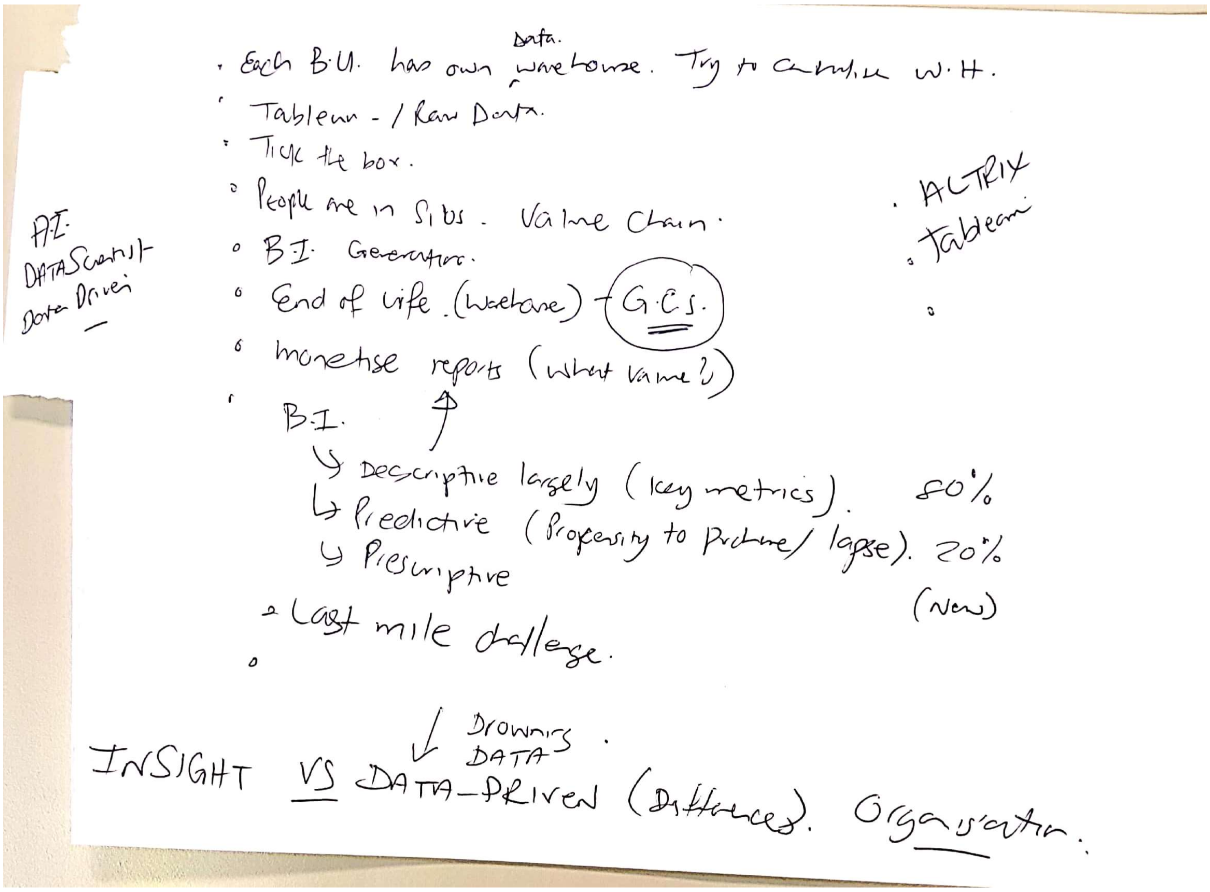
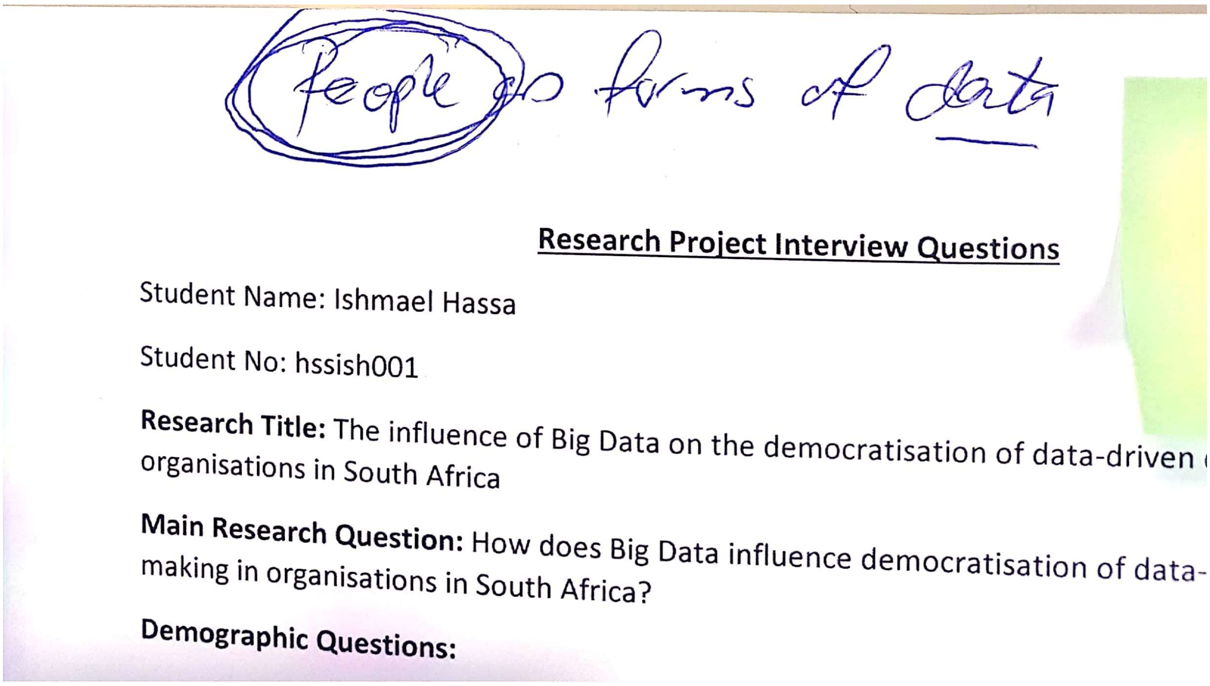


Figure 21: Sample of memo - data scientist discussion



People as forms of data

Research Project Interview Questions

Student Name: Ishmael Hassa

Student No: hssish001

Research Title: The influence of Big Data on the democratisation of data-driven
organisations in South Africa

Main Research Question: How does Big Data influence democratisation of data-
making in organisations in South Africa?

Demographic Questions:

Figure 22: CSA#31 People as forms of Data

8.1.2. Notes/Memos

For every interview, memos were captured in handwritten notes.

Memo 11 [Email to supervisors after analysing data - 21/02/19] Democratisation is not about self-determination or the ability to make decisions, but about effective collaboration (teamwork, consensus) to the betterment of all. Teamwork involves the contribution of experts, and experts rely on Big Data for therein lies truth, knowledge, and success.

Memo 12 24/01/2019. CSA#28. Value in unsolicited data. Value in the unknown. This comment was unexpected and yet profound declaration. But with GTM, these are the unexpected nuggets that contribute to uncovering theory.

Memo 13 August 2019, dilemma - what about democratisation of actors – animate and inanimate? The evidence is suggesting that democratisation is about affording choice. It is not about competing between freedom, empowerment and democracy.

Memo 14 Concerns raised about the use of "democratisation" in the title as this will turn possible respondents away due to companies wanting to ensure complete control of the data. So possibly an intellectual property and expectations related matter.

Memo 15 In meeting with CSA executive, Big Data was challenged as marketing and practitioner hype rather than a real phenomenon.

Memo 16 Week of 15/10/2018 - Had fruitful discussions with possible case study candidates—Retail1, Retail2 and Retail3, apart from CSA.

Memo 17 CSA appear to be dumbstruck with the democratisation concept.

Memo 18 I've exchanged emails with financial services organisation that is the leading competitor to CSA. All are interested in the research, mainly from an organisational development perspective.

Memo 19 Met with Prof Brown to discuss the concerns about the title (democratisation). We brainstormed how to let that particular concept emerge as opposed to leading with it.

Memo 20 Culture appears to be a broad term that could result in key points that could include power-centres, generational issues, centralised/decentralised decision-making, decision-making types (strategic, tactical, operational) and decision-making processes (intuition versus data-driven).

Memo 21 As can be seen, the retail industry appears to be where the sample lies. Prof B and I brainstormed how to get triangulation. One option is to introduce another industry like financial services and insurance into the mix. The second option is to see how brands within the same retail group sample respond. For example, Shoprite Group has several brands (Shoprite, Checkers, USave, OK) that cater to all types of markets/demographics and based on this could be similar or dissimilar.

Memo 22 Prof Brown also reminded me that ALL is data and what hinders or enhances the progress is to be documented.

Memo 23 24/01/19 – CSA#30 "Data whispers. Does not shout. You must listen attentively or you will miss it"

Memo 24 16/01/19 – CSA#16. "Attention span is limited. They [younger generations] want quick fixes. You have to think of different ways to communicate with them"

Memo 25 *16/01/19 - CSA#16. "Obviously, Big [Data] is a problem. But, relevance is bigger problem to make decision-making quicker"*

Memo 26 *20/12/18 – CSA#10. Encountered the term "death by consensus".*

Memo 27 *20/12/18 – CSA#05. "Big Data paints a picture"*

Memo 28 *18/12/18 – CSA#08. "Social media is a part of me"*

Memo 29 *19/12/18 – CSA#03. "Smaller, less impactful decisions or tactical decisions should not require consensus. Larger, more impactful decisions should undergo some consensus. In-depth analysis key to major decisions".*

Memo 30 *02/03/2020 - Review open codes to identify similarities in literature.*

Memo 31 *'people are different' > individual differences*

Memo 32 *Discussion with Prof Brown. Democratisation is the product of the whole.*

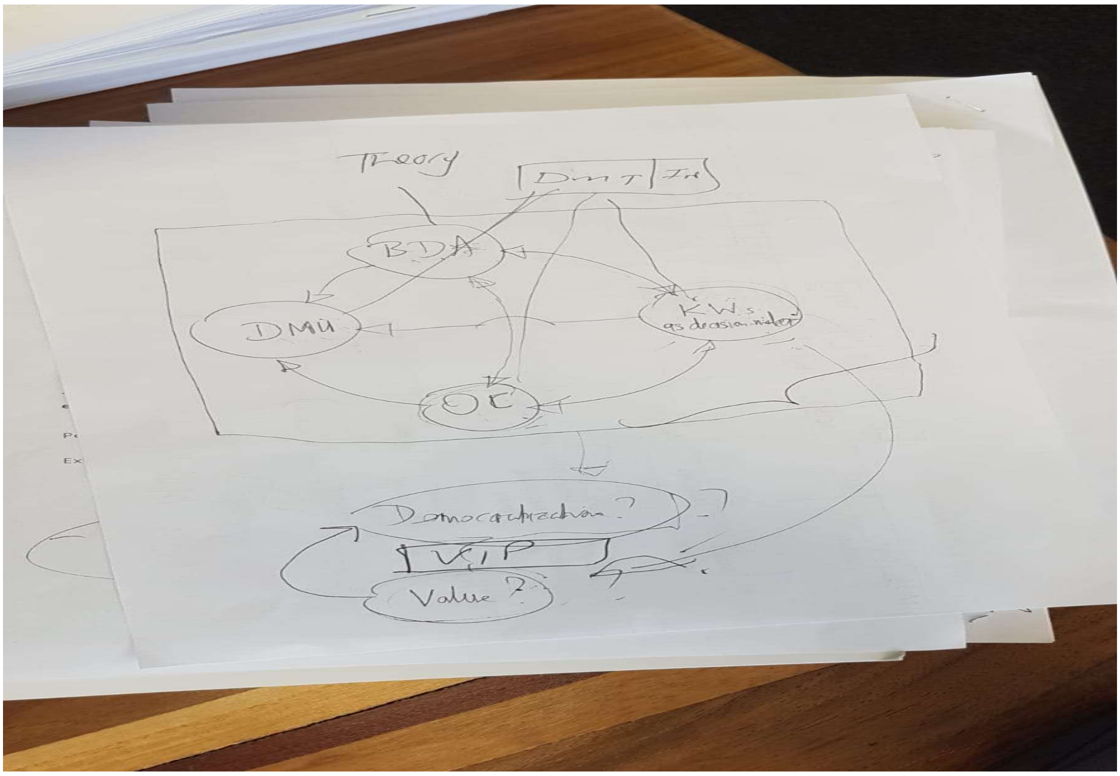


Figure 23: Democratisation is the product of the whole

Memo 33 Discussion with Prof Brown. The power of TH on DIP

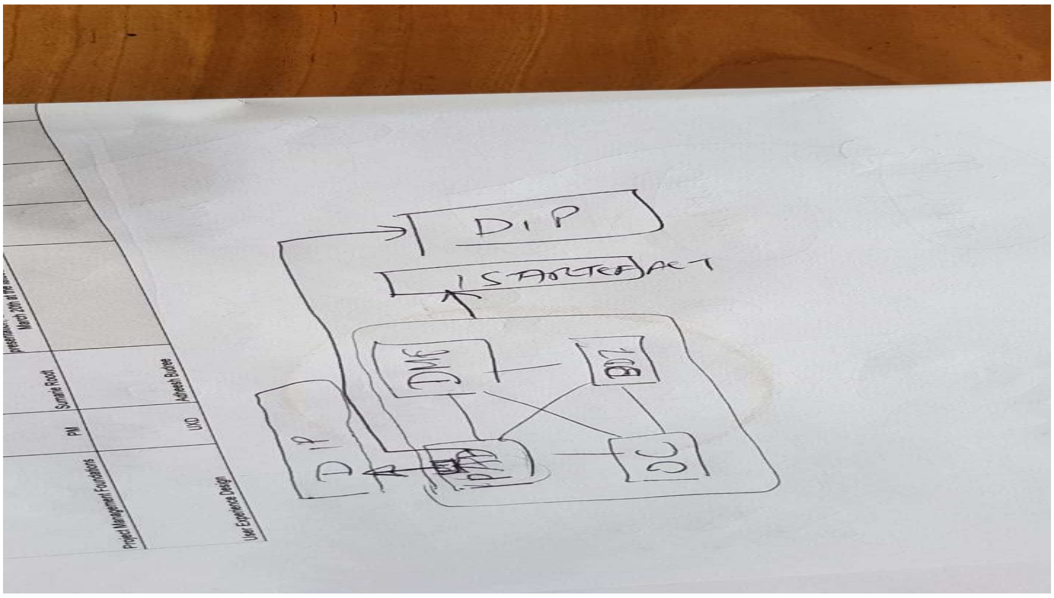


Figure 24: Discussion with Prof Brown

8.2. Research questions, coding and categorisation Process and Outcome

Research Questions				Coding and categorisation results			
MRQ	**SQ1**	**SQ2**	**SQ3**	**Core Category**	**Selective codes**	**Axial codes**	**Open codes**
√	√	√	√	***Democratisation Inflection Point (DIP)***	***Technology Infrastructure (TI)***	***Big Data Analytics (BDA)***	Insight begins with appropriate questions
√	√		√				Types of analytics
√	√		√				Big Data Analytics (BDA) needs to be relevant
√	√	√	√				The future of Big Data is the availability of analytical skills, not technology
√	√		√				Wasted opportunity to gain insight from Big Data
√	√	√	√			***Characteristics of Big Data (CoBD)***	Availability of, and access to, Big Data
√	√		√				Big Data is a headache
√	√		√				Vast amounts of knowledge are derived from Big Data
√	√	√	√				Data silos
√	√	√	√				Multiple data sources
√	√	√	√				Time Value of Big Data - velocity
√	√		√				Variety is key to completing the picture
√	√	√	√				Veracity of Big Data
√	√		√				Volume
√		√	√		***The Habitus (TH)***	***Individual differences***	Education
√		√	√				Experience
√			√				Historical implications
√		√	√				Individual's culture
√		√				***Workforce generations***	Generational issues
√		√	√				Newer generations forcing change
√	√	√	√			***KW's ability***	Skills
√	√	√	√				Power lies in the skill to analyse and interpret Big Data
√		√	√				Decision-making abilities
√		√	√			***Characteristics of decision-makers (CoDM)***	Decision-makers and empowerment
√		√	√				Effective decision-makers communicate
√		√	√				Decision-makers rely on competent people
√			√				Risk-averseness
√	√	√	√				Power centres rely on summary of information
√	√	√	√				Participation of people: Perceived enablers and constraints
√		√	√		***The Organisation (TO)***	***Organisational culture***	Collaboration is key to producing insight
√			√				Transparency
√			√				Freedom to contribute
√			√				Communication
√			√				Values
√		√	√			***Managing the business***	Business processes
√		√	√				Controlling risks
√		√	√				Financial constraints
√		√	√				Resource constraints
√	√	√	√			***Reliance on Big Data***	Access to Big Data improves productivity
√	√	√	√				Big Data is critical to CSA's decision-making
√	√		√				Big Data use leads to competitive advantage
√	√	√	√		***Decision-making entity (DME)***	***Legacy***	Big Data influences the transformation of traditional DM processes
√	√	√	√				Pace of transformation
√	√	√	√				New technologies not as reliable as legacy systems
√	√	√	√			***Decision-making capability (DMC)***	Big Data Analytics (BDA) supports decision-making
√	√	√	√				Big Data Analytics (BDA) supports agile decision-making
√	√	√	√				Decision-making based on trends and best practices
√	√	√	√				Quality of Big Data-driven decision-making
√	√	√	√				Decision-making is context-driven
√	√	√	√				Trust is vital to DDD
√	√	√	√				Insights-driven decision-making
√	√	√	√				Decision-making based on intuition
√	√	√	√			***Decision-making structures (DMS)***	Death by consensus
√	√	√	√				Evolution of decision-making processes
√	√	√	√				Organisational configuration and decision-making processes
√	√	√	√				Big Data promotes accountability
√	√	√	√				Decision-making is authoritarian
√	√	√	√				Governance and compliance policies affect power centres
√	√	√	√				Evolution of power centres

Table 51: Research questions, coding and categorisation results

8.3. DETAILS OF PARTICIPANTS

Participant Code	Population Group	Gender	Age	Generation	Role/ Responsibility
CSA#01	Coloured	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#03	White	Male	30-40	Gen Y-Millennial	Manager
CSA#05	Indian	Male	30-40	Gen Y-Millennial	Manager
CSA#06	Coloured	Female	30-40	Gen Y-Millennial	Manager
CSA#07	Coloured	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#08	Coloured	Female	20-30	Gen Y-Millennial	Non-Manager
CSA#09	Coloured	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#10	Indian	Male	20-30	Gen Y-Millennial	Manager
CSA#11	Coloured	Male	50-60	Gen X	Non-Manager
CSA#12	Indian	Female	20-30	Gen Y-Millennial	Manager
CSA#13	Black	Male	40-50	Gen X	Non-Manager
CSA#14	White	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#15	Coloured	Female	40-50	Gen X	Manager
CSA#16	Coloured	Male	40-50	Gen X	Manager
CSA#17	Coloured	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#18	Coloured	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#19	Coloured	Male	50-60	Gen X	Non-Manager
CSA#20	White	Female	50-60	Baby Boomer	Manager
CSA#21	White	Female	50-60	Baby Boomer	Manager
CSA#22	Coloured	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#23	Coloured	Female	40-50	Gen X	Manager
CSA#24	White	Female	40-50	Gen X	Non-Manager
CSA#25	Coloured	Female	30-40	Gen Y-Millennial	Manager
CSA#26	Coloured	Male	30-40	Gen Y-Millennial	Manager
CSA#27	Coloured	Male	20-30	Gen Y-Millennial	Non-Manager
CSA#28	Coloured	Female	40-50	Gen X	Manager
CSA#29	Black	Male	20-30	Gen Y-Millennial	Manager
CSA#30	Black	Male	20-30	Gen Y-Millennial	Non-Manager
CSA#31	Black	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#32	White	Male	50-60	Gen X	Manager
CSA#33	Coloured	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#34	Black	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#35	Coloured	Female	40-50	Gen X	Manager
CSA#36	Black	Female	30-40	Gen Y-Millennial	Manager
CSA#37	Black	Male	30-40	Gen Y-Millennial	Manager
CSA#38	Black	Female	30-40	Gen Y-Millennial	Non-Manager
CSA#39	Coloured	Male	40-50	Gen X	Non-Manager
CSA#40	Black	Male	40-50	Gen X	Non-Manager
CSA#41	White	Male	40-50	Gen X	Non-Manager
CSA#42	Indian	Male	40-50	Gen X	Non-Manager
CSA#43	White	Female	30-40	Gen Y-Millennial	Manager

Table 52: Participant list

8.4. Interview Questions and Interview template document

<u>Research Project Interview Questions</u>

Student Name: Ishmael Hassa

Student No: hssish001

Research Title: The influence of Big Data on the democratisation of data-driven decision-making in organisations in South Africa

Main Research Question: How does Big Data influence democratisation of data-driven decision-making in organisations in South Africa?

Demographic Questions:

1. What is your name?
2. What is your job title, role and responsibilities?
3. Are you a manager or individual contributor?
4. How long have you been in this role?
5. How many years are you with the company?
6. Where do you fit within the hierarchy of the organisation?
7. What tools and applications do you use in your job?
    a. Describe the sources you use.
    b. How do you get access to these data sources?
    c. Are there other tools and applications that help you do your job?

Harmonisation Questions:

1. What do you understand by the concept of Big Data?
    a. What are some of the characteristics of Big Data?

2. What does Big Data mean to you?

3. What does Big Data mean to your organisation?

<u>Start Recording</u>

I'm speaking to: ____

A. Guidelines used for interview based on research questions (note: turn it into a discussion)

B. Clarification Questions:

1. What role does culture, tradition, religion, education and age play in decision-making?

2. Do different generations make DDD differently? What makes you say that?

3. [culture, values,] How does CSA engage with employees.

4. How does CSA drive employee behaviour?

5. What role does politics, regulation, society and economics play in data-driven decision-making?

6. [Collaboration] – If democratisation in data-driven decision-making was a puzzle, what would be the key pieces?

7. [Transformation] - Has CSA transformed/Is CSA transforming? Why/What makes you say that?

8. [Markeplace] What is CSA's highest priority?

C. CSA Specific Questions

1. How does CSA improve?

2. How does CSA unlock blockages?

3. Is the environment changing to one where blockages/obstacles are easier to overcome?

4. In light of Big Data, do you feel your value has increased or decreased, why?

5. Is the data sufficient to make you successful?

Conclusion:

Do you have anything else you would like to mention, clarify or discuss?

Should I need to clarify anything after the data analysis, could I get back to you?

8.5. COMPANY INVITATION LETTER

Department of Information Systems
Faculty of Commerce
University of Cape Town, Private Bag 7701, Rondebosch, Western Cape, South Africa
4th Floor, Leslie Commerce Building, Engineering Mall, Upper Campus,
Tel: +27 (0) 21 650 2261 Fax: +27 (0) 21 650 4369
E-mail: linda.magodla@uct.ac.za (general enquiries)
Internet: http://www.commerce.uct.ac.za/InformationSystems/

REQUEST FOR PERMISSION TO CONDUCT RESEARCH AT YOUR COMPANY

Dear XXX

I am a doctoral student in Information Systems at the University of Cape Town. The research I wish to conduct for my thesis is entitled: **"The influence of Big Data on the democratisation of data-driven decision-making in organisations in South Africa"**. The purpose of this study is to better understand how Big Data influences organisational data-driven decision-making processes taking into consideration internal & external dynamics, the workforce and decision-making structures. This project will be conducted under the supervision of Associate Professor Maureen Tanner and Professor Irwin Brown (UCT, South Africa).

I am hereby kindly requesting your consent to carry out a case study within your organisation. The methodological approach will be to interview participants who would like to be part of the research study, in person. Questions regarding the company's Big Data and decision-making strategy would be posed to the research participants. The interviews will take approximately 60 minutes to complete. The nature of this type of research study is that follow up interviews may be required to verify and validate the research results. To improve the validity of the research results I would also like to include possible secondary data sources like decision-making processes or archival information.

The information obtained through the interviews and secondary data sources will be treated with the strictest confidence and the identity of the organisation and participants will be kept anonymous. The resulting framework will be reported at an aggregated level to further protect the identity of organisations and participants. Participation in this research is also completely voluntary. Participants could choose not to answer any question as well as to withdraw from the research at any time.

It is our hope that this information can be used to create organisational awareness and effectiveness of data-driven decision-making in relation to Big Data and importantly to the evolving workplace and workforce that are driven by "instant gratification" and transparency in how they approach their roles and responsibilities. The research results will provide an opportunity for your organisation to visit the key concepts that are identified and address those as the organisation sees fit.

Upon completion of the study, an executive summary of the research findings will be provided to your company which could be added to the company's knowledge library and could add future business value when revisiting the company's strategy linked to the use of Big Data in data-driven decision-making. If you require any further information, please do not hesitate to contact me on hssish001@myuct.ac.za.

Thank you for your time and consideration in this matter. Your assistance is greatly appreciated. Your signature below indicates that you have read the above information, understand the nature of the study being planned and give your permission for the research to be conducted at the site.

Yours sincerely, Ishmael Hassa (mobile no. 0742262222)

University of Cape Town

Supervisors: Associate Professor MC Tanner and Professor Irwin Brown

Company Representative (Print Name):

Date: 23.10.2018

8.6. PARTICIPANT INVITATION LETTER

Department of Information Systems
Faculty of Commerce
University of Cape Town, Private Bag 7701, Rondebosch, Western Cape, South Africa
4th Floor, Leslie Commerce Building, Engineering Mall, Upper Campus,
Tel: +27 (0) 21 650 2261 Fax: +27 (0) 21 650 4369
E-mail: linda.magodla@uct.ac.za (general enquiries)
Internet: http://www.commerce.uct.ac.za/InformationSystems/

Participant permission request letter

Dear research participant;

I am a doctoral student in Information Systems at the University of Cape Town. The research I wish to conduct for my thesis is entitled: **"The influence of Big Data on the democratisation of data-driven decision-making in organisations in South Africa"**. The purpose of this study is to better understand how Big Data influences organisational data-driven decision-making processes taking into consideration internal & external dynamics, the workforce and decision-making structures. This project will be conducted under the supervision of Associate Professor Maureen Tanner and Professor Irwin Brown (UCT, South Africa).

I am hereby kindly requesting your participation in the case study currently being conducted within the organisation. Based on your convenience, an interview session will be arranged on receiving your willingness to participate in the research study. In the interview session, a few questions regarding the company's Big Data and decision-making strategy would be posed and the interview will take approximately 60 minutes to complete.

The information obtained through the interview will be treated with the strictest confidence and the identity of the participant will be kept anonymous. The resulting framework will be reported at an aggregated level to further protect the identity of all the participants. Participation in this research is also completely voluntary. Participants could choose not to answer any question as well as to withdraw from the research at any time. It is our hope that this information can be used to create organisational awareness and effectiveness of data-driven decision-making in relation to Big Data and importantly to the evolving workplace and workforce that are driven by "instant gratification" and transparency in how they approach their roles and responsibilities. The research results will provide an opportunity for your organisation to visit the key concepts that are identified and address those as the organisation sees fit.

Upon completion of the study, an executive summary of the research findings will be provided to your company which could be added to the company's knowledge library and could add future business value when revisiting the company's strategy linked to the use of Big Data in data-driven decision-making. If you require any further information, please do not hesitate to contact me on hssish001@myuct.ac.za.

Thank you for your time and consideration in this matter. Your assistance is greatly appreciated. Your name below indicates that you have read the above information, understand the nature of the study being planned and you agree to participate in the study.

Yours sincerely, Ishmael Hassa (mobile no.: 0742262222)

University of Cape Town

Participant Printed Name:

Consent form

I, ____________________________________, consent to participate and be interviewed for the purpose of this research study.
I am aware that participation is voluntary and that I may choose to withdraw from this study at any time if I so wish.

__________________________ Signature

__________________________ Date

8.7. UCT ETHICS APPROVAL LETTER

Faculty of Commerce
Private Bag X3, Rondebosch, 7701
2.26 Leslie Commerce Building, Upper Campus
Tel: +27 (0) 21 650 4375/ 5748 Fax: +27 (0) 21 650 4369
E-mail: com-faculty@uct.ac.za
Internet: www.uct.ac.za
@Commerce UCT **UCT Commerce Faculty Office**

15th November 2019

Mr Ishmael Hassa
Department of Information Systems
University of Cape Town

Dear Mr Hassa

REF: REC 2019/10/067

THE INFLUENCE OF BIG DATA ON DEMOCRATISATION OF DATA-DRIVEN DECISION-MAKING IN A FINANCIAL SERVICES ORGANISATION IN SOUTH AFRICA

We are pleased to inform you that your ethics application has been approved. Unless otherwise specified this ethical clearance is valid for 1 year and may be renewed upon application.

Please be aware that you need to notify the Ethics Committee immediately should any aspect of your study regarding the engagement with participants as approved in this application, change. This may include aspects such as changes to the research design, questionnaires, or choice of participants.

The ongoing ethical conduct throughout the duration of the study remains the responsibility of the principal investigator.

We wish you well for your research.

Shandre Swain
Administrative Assistant
University of Cape Town
Commerce Faculty Office
Room 2.26 | Leslie Commerce Building

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9. ADDITIONAL SUPPORTING EVIDENCE

9.1. OPEN CODING

9.1.1.1. [DIP[33]-TI-BDA[34]] Insight begins with good questions

a) Information – reports and reporting

EFQ236. We make sure that data is accurate. So, if I think of monthly reporting or daily reporting that we do, the data that we finalize and report on it, helps management see what is working, what is not working and where do we need to improve" CSA#07.

b) Adding insight to information

EFQ237. "To our department, it means collating and analysing of information at your fingertips and making recommendations to others" (CSA#19).

EFQ238. "It is what allows me to understand the evolution that took place in my space, it allows me to understand things, to analyze things better, to improve processes, by collecting volumes of data I can understand things and basically make better contributions in my space" (CSA#27).

EFQ239. "I'll be able to measure month by month, day to day, hour by hour, second to second and then in that way we are able to then pick up spikes or pick up no signs of progress and things like that. That for me is a big thing" CSA#22.

9.1.1.2. [DIP-TI-BDA] Types of analytics

[33] DIP - Democratisation Inflection Point

[34] BDA - Big Data Analytics

a) Descriptive analytics describes what happened

EFQ240. "If you look at any decision that you make, you need to understand the trends to see what's going on. Historical data actually tells you that. It is mostly the influencing factor when you are making a decision" CSA#12.

EFQ241. "I think it just tells you where you are at the moment. What you're doing well. What you're not doing well" CSA#05.

b) Predictive Analytics facilitates operationalisation of historical learnings

EFQ242. "Knowing what the users want so you pick up the trends, the focus, be ahead of the curve so you' re not always waiting for somebody to complain or react so you' re trying to be ahead of things by analysing on your facts" CSA#17.

EFQ243. "We want to be like retail and already be prepared for it. A classic example is things like Black Friday, the first time you probably didn't know what is going to happen. But the third time now you can start creating a trend and you already understand, we're going to do this to either make more sales or reduce issues" CSA#04.

c) Multidimensional Analysis – looking at data from many angles

EFQ244. First I'd need to do a bit of trend analysis and see what I'm picking up from the trend analysis and then also maybe to have like my own sample of people to interview just to see if the data aligns. Almost like a sense check, to say the data does align to what I'm getting as feedback" CSA#12.

9.1.1.3. [DIP-TI-BDA] Big Data analysis needs to be relevant

EFQ245. I'm sure most of these reports that actually gets sent to everyone it doesn't actually add value. So, I think we spend a lot of time doing this stuff that adds no value at the end of the day" CSA#05.

EFQ246. "Something that is relevant for me or not relevant for me might be very relevant for the technician on the floor that needs to do certain things or the hands-on facilities manager that reports to me" CSA#16.

9.1.1.4. [DIP-TI-BDA] Future of Big Data is analysis, not technology

EFQ247. Companies they don't need on-premises technical guys looking at this thing because even those systems are now going to the cloud. Even your DBA [database administrator] looking at this chunk of tin in on-premises, it's going to be an analytical DBA who is looking at this interface and scaling up, scaling down or deploying a system that's cloud-based, probably not even in the country" CSA#04.

EFQ248. "Data analytics are now more available to help you analyse, to see the insight into the data" CSA#09.

9.1.2. Open codes related to characteristics

a) Access to Big Data

EFQ249. "Sometimes you find there is data that you think you could use to the good of growing yourself, but you find that some of that data is not available for you to use. Department politics is real" CSA#36.

9.1.2.1. [DIP-TI-CoBD] BIG Data contains a vast amount of knowledge

9.1.2.2. [DIP-TI-CoBD] Data silos

EFQ250. "Analysis of data is happening, I guess, in different pockets, in different disparate units within the entire organisation" CSA#32.

EFQ251. "Our dream for Big Data and CSA transformation, I think access to one consolidated system" CSA#12.

EFQ252. "Linking of data from one to another becomes difficult because everything is linked to everything and creating that link becomes a hassle" CSA#10.

EFQ253. Of most importance to achieving "one data" is to first understand what is going on in finest of details before power can be turned off to ICT assets and business processes modified.

9.1.2.3. [DIP-TI-CoBD] Multiple data sources

EFQ254. Basically what we'll do is pool data into a staging environment and that would be a subset of what we are basically looking for from these different sources. Data warehouse's got all the business rules embedded in there and what it'll do is basically take a subset of the data from the different sources and it will pre-populate that in a data mart for reporting etc." CSA#03.

EFQ255. "Now you have to look at financial data as well to make sure that you're managing things appropriately. I mean, there's markers everywhere" CSA#16.

9.1.2.4. [DIP-TI-CoBD] Variety is key to completing the picture

EFQ256. We use like Department of Home Affairs websites as well for various reasons.

EFQ257. So, there are lots of different types of structured data, unstructured data. We have to look at all to be competitive" CSA#08

EFQ258. "Positives are definitely the fact that there's such a big variety of data. It comes from everywhere" CSA#07.

EFQ259. Several factors emerged from discussions with CSA participants around 'variety' as a characteristic of Big Data.

EFQ260. "When you talk about Big Data you are talking about the big picture" CSA#15.

EFQ261. In my space, the financial data is obviously one because you always looking to either save money somewhere. That's a big thing but I look at the quality [of data] first, which is back to the service that is provided, which we don't mind paying for it so financial participation has to be matched by delivery. But you need to monitor it [data quality] to provide knowledge to others" CSA#26.

EFQ262. "Company wise when you sure of the data you must make sure that the way you get data it's user-friendly and it avoids a lot of mistakes. For example, you can ask the people to type the information via specific software so that you don't re-type the information to avoid misprinting or misunderstanding. We found this minimized the errors" CSA#30.

a) Awareness of veracity aspects of Big Data

EFQ263. "You trust the data depends on what type of data it is. The type of data source, so where it's coming from" CSA#14.

EFQ264. Of course. Not really trust but I have faith in it that it might not be harmful" CSA#30.

EFQ265. My trust is based on myself. Trusting in myself is can I get it done? When am I going to get it done? How long is it going to take me to get it done? Am I committed to doing this? That is it" CSA#22.

EFQ266. "No, I don't think I can give you a definitive answer because there is a level of trust in both that can be influenced. So, you cannot trust the one more than the other or only trust one or *the other. I think in the world that we live in we' ve become so accustomed to living in harmony or being available simultaneously, people and data, data and people. People providing data, data informing people" CSA#23.*

EFQ267. I think we should go back to the old days where it was more satisfied people, people' s minds weren' t all over the place because of data. Because of the speed of the world, it will never go back to that" CSA#24.

9.1.2.5. [DIP-TI-CoBD] Volume

EFQ268. "Volume is volume. But, how much of it is relevant versus irrelevant" CSA#05.

EFQ269. "Its all the stuff happening around us" CSA#14.

EFQ270. "My understanding of Big Data is the numerous information that we as people and organisations are exposed to which unfortunately we cannot control, how it happens, what happens, you just need to respond" CSA#13.

EFQ271. "I mean just that it's anything and everything, it's everything digital, its interesting" CSA#09.

9.1.2.6. [DIP-TI-CoBD] Wasted opportunity to gain insight from Big Data

EFQ272. "And as much as we like your Facebooks and all of that plays into considerations, but when some of the decisions are made, I just feel we not where we should be as a company when it comes to our data and also utilising the tools that we have in order to make sure that we stay relevant in this field. So, I could say that those are the barriers that don' t allow us to use our data to the maximum that we should be" CSA#36.

9.1.3. Open codes related to individual differences

9.1.3.1. [DIP-TH-INDIVIDUAL DIFFERENCES] Education

EFQ273. "I want to consider education as being a factor in terms of whether people are likely to trust what they understand more. But then it could go the other way in that if they understand more about the way things work, then they question more or are less trusting. I guess education works both ways" CSA#09.

9.1.3.2. [DIP-TH-INDIVIDUAL DIFFERENCES] Experience

EFQ274. "I go on the knowledge that I've got in my head from my experiences and what I think is best for the company and where I know the company wants to go" CSA#21.

9.1.3.3. [DIP-TH-INDIVIDUAL DIFFERENCES] Historical implications

EFQ275. "

EFQ276. "When I started [12 years ago] you could sense the culture into the business. It was almost, I don't want to bring race into it, but there was a bit of that [race related issues]. In the end, I see the shift happening now" CSA#05.

EFQ277. "Everybody has different experiences in their life journey. We are here now but we didn't come from the same place" CSA#37.

9.1.3.4. [DIP-TH-INDIVIDUAL DIFFERENCES] Individual's culture

EFQ278. "In order to make sure that we are doing what needs to be done. And sometimes you find it is not a good decision you are making for the person, but it is a good decision that you are making for the business. It is a conflicting thing because obviously, it is the business, it is the other party and it is you. And especially when it comes to religion, we got this belief "that do unto others as you would like to be done unto you" CSA#36.

EFQ279. "Being a [religious belief], I think we need to look after our environment. God grants us this planet. I find great joy in knowing that I've made a small change environmentally [eco-friendly property] so that at least I've shifted us in a better position" CSA#16.

a) Decision-making and culture connection

EFQ280. "From traditional, I think it plays a good role. To know where you come from because we only know that this after being an adult, like what decision to make when you have five or six [options]. There's no decision that you can make or do stuff without your parents" CSA#29.

EFQ281. "In our culture, decisions made on principle and "what will people say?". Community before individual" CSA#38.

9.1.4. Open codes related to workforce generations

9.1.4.1. [DIP-TH-WORKFORCE GENERATIONS] Generational issues

EFQ282. "So, I don't need to be sitting here and watching you for eight hours in the day, because I can use my reports to check your production. To check that you've done what you're supposed to be doing for the day. So I think how we manage is different from that point of view" CSA#12.

EFQ283. "So, changing the mind-set [of older generations] is very difficult. They need to realise times have changed and we are now gaining technologies and is improving all the time. But they have got a discipline, a very discipline when it comes to behaviour and adherence you know" CSA#35.

EFQ284. "So, whereas they [millennials] tend to speak like they're on Twitter or on WhatsApp or whatever so that comes out in their writing style. But so there's still a level or corporate etiquette that must be maintained so often I think they struggle with that divide more than what the older folk do" CSA#19.

EFQ285. "But the older generation morals and values are better. You know but I find that the older generation morals and values are really old school, more disciplined. Where the younger generations speak their mind and it doesn't matter who you are, they would just say whatever they want" CSA#35.

EFQ286. "Attention span is limited. They [younger generations] want quick fixes. You have to think of different ways to communicate with them" CSA#16.

EFQ287. Where I sit, where the generational gaps are, it's a bit in the middle of where ridiculous demand is and where people still want to go paper, old route. It's difficult when you are dealing with a young client or you've got an old client. That always determines how things are going to go. We're either going to have a quick process or we're going to have somebody that's been here for 40 years and does things a certain way and I want to do it this way, then it takes months to get done" CSA#18.

9.1.4.2. [DIP-TH-WORKFORCE GENERATIONS] Newer generations forcing change

EFQ288. "Social media is a part of me" CSA#08.

EFQ289. "Age is very important because we are evolving with time and the younger generation is a lot more tech-savvy, and that is the way we are going" CSA#35.

EFQ290. "With the new generation, it is a case of always try and find better ways of doing something. They are more innovative" CSA#35.

EFQ291. "That generation is sitting with a hand-held device and live off the internet. Sending emails in my time would be, maybe, the advanced way of communicating with people. These days it is WhatsApp, Instagram, or immediate photographs being taken. The new generation is looking for a single source of data as well" CS#16.

EFQ292. "My generation, I'm almost 40 years old, we'd be able to sit down, read a book, read an article, [...]. Whereas, the new generation has a very short attention span. If they don't find stimulation within a short time you've lost them immediately" CSA#16.

EFQ293. "We want more now and don't want to wait and that's our generation, the younger we are the faster we want things. We don't want to wait. That push is coming right through and that's why we've got to do things faster. We've got to be more agile. You got to think on your feet and that's becoming more and more normal" CSA#18.

9.1.5. Open codes related to KW's ability

9.1.5.1. [DIP-TH-KW's ABILITY] Power lies in Big Data analysis and interpretation

EFQ294. *"For example, if you look at the Big Data, the most important thing about the Big Data is to clean it so that you can get the information that you're looking for. Me and you can use the same data but depending on cleaning you might get different results" CSA#30.*

EFQ295. *"It's more understanding the data because you will have all of this information at your fingertips, but now the interpretation of that data and then obviously applying it is everything" CSA#08.*

a) Effective Power Lies in Value Creation through reliable analysis and interpretation of Big Data

EFQ296. *"I understand the data, because people looking at data might not always understand what they are looking at. They just get told what to do but if you understand what you are looking at, that adds value and you are able to provide more. You are able to provide value to others as well which makes you valuable" CSA#15.*

9.1.5.2. [DIP-TH-KW's ABILITY] Ability to make decisions

EFQ297. *"Not everyone is a subject matter expert. On all subject matters, knowing a little bit about everything in order to understand the dependency on everything and to know the impact is better in decision-making. So, knowledgeable on one subject matter or expert, it's not the best decision-maker" CSA#10.*

EFQ298. *"You know if you are dealing with a person that is not necessarily the right fit. One that does struggle to actually consume that data effectively and play it back and make, and extract the full benefit of that data" CSA#32.*

9.1.6. Open codes related to characteristics of decision-makers

9.1.6.1. [DIP-TH-CoDM[35]] Decision-makers and empowerment

EFQ299. "They must create an environment that allows growth and development. They must create an environment where there's openness and transparency" CSA#19.

9.1.6.2. [DIP-TH-CoDM] Effective Decision-makers communicate

EFQ300. "I think that sometimes the management needs to engage more with role players in all areas to see is this going to be a good decision" CSA#11.

EFQ301. "So currently we are told what to report on and how to report on it. Sometimes I maybe have other ideas on how it can be reported on. So, using the same data but just report on it differently. So, they need to listen to their professionals and their specialists because maybe someone has a better idea and can bring that forward" CSA#15.

EFQ302. "And I asked what are the options that we have? Why are we not doing this? And why are we not doing that? Or could we do this?" SA#06.

9.1.6.3. [DIP-TH-CoDM] Decision-makers rely on good people

EFQ303. "I believe a good boss is a guy that doesn't necessarily have the knowledge. But he basically arms himself with the knowledge of people that he employs to be able to give him that knowledge for him to make the right decision" CSA#32

EFQ304. "You need to involve yourself with experts. According to Steve Jobs, "we don't hire smart people to tell them what to do; we hire smart people so that they can tell us what to do " CSA#16.

[35] Characteristics of Decision-makers

EFQ305. "You have to accept that as a senior person that you actually have to trust that the person's expertise is what you are actually employing them for. And it doesn't diminish your authority if I can say so" CSA#16.

EFQ306. "It's nice to have a team of people you can clarify and get information from before you make a final decision and the resources available in terms of being able to do your job or getting a message across" CSA#24.

EFQ307. "They [management] understand what they want and they'll understand that someone else will understand it and then they'll get that person to actually work on it and decipher it and then give them the information, the results and then they make a decision" CSA#23.

9.1.6.4. [DIP-TH-CoDM] Risk-averseness

EFQ308. "Let's say the manager is not there, obviously depending on the impact of the risk, you need to make a decision in order to get the job done and so you need to just go with your gut and make a call" CSA#25.

EFQ309. "Some people use this more than others to make decisions because they are comfortable with risk. They're comfortable with taking ownership. Others aren't and I'm not going to hold it against you because you don't make a decision" CSA#10.

EFQ310. "So in the environment that we find ourselves in, there are lots of risk factors that we need to take into consideration. So its health and safety regulations, from a contractual perspective there's the legal, there are reputational risks. Who is it going to impact? How is it going to impact? " CSA#25.

EFQ311. "If it's something legislative that I need to comply with. Obviously, the risk appetite is much lower. I would then sway more towards using fact, evidence, data in order to come to a conclusion because I can back it up. In my job, dealing with customers, dealing with employees, I use gut, evidence, depending on the risk level" CSA#28.

9.1.6.5. [DIP-TH-CoDM] Power Centres rely on the summary of information

EFQ312. So, you know you quite often find when you have a hierarchy, that it is an Exec that makes the decision, but they might not have had sight of the data that you hold. And so, your decision might be in conflict with the decisions they make" CSA#12.

EFQ313. "I think not everyone has access to the same information. Not everyone has time to drill down into the information in the same manner as I would. And I think we also struggle with how we convey a message using data in that we are away from the actual decision" CSA#12.

EFQ314. "I think it helps to make decisions without actually diving into detail or without exactly understanding how things work or how processes work. So they're [management] able to make decisions without actually understanding how things work" CSA#12.

9.1.7. Open codes related to participation of people

9.1.7.1. [DIP-TH-PARTICIPATION OF PEOPLE] Perceived enablers and constraints

a) Perceived enablers

EFQ315. "I can look at the things around me that can either restrict or hinder me but it starts with me as an individual which is key. So firstly, I'm the one that makes that initial decision or sees what's going on around me and decide whether, from an emotional point of view or just the analytical point of view, I need to make a decision" CSA#39.

EFQ316. "I'm a very firm believer in everything lies with the individual. I do believe there is some degree of influence that an individual has over; regardless of what the role is, you as the individual have that ability or that mandate to use Big Data to an extreme extent in terms of getting things done if you want to empower yourself" CSA#37.

EFQ317. "Collaborative information, your collaborative decision-making basically. What's that saying, are you autocratic or democratic in the way you make a decision. You sit around the table with your team and discuss it. Leverage off everybody's experiences and make a much more *informed decision because one person who's looking at a set of data will not necessarily absorb everything. You sit in a room and you workshop it if I could say so" CSA#16.*

EFQ318. "I think of it [democratisation] in simple ways and that would be getting input from the different players to get an end result. It's getting the input from the employees to feedback to management and fulfil my job" CSA#21.

EFQ319. It comes with the ability and the flexibility of me working within the industry and having the right tools. For example, the things that I need to extract my data, the software package, the flexibility that I can go around and ask other people freely for advice" CSA#30.

EFQ320. "It's [democratisation] more about making decisions based on how it's going to affect people. It's event-driven based on making a decision based on a particular event at that particular time" CSA#29.

EFQ321. "So what helps is again, is ease of access to information. What retards is if you have all that information, but you're not empowered to make a decision" CSA#19.

EFQ322. "I probably would lean towards the way the organisation is moving is that it's changing the culture where people are empowered to make decisions so you're eliminating the whole bureaucracy" CSA#19.

EFQ323. "I think it helps if you have the right tools and if you have the appropriate knowledge. Without those two things, I think it's going to be really difficult and I think your understanding of something, leads to wanting to be involved in decision-making" CSA#14.

EFQ324. "Empowerment, granting access and tools provided in order for me to fulfil my job to do what's there what I need to do or to satisfy the broker or the caller" CSA#31.

b) Perceived constraints

EFQ325. "I think there is also a lot of empowerment that took place. They allow you to make decisions based on the data but I think there is a missing portion, I wonder if there is a confidence issue. The company having confidence in you or you having confidence in yourself. You having *confidence in yourself taking those decisions. Many years ago it will be only the bosses taking decisions but now that you sit with this wall of data in front of you, you cannot do all those decisions on your own so people on lower levels need now to also take these data and call some shots here" CSA#20.*

EFQ326. "There are also policies and guidelines and people that uphold these, like risk officers and checks and balances in the system that sort of are there to police and control who has access to what. All of these sort of second-level checks, next level signing, it is democracy basically that is sort of in place but at the same time with assurances. CSA will not budge but you can effectively do things as you want but within the boundaries" CSA#32.

9.1.8. Open codes related to Organisational culture

9.1.8.1. [DIP-TO-ORGANISATIONAL CULTURE] Freedom to contribute

EFQ327. "CSA had a competition to gather ideas. The thing is those are big ideas. They need to be able to listen to the smaller ideas because I think they all add value" CSA#15.

EFQ328. "What ideas do you have and just open it up and you know people mustn't be afraid to talk about it or say what they feel. If they think that something will work better a certain way, they must come forward and give their input" CSA#15.

EFQ329. "People are expecting step by step instructions rather than taking initiative"

9.1.8.2. [DIP-TO-ORGANISATIONAL CULTURE] Communication

EFQ330. "I think to speak more to the people that are actually doing the actual work, that's actually being exposed to the operational side of things to help them understand what the needs are and to act quickly and you know to be this agile organisation that they want us to be" CSA#25.

EFQ331. "Half the time we don't know why a decision is made" CSA#28.

EFQ332. "Currently there is an open-door policy with management that is so critical because of the way a call centre functions you know you need things to happen very quickly and you need *to have that constant flow of information on all levels. If there' s a bit of a block, it delays not just a problem from being solved but it delays growth in the business and with the open door policy you can actually see the results of it" CSA#39.*

9.1.8.3. [DIP-TO-ORGANISATIONAL CULTURE] Values

EFQ333. "Also, with the change, older baby boomers are very resistant to quick change because they're used to "I go work for a company for 40 years". Whereas the younger generation, I don' t like what I see here I'll just go to the next one and the next one. There's no like loyalty in your organisation, they'll just move on" CSA#18.

9.1.9. Open codes related to managing the business

9.1.9.1. [DIP-TO-MANAGING THE BUSINESS] Controlling risks

a) The internet, social media, and other media outlets

EFQ334. "People when they are not happy, they go on Facebook or if they are happy they express on Facebook which is data, and people that have never heard of CSA, now they get to know of CSA through data" CSA#36.

EFQ335. "On social media, they can portray your company in a bad light and other people also have access to that and so we know that when people are unhappy then they tell a lot more people than when they are happy and decision-making can happen a lot quicker" CSA#19.

EFQ336. "I mean people when they are not happy, they go on Facebook and people that have never heard of CSA, now they get to know of CSA through data" CSA#36.

b) Data Security

EFQ337. To be honest with you, you have your mobile phone with complete internet access on it and this your Big Data as well. So it is hard for the security team, as much as they'd like to control it, they can't control your world, which is the phone. So, they really good at controlling this world *because all they can do is lockdown with a firewall. But this the reality. And you have access to everything, without firewalls" CSA#08.*

EFQ338. "To our organisation, it [Big Data] means collating and analysing of information at your fingertips. That's the good. [But] it also means there have to be secure features to protect the personal information of staff or the organisation. I think probably the most important one is protecting the personal information of clients' confidentiality" CSA#19.

EFQ339. "From a work perspective, it forces you to be careful so that you don't access sites that might be harmful or allows you to be hacked or infiltrated or allows you to give away a secret or confidential information" CSA#19.

c) Managing Access

EFQ340. In a highly meshed environment such as CSA, ICT service management faces major challenges not only in linking ICT assets but discovering access control privileges that have managed to slip through […]" CSA#09.

EFQ341. We are getting [data] feeds from 65 different data sources, normalising to understand everything about the data and how it's linked to each other. So, services links to databases links to switches links to networks links to applications links to people link to cost centres links to the total cost of ownership links to security management. This what we try to understand. So we've moved on from the day when one server had one application. Now one server has 1,000 databases linked to 1,000 applications. Someone having admin rights to one server before as the person who initially bought the server without asking for permission is given admin rights to everything" CSA#10.

d) Corporate Governance

EFQ342. "If there are no policies and laws in place governing the use of this data, a lot of bad can happen. But, there has to be a mid-point where it's not so restrictive. We have to find that" CSA#41.

EFQ343. "It's easier to be in control because you have the data at hand and always working to make it better. Simple tools are needed to analyse data, mitigate risks, and plan proactively by thinking a few steps forward to predict further down" CSA#26.

e) External Influencing Factors

EFQ344. "The completeness and conformance to governance processes place the largest burden on ICT assets in the organisation" (CSA#43).

EFQ345. "There's constant political stuff that's going on that affects whether we're doing it [human capital management] for the right reasons. If I look at BEE [black economic empowerment] being one of the factors. That's an economic and a political thing. I understand it's also to better some people, but I don't think some of those people can move as fast. Maybe not everybody is embracing it as they should. That can be a bit of a drawback. An inhibiter" CSA#21.

9.1.9.2. [DIP-TO-MANAGING THE BUSINESS] Financial constraints

EFQ346. "We had a previous tool, which at the moment is the number one industry standard. But, we actually downgraded ourselves and I said downgraded you know some people might say no. But, we downgraded to this apparently number 2 tool because of cost. So, Big Data analysis was costly. I mean the previous tool but was probably a better tool. But, you know cost-wise we saving now" CSA#11.

EFQ347. "Money. I mean money and obviously costs. I mean extracting data from various sources for decision-making requires time, energy, and money. So, the extent to which you decide to do so, meaning the granularity, that also definitely plays a part in how much data you actually have at your fingertips to make decisions" CSA#09.

EFQ348. "So in my role, I would say it [Big Data] plays an instrumental part in how we run operations. If you look at things like what we measure. So in the call centre, we measure NPS [net promoter score], resolution, availability, etc. We measure the time that it takes for us to answer a *call. We measure the call parameters very well. Where we lack is looking inside the content of the call" CSA#12.*

9.1.9.3. [DIP-TO-MANAGING THE BUSINESS] Resource constraints

a) People constraints

EFQ349. "There are more resources available in terms of Big Data. I suppose it's easier, but there are fewer people to make sense of it. But, then they're introducing robots. Which is the right way, time will tell I suppose" CSA#24.

EFQ350. "The fact that they're not replacing staff, so when somebody leaves and not replace somebody, I think the bots would come in and do the job somebody else would do" CSA#24.

b) Time Constraints

EFQ351. "The problem with the data that we get though is it is raw data and working to manipulate the data takes a while. That is the only thing so the actual data itself, there is enough data but panel beating it into something you need in the end takes a bit longer" CSA#15.

9.1.10. Open codes related to reliance on Big Data

9.1.10.1. [DIP-TO-RELIANCE ON BIG DATA] Big Data use leads to competitive advantage

EFQ352. "Focus on unsolicited contributions as opposed to solicited contributions, because therein lies competitive advantage" CSA#28.

EFQ353. "CSA employs over xx% of actuaries in South Africa[36]. From that, alone you can understand they take data seriously in looking at what our markets are, what the gaps in the markets

[36] Reworded to maintain confidentiality

are. Developing new systems, tools, anything to have a competitive edge. Because the environment is quite competitive within the financial space. So, that is very important" CSA#16.

EFQ354. "Big Data means everything to us. Because of our competitive nature you need data to support yourself, otherwise you will get nowhere. So that is a tool that you cannot go without. Otherwise, it is only assumptions and assumptions will bring you nowhere" CSA#20.

9.1.11. Open codes related to Legacy

9.1.11.1. [DIP-DME-LEGACY] Big Data influences the transformation of traditional DM processes

9.1.11.2. [DIP-DME-LEGACY] Accelerate pace of transformation

EFQ355. "To stay relevant in the game of investments and all of that, that is where obviously data came in" CSA#36.

9.1.12. Open codes related to decision-making capability (DMC[37])

9.1.12.1. [DIP-DME-DMC] Agile decision-making

EFQ356. "You've got to change to a new way of making decisions. You got to work agile. If you want to do that then you've got to take those traditional ways of thinking and working it out the door" CSA#18.

EFQ357. "I do the right thing for the company and for the cause at the time. Often in my job, I have to please a customer who is maybe a bit pedantic about something. I make the decision there and then" CSA#21.

EFQ358. At the end of the day, yes, it has influenced decision-making at all levels but at the middle level; it's not as fast as you would like it to be" CSA#13.

[37] DMC – Decision-making Capability

9.1.12.2. [DIP-DME-DMC] Decision-making based on trends and best practices

EFQ359. "In the end, we go in for the best practice syndrome. So, what is the trend? What is the rest of the world doing? And we tend to do that" CSA#29.

9.1.12.3. [DIP-DME-DMC] Quality of Big Data-driven decision-making

EFQ360. I wouldn't just jump in and use it [Big Data]. You know, there are always teething problems in some things. It's always better to be a bit more cautious when you make that decision, because it gives you a bit of a buffer for error" CSA#18.

EFQ361. "How do I know it's the wrong information? And that's why I say the system should be audited. There should be a check, a control in place to ensure the data integrity. You have to ensure that what is on there is correct. I base my decisions on that and I am liable for the decision. I hesitate to make a call" CSA#22.

EFQ362. "There's a lot of misinformation everywhere. It makes us cautious, and we have to double-check everything" CSA#11.

EFQ363. Everything. I mean you cannot make these decisions without data. I do not even think you will be sitting there without data. You cannot make an instinct decision even, because you basically making it blindly. If it is less impactful, you can get away with it. But if trying to justify a contract you need to you have data, facts and prove the quality and necessary governances in place " CSA#26.

EFQ364. The quality of data is the only criteria for me making decisions. I make big [impactful] decisions. The better the quality the easier it is to absorb, the easier, no, the better the decision. I mean if you've got bad data then obviously it constrains you" CSA#16.

9.1.12.4. [DIP-DME-DMC] Decision-making is context-driven

EFQ365. "Decision-making boils down to accessing, analysing, looking at the facts, everything in context, whether it be health and safety, what's for the good of the company, the integrity, the *system, all that plays a role in quick thinking, spot-on thinking. Sometimes you make a bad decision, sometimes there's certain risks to it, but at the end of the day it's always, the method that you apply, given the context of things" CSA#17.*

EFQ366. "It was the right decision at that point in time, but later in the day, we saw that you know, it was not that way, but at that point in time at 12:00 when we made the decision it was probably the best one to make. So the point that I made, was context has an impact" CSA#06.

EFQ367. "You also have to use personal judgment in certain respects and not when necessarily making financial decisions but managing people. People are complicated, and there's no one way to deal with everyone" CSA#11.

9.1.12.5. [DIP-DME-DMC] Trust is vital to DDD

EFQ368. "It's interesting, because regardless of what industry you're sitting in, I think your raw form of data or data in its raw form is actually fairly useless. Some might prove me wrong, but that has just been generally my experience. Over time, with the ten, eleven years, we've realised that you need to massage your data to be applicable for what you want to focus on" CSA#16.

9.1.12.6. [DIP-DME-DMC] Insights-driven decision-making

EFQ369. "You will never get the approval of any big decision without having some sort of proof. So you can forget about going into an EXCO, taking a decision, without having your ducks in a row and that is based on data" CSA#20.

EFQ370. "Normally I like to research something properly before I make a decision. But, I use tools in order to make that decision, so not really applying myself" CSA#24.

EFQ371. "When you talk about Big Data you are talking about the big picture. You can make informed decisions based on the data" CSA#15.

EFQ372. "I think as you are exposed to more data and as your experience grows, that allows you to make more informed decisions, but we are not there yet" CSA#25.

9.1.12.7. [DIP-DME-DMC] Decision-making based on intuition

EFQ373. *"I would say that the focus would lean more towards your data, and if I look at people's personalities of the younger generation, I would actually think that there's a greater lean towards data influencing decisions and less of that intuition and less of that experience coming through. So, almost to shift to a clinical way of decision-making based purely on numbers" CSA#12.*

EFQ374. *"It comes down to knowledge and instinct. You produce the knowledge that resides inside you so when there is a lack of data, that is your instinct. Maybe something you think has been there forever, but it is also built on my years of experience and exposure, living. You are now able to call upon those knowledge resources and say this right or this wrong" CSA#14.*

EFQ375. *"Information that's been gathered in the past, you have that gut feeling and that is taken from past experience and information that you've gathered" CSA#24.*

EFQ376. *"The only time you don't have answers when it comes to people and emotion. So that's where you go with gut" CSA#10.*

EFQ377. *"Well, you make more decisions based on assumptions and intuition, but you want to make more decisions based on thorough analytics than own assumptions. So I think now with the Big Data spanning years, you can actually look and have a proper trend and actually be able to preempt, or shall I say forward-thinking, and say this what's most probably going to happen" CSA#03.*

9.1.13. Open codes related to Decision-making Structures (DMS[38])

9.1.13.1. [DIP-DME-DMS] Death by consensus

EFQ378. *"Too many people involved in decision-making" CSA#24.*

[38] DMS – Decision-making Structures

9.1.13.2. [DIP-DME-DMS] Evolution of Decision-making processes

a) Workflow automation

EFQ379. "Decision processes should be easy. It should not be difficult. It shouldn't be hard because we should have all the facts at hand so we need to just make it flow" CSA#22.

EFQ380. "Decision-making will follow standards, so standardisation of processes" CSA#08.

EFQ381. "We could actually automate some of those workflows and have people not have to log things from scratch" CSA#09.

b) Real-time decision-making

EFQ382. "I can't say that it will be too technical, because you still have an element of human nature in it. You know, decision making can take three days now, I think it's going to go down to one day, then here and now for the right reasons" CSA#21.

c) Automation of decision-making processes

EFQ383. "So basically the computer will spit out the results and say this what we recommend " CSA#15.

EFQ384. "I'm envisioning computers and robotics making most of the decisions" CSA#14.

EFQ385. "I think that machines are going to be making decisions for us. I heard a guy on the radio the other day saying that applications are going to be building applications" CSA#32.

EFQ386. "We bring robotics processing in, but people are starting to become robots. Because there is not that leeway for them to think out of the box and make a decision or feel confident when *they make a decision that' s not going to blow up or something is going to happen. That is why I am thinking it [decision-making] has regressed. Not intentionally but it has" CSA#28.*

9.1.13.3. [DIP-DME-DMS] Organisational configuration and decision-making processes

a) Perceived tall hierarchical decision-making chains

EFQ387. *"Cut down on wasteful decision-makers, clean up the process" CSA#22.*

EFQ388. *"It was a lot of managers that were in a senior role but that' s tapered down and streamlined in terms of giving people the opportunity in decision-making" CSA#26.*

EFQ389. *"I can see that this not working [process] and I feel that there is a better way of doing it, so take that forward to your Senior Management. Then they have to play it to their management and they take a while to come back to you. So that for me is a big constraint because who knows my business better in my team that what I do. So I should be able to implement the changes immediately" CSA#35.*

EFQ390. *"Before, one was not empowered to make decisions. Normally there was a manager who had to make a decision. They did not necessarily understand the business. Sometimes not even your manager could make a decision and then it' s got to go through so many iterations that you didn't even get to actually make a decision and somewhere in between the information got lost" CSA#19.*

EFQ391. *"Hierarchy is definitely one that has been affected by Big Data. I think that, with so much data, it has increased people's level of knowledge on certain subjects that help people grow. Also, streamline certain things to see that the hierarchy structure is no longer required or just doing more with less became so much easier if I might put it that way. And things are happening faster than you could see. Look with all this knowledge filtering through and all this information filtering through and all the data that you can draw from IT system or whether it's from a simple process make things happen quicker faster and the ability to make that decision better" CSA#26.*

9.1.13.4. [DIP-DME-DMS] Big Data promotes accountability

EFQ392. "So for me, accountability is very important. As a manager, I'm accountable for certain things but what I find is that there's not a consistent approach to hold people accountable, especially as we embrace the volumes and different sources of data. That's going to bite us if we don't put processes in place" CSA#06.

EFQ393. "I see it happening right now. Look at information. Make a decision [and] take accountability. If it is the wrong decision, we will fix it afterwards. That is how I see it. It's always adjusting" CSA#21.

9.1.13.5. [DIP-DME-DMS] Decision-making is authoritarian

EFQ394. "I think we are still sometimes sitting in an environment where you do as I say and don't ask questions in certain instances" CSA#25.

EFQ395. "They [management] are not aware of data relevance and cannot recognise the value of it. So they ignore just to be safe" CSA#32.

EFQ396. "Decisions are made for you" CSA#24.

9.1.13.6. [DIP-DME-DMS] Governance and compliance policies affect power centres

EFQ397. "Ease up on governance excuses and reasons. Collect information. Listen and then decide" CSA#27.

EFQ398. "So obviously like in the old days, the information could be hidden and now obviously there's a lot more transparency and there are obviously greater consequences and there are various statutory bodies and legal frameworks that they need to operate within, so it's not as easy as before to keep things undercover or secret" CSA#19.

EFQ399. "Decision-makers are governed by legislative parameters" CSA#33.

9.2. SELECTIVE CODING – THE MAIN ACTORS

9.2.1. [DIP] Decision-making entity (DME)

EFQ400. "Yes, it [Big Data] has made a difference because we now have to make faster, quicker decisions but still a lot of red tape. But if I need a decision now because it's business critical I can WhatsApp, phone, email and it's on hand it's available to me to get a decision. They are a lot quicker in making a decision which is necessary in today's life. Because work wants everything to be quicker paced, so their decisions need to be quicker paced as well' CSA#18.