Data-driven Organisation through the Sociomateriality Lens: Towards an Understanding of Enablers and Constraints

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Declaration

I declare that I have composed this thesis myself and that it embodies the results of my own research. Where appropriate, I have acknowledged the nature and extent of work carried out in collaboration with others included in the thesis.

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ABSTRACT

A data-driven approach has become increasingly promoted as an important goal for organisations as it provides opportunities and triggers for actions relating to performance and competition. Organisations in all sectors, including education, are moving on a journey towards the goal of becoming a data-driven organisation, but this remains a significant challenge. However, as the amount of data continues to rise and be of importance in business and society, using analytical data to support decisions and actions has also become increasingly more acceptable than intuition and experience. This indicates the need for data-driven organisations in the data-driven era.

The dissertation discusses enablers and constraints and their impacts on the move and development towards becoming a data-driven organisation underpinning the sociomateriality lens, which to date, has not been investigated as the main focal area. Data for this study was collected using a face-to-face semi-structured interview and had to be gathered remotely using an online survey due to the COVID-19 restrictions in conducting fieldwork. The research investigation took place in a UK university as a research site that has been working to become more data-driven.

Drawing on the empirical evidence and analysis, two enablers and eight constraints, and their multi-faceted complex impacts were identified. The two enablers are (1) data insights underpinning decisions and performance and (2) data insights facilitating multiple perspectives for holistic understanding. The eight constraints are (1) the human element underpinning data insights but being ignored while implementing a more data-informed approach, (2) data quality and data silos, (3) distrust in data and analysis credibility, (4) lack of harnessing multiple perspectives on data, (5) lack of human capability to engage with data, (6) emerging gap between data user, data provider, and implication of being data-driven, (7) differences in people's perceptions of revealing the story in a data, and (8) diverse vision and attitudes of leaders/people alignment on being data-driven. These contribute to the theoretical model in this study. The proposed theoretical model demonstrates the following three aspects: the complex and dynamic movement of becoming a data-driven organisation, the sensitivity to those enablers and constraints, and the fragmentation among data users, data providers and technology (i.e., a data-driven approach). It is argued that the enablers and constraints, and their

consequences need to be recognised. A full understanding of the organising and the dynamic interactions are, therefore, critical as an organisation moves on its journey to become data-driven.

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CHAPTER 1: Introduction

1.1 Introduction

Chapter 1 is set out as follows. First, definitions of terms in relation to this study will be discussed; next, the statement of the problem will justify why the study was undertaken and the section will accordingly present the research objectives and research questions. The theoretical framework underpinning this study is then given, along with context and research site background, the significance of the study and research contributions.

1.2 Definitions of Terms

This thesis, 'Data-driven Organisation through the Sociomateriality Lens: Towards an understanding of Enablers and Constraints', relates to three terms: data-driven organisation, sociomaterial imbrication, and enablers and constraints. At the outset, this section defines and details these three terms.

The first term is 'data-driven organisation'. An organisation incorporates and encourages a data-driven approach, which can provide people with tailored information and guidance, into their organisation to create a data-driven organisation. They share a pattern of behaviours and practices in respect of prioritisation, deriving value from data rather than intuition or personal opinions throughout the entire organisation. (Kiron and Shockley 2011; Kiron, Ferguson and Prentice 2013; Kiron, Prentice and Ferguson 2014; Mikael et al. 2018; Davenport and Mittal 2020). Anderson (2015) similarly mentions that it is critical that analytically derived insights must be considered or acted upon for the rise of a data-driven organisation. In this study, a data-driven organisation is defined as an organisation where data outweighs human intuition in their decision process across all levels of the organisation.

The second term is 'sociomateriality'. The concept of sociomateriality was posited by Orlikowski in (2007) and later working in collaboration with Scott (2008). They defined technologies and organisations in the same way, which does not prioritise either humans or technologies. Later, the imbrication metaphor was used to suggest how they become sociomaterial, and this term was introduced by Leonardi (2011 and 2012). He explains that people come to technology with different goals, and then make choices and decide on the agency to imbricate with technology. This depends on whether they perceive that a technology affords or constrains their ability to carry out their work to achieve their goals. This research therefore views the move and development towards becoming a data-driven organisation from the point of view of a sociomateriality lens to find enablers and constraints of becoming a data-driven organisation (Research Question 1) as well as to investigate the impacts of these enablers and constraints towards becoming a data-driven organisation (Research Question 2).

The third term is ‘enablers and constraints’. Leonardi (2011 and 2012) describes the way in which people choose to interact with technology differently depending on whether they perceive that technology affords or constraints their ability to carry out their work to achieve their goals. Acting on the perceived affordances or constraints of the technology can then lead people to realise new intentions that could be achieved through the technology’s functionality. This study, drawing on this concept, defines enablers as factors perceived to be relevant for the move and development towards becoming a data-driven organisation, whilst constraining factors are perceived to inhibit the goal of becoming a data-driven organisation (Research Question 1).

1.3 Statement of the Problem

Organisations appear to be increasingly engaged in developing a data-driven approach, since data is now ubiquitous with the advancement of technology which “change[s] the way businesses interact with the world” (Patil and Masaon 2015, p.1). Why does data matter to organisations? Existing research findings signify that data can be used to gain insights and then guide action. Being data-driven has important implications for supporting organisations whether to improve performance or gain competitiveness. For instance, LaValle et al. (2011) discovered “top-performing organisations use analytics five times more than lower performers” (p. 22). Kiron, Ferguson and Prentice (2013) reveal that “fully 67% of survey respondents report that their companies are gaining a competitive edge from their use of analytics” (p. 2). McAfee and Brynjolfsson (2012) also claim that “data-driven decisions tend to be better decisions” and “the data tells us that’s the surest bet” (p. 68). Moreover, Kiron, Prentice and Ferguson (2014) said that “some observers acknowledge the importance of culture as a “secret sauce for creating business value with analytics” (p. 9). In Kiron, Prentice and Ferguson (2014)’s survey, advanced analytics culture outweighs other analytics factors including data management, technologies and skills that enable companies to achieve a competitive advantage with analytics. Even now, data is being collected on an unprecedented scale. Big data is a consequence of using new forms of technology i.e., social media, smart phones, and cloud computing (Gupta and George 2016; Bhadani and Jothimani 2016). Big data is a term used to describe massive (volume), diverse (variety) and real-time (velocity) data which require technological advancements (in data storage, collection, and analysis), tools, and techniques used to process big data (Bhadani and Jothimani 2016). For instance, traditional tools are no longer able to process unstructured data such as videos, photos, images, social media comments. A big data analytics (BDA) approach is then increasingly adopted by organisations to extract valuable information (Sirarajah et al. 2017), such that BDA has become an important factor for an organisation's success regardless of size or sectors (Gandomi and Haider 2015; Gupta and George 2016; Gemignani et al. 2014). So, the value of data-driven organisations is clear. A more data-driven organisation has emerged as a major interest for more organisations and research studies working on changes in organisations' decision-making culture as a data-based approach in this regard.

There are, however, three main challenges arising when organisations become data-driven. First, while organisations have been working to become more data-driven, gaining potential benefits from a data-driven technology may not be fully achieved. As organisations are awash with data, investments of money and effort in data are growing; scholars are encouraging organisations to become data-driven. It has been assumed that being a data-driven organisation can produce benefits, i.e., better decisions, better performance and the creation of a competitive position. Organisations have a growing belief in the value and impact of being data-driven, in which they are fully committed to the analytically derived insights and as being the way forward for a data-driven organisation. Organisations are then increasingly interested and are investing in digital platforms, data and analytical talent. Although the use of a data-driven approach in organisations is now widespread, its full potential is yet to be realised. However, a data-driven organisation has difficulties in being successful. The number of data-driven organisations gaining the potential value from being data-driven is small, even in those organisations that are large (Henke et al. 2016; Gupta and George 2016; Mayhew, Saleh and Williams 2016; Diaz, Rowshankish and Salen 2018; Lunde, Sjusdal and

Pappas 2019). More recently, Troyanos (2020) indicates a similar point in his study claiming that:

> "Gartner stated that the global analytics and business intelligence software market reached $21.6 billion in 2018. The firm has also predicted that, 'through 2022, only 20% of analytic insights will deliver business outcomes.' That means that organizations are investing billions of dollars in analytics with minimal return—hardly a recipe for success" (p. 2).

According to Troyanos (2020), it has been shown that a divide remains between data-driven insights and business value on the move towards becoming a data-driven organisation. So, while more organisations are finding it more difficult to achieve their goals to turn data into an advantage, becoming data-driven organisations will be brought into focus in this research.

Second, implementing a data-driven approach in organisations is commonly accompanied by a goal for using data to make decisions that overcome historically accepted decision making, but this is still challenging. On the one hand, McAfee and Brynjolfsson (2012) highlight that the success of a data-driven implementation and being a data-driven organisation require a new culture of decision making, which decides on using data and other quantitative evidence rather than intuition. Kiron, Prentice, Ferguson (2014) make a similar point that having an analytics culture is the key to gaining the analytics advantage. But on the other hand, Thusoo and Sarma (2017) define a data-driven organisation as "one that understands the importance of data. It possesses a culture of using data to make all business" (p. 6). Building a data-driven organisation is difficult since "it requires a major shift in the thinking and business practices of all employees at an organisation" (Thusoo and Sarma 2017, p. 10). Developing a data-driven culture is defined as the biggest barrier organisations face to becoming a data-driven organisation, rather than technical issues (Lavelle et al. 2011; Viden, Shaw and Grant 2017; Bean and Davenport 2019). As such, a strong data-driven culture remains elusive (Waller 2020). In recent years, there is also evidence that organisations are struggling and failing in their efforts at becoming data-driven because the difficulty of cultural change has been underestimated (Ross, Beath, and Quaadgras 2013; Henke et al. 2016; Diaz, Rowshankish and Saleh 2018; Lunde, Sjusdal and Pappas 2019; Bean and

Davenport 2019; Waller 2020; Bean 2021; Nair 2020). Due to this, there is a lack of evidence and guidance on what actions must be taken to tackle the cultural barriers (Bean and Davenport 2019). Although this second challenge is mentioned in the literature, a better understanding of the move and development leading towards a data-driven organisation is still lacking, which is regarded as the third challenge.

This third challenge involves a lack of empirical research that tackles a discussion on the evolution of an organisation, and, as a result, the benefits gained by a data-driven approach have been limited (Vidgen, Shaw and Grant 2017; Lunde, Sjusdal and Pappas 2019; Sejahtera et al. 2018). Vidgen, Shaw and Grant (2017) argue that there is very little empirical insight on the challenges faced by managers in organisations trying to implement data-driven methods. Lunde, Sjusdal and Pappas (2019) similarly state that "several studies have been done into the different challenges and benefits that may occur during the process of adopting and using BD" (p. 164). To date, there has also only been limited attention paid to enablers and constraints, which is a necessary step towards providing guidance for organisations (Sejahtera et al. 2018) as well as their consequences on the move and development towards becoming a data-driven organisation, while there is a growing interest in the creation of a data-driven organisation.

This raises the question: what are the enablers and constraints of becoming a data-driven organisation? And what are the impacts of these enablers and constraints towards becoming a data-driven organisation? By understanding these key enablers and constraints, and their consequences, this research can help organisations to act efficiently regarding the challenges of becoming a data-driven organisation that they are likely to face, such as having a data-driven approach and driving the intended outcomes or goals.

Also, as Leonardi and Barley (2008) claim, understanding how people deal with a technology's materiality is critical for developing a broader and fuller understanding of organising. Sociomateriality is then introduced into becoming data-driven and adopted as the theoretical framework in this study. This study is grounded in a sociomaterial perspective, which emphasises the need to be attentive to both humans and a data-driven approach in the creation of a data-driven organisation. The key enablers, constraints, and their consequences have been conceptualised based on a combination of existing studies and the expanded sociomaterial lens, which is in accordance with research objectives (see

Section 1.4). The sociomateriality will be further discussed in Section 1.5 as a theoretical framework and again, in Chapter 2.

Furthermore, gaps in knowledge, research objectives and research questions are summarised in Table 1. It should be noted that not much research has been conducted into findings and the investigation of enablers and constraints and their consequences towards becoming a data-driven organisation through the sociomateriality lens. This study therefore intends to address the gaps with respect to the two research questions (see Section 1.4).

1.4 Research Objectives and Research Questions

This research sets out to explore and understand the factors that enable and constrain an organisation as it aims to become data-driven through sociomateriality: the imbrication lens described by Leonardi (2011 and 2012). As organisations move on a journey towards becoming a data-driven organisation, this remains a significant challenge (Vidgen, Shaw and Grant 2017; Lunde, Sjusdal and Pappas 2019; Bean and Davenport 2019). Also, previous studies have been limited in their investigations with respect to enablers and constraints, and their consequences on becoming a data-driven organisation (Sejahtera et al. 2018). There are then two objectives for this study. First, to find the enablers and constraints in the development towards becoming a data-driven organisation. Second, to investigate the impacts of these enablers and constraints in the move and development towards becoming a data-driven organisation. Due to the current paucity of academic research conducted on this area, the two main research questions were accordingly formulated to elicit data relevant to the objectives and were the following:

1. What are the enablers and constraints of becoming a data-driven organisation?
2. What are the impacts of these enablers and constraints on becoming a data-driven organisation?

Enablers and constraints that shape a data-driven organisation were discovered through the sociomaterial imbrication lens, where organisational change (routines) and technological change are considered as the sociomaterial entanglements of social and material (technological) agencies, determined by a perception that a technology either affords or constrains people's ability to carry out their work (Leonardi 2011 and 2012), which is summarised in the following section. By working around these enablers and constraints, their major impacts on becoming a data-driven organisation were therefore identified. Table 1 summarises the research gaps, objectives and questions in this study.

Table 1: Summary of research gaps, research objectives and research questions in this study

Research gaps	Research objectives	Research questions
1.Organisations are moving on a journey towards the goal of becoming a data-driven organisation, but this remains a significant challenge (Vidgen, Shaw and Grant 2017; Lunde, Sjusdal and Pappas 2019; Bean and Davenport 2019).	1. To find the enablers and constraints of becoming a data-driven organisation.	1. What are enablers and constraints of becoming a data-driven organisation?
2. To date previous studies have been limited in their investigation with respect to enablers and constraints, which is a necessary step towards providing guidance for organisations (Sejahtera et al. 2018) as well as their consequences on becoming a data-driven organisation.	2. To investigate the impacts of theses enablers and constraints of the move and development on a data-driven organisation.	2. What are the impacts of these enablers and constraints on a data-driven organisation?

1.5 Theoretical Framework

This study adopted a position based on the sociomateriality theory proposed by Leonardi (2011and 2012) as a complementary but distinct approach to the sociomateriality posited by (Orlikowski 2007). A sociomateriality view offers a perspective that the technical and the social are constitutive entanglements in everyday life that focuses on agencies, rather than discrete entities (whether technologies or organisations in which the technologies become enrolled) that influence each other (Orlikowski 2007; Orlikowski and Scott 2008). As Orlikowski and Scott adopted Barad (2003), they claim that "agencies are not attributes [of either humans or technologies] but ongoing reconfigurations of the world" (p. 818). Through a position of constitutive entanglement, the social and material agencies are inherently inseparable. The commitment to conceptual inseparability, however, results in the empirical difficulties regarding how this analytical inherent inseparability can be carried out in practice (Kautz and Jensen 2012). For this reason, scholars find themselves unclear regarding their data collection and analytics methods when adopting a sociomateriality approach (Elbanna 2016). This research then adopts the sociomaterial imbrication lens to overcome such limitations to explore functions/disciplines to understand their views on becoming a data-driven organisation (see Figure 1 below). The sociomaterial imbrication will be developed further in the next paragraph.

By adopting a technology affordance perspective, Leonardi (2011and 2012) develops the sociomaterial imbrication so as to address the empirically inseparable difficulties. He uses the metaphor imbrication as a mechanism to explain how the social and the material become entangled. According to Leonardi, the imbrication of social and material agencies generates organisational (routines) and technologies that people use to carry out their work. Namely, organisational and technological changes are considered the sociomaterial imbrication of multiple social (human) and material (technological) agencies. A human agency approach to a technology is determined by a perception that a technology either affords or constrains people's ability to carry out their work. Perceptions of affordance lead people to change their routines, whereas perceptions of constraint result in people changing the currently used technologies at organisations (see Figure 1 below). Consequently, technologies and organisations are sociomaterial, consisting of the same basic building blocks: social and material agencies. Technologies and routines at any given moment are the result of previous imbrications of social and material agencies.

Social agency is the human intentionality approach to a technology in response to material agency according to perceptions of a technology's material agency, whereas material agency is the ways in which a technology's materiality acts without human intervention. A technology's materiality is defined as 'the arrangement of an artifact's physical and/or digital materials into particular forms that endure across differences in place and time and are important to users" (p. 31, Leonardi 2012). Both social and material agencies thus represent action but differ with respect to intentionality. In this view, social and material agencies are distinct from one another, as opposed to Barad (2003). Affordances and constraints are thus constructed in the space between social and material agencies as people approach the technology with perceptions of affordance or constraint.

In this study, the sociomateriality lens understands a data-driven organisation—the effects of implementing a data-driven approach into an organisation—as the consequences of multiple actor intentions (social agencies) in response to a data-driven approach capability (material/technological agencies), triggered by perceptions of what a data-driven approach can or cannot do for people's ability to carry out their work. On the one hand, people make the choice to let a current data-driven approach influence their work, if a data-driven approach is perceived as affording results in a change in people's work routines to align with a current data-driven approach. But on the other hand, if people perceive a data-driven approach as constraining, they will decide not to adopt a current data-driven approach to support their work, and that data-driven approach is left intact. Leonardi and Barley (2008) claim that understating how people deal with a technology's materiality is critical for developing a broader and fuller understanding of organising. Hence, this study focuses on an understanding of enablers and constraints, and their impacts on the move and development towards becoming a data-driven organisation through the sociomateriality lens.

The sociomateriality perspectives from Leonardi (2011 and 2012) serve as the theoretical framework in this study as shown in Figure 1 which is used to develop to conceptualise enablers and constraints, and their impacts on the move and development towards becoming a data-driven organisation.

Therefore, from the findings of this study, the key enablers and constraints perceived to influence a data-driven organisation which remains a significant challenge, are revealed (Vidgen, Shaw and Grant 2017; Lunde, Sjusdal and Pappas 2019; Bean and Davenport 2019).

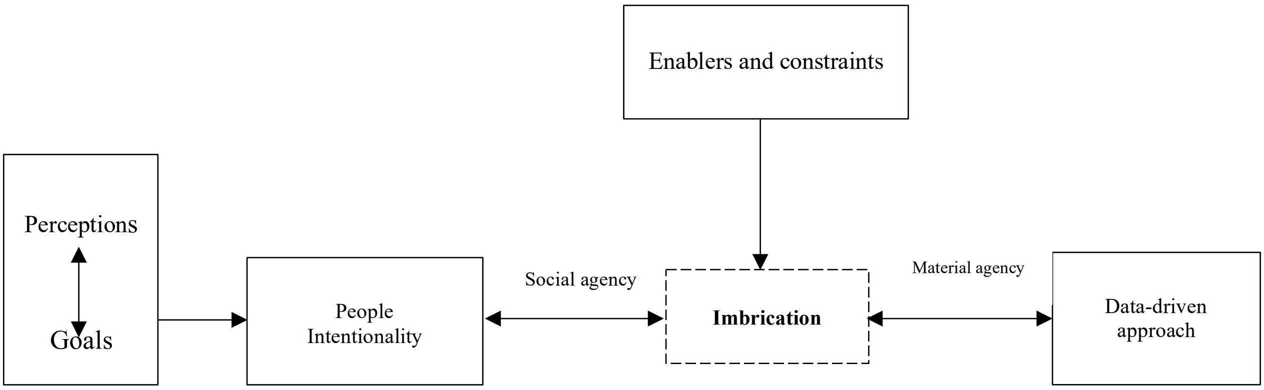

Figure 1: The sociomateriality that underpins this study as the theoretical framework

Through the analysis, these key enablers and constraints of becoming a data-driven organisation, and the impacts of these enablers and constraints on becoming a data-driven organisation, which most organisations are now struggling to achieve, (Henke et al. 2016; Gupta and George 2016; Mayhew, Saleh and Williams 2016; Diaz, Rowshankish and Salen 2018; Troyanos 2020) are subsequently investigated. The next section provides context and the research site background in this study.

1.6 Context and Research Site Background

To inform the reader of the context and research site background in this study, this section presents an overview of a university in its attempt to become a data-driven organisation. In order to empirically find the enablers and constraints (Research Question 1) and investigate their impacts on the move and development towards a data-driven organisation (Research Question 2), this study undertook face-to-face semi-structured interviews and an online survey, due to COVID-19 restrictions in conducting fieldwork, with a UK university.

The following are two justifications for choosing a university. First, because being data-driven is important in higher-education institutions (Park 2021; Larsen et al. 2022).

Leaders in most higher-education institutions generally understand that using advanced analytics can significantly transform the way they work, however many college and university leaders remain unsure of how to incorporate analytics into their operations to achieve intended outcomes and improvements (Krawitz, Law and Litman 2018). Transforming into a data-driven organisation in such a context can be challenging as higher-education institutions have created a framework for evidence-based action from the C-suite to academic staff, marketing, finance, student affairs, etc. Also, the higher education landscape has become increasingly competitive in the UK. The research site has thus undertaken to become a data-driven organisation seeking the advantages this transformation has to provide in their operations. In this study, the focus was on student recruitment and marketing. Second, because the researcher is an international student and had few networks within business, the researcher drew on the proximity of the university as the research site.

At the time of research, the research site had already implemented data and advanced analytics, however, this remains a challenge. This study adopts the sociomateriality lens to look at the relationship between humans and technology/technology and humans, and the relationship between humans across different organisational functions, in an attempt to understand the move towards a data-driven organisation. In this study, the focus was only on student recruitment and marketing. The participants were recruited from a diverse range of functions within the research site, namely, the communications team, marketing team, recruitment team, web and digital media team, faculty, and academic staff (programme directors) as they engaged and implemented a data-driven approach for student recruitment and marketing. The following lists the participants from a diverse range of functions within the research site that took part in the study:

- Marketing manager
- Faculty managers
- Programme directors
- Analyst
- Web and content manager
- Director of admissions
- Admissions managers
- Admissions officers

1.7 Significance of the Study

This study has five significant points. First, this study provides insights into the development of a data-driven organisation and concludes that dynamic interaction between people and a data-driven approach are critical, as both need to be regarded as equals. Second, this study identifies the factors functioning as enablers and constraints in the development of a data-driven organisation and recognises that all need to work together dynamically. Third, this study provides information that accounts for the gap that has emerged between people and a data-driven approach. Fourth, this study has practical implications for organisations of all types wanting to be data-driven and those responsible for data-driven transformation. Fifth, this study adds some ideas to the literature of management and organisational studies in the context of a data-driven organisation.

1.8 Research Contributions

The resulting insights from the empirical findings and analysis of the enablers and constraints in this study help shape a proposed theoretical model of enablers and constraints towards becoming a data-driven organisation as demonstrated in Figure 2. The model to which the enablers, constraints and their consequential elements were added, form the basis of the originality of this work. Through the use of this model, the intention is not only to expand the existing literature on the attempts of organisations to become data-driven, but also for this model to be questioned in practical ways.

The empirical findings allow the researcher to enhance the sociomateriality lens into the context of a data-driven organisation. Developing insights from the research site, the theoretical model proposed in this study found three important contributions. First, the proposed model, as can be seen from Figure 2 below, identified the complex and dynamic movement of becoming a data-driven organisation. Second, the sensitivity to those enablers and constraints was identified. Third, the fragmentation among data users, data providers and technology (namely, a data-driven approach) was uncovered. Arguably, the enablers and constraints, and their consequences need to be recognised. A full understanding of the organising and the dynamic interactions are therefore critical once an organisation starts on its journey to becoming data-driven. Otherwise, the organisation will grow further away from achieving its goals of becoming a data-driven organisation.

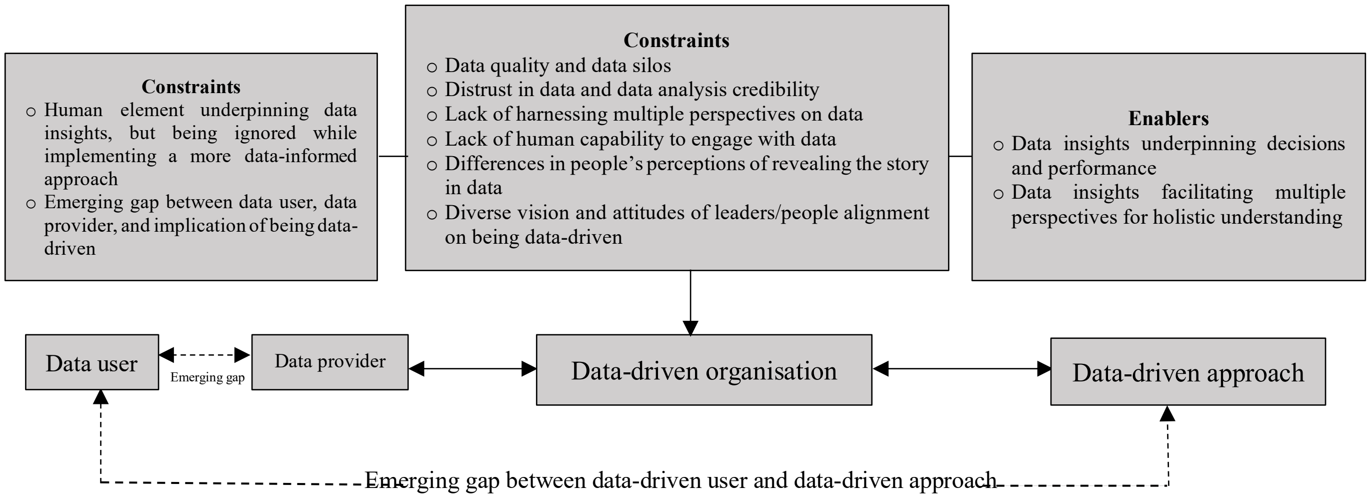

Figure 2: The proposed theoretical model of enablers and constraints on becoming a data-driven organisation derived from the findings of this study

1.9 Outline of the Study

This study contains five chapters:

Chapter 1 provides the introduction and roadmap of the chapter, definitions of terms, the statement of the problem justifying the importance of this study and presenting the research objectives and research questions. The sociomateriality that underpins this study as the theoretical framework is discussed, the research site for this study is provided and the significance of the study and research contribution is ultimately described.

Chapter 2 reviews the literature relevant to the study topic. A data-driven organisation is first discussed before focusing on its challenges. As a data-driven organisation works, it requires developing a data-driven approach but also people to embrace that data-driven approach. Nine issues impacting organisational transformation to becoming a data-driven organisation, the theoretical foundation of sociomateriality and sociomaterial imbrication are also covered.

Chapter 3 of this dissertation presents the methodological framework drawn on for the study including the philosophical research position, research method, defining the case study, introducing the research participants, pilot study, data gathering procedure, data analysis, the strategies for ensuring rigour of the study, and the ethical considerations

Chapter 4 presents the findings and analysis from the empirical case study. In this chapter, a multifaceted, complex and interconnected issue that impacts organisational transformation in becoming a data-driven organisation as enabling and constraining factors are identified and discussed.

Chapter 5 highlights the theoretical model and contributions, practical implications, and methodological contribution of this study and supplies a conclusion. In addition, research limitations are acknowledged, and recommendations for future research are provided.

CHAPTER 2: Literature Review

2.1 Introduction

This research aims to find enablers and constraints perceived towards becoming a data-driven organisation, and their impacts on the move and development in becoming a data-driven organisation. Exploration through a sociomateriality lens will help in discovering factors that have a dynamic impact on the imbrication relationship between human and technological agencies. In order to develop a deeper understanding of enablers and constraints that are perceived to help organisations become data-driven, this study applied and analysed the results through the sociomateriality lens. Issues impacting organisational transformation to becoming a data-driven organisation (i.e., technical and non-technical factors) will be explored during the data gathering process. The literature review chapter was conducted to provide a theoretical foundation for this research, which has five parts that look at: (i) data-driven organisations, (ii) the challenges of becoming a data-driven organisation, (iii) the issues impacting organisational transformation to become a data-driven organisation, (iv) sociomateriality, and (v) sociomaterial imbrication, which takes a complementary yet distinct approach to the concept of sociomateriality since it concords with the philosophical assumptions of this study that a data-driven organisation is regarded as an integrative phenomenon of people engaging (i.e., users who make decisions and analysts) with a data-driven approach. Sociomateriality can be leveraged to explain the insights gained and their consequential elements at the research site using the study's theoretical framework.

This chapter is set out as follows. First, a data-driven organisation and its challenges are discussed. The following section discusses issues impacting organisational transformation to becoming a data-driven organisation, which are (i) being data-driven and its potential impact on organisational capabilities, (ii) the human component in the drive to become a data-driven organisation, (iii) data silos, (iv) data quality, (v) data and data analysis credibility, (vi) data literacy skills, (vii) leadership involvement, (viii) data communication to enhance data user's engagement, and (ix) a data-driven culture. Eventually, the foundation of sociomateriality and then sociomaterial imbrication used to address the two research questions in this study are discussed, respectively.

2.2 Data-driven Organisation

As massive amounts of information are more consistently available in business and society, the need for organisations to become data-driven to derive meaningful insights from those large datasets arises. To be data-driven is subsequently crucial for any organisations wishing to compete in the age of digital transformation. This is recognised by Bean and Davenport (2019) who note that, "becoming "data-driven" has been a commonly professed objective for many firms over the past decade or so" (p. 2). A recent report also stated that "big data will fundamentally change the way businesses compete and operate. Companies that invest in and successfully derive value from their data will have a distinct advantage over their competitors" (EY Report 2014, p. 1). According to Bean and Davenport (2019) and EY Report (2014), the digital transformation itself is forcing organisations moving to be data-driven to cope with its effects. Moreover, Henke et al. (2016) contend that, "most companies are capturing only a fraction of the potential value of data and analytics" (p. 1). Waller (2020) also argues "yet for many companies strong data is rarely the universal basis for decision making" (p. 2) and problematic in forging a data-driven organisation.

A data-driven organisation refers to an organisation incorporating a data-driven approach, which can provide people with tailored information and guidance in their organisation. As such, they share a pattern of behaviours and practices with respect to prioritising deriving value from data rather than intuition or personal opinions throughout the entire organisation. (Kiron and Shockley 2011; Kiron, Ferguson and Prentice 2013; Kiron, Prentice and Ferguson 2014; Mikael et al. 2018; Davenport and Mittal 2020). Anderson (2015) similarly mentions it is critical that analytically derived insights need to be considered or acted upon for the emergence of a data-driven organisation. In this study, a data-driven organisation is defined as an organisation where data outweighs human intuition in their decision process across all levels of the organisation.

The use of a data-driven approach has the potential to transform traditional businesses, namely for making better predictions and smarter decisions, improving business performance, and greater opportunities for competitive advantage (e.g., LaValle et al. 2011; McAfee and Brynjolfsson 2012; Kiron, Ferguson and Prentice 2013; Gemignani et al. 2014; Gandomi and Haider 2015; Gupta and George 2016). It is no wonder that organisations invested efforts to shift to more data-driven methods. However, looking at the agenda to become data-driven, previous studies have highlighted that it remains a significant challenge to bring about this transformation and to nourish a data-driven approach despite the high priority of the move for organisations (Vidgen, Shaw and Grant 2017; Lunde, Sjusdal and Pappas 2019; Bean and Davenport 2019). The next section presents and discusses the challenges of becoming a data-driven organisation in detail.

2.3 Challenges of Becoming a Data-driven Organisation

A data-driven organisation creates values and new possibilities with data, but that happens in few companies (Mayhew, Saleh and Williams 2016; Henke et al. 2016): 'The gap between leaders and laggards in adopting analytics, within and among industry sectors, is growing' (p. 1, Diaz, Rowshankish and Saleh 2018). Organisations are still struggling with the challenges of becoming a data-driven organisation; according to the extant literature, there are three main challenges, which are identified below.

The first challenge is that organisations face a lack of organisational strategic alignment, culture resistance, siloed data or data sharing challenges, leadership challenges, talent shortage and the divide between insights produced by analytics and business values, and so on, in which only a fraction of organisations are able to capture the potential value from creating data-driven organisations (Henke et al. 2016; Gupta and George 2016; Mayhew, Saleh and Williams 2016; Diaz, Rowshankish and Salen 2018; Lunde, Sjusdal and Pappas 2019; Troyanos 2020). Instead of being a data-driven organisation, "these organizations are "masquerading" as data-driven, meaning they have the data, technologies, and even the expertise, but their culture and processes are not aligned with those elements to produce the best outcomes. For example, data might be a part of every decision made, but employees may be making decisions first, then looking for data to back them up" (Nair 2020, p. 3). This first challenge leads to the second.

The second challenge is highlighted by using data for decision making that overcomes historically accepted decision making (Lavelle et al. 2011; Chaffey and Patron 2012; Ross, Beath, and Quaadgras 2013; Henke et al. 2016; Clark and Wiesenfeld 2017; Diaz, Rowshankish and Saleh 2018; Sejahtera et al. 2018; Bean and Davenport 2019; Waller 2020). Consequently, these organisations cannot 'move away from acting solely on hunches and instinct’ (McAfee and Brynjolfsson, p. 9). Despite the second challenge being mentioned in the literature, a better understanding of the development of a data-driven organisation is still lacking, which may be regarded as the third challenge.

This lack of empirical research that tackles empirical discussion on the evolution of an organisation means that the benefits gained from a data-driven approach have been limited (Vidgen, Shaw and Grant 2017; Sejahtera et al. 2018; Lunde, Sjusdal and Pappas 2019). To date, there has also been only limited attention paid to enablers and constraints, which is a necessary step towards providing guidance for organisations (Sejahtera et al. 2018) as well as their consequences on developing a data-driven organisation whilst there is a growing interest in creating one. As Vidgen, Shaw and Grant (2017) state:

> “The popularity of big data and business analytics has increased tremendously in the last decade and a key challenge for organizations is in understanding how to leverage them to create business value. However, while the literature acknowledges the importance of these topics little work has addressed them from the organization’s point of view” (p. 626).

Lunde, Sjusdal and Pappas (2019) make a similar point that:

> “Our findings revealed that organizational culture is still a somewhat new aspect in the field of big data, the reason being that the majority of the papers only mentioned organizational culture as an important factor in the adoption of big data and did not have it as one of the main focus areas. Our findings also showed that the literature was very supportive of the notion that organizational culture played a critical role for organizations when trying to succeed with big data adoption. This demonstrated that there is a gap in the research about exactly how much organizational culture effect the big data adoption, and how one can strategically plan to cultivate an organizational culture that is fully supportive of big data, which will increase the benefit an organization get from big data” (p. 9).

In addition, Sejahtera et al. (2018) identified (1) adequate system capabilities, (2) an established culture of collaboration, and (3) good working attitude as the key enablers of effective use of big data, whereas (1) poor data quality, (2) lack of data understanding, (3) data silos, (4) lack of time, (5) lack of cost-benefit analysis, (6) lack of top management support, and (7) lack of technical skills worked as inhibitors. They also argue that:

> "At the same time, however, research indicates that while most organisations have access to big data, they don't necessarily have the capacity to use it effectively (LaValle et al. 2013 cited in Sejahter et al. 2018). Accordingly, understanding the enablers and inhibitors that influence effective use of big data is a necessary step towards providing guidance for organisations, such that the full potential and value of big data can be realised. (p. 2). The lack of studies and lack of core knowledge on enablers and inhibitors that impact effective use of big data is an impediment to the success of projects involving new and large datasets. Such enablers and inhibitors may stem from technology, human sources, and organisational capabilities and from the data itself. Thus, developing a comprehensive model of effective use of big data requires substantial theoretical development, which, in turn, requires the identification of enablers and inhibitors as a prerequisite" (p. 4).

The three challenges of becoming a data-driven organisation expressed in the extant literature discussed above indicate that the goal of becoming driven by data is full of possibilities but also has inevitable challenges, mainly connected with the potential factors organisations encounter (e.g., lack of organisational strategic alignment, culture resistance, siloed data or data sharing challenges, leadership challenges, talent shortage and the divide between insights produced by analytics and business value, etc.). They also reveal the need for more empirical studies to create a better understanding of becoming a data-driven organisation, and this is where there appeared to be a gap in the knowledge which required further investigation. This research on the topic of "Data-driven Organisation through the Sociomateriality Lens: Towards an Understanding of Enablers and Constraints" is an attempt to bridge this gap as this can benefit those organisations that are struggling in their efforts.

In the next section, discusses the issues impacting organisational transformation to becoming data-driven.

2.4 Nine Issues Impacting Organisational Transformation to Becoming a Data-driven

Becoming a data-driven organisation is not about a technical or technological matter, rather there are many factors that influence the move and development of a data-driven organisation, including technical and non-technical issues (LaValle et al. 2011; Chaffey and Patron 2012; Sejahtera et al. 2018; Bean and Davenport 2019; Waller 2020; Nair 2020). Specifically, while the technology may be the most effective part of the transformation, its benefits are limited as a standalone tool.

The results from the literature review revealed nine issues that impact organisational transformation to a data-driven organisation. These include (i) being data-driven and its potential impact on organisational capabilities, (ii) the human component in the drive to become a data-driven organisation, (iii) data silos, (iv) data quality, (v) data and analysis's credibility, (vi) data literacy skills, (vii) leadership involvement, (viii) data communication to enhance data user's engagement, and (xi) data-driven culture. The following paragraphs elaborates on each of the nine issues.

The first issue is being data-driven and its potential impact on organisational capabilities. Due to its potential, such data can help organisations make evidence-based decisions, rather than those based on gut feelings and one's intuition, thereby resulting in better decisions. Hence, the results are improved performance and competitiveness.

The second issue involves the human component in the drive to become a data-driven organisation. Even though becoming a data-driven organisation focuses attention on analytically derived insights for making decisions, the human element is still important to assist in developing a data-driven approach.

The third issue is data silos. When data is still siloed, it divides an organisation and hinders collaboration, and therefore can undermine a data-driven transformation.

Issue four is related to data quality, which is key, as it could also impact on data and the credibility of data analysis which is the fifth issue. Without data and credible data analysis, organisations will continue to grapple with a data-driven operation.

Issue six is data literacy skills because transforming an organisation into a data-driven one requires developing their analytical skills, but also their ability to work with data, such as interpreting it, to drawing insights and asking the right questions in the first place.

Issue seven highlights the role of senior management, its commitment and communication including their attitudes and skills. Leadership involvement is clearly a critical factor in shaping a data-driven organisation.

The eighth issue is data communication to enhance the engagement of data users. This involves connecting and building collaborative work with data among groups of people, namely, data providers and data users. This has the potential to unlock the value of the data already held by an organisation.

Lastly, issue nine involves a data-driven culture. While organisations are moving towards being data-driven, they need to create a culture that encourages data-driven decisions. Yet, this remains elusive. Data-driven culture is regarded as one of the areas impacting organisational transformation in becoming a data-driven organisation.

This section throws light upon these nine issues impacting organisational transformation to becoming a data-driven organisation as follows.

2.4.1 Being Data-driven and its Potential Impact on Organisational Capabilities

When defining the value that organisations could derive, add and create by being a data-driven organisation, scholars usually include marketing strategy, making decisions, performance improvements and competitive advantage, all of which will be discussed in the three following sections.

Marketing Strategy

Scholars have claimed that a data-driven approach becomes crucial in several key marketing areas with regards to customer analysis and sales growth. Davenport, Mule and Lucker (2011) state that companies that have systematically collected information about basic customer demographics, product attributes, and customer purchase histories can make much more sophisticated and potentially effective offers to customers' buying needs. Khade (2016) claims that big data analytics significantly change the way businesses perform customer behaviour analysis. According to Gandomi and Haider 2015, 95% of data nowadays relates to unstructured data—not organized in a data base (McAfee and Brynjolfsson 2012)—which comes from various sources (e.g., websites and social media platforms) and different formats (e.g., text, images and video). Subsequently, (big) data analytics is used to discover the hidden information and provide meaningful insights (e.g., customer behaviour and customer journey) that become beneficial for maximising marketing efforts and improving marketing activities, such as the best possible offers and messages for key customers. Despite the fact that the performance impact has shown little increase from marketing analytics, companies plan to increase spending on data analytics (Mela and Moorman 2018). Moreover, Johnson (2020) asserts that this is even more crucial during an unprecedented global health and economic crisis because marketers no longer depend on previous assumptions about their customers e.g., previous behaviour, customer's decision to purchase, marketing and advertising efforts. As more people have been able to work remotely from home and spend more time watching TV and participate in online activity and in-person social interaction has been reduced during the pandemic, data-driven organisations gained critical advantages to "help marketers stay anchored to their customers' changing reality and focused on their moments of truth" (p. 4). It therefore appears that organisations integrate a data-driven approach into their marketing strategy to obtain the right data and achieve better insights that engage with target customers and future plans/campaigns to drive more sales.

Making Decisions

Scholars also emphasise the importance of a data-driven culture and a data-driven organisation in making decisions based on objective information e.g., meaningful data and insights rather than fully committing to gut feelings and one's intuition (Davenport 2006; McAfee and Brynjolfsson 2012; Cao, Duan and Li 2015; Ghasemaghaei, Ebrahimi and Hassanein 2018). McAfee and Brynjolfsson (2012) claim that, "data-driven decisions are better decisions—it's as simple as that. Using big data enables managers to decide on the basis of evidence rather than intuition" (p. 63). They also quote W. Edwards Deming and Peter Drucker's in saying that "you can't manage what you don't measure" (p. 62) as supporting evidence and provide the explanation that "simply put, because of big data, managers can measure, and hence know, radically more about their businesses, and directly translate that knowledge into improved decision making and performance" (p. 62). For McAfee and Brynjolfsson, the objectivity in data seems to enable organisations to measure and, therefore, manage more precisely. This ultimately leads to improved decision making and performance.

Elgendy and Elragal (2016) claim that exploited and applied big data analytics enhance traditional decision making and support informed decisions in organisations by revealing hidden insights and valuable information. As a result, decision makers arrive at more insightful decisions. In addition, Monino (2021) assets that "we must get the message that data in itself is not power.... It is the use of data that empowers decision-making" (p. 2). Accordingly, data and information are essential to build the knowledge to make a better decision, and therefore data leads to better decisions. A data-driven approach justifies and supports pre-decision-making proposals. As Davenport (2013) states: "a hypothesis is an intuition about what's going on in the data you have about the world. The difference with analytics, of course, is that you don't stop with the intuition—you test the hypothesis to learn whether your intuition is correct" (p. 2). However, Janssen, Voort and Wahyudi (2017) who conducted a study on the quality of decision making in the context of big data, argue that "the quality is not solely dependent on the data, but also on the process in which the data is collected and the way data is processed" (p. 338). Janssen, Voort and Wahyudi also claim that "big data provides little value if it is not accurate, and people are not able to interpret the decisions" (p. 342). Along the same lines, Davenport (2009) provides cautionary messages that correct assumptions are crucial when using data analytics to support decision making.

Performance Improvements and Competitiveness

Performance improvements and competitiveness are highlighted by scholars as the significant advantage a data-driven approach brings to organisations. Wilson (2010) claims that clickstream data—a source of information about how internet users navigate through website marketing offers and order online—is an efficient way to evaluate and improve B2B (Business-to-Business) web site performance since clickstream data and web analytics can be used to keep web site visitors moving through the buying process ultimately to conversion as well as to encourage customers to return for additional purchases. In addition to web site design and evaluation, insights from clickstream data can be used to guide internet marketing strategy, which improves performance. LaValle et al. (2011) claim that organisations using insights to guide their future strategies are twice as likely to be top performers as lower performers. Data analysis results show patterns and themes that can recommend the available possibility of improving strategic directions and competitive performance to organisations. McAfee and Brynjolfsson (2012) also provide case studies that using data improves business performance. The airlines, for example, utilise PASSUR Aerospace to estimate arrival times. Over time, the company can create and keep more digital data which allows sophisticated analysis and pattern matching. In doing so, a gap between estimated and actual arrival times of the airline company is eliminated which can save several million dollars a year at each airport. Another example of using data to create a competitive edge mentioned in McAfee and Brynjolfsson is that of researchers at an MIT media lab who use location data from mobile phones to track how many people were in a Macy's parking lot on Black Friday. By tracking location data, the rapid insights of retail sales on that pre-Christmas shopping day can be estimated, which allows Wall Street analysts and Main Street managers to gain a great competitive advantage. Sharing this view, Henke et al. (2016) claim that data and analytics are now regarded as a game changer on the basis of competition. Moreover, recent scholars increasingly provide empirical evidence using quantitative research methods to claim a positive and significant impact between BDA (Big Data Analytics) capability and performance improvement, which ultimately deliver competitiveness (Akter et al. 2016; Gupta and George 2016; Wamba et al. 2017; Mikalef et al. 2020). Hence, being data-driven is now essential to assist organisations in improving their performance and competitiveness.

Thus, these three values are derived from being data-driven: namely, marketing strategy, making decisions, performance improvements and competitiveness. These three elements could, therefore, encourage the widespread organisational use of a data-driven approach and leverage insights at fostering a data-driven culture and becoming a data-driven organisation. Aside from Factor 1 (Data and its potential impact on organisational capabilities), a data-driven culture and organisation will be incomplete if the human element is underrated. In addition to a data-driven approach, humans have also contributed to reaping the values of data. The next section presents and discusses this.

2.4.2 The Human Component in the Drive to Become a Data-driven Organisation

Whilst a data-driven approach plays a critical role in encouraging evidence-based decision-making rather than opinion and gut instinct and becoming part of the basis of an organisation's competitive advantage, the human component behind change remains crucial for achieving a data-driven organisation. The human aspect in the drive to become a data-driven organisation is highlighted by scholars (i.e., Mikalef et al. 2018; Davenport and Prusak 1998; Chamorro-Premuzic 2020; Roberts 2015; Wilson and Daugherty 2018). Mikalef et al. (2018) have directly highlighted the importance of the human component needed to create a data-driven organisation specially to assist the discovery, interpretation, and communication of meaningful data insights while a majority of research has primarily focussed on the technical aspects. As the Chartered Global Management Accountant (CGMA)'s report (2016) notes:

> "Personal opinions and hunches are still important, but they should be considered in the context of what the data now available tells us. Artificial intelligence can generate algorithms and identify correlations, but there is still a need to add this human dimension to generate insights" (p. 2).

Davenport and Prusak (1998) note "data is a set of discrete, objective facts about events...the data tells nothing about why...data describes only a part of what happened; it provides no judgment or interpretation and no sustainable basis of action...data says nothing about its own importance or irrelevance. But data is important to organisations.... Data becomes information when its creator adds meaning" (p. 2). So, data can have no usefulness without the human dimension. Chamorro-Premuzic (2020) also mentions this:

> "To be sure, in most relevant areas of life, we still need human expertise to translate data into insights, and the willingness to act on those insights is what ultimately makes someone data-driven. Data without insights is meaningless, and insights without action are pointless" (p. 2).

A broadly similar point has been made by Roberts (2015), who highlights the human element needed in the acquisition, retention, and transfer of knowledge. He shows that:

> "Although explicit knowledge can be transferred in a codified form independently of humans, if organisations are to absorb and apply such knowledge, people must interpret it.... Moreover, the acquisition and transfer of knowledge depend on interaction between people.... It is not possible to take people and their need for trust and mutual understanding out of knowledge management equation. This is because knowledge is acquired, retained, transferred, and applied in a social context" (p. 78).

Although a data-driven approach has the capability for non-human entities to act on their own, independently of human intervention (Leonardi 2011 and 2012), a data-driven approach and humans should both be of equal importance (Orlikowski and Scott 2008) in a data-driven world. Data and people are thus brought together to create values for organisations. Wilson and Daugherty (2018) similarly claim in their study that "firms achieve the most significant performance improvements when humans and machines work together" (p. 117). Humans and AI are conjoined forces, which are regarded as collaborative intelligence.

From the research discussed above, the human element is still pivotal to assist in developing a data-driven approach within an organisation. In this regard, alignment and equal weighting of people and a data-driven approach is clearly linked to make an organisational shift towards evidence-based decision making which in turn raises performance and drives up value.

2.4.3 Data Silos

The third issue that hinders the adoption of data-driven methods is data silos, which are discussed in this section. A data silo is a collection of data, where the data is isolated from other departments and the rest of the organisation (Gemignani et al. 2014; Wilder-James 2016; Nair 2020; O' Tools 2020). Subsequently, it is difficult for the entire organisation to share, fully access, and work with the same set of data. It also appears that data silos reflect a gap between a data-driven approach, data creators, and data users which ultimately hold back organisations from becoming data-driven. Data silos subsequently undermine the true potential of being data-driven. The studies from the reviewed literature i.e., Gemignani et al. (2014); Wilder-James (2016); Nair (2020); and O'Tools (2020), emphasise the issue of data silos in relation to data-driven organisations.

First, Gemignani et al. (2014) illustrate the pitfalls which can act as roadblocks on the path to transforming an organisation's use of data and reaching data fluency. From their perspectives, "a department in an organisation can easily become independent silos, operating with their own set of norms, conventions, and terminology. This impacts what you can do with your data and what you can understand" (p. 36). One of the pitfalls thus related to "balkanised data" (p. 36) is that each department in an organisation "may use different data systems and terminology, processes, and conventions in data conversations and products" (p. 37). Second, Wilder-James (2016) similarly claims that the biggest obstacle to using advanced data analysis is obtaining access to the data that decision makers need. However, "there is a bigger and costlier demon that lurks in enterprises. A demon that can drive up that 80% and often makes initiatives impossible: data silos. These silos are isolated islands of data, and they make it prohibitively costly to extract data and put it to other uses" (p. 3). And they arise for myriad reasons, such as structural, political, growth and vendor lock-in, resulting in multiple incompatible systems and not encouraging data sharing. Thus, "to move to the higher value uses and maintain a competitive edge, we need to lessen the impact of data silos on our businesses" (p. 4). Third, Nair (2020) suggests one of the symptoms that an organisation is masquerading as data-driven lies in the difficulty obtaining a common version of truth, and this is caused by data silos. Since:

> "Each team may be acting on data, but if they have different information, they are bound to disagree, and some may even be misled. The cause may be siloed data, where each team looks at their own slice of reality. Or there may be a lack of agreement about which data should drive a particular decision…. Getting stakeholders to agree on which data is important establishes a common source of truth to guide decisions and strategy" (p. 3–4).

Lastly, O' Tools (2020) also suggests that "data science can't happen in a silo. It must be tightly integrated into the business organization, operations and processes" (p. 4).

Supported by the research mentioned above, the issue of data silos hinders an organisation obtaining meaningful insights and transforming data into actionable insights. By doing so, organisations struggle to become data-driven when data is still siloed. The next sections will discuss data quality (section 2.4.4), and data and analysis's credibility (section 2.4.5), which is required for organisations to successfully move towards becoming a data-driven organisation.

2.4.4 Data Quality

The fourth issue to a successful data-driven transformation is data quality.

> "Data is the foundation of a data-driven organization. If you don't have timely, relevant, and trustworthy data, decision- makers have no alternative other than to make decisions by gut. Data quality is key" (Anderson 2015, p. 19).

The above statement reflects Anderson's (2015) contention that data quality is important to creating a data-driven organisation because being data-driven places emphasis on analytically derived insights and on making decisions where data outweighs human intuition (Kiron and Shockley 2011; Kiron, Ferguson and Prentice 2013; Kiron, Prentice and Ferguson 2014; Anderson 2015; Mikael et al. 2018). He argues that a lack of confidence in data quality makes it challenging as it limits the questions people can answer and the quality of insights that they can derive from the data. For Anderson, facets of data quality involve it being accessible, accurate, coherent, complete, consistent, defined, relevant, reliable, and timely. It should be noted that "being a data-driven organization takes more than great technology and quality data" (Nair 2020, p. 3); nevertheless, the data quality issue has been mentioned by scholars (Shah, Horne and Capella 2012; Redman 2013; Sivarajah et al. 2017; Redman 2016; Data & analytics case study roll-up report 2016; Nagle, Redman and Sammon 2017; Waller 2020; Redman 2020; Svensson and Taghavianfar 2020).

Furthermore, as Svensson and Taghavianfar (2020) claim:

> "When making decisions based on data, trust in data insights and findings, having trustworthy data, and trust in that the relevant data is presented to the decision makers are of out most importance" (p. 10).

For Svensson and Taghavianfar (2020), the issue of data quality also affects the issue of data and analysis's credibility.

2.4.5 Data and Data Analysis Credibility

The fifth issue is data and data analysis credibility. Despite the data's potential value on evidence-based decision making, transparency and trust in data and analysis are considered as an essential facilitator that encourages people's willingness to perform and rely on what data is telling them (Svensson and Taghavianfar 2020). Barton and Court (2012) suggest three keys to building a data-driven strategy which consist of the integrated approach to data sourcing, model building, and transforming organisational culture. According to Barton and Court, organisational culture matters to fully exploiting data and analytics as they mention that "third, and most critical, management must possess the muscle to transform the organization so that the data and models actually yield better decisions" (p. 80). Their findings also reveal that:

> "The lead concern expressed to us by senior executives is that their managers don't understand or trust big data-based models...the reason soon became evident: the frontline marketers who made key decisions on ad spending didn't believe the model's results and had little familiarity with how it worked. Many companies grapple with such problems, often because of a mismatch between the organization's existing culture and capabilities and the emerging tactics to exploit analytics successfully" (p. 82).

Shah, Horne, and Capella (2012) held a similar view, asserting that making performance metrics transparent is important if companies want to make better use of the data they have as data-driven cultures.

Lacking trust in data and analysis seems to be problematic in organisations. People are reluctant to use solid evidence they do not trust, and therefore they rely on their intuition to help make decisions instead of analysis (Anderson 2015; Pugna, Dutescu and Stanila 2019). Redman (2013) also mentions this point:

> "When data are unreliable, managers quickly lose faith in them and fall back on their intuition to make decisions, steer their companies, and implement strategy.

They are, for example, much more apt to reject important, counterintuitive implications that emerge from big data analyses" (p. 86).

To improve data and analysis credibility requires closing the gap between data creators and end users, which is better for communication than better technology. Redman asserts:

> "Fifty years after the expression 'garbage in, garbage out' was coined, we still struggle with data quality. But I believe that fixing the problem is not as hard as many might think. The solution is not better technology: It's better communication between the creators of data and the data users.... If the quality is deemed to be poor, people typically react by working around the data or correcting errors themselves. But improving data quality isn't about heroically fixing someone else's bad data. It is about getting the creators of data to partner with the users—their 'customers'—so that they can identify the root causes of errors and come up with ways to improve quality going forward" (p. 86).

Therefore, according to Redman, the solution to data credibility can be addressed by management, not technology. Data creators should be linked organisationally to data users in order to improve data quality to ensure data users' willingness to accept the available information into their decision-making process. Moreover, Redman (2015) reflects that:

> "While many managers are skeptical of new data and others embrace it wholeheartedly, the more thoughtful managers take a nuanced approach. They know that some data (maybe even most of it) is bad and can't be used, and some is good and should be trusted implicitly. But they also realize that some data is flawed but usable with caution. They find this data intriguing and are eager to push the data to its limits, as they know game-changing insights may reside there" (p. 2).

This indicates that people hesitate to act on a given piece of information if they do not trust it, which can inhibit the organisation from being data-driven.

Clark and Wiesenfeld (2017) found three main obstacles which hold back analytics' value: organisation's structure, and the culture and approach to problem solving.

Interestingly, all of the three obstacles are not related to technology but rather to people. Clark and Wiesenfeld also discovered that:

> “Data science groups that are too independent of the business tend to produce impressive and complex models that prove few actionable insights.... The result was an isolated department that business partners viewed as unresponsive, unreliable, and not to be trusted with critical initiatives” (p. 3).

For Clark and Wiesenfeld, trust in analysis seems to be connected to turning analytics into actionable insights that organisations need to compete. Pugna, Dutescu and Stanila (2019) similarly reveal that “managers were not yet willing to fully trust data and to let it replace their judgments or intuitions in a particular decision-making context (especially when that data contradicts their judgment and intuition)” (p. 19–20). According to Pugna, Dutescu and Stanila, a lack of trust in data accuracy and quality requires attention. Even though data does not need to be precise, accurate and perfect to yield new insights, the majority of the managers’ attitudes towards data reflect their existing experience, suspicion and frustration regarding making sense of the available data that they currently use.

In summary, it has been shown that data analysis credibility illuminates difficulties relating to others: data quality (Anderson 2015; Svensson and Taghavianfar 2020), relying more on intuition (Anderson 2015; Pugna, Dutescu and Stanila 2019), gap between data creators and users (Redman 2013), and few actionable insights (Clark and Wiesenfeld 2017; Pugna, Dutescu and Stanila 2019). Together, these studies indicate that data and analysis’s credibility have a significant influence on people’s willingness to embracing a data-driven mindset. Without data and analysis’s credibility, organisations continue to grapple to operate in a data-driven manner.

2.4.6 Data Literacy Skills

The sixth issue that moves an organisation towards a data-driven decision-making world is data literacy skills. Data skills relate to the competence to turn data into insight and action (Littlewood 2018). Data skills, which include both hard (i.e., skilled analytics) and soft skills (i.e., problem-solving and communicating, storytelling and the ability to work with data), are needed to implement a data-driven approach into a decision-making process (Barton and Court 2012). Existing research on becoming a data-driven organisation show that the lack of data skills tends to be problematic for developing a data-driven organisation (Shah, Horne, and Capella 2012; Basin and Zao-Sanders 2020).

Shah, Horne, and Capella (2012) contend that "investments in analytics can be useless, even harmful, unless employees can incorporate that data into complex decision making" (p. 23). Their analysis shows that most companies have too few analytics-savvy workers, and analytics skills are concentrated in too few employees, which is one of the main problems that "prevent organisations from realising better returns on their investment in big data" (p. 24). As such, they suggest two things that help organisations to make better use of data they gather: "training workers to increase their data literacy and more efficiently incorporate information into decision making and giving those workers the right tools" (p. 24). For Shah, Horne, and Capella, good data will not guarantee good decisions unless organisations have the right tools. Organisations also must improve data literacy across their organisations, which is challenging for organisations. Barton and Court (2012) similarly assert that transforming organisational culture into being data-driven requires developing the capabilities of its members regarding their analytical skills and data literacy.

In addition, Basin and Zao-Sanders (2020) state that "while we have all this data, and it's becoming more influential than ever, there's still a big problem at hand: Most of us are not very good at interpreting and making sense of it" (p. 3). Basin and Zao-Sanders have also revealed interesting results in their study t recently conducted on a focus group of 20 sophisticated companies. The results showed that data skills were missing in the companies for all they have is data related to skills in data-driven problem solving, rather than a lack of technical skills. The participants in Basin and Zao-Sanders's study specifically mentioned people lacking the skills to ask the right questions, understand which data is relevant, how to test the validity of the data they have, and interpret the data well and therefore how to know which results are useful and meaningful, how to test hypotheses using A/B tests where is a process of comparing two different versions of a website to gauge the target audience's preferences in digital marketing to see what results pan out, create easy-to-understand visualizations so leaders understand the results, tell a story to help decision-makers see the big picture and act on the results of analysis. According to Basin and Zao-Sanders, their study confirms that data literacy skills have become critical for organisations that utilise data and see its potential to make value. In addition, data capabilities organisations need to have advanced technical skills but also an ability to work with data, such as the ability to interpret data, the ability to draw insights and the ability to ask the right questions in the first place. Interestingly, Basin and Zao-Sanders reveal that soft skills make an even bigger difference.

Taken together, these three studies support the notion that data literacy facilitates data-driven decision making, and it could then be the case that organisations lacking these skills, especially in data-driven problem solving, are unable to be fully data-driven.

2.4.7 Leadership Involvement

The seventh issue is leadership involvement. Scholars have highlighted that senior management's role, commitment and communication, including mindsets and skills are increasingly considered as a catalyst (or inhibitor), a substantial contributor, towards an organisation being data-driven (i.e., McAfee and Brynjolfsson 2012; Brown and Gottlieb 2016; Waller 2020; Davenport and Mittal 2020; Feinzig and Guenole 2020). McAfee and Brynjolfsson (2012) assert that "companies that figure out how to combine domain expertise with data science will pull away from their rivals" (p. 9). For McAfee and Brynjolfsson, exploiting data analytics can radically improve an organisation's performance only if the decision-making culture has been changed to lessen reliance on experience and intuition, starting with the senior executive team. Organisations that often rely on the 'HIPPO's'—the highest-paid person's—opinion for particular important decisions, struggle to see their data's full potential. In addition, McAfee and Brynjolfsson emphasise that "senior executives are genuinely data-driven and willing to override their own intuition when the data don't agree with it" (p. 7) to ensure that a decision-making culture changes into a data-driven one. In a survey by Brown and Gottlieb (2016), they found that, according to their respondents, who are defined as high-performers of analytics capabilities, senior-leadership involvement plays a critical role in organisations' effectiveness at data and analytics even more than its technical capabilities or tools. Their results reveal that "high performers attribute their data and analytics success to involved leaders" (p. 2). For Brown and Gottlieb, organisations can lack communication from the top. As a result, they can confuse the groups responsible for implementing analytics and can inhibit collaboration among functional teams in creating a data-driven culture.

Pugna, Dutescu and Stanila (2019) conducted a study to investigate the organisational challenges raised by big data and its impact on performance management. They also found that leaders committed to an embedded data-driven culture are a critical component to successful data-driven companies, alongside technological challenges. In a similar vein, Carande, Lipinski and Gusher (2017) address the significance of people and organisational components to building data-driven success. They note that successful data analytics starts at the top: “leaders need to be honest with themselves about their willingness to incorporate the insights into their decision making and hold themselves and their teams accountable for doing so” (p. 4), namely, the support of executive leadership enables the data insights are aligned with the entire organisation. Waller (2020) held a similar view, asserting that data-driven culture starts at the (very top). As evidenced by companies with strong data-driven cultures, senior leadership is committed to the concept that “decisions must be anchored in data” (p. 3). It is important because “a few at the top can catalyse substantial shifts in company-wide norms” (p. 3). Waller gives supporting evidence of one retail bank where senior executives spent 30 minutes reading detailed summaries of proposals and supporting facts in order to take evidence-based actions. By doing so, leaders promote a shift in mindset downwards, as employees who want to be taken seriously have to communicate with senior leaders on their terms and in their language. As a result, data-driven cultures can flourish. Furthermore, Davenport and Mittal (2020) reiterate what the CEO’s role is in a data-driven culture; that “in companies with strong data cultures, important decisions are informed by data and analytics and executives act on analytically derived insights rather than intuition or experience” (p. 2). The literature reviewed in this section highlights senior management’s involvement as a contributing factor to (or preventative of) organisational analytics success; without executive support, organisations lose out on the opportunity to create a data-driven competitive advantage. Leadership’s role, commitment, mindset and skills are critical factors in shaping a data-driven organisation.

2.4.8 Data Communication to Enhance Data User’s Engagement

Issue eight concerns data communication to enhance data user’s engagement. Three independent researchers have claimed that connecting and collaborating work with data, placing a particular emphasis on an end-user data-driven approach or data user’s engagement with data are important factors for organisations to gain the potential of data they already have. First, Davenport and Prusak (1998) highlight the data user's important role in information sharing. They define the meaning and differences in data, information and knowledge, where knowledge is neither data nor information but is related to both. Data is a set of discrete, objective facts about events. Data tells us nothings about the 'why'. It says nothing about its own importance or irrelevance, but data is important to organisations because it is crucial raw material for the creation of information. To understand information, Davenport and Prusak describe it as a message that has a sender and a receiver. They elaborate:

> "Information is meant to change the way the receiver perceives something, to have an impact on his judgment and behaviour. It must inform; it's data that makes a difference. The word 'inform' originally meant 'to give shape to' and information is meant to shape the person who gets it, to make some difference in his outlook or insight. Strictly speaking, then, it follows that the receiver, not the sender, decides whether the message he gets is really information—that is, if it truly informs him" (p. 3).

According to Davenport and Prusak (1998), information produced by the data sender needs to be communicated and connected to the data receiver; thus the data receiver is regarded as important in deciding whether to rely on that information or not.

Second, Redman (2013) highlights the importance of data users for improving data quality. He claims, "data's credibility problem management—not technology—is the solution" (p. 84). And he notes, "The solution is not better technology: It's better communication between the creators of data and the data users" (p. 86). Redman found that people are able to identify the root causes of data quality problems and creating ways to improve data quality is the responsibility of not only the data creators but also the data users. And frequently, data creators are not linked organizationally to data users. Because of this, organisations still wrestle with improving data quality; therefore, connecting data creators with their users—their customers—is vital while organisations struggle with the data quality challenge. His finding indicates that the data quality challenge can be tackled by ensuring data creators partner with the users.

Third, Gemignani et al. (2014) similarly assert that the root cause of failing to use data is a social problem, rather than technological one. Organisations continue distancing analysis from the people who must use it in support of their decision-making process:

> "Data communication is a social problem, not a technology problem...many organisations found it important to strive for data volume and invest in bigger databases and feature-rich platforms. Lost in the focus on size was the real prize—actionable insights in the hands of people who can do something about it.... Yet vast quantities of data collected by organisations remain disconnected from the people who might make use of it. Making data useful is a problem that ultimately must be solved by people.... People are the missing ingredient...Unlocking the value of data takes more than individual efforts. It takes the interactions between people who communicate with data, discuss meanings, and debate what actions to take. There is a need for a data culture within organisations that embraces informed decision making" (p. xxiv).

Gemignani et al.'s claim above reflects their contention that to unlock the potential of data, an organisation needs data users who can act on the data analysts' work. As such, data communication is a social problem rather than a technological one. Gemignani et al. also claim that distancing analysis from the people who must work with the data results in a disconnect between the data creator and their product and the decision-making process. In doing so, this decreases data-end user engagement. Therefore, unlocking the value of data requires connecting analysis and the data users' engagement with that data, creating a culture that embraces data-informed decision making.

The studies mentioned above indicate that becoming a data-driven organisation must be cultivated by a harmonious collaboration between the three key elements to drive the change: a data-driven approach and the group of people who create it and deploy it to make data-driven decisions as demonstrated in Figure 3.

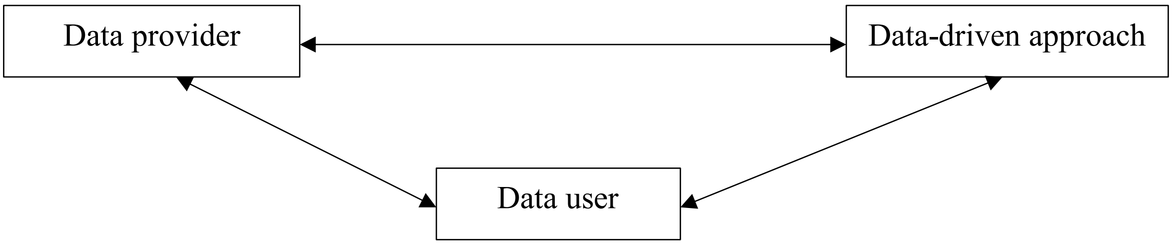

Figure 3: Collaboration between data-driven approach, data creator and data user

Taking these three pieces of research together—connecting and collaborating work with data among groups of people e.g., the data creators and the data end users—has the potential to unlock the value of data they already have, rather than increasing investment in technology. On the other hand, a lack of connection and collaborative work with data among groups of people can lead to actionable insights and data credibility problems, and thus, despite having data communication to enhance the data user's engagement, the goal of becoming driven by data is unachievable.

2.4.9 Data-driven Culture

Finally, the ninth issue is data-driven culture. Due to the complexity of organisational culture, there is no consensus on a single definition (House et al. 2002 cited in Gupta and George 2016). The concept of data-driven culture seems to be typically in line with the definition of an organisational culture that refers to "an amalgam of shared belief, values, assumptions, significant meanings, myths, rituals, and symbols that are held to be distinctive for each and every organisation" (Green 1988, p.6) that become embedded from data-driven insights into their organisation. According to Kiron, Ferguson and Prentice (2013) and Kiron and Shockley (2011), a data-oriented culture is "a pattern of behaviours and practices by a group of people who share a belief that having understanding and using certain kinds of data and information plays a critical role in the success of their organisation" (p. 18).

Kiron and Shockley (2011) identify three key elements of a data-oriented culture: "1) analytics is used as a strategic asset, 2) management supports analytics throughout the organisation and 3) insights are widely available to those who need them" (p. 60). Kiron, Prentice and Ferguson (2014) describe an analytics culture through four components: behaviours, values, decision-making norms and outcomes. Kiron, Prentice and Ferguson (2014) amplify this by stating: "analytics culture unites business and technology around a common goal through a specific set of behaviours, values, decision-making norms and outcome" (p. 10). Similarly, Anderson (2015) defined "data-drivenness is about building tools, abilities, and, most crucially, a culture that acts on data" (p. 1). Mikael et al. (2018) suggest "a data-driven culture is characterized by a decision process that emphasises testing and experimentation, where data outweighs opinions, and where failure is accepted as long as something is learnt from it" (p. 1–2). As prior studies suggest, a data-driven culture may differ in terminology, but a key aspect shared by all definitions seems to be a pattern of behaviours and practices in respect to making evidence-based decisions rather than intuition or personal opinions spreading widely throughout the organisation.

The Importance of Data-driven Culture in Forging Data-driven Organisations

Bean and Davenport (2019) argue that:

> "Firms need to take a hard look at why these initiatives are failing to gain business traction, and what actions must be taken to reduce the cultural barriers to business adoption. Many companies have invested heavily in technology as a first step toward becoming data- oriented, but this alone clearly isn't enough. Firms must become much more serious and creative about addressing the human side of data if they truly expect to derive meaningful business benefits" (p. 4).

For Bean and Davenport, organisations have experienced continual trouble in developing their data-driven approach and failing in their efforts to become data-driven; and unless the culture barriers and the human side of data is resolved, such critical obstacles to become data-driven would continue to impact organisations to achieve the goal of a data-driven organisation in the future. In this regard, a data-driven culture becomes one of the important issues impacting becoming a data-driven organisation.

To conclude this section, a data-driven culture is vital to organisational success, achieving a better performance and obtaining competitiveness, and thus result in becoming a data-driven organisation. Organisations with a strong data-driven culture must develop into a data-driven organisation (McAfee and Brynjolfsson 2012; Kiron, Prentice, Ferguson 2014; Anderson 2015; Thirathon et al. 2017; Diaz, Rowshankish and Saleh 2018). However, organisations continuously confront cultivating a data-driven culture.

Given the importance of a data-driven culture in forging a data-driven organisation as noted by the literature, two key critical findings have been demonstrated. These will be discussed and developed in the following sections.

Two Key Findings of Previous Studies

There are nevertheless two key research findings existing in organisations with respect to a data-driven culture emerging from the review of literature. The first research finding is that a data-driven culture remains elusive; as a result, a data-driven culture is a critical obstacle as organisations move towards evidence-based decision making; and the second research finding is a data-driven culture barrier related to alignment and equal weighting of people, data and technology. Consequently, the adoption barriers organisations encounter are related to management and culture rather than technology. These two key findings from prior research will now be discussed.

First Finding of Previous Studies: A Data-driven Culture Remains Elusive

That generating a data-driven culture remains elusive means that organisations still lack a data-driven culture (Ross, Beath, and Quaadgras 2013; Henke et al. 2016; Clark and Wiesenfeld 2017; Diaz, Rowshankish and Saleh 2018; Waller 2020), and the extant literature defines establishing a data-driven culture as the biggest obstacle in becoming a data-driven organisation. Because of this, a data-driven culture is difficult for organisations to achieve. Ross, Beath, and Quaadgras (2013) state that "companies are investing like crazy in data scientists, data warehouses, and data analytics software. But many of them don't have much to show for their efforts. It's possible they never will" (p. 90). They also state that "adopting evidence-based decision making is a difficult cultural shift" (p. 92). Henke et al. (2016) similarly content that "turning a world full of data into a data-driven world is an idea that many companies have found difficult to pull off in practice" (p. 1). They found that the biggest barriers companies face in extracting value from data and analytics are organisational. Clark and Wiesenfeld (2017) reveal that the three main obstacles to realising analytics' full value are: the organisation's structure, culture and approach to problem solving. Interestingly, culture is suggested as one of the three obstacles. Clark and Wiesenfeld assert that, on the one hand, "culturally, organizations that are too data-driven (yes, they exist) will blindly follow the implications of flawed models even if they defy common sense or run counter to business goals" (p. 3). On the other hand, "organizations that rely too heavily on gut instinct resist adjusting their assumptions even when the data clearly indicates that those assumptions are wrong" (p. 4). This is supported by McKinsey's research that indicates the gap between top- and lower-performers in adopting data analytics is now growing, which means that "a healthy data culture is becoming increasingly important.... And, especially: the competitive advantage unleashed by a culture that brings data talent, tools, and decision making together" (Diaz, Rowshankish and Saleh 2018, p. 1-2). As prior research suggests, a strong data-driven-culture is not only difficult for organisations to achieve but also linking the organisation's success with data analytics is also lagging now. Waller (2020) makes a similar point, that a strong data-driven culture remains elusive for many organisations as well as data being rarely the universal basis for decision making. From a previously mentioned study, it has been suggested that since a data-driven culture remains elusive, it is difficult for an organisation to become data-driven.

This review has demonstrated that running on data-driven decisions cannot guarantee the success of cultural shift in mindset to data-driven decisions. As pointed out in the preceding discussion, while the majority of organisations are moving towards evidence-based decisions, building a strong data-driven culture is difficult to achieve. The summary of the first finding of previous research is demonstrated in Table 2 below.

Table 2: The first finding of previous studies: a data-driven culture remains elusive, as a result, a data-driven culture is a critical obstacle as organisations move towards evidence-based decision making highlighted by the authors' articles.

The first finding of previous studies: a data-driven culture remains elusive	**Authors/Articles**
Developing a data-driven culture is difficult for organisations to achieve.	Ross, Beath, and Quaadgras (2013)/You may not need big data after all

The biggest barriers companies face in extracting value from data and analytics are organisational.	Henke et al. (2016)/The age of analytics: competing in a data-driven world
Three main obstacles to realising analytics' full value: organisation's structure, culture and approach to problem solving. Culture is suggested as one of the three obstacles.	Clark and Wiesenfeld (2017)/3 things are holding back your analytics, and technology isn't one of them
The gap between top-performers and lower-performers in adopting data analytics is now growing. It means that a healthy data culture is becoming increasingly important, and especially the competitive advantage unleashed by a culture that brings data talent, tools, and decision making together.	Diaz, Rowshankish and Saleh (2018)/Why data culture matters
A strong data-driven culture remains elusive for many organisations as data is rarely the universal basis for decision making. The biggest obstacles are cultural not technical preventing them from becoming a data-driven.	Waller (2020)/10 Steps to creating a data-driven culture

Second Finding of Previous Studies: A Data-driven Culture Barrier Related to Alignment and Equal Weighting of People, Data and Technology

Previous literature also placed emphasis on a data-driven culture barrier related to alignment and the equal weighing of people, data and technology. Despite the growth of interest in becoming a data-driven organisation, research has consistently shown the major challenge in developing a data-driven organisation is cultural, rather than technical (LaValle et al. 2011; Chaffey and Patron 2012; Sejahtera et al. 2018; Bean and Davenport 2019; Waller 2020; Nair 2020). Surveys such as those conducted by LaValle et al. (2011) have shown that "the adoption barriers that organizations face most are managerial and cultural rather than related to data and technology" (p. 23). In the same vein, Chaffey and Patron (2012) claim that many companies are failing to utilise core web analytics best practices and that the major barrier involves people and processes (e.g., lack of resources, lack of strategy and company culture) rather than technology and data integration challenges. Furthermore, Sejahtera et al. (2018) state that “the failure is often not due to technology but due to problems associated with organising and managing the socio-technical complexity of big data projects” (p. 2).

In a recent work by Bean and Davenport (2019), they revealed a similar point in the findings of New Vantage Partners’ 2019 big data and AI executive surveys, that companies are failing to become data-driven despite their attempts to invest more to enable use of data and analytics. The results show that cultural barriers are highlighted by 93% of respondents as the challenges to successful business adoption. Only 7.5% of participants cited technology as the challenge. Bean and Davenport also mention that “the difficulty of cultural change has been dramatically underestimated in these leading companies—40.3% identify lack of organisation alignment and 24% cite cultural resistance as the leading factors contributing to this lack of business adoption” (p. 3). As such, the majority of organisations clearly struggle to evolve their culture in a more data-oriented direction. Moreover, Waller (2020) states that “the biggest obstacles to creating data-based businesses aren’t technical; they’re cultural. It is simple enough to describe how to inject data into a decision-making process” (p. 3). Nair (2020) also mentions this point, that “being a data-driven organization takes more than great technology and quality data. Like other aspects of digital transformation, it requires the right internal processes and culture” (p. 3). Together, the studies indicate that a data-driven cultural barrier related to alignment and equal weighting of people, data and technology, is the main reason behind ineffective and unproductive efforts by organisations to adopt a data-driven approach. The summary of the second finding as highlighted by previous research is demonstrated in Table 3.

Table 3: The second finding of previous studies: a data-driven culture barrier related to alignment and equal weighting of people, data and technology highlighted by the literature.

The second finding of previous studies: a data-driven culture barrier related to alignment and equal weighting of people, data and technology	**Authors/Articles**
The adoption barriers that organisations face most are managerial and cultural rather than related to data and technology.	LaValle et al. (2010)/Big data, analytics and the path from insights to value
Companies are failing to utilize core web analytics' best practices. The major barrier involves one of people and processes (e.g., lack of resources, lack of strategy and company culture) rather than technology and data integration challenges that prevent those companies from improving and getting the potential return from web analytics that they could.	Chaffey and Patron (2012)/From web analytics to digital marketing optimization: increasing the commercial value of digital analytics
The failure is often not due to technology but due to problems associated with organising and managing the socio-technical complexity of big data projects.	Sejahtera et al. (2018)/Enablers and inhibitors of effective use of big data: insights from a case study
The results show that culture barriers are highlighted by 93% of respondents as the challenges to successful business adoption. Only 7.5% of participants cited technology as the challenge.	Bean and Davenport (2019)/Companies are failing in their efforts to become data-driven
The biggest obstacles to creating data-based businesses aren't technical; they're cultural. It is simple enough to describe how to inject data into a decision-making process.	Waller (2020)/10 Steps to creating a data-driven culture

Being a data-driven organisation takes more than great technology and quality data. Like other aspects of digital transformation, it requires the right internal processes and culture.	Nair (2020)/Is your business masquerading as data-driven?

From the second finding, people within organisations with shared basic assumptions and beliefs on a data-driven approach continue to significantly impact an organisation's move towards becoming data-driven. As Shah, Horne and Capella (2012) argue: "investments in analytics can be useless, even harmful, unless employees can incorporate that data into complex decision making" (p. 23).

Carande, Lipinski and Gusher (2017) state that:

> "Many conversations about data and analytics (D&A) start by focusing on technology. Having the right tools is critically important, but too often executives overlook or underestimate the significance of the people and organizational components required to build a successful D&A function" (p. 2).

Unless people are able and willing to incorporate the insights extracted into all key decision making across an organisation, organisations have no potential to building a data-driven organisation and to gain benefits from data analytics (i.e., performance improvements and competitive advantage). Succeeding in developing a data-driven organisation is also dependent on people within organisations with shared basic assumptions and beliefs on a data-driven approach rather than just a data-driven approach. Meanwhile, while organisations tend to spend more of their money on data and analytics, they struggle to become data-driven. It is obvious in the literature that the biggest barrier to success is cultural; however, it is slightly more nuanced. For instance, enablers and constraints arise through causes and conditions that impact people's intentions to use their organisation's existing data-driven approach. By doing so, developing a deeper understanding of enablers and constraints that are perceived to help organisations become data-driven would be able to add some interesting information to current knowledge in the literature with regard to a data-driven organisation, as presented in section 2.2–2.3. Figure 4 illustrates the relationship between people, a data-driven approach, and developing a data-driven organisation.

Figure 4: Relationship between people, a data-driven approach, and a data-driven organisation

Furthermore, this second finding also related to the shift from intuition-based decision making to evidence-based decision making. Since developing a data-driven organisation often implies the idea that data and analytics tend to overemphasise intuition for decision-making, data-driven culture, on the one hand, is suggested as a pattern of behaviours and practices to act on analytically derived insights and to make decisions where data outweighs human intuition across all level of the organisation (Kiron and Shockley 2011; Kiron, Ferguson and Prentice 2013; Kiron, Prentice and Ferguson 2014; Anderson 2015; Mikael et al. 2018); data dominates over intuition in data-driven organisations.

On the other hand, Shah, Horne, and Capella (2012) argue that “good data won’t guarantee good decisions” (p. 23), and companies need more informed sceptics who apply judgement to analytics, rather than trust analysis over judgement and seldom trust analysis. They encourage companies to have informed sceptics who can find the middle ground when applying judgement to analysis as well as listen to others’ opinions but with a willingness to dissent, rather than seldom trust analysis or trust analysis over judgement. Data and intuition are subsequently suggested to be complementary to each other. McAfee and Brynjolfsson (2012) suggest that data-driven decisions can radically improve a company’s performance; however, “companies succeed in the big data era not simply because they have more or better data, but because they have leadership teams that set clear goals, define what success looks like, and ask the right questions. Big data’s power does not erase the need for vision or human insight” (p. 66). Davenport (2013) similarly states that human intuition still has its place in the data-driven organisation: “One might even say that developing the right mix of intuition and data-driven analysis is the ultimate key to success with this movement. Neither an all-intuition nor an all-analytics approach will get you to the promised land” (p. 3).

Fragmentation between shared basic assumptions regarding the shift from intuition-based decision making to evidence-based decision making, as discussed earlier, also becomes a data-driven culture barrier related to alignment and equal weighting of people, data and technology, as demonstrated in Table 4 below.

Table 4: The second finding: a data-driven culture barrier related to alignment and equal weighting of people, data and technology highlighted by reviewed articles.

The second finding: a data-driven culture barrier related to alignment and equal weighting of people, data and technology (Cont.)	**Authors/Articles**
Investments in analytics can be useless, even harmful, unless employees can incorporate that data into complex decision making.	Shah, Horne and Capella (2012)/Good data won't guarantee good decisions
Many conversations about data and analytics (D&A) start by focusing on technology. Having the right tools is critically important, but too often executives overlook or underestimate the significance of the people and organizational components required to build a successful D&A function.	Carande, Lipinski and Gusher (2017)/How to integrate data and analytics into every part of your organization
Data-driven culture is suggested as a pattern of behaviours and practices to act on analytically derived insights and to make decisions where data outweighs human intuition across all levels of the organisation.	Kiron and Shockley (2011)/Creating business value with analytics Kiron, Ferguson and Prentice (2013)/From value to vision: reimagining the possible with data analytics Kiron, Prentice and Ferguson (2014)/The analytics mandate Anderson (2015)/Creating a data-driven organization Mikael et al. (2018)/Becoming a data-driven organization

Supported by these two key findings that emerged from the literature review, the thesis argues that cultural issue impacts the movement and development towards becoming a data-driven organisation. This appears to contrast with the data growth explosion to back up decisions, new ideas, predictions or strategies with solid evidence rather than gut-based thinking and decision making, resulting in a better solution. In this regard, the two key findings from the existing literature can cause organisations to continue struggling to operate in a data-driven manner as well as its potential consequence that the value in data-driven decisions appears to be elusive. So, a data-driven culture barrier related to alignment and equal weighting of people, data and technology should be considered as one of the issues impacting organisational transformation in becoming data-driven.

2.5 Summary of the Nine Issues Impacting Organisational Transformation in Becoming a Data-driven Organisation

The nine issues impacting organisational transformation in becoming a data-driven organisation based on the literature review as mentioned in sections 2.4.1–2.4.9 above are summarised in the following table.

Table 5: Summary of the nine issues impacting becoming a data-driven organisation based on the literature review

Issues impacting organisational transformation in becoming a data-driven organisation		**Supporting references**
1. Being data-driven and its potential impact on organisational capabilities	Being data-driven and its potential impact on organisational capabilities are classified into three groups: namely, marketing strategy, making decisions, and performance improvements and competitiveness.	Davenport, Mule and Lucker (2011); Khade (2016); Gandomi and Haider (2015); McAfee and Brynjolfsson (2012); Mela and Moorman (2018); Johnson (2020) Davenport (2006); Davenport (2009); McAfee

		and Brynjolfsson (2012); Power (2014); Agrawal (2014); Cao, Duan and Li (2015); Ghasemaghaei, Ebrahimi and Hassanein (2018). McAfee and Brynjolfsson (2012); Elgendy and Elragal (2016); Monino (2016); Davenport (2013); Janssen, Voort and Wahyudi (2017); Davenport (2009) Wilson (2010); LaValle et al. (2011); McAfee and Brynjolfsson (2012); Henke et al. (2016); Akter et al. (2016); Gupta and George (2016); Wamba et al. (2017); Mikalef et al. (2020)
2. Human component in the drive to become a data-driven organisation	Humans enhance data by adding value throughout the data analytics process such as discovering, interpreting, and communicating of the meaningful data insights.	Mikalef et al. (2018); Davenport and Prusak (1998); Chamorro-Premuzic (2020); Roberts (2015); Wilson and Daugherty (2018); Chartered Global Management Accountant (CGMA)'s report (2016); Chamorro-Premuzic (2020); Roberts (2015);

		Leonardi (2011 and 2012); Orlikowski and Scott (2008); McKinsey & Company (2013); Wilson and Daugherty (2018)
3. Data silos	Data silos are a collection of data where data is isolated from other departments and the rest of the organisation. Subsequently, it is difficult for the entire organisation to share, fully access, and work with the same set of data.	Gemignani et al. (2014); Wilder-James (2016); Nair (2020); O'Tools (2020)
4. Data quality	Data quality is important for creating a data-driven organisation. Lack of confidence in data quality limits the questions people can answer and the quality of insights that they can derive from the data.	Anderson (2015); Kiron and Shockley (2011); Kiron, Ferguson and Prentice (2013); Kiron, Prentice and Ferguson (2014); Anderson (2015); Mikael et al. (2018); Nair (2020); Shah, Horne and Capella (2012); Sidi et al. (2012); Redman (2013); Sivarajah et al. (2016); Redman (2016); Data & analytics case study roll-up report (2016); Nagle, Redman and Sammon (2017); Waller (2020);

		Redman (2020); Svensson and Taghavianfar (2020).
5. Data and data analysis credibility	Data and analysis credibility have a significant influence on people's willingness to embrace a data-driven mindset. To improve data and analysis credibility, it requires closing the gap between data creators and data end users. Without data and analysis credibility, organisations continue to grapple to operate in a data-driven manner.	Svensson and Taghavianfar (2020); Barton and Court (2012); Shah, Horne, and Capella (2012); Anderson (2015); Pugna, Dutescu and Stanila (2019); Redman (2013); Redman (2015); Clark and Wiesenfeld (2017).
6. Data literacy skills	The data skills including hard skills (i.e., skilled analytics) and soft skills (i.e., problem-solving and communicating, storytelling and the ability to work with data) are equally important for implementing a data-driven approach into a decision-making process.	Littlewood (2018); Barton and Court (2012); Shah, Horne, and Capella (2012); Basin and Zao-Sanders (2020).
7.Leadership involvement	Senior management's role and commitment, including mindsets and skills, are increasingly considered as either a	McAfee and Brynjolfsson (2012); Brown and Gottlieb (2016); Waller (2020); Davenport and Mittal (2020); Feinzig

	substantial catalyst or inhibitor with respect to and organisation being data-driven.	and Guenole (2020); Pugna, Dutescu and Stanila (2019) Carande, Lipinski and Gusher (2017).
8. Data communication to enhance data user's engagement	Connecting and collaborative work with data among groups of people e.g., the data creators and the data end users have the potential to unlock the value of data they already have, whereas a lack of connection and collaborative work with data among groups of people can lead to a lack of actionable insights and data credibility problems. Without data communication to enhance the data user's engagement, a culture that reinforces a shared understanding for a data-driven and a data-driven organisation is incomplete.	Davenport and Prusak (1998); Redman (2013); Gemignani et al. (2014)
9. Data-driven culture	A data-driven culture is vital in regard to organisational success, achieving a better performance and obtaining competitiveness, and result in achieving a data-	Ross, Beath, and Quaadgras (2013), Henke et al. (2016); Clark and Wiesenfeld (2017); Diaz, Rowshankish and Saleh (2018); Waller (2020); LaValle et

	driven organisation. However, cultivating a culture driven by data is an ongoing issue encountered by organisations.	al. (2011); Chaffey and Patron (2012); Sejahtera et al. (2018); Bean and Davenport (2019); and Nair (2020).

Overall, the nine issues impacting organisational transformation in becoming data-driven suggest the complexity associated with the transition. The next section discusses the theoretical foundation of sociomateriality, which allows the researcher to find enablers and constraints (Research Question 1) and investigate their impacts (Research Question 2) on the move and development towards becoming a data-driven organisation.

2.6 Sociomateriality

Orlikowski (2007) posits that the social and the material are constitutively entangled in everyday organisational life by the following two realms:

1. The role and implication of technologies are not used as separate and distinct phenomena, and specific technological events occurring in certain particular organisational circumstances but rather technologies and organisations are always integral to each other in everyday organisational life.
2. As a result of this, the position of constitutive entanglement does not privilege to either the social (human actors) or the material (technologies) through one-way interactions and two-way interactions as the tendency in much practice research: "Instead, the social and the material are considered to be inextricably related—there is no social that is not also material, and no material that is not also social" (Orlikowski 2007, p. 1,437).

However, the sociomaterial entanglements identified by Orlikowski presume that the social and the material are inextricably related, and as a result, it has been argued by Leonardi (2012) that:

> "Affordances and constraints are constructed in the space between social and material agencies. People's goals are formulated, to an important degree, by their

perceptions of what a technology can or cannot do, just as those perceptions are shaped by people's goals. Depending on whether they perceive that a technology affords or constrains their goals, people make choices about how they will imbricate social and material agencies. Thus, while it makes sense to talk about material and social agencies as attributes that are activated in response to one another in the space of practice, it seems empirically inaccurate to say that agencies themselves are 'reconfigurations of the world'. Social and material agencies are distinct from one another, and it is only once they become imbricated in particular ways that they can then reconfigure technology's materiality and organizations' communication patterns" (p. 38).

The sociomaterial perspective has emerged as an alternative way of understanding the relationships between the social and the material. Since the privileged deterministic stance began in the 1950s, when Joan Woodward claimed that organisational structure was caused by the change in technology, social dynamics has subsequently become overlooked. In contrast to the social constructivists, it was contended that technology's effects on organisations are socially constructed (Leonardi and Barley 2010). Namely, the technological artifacts would have no meaning nor bring particular effects to an organisation's work regardless of whether people developed or used them. Due to this, the role and influence of technological artifacts has been downplayed in technological and organisational studies. To reconcile the two deterministic positions, the sociomateriality concept emerges in which both people and technological elements are constitutively entangled in work practices (Orlikowski 2007; Orlikowski 2010; Orlikowski and Scott 2008). Sociomateriality is given more importance in technology, work and organisation studies as the ways to research, understand and conceptualise the relationship between the social/human and the material/technical.

Sociomaterialism is claimed to truly contribute better comprehension of the implications of Information System (IS) research in comparison with traditional approaches e.g., unidirectional conceptualisation and unrelated conceptualisation. Unidirectional conceptualisation considers that the elements (e.g., IT personnel, IT infrastructure, and IT management) that constitute IT capability are distinct and independent; the relationship between them is causal. Unrelated conceptualisation, on the other hand, promotes that there is no causal relationship among the elements that constitute IT capability (Kim, Shin and Kwon 2012). Sociomaterialism presents a balanced view with the integration of the social and material, which helps to more efficiently study and understand the dynamic interaction between technology and people, and people and technology that constitute contemporary organisational practices. In recent years, for instance, a number of studies in Information Technology (IT) capability research have adopted the sociomaterialism perspective to conceptualise hierarchical models such as IT capability and Big Data Analytics (BDA) capability which are regarded as an emergent characteristic of sociomaterial activities. These hierarchical models have been empirically proved to be have a positive and significant relationship with regard to superior firm performance (Akter et al. 2016; Gupta and George 2016; Wamba et al. 2017; Mikalef et al. 2020). Hence, the findings of previous studies indicate that the sociomaterial perspective is promoted in the IS community.

Despite general agreement that work practice is inherently sociomaterial and should be a significant aim in contemporary organisational studies, its theoretical basis and implications are still being debated. Different views of the ontological claims lead to different opinions on whether a sociomaterial perspective should be built on 'separate entities' or 'inseparable entities' between humans and technology. Although this distinction seems trivial, it is the result of significant differences in practical application.

As Orlikowski and Scott (2008) note:

> "For researchers in this stream, practices are always sociomaterial, and this sociomateriality is integral, inherent, and constitutive, shaping the contours and possibilities of everyday organizing. As Barad (2003, p. 818) puts it, 'agencies are not attributes [of either humans or nonhumans] but ongoing reconfigurations of the world'. Thus, an important challenge for research going forward is developing ways of thinking and talking about the social and material worlds as inseparable, as constitutively entangled" (p. 463).

Moreover, Orlikowski and Scott (2008) mention: "any distinction of humans and technologies is analytical only and done with the recognition that these entities necessarily entail each other in practice" (p. 456). They have no further elaboration about how this analytical inherent inseparability between the social and the material can be carried out in practice (Kautz and Jensen 2012). Thus, many scholars find themselves confused regarding their data collection and analytics methods when adopting a sociomateriality approach (Elbanna 2016). As Leonardi (2013) cited in one of Mutch's critiques on the agential realism stance, it results in empirical difficulties. This is because:

> "Actors in the empirical world do not perceive the material and the social or the technological and the organisational as interpenetrated entities. Instead, they can relatively easily point to a hammer or a piece of software and say 'this is material' but they would likely have a hard time fathoming that a hammer was in anyway social" (p. 66).

Sociomateriality asserts that the social and the material are constitutively entangled in everyday life and every organisational practice. The constitutive entanglement is committed to treating social and material agencies as ontologically inseparable. Nevertheless, the approach has been criticized on two fronts. First, the ontologically inseparable perspective on sociomateriality results in empirical difficulties, as mentioned previously. Subsequently, Leonardi (2011) suggested the imbrication metaphor (See section 2.6 below), which takes a complementary yet distinct approach to the notion of entanglement and has treated social and material agencies as being distinct from each other. It is only once they become imbricated in particular ways to create the sociomaterial, which in turn produce changes in routines and technologies. In this view, the metaphor of imbrication can be used to suggest how the social and material become entangled or sociomaterial. By allowing independent elements, it creates a better understanding for people in empirical studies, as opposed to a constitutive entanglement concept. Second, the ontologically inseparable perspective on sociomateriality results in redesigning system difficulties. Leonardi and Rodriguez-Lluesma (2012) argue that 'this commitment to inseparability makes it very difficult to think about redesigning systems to work better because they cannot be dismantled into their component parts and re-arranged' (p. 1). The ontological entanglement concept and its commitment to the idea that the social and material are inseparable limits the views to improve the technical design because they are viewed as entangled and cannot be rearranged (Quimno, Imran and Turner 2013).

To conclude this section, Orlikowski (2007) introduces sociomateriality and explains that the social and material are constitutively entangled in everyday organisational life.

However, the sociomateriality relationship entanglement from Orlikowski is built on inseparable entities between humans and technology, which results in empirical difficulties and a limiting of the views to improve the technical design. Alternatively, Leonardi (2011 and 2012) suggests sociomaterial imbrication to explain how the social and the material become imbricated depending on whether people perceive that a technology affords or constrains their goals, that people make choices about how they will imbricate social and material agencies. According to Leonardi, humans and technology are treated as separable entities, but once they become imbricated or sociomaterial, they are constitutively entangled as inseparable entities.

The sociomaterial imbrication concords with the philosophical assumptions of this study that a data-driven organisation is viewed as an integrative phenomenon of people (data users and technology providers) and technology (namely, a data-driven approach). An organisation wishing to develop a data-driven approach is determined by people's perceptions according to whether using a data-driven approach enables or constrains their ability to carry out their goals, which subsequently leads to technological or organisational change. The sociomaterial imbrication is used as this study's theoretical framework and is thus presented in detail below.

2.7 Sociomaterial Imbrication

The concept of 'sociomateriality' was posited by Orlikowski in 2007 and developed further later working in collaboration with Scott in 2008. They defined technologies and organisations in the same way. It does not prioritise either humans or technologies. Later, the imbrication metaphor was used to suggest how they become sociomaterial and this term was introduced by Leonardi in 2011 and 2012. He explains that people come to technology with different goals, and then make choices and decide on the agency to imbricate with technology. This depends on whether they perceive that a technology affords or constrains their ability to carry out their work. This research therefore views the development towards a data-driven culture and ultimately becoming a data-driven organisation from the point of view of sociomaterial imbrication to address the two research questions (see Chapter 1).

Imbrication is a joining together an overlap between people and technology which brings a change in routine or a functionality in technology. The verb ‘imbricate’ is derived from the name of Greek and Roman interlocking tiles, known as ‘inbred’ and ‘tegula’. Leonardi employs the metaphor of imbrication to suggest how social and material agencies become sociomaterial. They are considered distinct from one another and function interdependently, like the imbrex and tegula (but sometimes they become imbricated in ways that can then create or change routines; and at other times produce or alter technologies).

Sociomaterial imbrication has been found to be a framework to help identify enablers and constraints in the development towards a data-driven culture and become a data-driven organisation. sociomaterial imbrication was introduced by Leonardi (2011) to highlight the ways people decide to interact with a technology embedding in the organisation. It posits that people’s decisions are shaped through the perceptions of how a technology affords or constrains people’s ability to achieve their own goals, which subsequently leads to technological or organisational change.

A technology’s materiality refers to “the ways that its physical and/or digital materials are arranged into particular forms that endure across differences in place and time” (Leonardi 2012, p. 29). A technology’s materiality has its own capacity to act without human intervention by the so-called material agency. People, on the other hand, can act independently in response to technology’s materiality, which is defined as social (human) agency. As argued by Leonardi (2011), routines and technologies are produced by the same building blocks: human and material agencies even though they are distinct phenomena. Coordinated social agencies and material agencies result in change in the form of both routines and technologies. The social and material agencies are explained by Leonardi (2011) as: “human agency is typically defined as the ability to form and realise one’s goals” (Giddens 1984 and Emirbayer and Mische 1998 cited in Leonardi 2011, p. 147) while “material agency is defined as the capacity for nonhuman entities to act on their own, apart from human intervention” (p. 148).

The difference between material and social agencies is the intentionality. Materiality does not act to realise its own goals because it has none of its own making, and material agency lacks intention for its action. People will decide how they will imbricate their social agency in response to technology's material agency. People are likely to align their routines through a technology's feature if a technology is perceived as enabling. In contrast, if people perceive a technology to have no advantages, they will decide not to use a technology's feature or decide to change it (if they can) to meet their needs.

In this view, material agency is constructed not only from its functions, but also from people's perceptions about how technology either helps or constrains their ability to achieve their goals. Because of this, "materiality exists independent of people, but affordances and constraints do not. Because people come to materiality with diverse goals, they perceive a technology as affording distinct possibilities for action. The perceptions of what functions an artifact affords (or constrains) can change across different contexts even though the artifact's materiality does not" (Leonardi 2012, p. 37). Human and material agencies are then woven together in ways which create routines and technologies regularly used by organisational members as a sociomaterial process.

Subsequently, organisational change emerges when people perceive a technology as affording their ability to perform their goals at work. People will decide to use the technology which results in organisational change. On the other hand, if people perceive a technology as constraining their ability to perform their goals, they will decide not to use the technology or adjust the technology if they can, which results in technology change. Routines and technologies are viewed as a sociomaterial process as the space between the human and the material agencies become intertwined through imbrication over time. Affordances and constraints are also constructed in the space between social and material agencies in this regard. The sociomaterial imbrication claims that changes in organisation and technology have the same basic building blocks, which are human and material agencies. A summary of sociomaterial practice is presented in Figure 5.

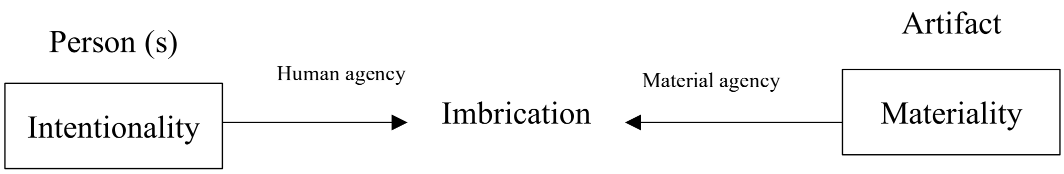

Figure 5: The sociomaterial practice from Leonardi (2011 and 2012)

Applying the sociomaterial imbrication to the current study, a data-driven organisation will be determined by people' perceptions according to whether using a data-driven approach enables or constrains their ability to carry out their goals. If a data-driven approach is perceived as enabling, people are likely to use it and evolve their culture in a more data-oriented direction (e.g., altering their pattern of decision making). In contrast, acting on the perceived constraints of data analytics can lead people to decide not to use a data-driven approach, or decide to change a data-driven approach to meet their needs and goals instead. In order to develop a deeper understanding of enablers and constraints perceived to impact developing a data-driven approach, this study therefore applied and analysed the results through sociomateriality—the imbrication lens.

Given the importance of being data-driven, substantial opportunities and challenges are brought about with the data movement. On the one hand, it profoundly attracts people to embrace data into their work, but on the other hand, the challenges have been increasingly raised by using them, such as the culture issue. This suggests that an organisation's evolution to become data-driven is linked to multifaceted influential factors.

2.8 Summary

The literature review has presented the theoretical foundation of this research which consists of five sections related to a data-driven organisation: (i) the definition of a data-driven organisation, (ii) the challenges of becoming a data-driven organisation, (iii) the nine issues impacting organisational transformation in becoming a data-driven organisation, (iv) sociomateriality, and (v) sociomaterial imbrication.

According to the literature reviewed here, a data-driven organisation opens up new business opportunities with data, but brings along with it three challenges: (i) organisations still have not created a data-driven organisation to reach their full potential as a data-driven organisation, (ii) using data for decision making that overcomes historically accepted decision making has been identified to be challenging the more data-driven decision-making organisations become, and (iii) a lack of empirical research to address empirical discussions on the evolution of an organisation. This is important since, although a data-driven approach has been widely used to enhance strategic decisions within a wide range of organisations, organisations are struggling with becoming data-driven as a result of a major issue with the shift from intuition-based decision making to evidence-based decision making, but also from the empirical research gap in tackling a data-driven organisation. Because of this, organisations are still prevented from developing a comprehensive understanding of how to establish a data-driven organisation to unlock its data's full potential. Addressing the gap about becoming a data-driven organisation is the focus of this research. The two research questions were therefore formulated as follows:

1. What are enablers and constraints of becoming a data-driven organisation?
2. What are the impacts of these enablers and constraints on becoming a data-driven organisation?

Thus, this research aims to answer these two research questions by identifying enablers and constraints and their impacts on the move and development to becoming a data-driven organisation. To do this, the nine issues impacting organisational transformation, as suggested in the extant literature, are reviewed and discussed to ensure all possibilities during the data collection are opened up: (i) being data-driven and its potential impact on organisational capabilities, (ii) the human component in the drive to become a data-driven organisation, (iii) data silos, (iv) data quality, (v) data and data analysis credibility, (vi) data literacy skills, (vii) leadership involvement, (viii) data communication to enhance data user's engagement, and (ix) data-driven culture. As described above, sociomateriality and sociomaterial imbrication will be used to address the two research questions, and the research methodology applied in this study will be elaborated on in the following chapter.

CHAPTER 3: Research Methodology

3.1 Introduction

In reviewing the literature, Chapter 2 reveals that becoming a data-driven organisation emerges as a major interest for more organisations as it is assumed that this produces/provides opportunities and benefits. Organisations in all sectors, including education, are moving on a journey towards the goal of becoming data-driven, but this remains a significant challenge. This research is exploratory as it looks at the perceptions, the relationships between people and technology/technology and people, and the relationship between people across different organisational functions, in an attempt to understand the move and development towards a data-driven organisation. The two research questions were accordingly formulated:

1. What are enablers and constraints of becoming a data-driven organisation?
2. What are the impacts of these enablers and constraints on becoming a data-driven organisation?

The issues experienced by individuals, from a diverse range of functions, within the research site (namely, data users and technology providers) as they engage with technology (namely, a data-driven approach) and other people were investigated. The enablers and constraints of becoming a data-driven organisation (Research Question 1) were identified through people's perceptions according to whether using a data-driven approach affords or constrains their ability to carry out their work, a so-called sociomaterial imbrication (Leonardi 2011 and 2012) and then investigated. In order to develop a deeper understanding of enablers, constraints, and their impacts on the move and development towards becoming a data-driven organisation, this study applied the methodology and analysed the results in alignment with the sociomateriality lens.

In this chapter, the research methodology presents a detailed discussion and the rationale on which the research design was based in this study. Chapter 3 also explains and justifies the selection of each research methodological element and how this study was conducted. In this regard, issues impacting organisational transformation were identified in the literature review to ensure that all possibilities during the data gathering were accounted for in the process of coding and identifying themes.

The structure of this chapter begins with Section 3.1 providing the introduction. Section 3.2 reviews the research paradigm employed in this study. Section 3.3 justifies the use of the research site as the research strategy and describes the role of a qualitative researcher to ensure that the researcher's close engagement in the research context would not threaten the study's rigour. The pilot study was conducted to ensure the applicability of the research method in the main study, as explained in Section 3.5. Section 3.6 gives the criteria and the approach for recruiting participants in the main study. Challenges while doing the main study are reflected in Section 3.7, and Section 3.8 provides details of the data collection process using a semi-structured face-to-face interview. The use of an online survey due to the COVID-19 pandemic is then described in Section 3.9, and Section 3.10 explains the process of data analysis. Section 3.11 elaborates on the criteria for ensuring this study's research rigour. The final part, Section 3.12, details that this study was undertaken ethically, and the ethical considerations met the core requirements. The research methodology is summarised in Section 3.13.

3.2 Research Paradigm

Given the research to understand people's perceptions of being data-driven, every person is considered to be unique. As a result, there are different interpretations of those experiences which affect their engagement with a data-driven approach and other people. This then informed the research philosophy of interpretivism (Grix 2002; Bryman and Bell 2015 Braun and Clarke 2013; Saunders, Lewis and Thornhill 2016). Using a qualitative research paradigm allowed the researcher to explore and collect the participants' data from their experience of different circumstances. However, the DBA project was impacted by the COVID-19 restrictions in conducting fieldwork, especially the intention to carry out face-to-face interviews, which was impossible. Accordingly, data for the main study were gathered using one face-to-face interview and the rest were based on responses to an online survey. Both sources were treated as being similar for data analysis, and subsequently, the data collected was analysed using thematic analysis.

3.3 Research Strategy

An organisation wishing to become data-driven is determined by people's perceptions regarding whether the approach affords or constrains their ability to carry out their tasks and achieve their goals, which subsequently leads to technological or organisational changes. Due to the situated nature of the context, the characteristics of the selected research site, and the intention to understand the views of people in their engagement with technology and other people, the sociomaterial imbrication lens introduced by Leonardi (2011 and 2012) was adopted. Leonardi suggests the sociomateriality: imbrication lens to describe how the social and the material become entangled in the workplace, and "depending on whether people perceive that a technology affords or constraints their goals, people make choices about how they will imbricate social and material agencies" (p. 38, Leonardi 2012). According to Leonardi, the social context and the materiality that exist in it are treated as separable entities, but once people imbricate social and material agencies, the social and material become sociomaterial. Sociomaterial practice is the space in which multiple human (social) agencies and material agencies become constitutively entangled to work together.

Given the task of understanding the views of people in their engagement with technology and other people, and to identify enablers, constraints, and their impacts on the move and development towards and becoming a data-driven organisation, the research site was selected to allow the researcher to focus and acquire/gain a multifaceted understanding the case's complex issues. In this study, the selected research site is an organisation which has been working to become a data-driven organisation. The research site is then relevant to acquiring an extensive and in-depth description to fulfil this task, although there are some issues about the research site as a case study i.e., its rigour and generalising (Yin 2018). With respect to the rigour of a case study, Blumberg, Cooper, and Schindler (2014) argue that this is also true of studies based on any other research approach. These challenges can be overcome by following systematic procedures and making the process of data collection and analysis as transparent as possible, comprising well-defined research objectives(s) and question(s); designing a good case study; and collecting, presenting and analysing data fairly (Yin 2018; Blumberg, Cooper, and Schindler 2014). A detailed illustration on the rigour used at the research site is presented in Section 3.11. In addition to the rigour, Yin (2018) claims that "case studies are generalizable to theoretical propositions and not to populations or universe" (p. 20) which accords with Blumberg, Cooper, and Schindler (2014). Accordingly, this study chose to collect the data from a research site, namely, a UK university, as it was moving towards the goal of becoming data-driven. Additionally, as the researcher is an international student and has few networks within business, the researcher has, therefore, drawn on the proximity of the University as the research site.

3.4 Role as a Qualitative Researcher

Reflexivity was crucial during this qualitative study. As Mann (2016) puts it, "reflexivity involves examining yourself as researcher and also your research relationships" (p. 27). Because of this, the researcher practiced reflexivity by using a diary to constantly record feelings, ideas, biases, and subjectivity so that she was aware of them. For instance, during the pilot study, some of the interviewees identified themselves as just data users, and not the main drivers in shaping a data-driven organisation. However, the researcher found that they regularly received data reports, dashboards and attended meetings to discuss the results of analysis as this came up during interviews. It occurred to the researcher that they were resourceful, but the researcher then put questions to them in a way that might have made them uncomfortable. After reflection, the researcher realised and learned that maybe the researcher should take more care about their feelings and responses, and that raised awareness when doing other interviews and formulating the questions in the survey.

3.5 Pilot Study

The pilot study was undertaken to ensure the applicability of the research methods. The pilot study allowed the researcher to verify:

a) The comprehensibility of interview questions, namely whether the interview questions were properly delivered, comprehensible and unambiguous in a consistent manner.
b) The effectiveness of interview questions, namely whether an interview schedule was effective to accurately address the research questions for the main case study protocol.

c) The practicality of using a digital voice recorder protocol of interviews, namely whether the use of a digital voice recorder was practical while conducting the interviews.

In addition to verifying the study's executability, the pilot study cultivated desirable research skills including the research's inquiry skills and helped the researcher become familiar with the procedures in the research protocol (Hassan, Schattner and Mazz 2006) which, to some extent, minimised bias and enhanced the reliability of the case study due to "the continuous interaction between the issues being studied and the data being collected" (Yin 2018, p. 82).

When the pilot study began, the participants were asked to look at a data-driven approach which was Google Analytics (GAs)—a web analytics that collects data of how users interact with the university's website content. However, GAs was found not to be the only data-driven approach that people on the research site used to carry out their tasks to achieve their goals as they mentioned this whilst being interviewed. It appeared that a varied data-driven approach/various data-driven approaches could be used in an organisation. Furthermore, in order to gain insights into an organisation wishing to develop a data-driven approach, the key informants were not only data creators—e.g., data analysts—but also data end users who must use the analysis results to carry out their work. The researcher thus altered the questions into a data-driven approach rather than explicitly mentioning GAs in the interviews. The research questions in the study were subsequently refined from the initial inquiry based on the original purpose of the case study and application of ethics.

The pilot study was conducted from June to August 2019. Using the supervisor's connections, the potential participants were first contacted. Some participants also first made contact with their colleagues to take part in the pilot study on behalf of the researcher. The participants were four people who used a data-driven approach for their work at a UK university (consisting of females = 3, male = 1). Their roles and responsibilities were at the core of the faculties and marketing teams which were able to provide and contribute further knowledge to the study. The study used semi-structured face-to-face interviews. Potential lessons were learned regarding the research design and the field procedures from the pilot study:

a) Empowering the participants to arrange their interview time and place wherein they felt most comfortable and confident to share experience.
b) Creating a rapport with the participants facilitated a relaxed atmosphere and encouraged them to be more inclined to talk during the face-to-face interviews. It also reduced anxiety for the researcher.
c) Attentive listening to elicit significant facts and information during interviews.
d) Avoiding correcting the participants' ideas and feelings, expressing the researcher's own thoughts, and asking leading questions so as to obtain the appropriate answers.
e) Reflecting significant issues and emerging/revealing/ considerable insight into the issues to be studied in the final research study.
f) Using a digital voice recorder enabled the researcher to capture all information provided and to reduce worrying about the missing important and interesting information throughout the interviews as English is not the first language.
g) Jotting down any interesting points during the interviews proved to be helpful to follow and understand the participants' ideas more easily even though the data was audio-recorded.

3.6 Research Participants in the Main Study

This study investigates people's perceptions in their engagement with technology and others, which subsequently obtain what implications this has for organising. And as the focus in this study was on student recruitment and marketing, the participants were recruited from a diverse range of functions within the research site, namely, the communications team, marketing team, recruitment team, web and digital media team, faculty, and academic staff (programme directors) as they engage and implement a data-driven approach for student recruitment and marketing. The recruitment of a UK University (the participants) in doing/working on the research site had to meet the following three criteria: work with a data-driven approach (i.e., relevant data and insights) and organising (i.e., marketing manager, faculty managers, programme directors, analyst, web and content manager, director of admissions, admissions managers, and admissions officers), a willingness to take part in the study, and their ability to provide data to analyse. For working through a data-driven approach, it was anticipated that the participants would be able to provide valid and insightful data. Due to COVID-19 restrictions in conducting fieldwork, one semi-structured face-to-face interview was conducted and the rest responded to an online survey. Thus, there were 20 participants in the main study, comprising one interviewee and 19 respondents. Importantly, they all shared substantial experience in working through a data-driven approach, as well as organising.

This study adopted a snowball approach as a recruitment technique to help expand the sample (Biernacki and Waldorf 1981). The researcher used a snowball nonprobability convenience sampling by initially connecting with their supervisor who closely aligned with the target population. So, the potential participants were first contacted using the supervisor's personal connections. Also, some participants first made contact with other potential participants on behalf of the researcher. Others suggested their colleagues to the researcher. After that, the researcher approached potential participants through emails. Some agreed to take part in the study. Other participants were subsequently invited to take part in the study using the online survey instead. Some difficulties were experienced as a surrogate approach had to be adopted. These included the impact of changes to work practices for those working from home once the researcher sent them the questionnaire and the difficulty in receiving responses back. Supervisor support resulted in follow-up emails and the subsequent receipt of responses. Each research participant in this study was assigned a fictitious name such as Interviewee Number 1 and Respondent Number 1 throughout data collection, data analysis, and reporting and discussing findings so as to maintain anonymity for all participants.

3.7 Challenges while Conducting the Main Study

The challenges found while doing this work included difficulties due to adopting an online survey instead of the intended face-to-face interviews to collect data in adherence with COVID-19 guidance and Government rules, but the main research was still based on its original purpose, framework and ethical application. Accordingly, data for the main study were gathered using one face-to-face interview and the rest were based on responses to an online survey. Both sources were treated as being similar for data analysis and subsequently, the data collected was analysed using thematic analysis.

Using an online survey appeared to be a practical type of data collection with increasing adherence to COVID-19 guidance and rules from the Government. It also seemed safe and convenient for all participants to complete in their own time and pace while physically distancing. Finally, it allowed the researcher to complete the project on time during the pandemic. However, the researcher realises that it did not give the participants' opportunities to expand on their ideas or for the researcher to ask for additional ideas or clearer statements. So, the survey questions relied heavily on those used in the pilot interviews. Some questions were then revised to be easier for the participants to understand because of the pilot experience, and these were verified by four peers.

Potential participants were first contacted using the supervisor's personal connections. Some participants first contacted other potential participants on behalf of the researcher. Others suggested their colleagues to the researcher. After that, the researcher contacted them through emails. Apart from those participants, the researcher used emails to recruit research participants in which all staff member details, such as department, name and email address on a university chosen for a research site website were listed and were then contacted through emails by the researcher. Ethics were a priority throughout the main study. The researcher asked for permission and received consent from the participants before conducting the study. However, the participants retained the right to withdraw from this study at any time without needing to give any reason. For instance, while one participant suggested another potential participant to the researcher, and he consented to be part of the study, he later had to withdraw because of the COVID-19 outbreak.

Difficulties arose due to adopting an online survey as a surrogate approach, once the researcher set out the survey. There was the impact from the changes to work practices for those working from home and the difficulty and delay in receiving responses. Support was required from the supervisor who sent follow-up emails, which resulted in late responses. Twenty participants willingly participated in the main study. Even though only 20 were recruited, their co-operation was helpful, and the data obtained seemed insightful and represented interesting ideas for research discussion. Moreover, a robust research process has been utilised throughout the DBA project. The four criteria to ensure data trustworthiness proposed by Lincoln and Gupta (1985)—credibility, transferability, dependability (or reliability) and confirmability as discussed in section 3.10—were followed. The researcher was also confident in the data as some was consistent with the literature and some emerging ideas were also discovered (see Chapters 4 and 5).

3.8 Data Collection Method

In this study, the research method was planned to collect data, which understood the views of humans in their engagement with technology and other humans. The data gathering instrument with/using a research site was therefore selected in accordance with the concept of sociomateriality. Traditionally, the method applied were semi-structured face-to-face interviews. In order to comply with social distancing policies, the data collection method was changed to an online survey as a surrogate approach. This study used a semi-structured face-to-face interview prior to February 2020, whilst an online survey was employed after that. Both sources were treated as similar for data analysis.

Thus, the study undertook two data collection methods: one semi-structured face-to-face interview and an online survey. The semi-structured face-to-face interviewing was used as the planned data gathering technique, which is beneficial in five ways:

a) Flexibility in terms of questions or the order in which questions are asked, but also offering the opportunity for participants to provide in-depth and detailed responses and to discuss issues that are important to them and which the researcher has not anticipated and are unplanned on the interview guide (Braun and Clarke 2013).
b) Helping the researcher explore and inquire into the research participants' perspectives on the investigated topics (Blumberg, Cooper and Schindler 2014) and gain detailed data regarding individual experiences and views.
c) Providing the researcher with large amounts of rich data (Jankowicz 2016).
d) Allowing the researcher to encourage more detailed responses using probing and prompting as well as clarifying any ambiguities that arise (Gilbert and Stoneman 2016).
e) Allowing the researcher to modify the question or to compose another where appropriate, as opposed to other approaches (Saunders, Lewis and Thornhill 2016).

The use of a semi-structured face-to-face interview resulted in confidence in conducting an interview as well as maintaining rigour in the study. Additionally, the pilot study cultivated the qualitative inquiry skills of the researcher, which to some extent, enhanced the credibility of the study.

The questions in the interview schedule were prepared beforehand and were determined by the research questions. The questions were then discussed with the supervisor and ambiguous questions were revised, irrelevant questions were eliminated, and other important questions emerging from the pilot study were deliberately considered and added. The amended interview schedule is presented in Appendix A and falls under mainly three areas, but some examples are given below:

a) Could you please describe your role and responsibilities?
b) How does a data-driven approach (data technological driven or reports) help you to achieve your work? Why is it important?
c) What do you think about how a data-driven organisation in your organisation looks like?

Accordingly, the questions in the interview schedule were classified into three sections: introduction and background questions, perceptions of technology (a data-driven approach) and organising questions, as well as questions concerning perceptions of a data-driven organisation. Introductory and background questions were used not only to elicit the data that was relevant to the study, but also to serve as ice-breakers to set the interviewee at ease (Creswell and Creswell 2018).

The use of semi-structured face-to-face interviews was tested throughout the pilot study and proved to be effective. However, the DBA research project was impacted by the COVID-19 outbreak, especially carrying out the intended face-to-face interviews that were not possible due to lockdown restrictions. Only the first participant had a face-to-face interview for the main research project, which was conducted in January 2020 before the spread of the COVID-19. As a result, some changes were subsequently made to overcome the impact of COVID-19 restrictions:

a) The manner of conducting the big project of the DBA was changed from semi-structured face-to-face interviews to an online survey with open-ended questions. Open-ended questions were asked because an online survey did not give the participants opportunities to expand on their ideas nor the researcher to ask for additional ideas or clearer statements. Open-ended questions were beneficial in this regard. The use of an online survey could be regarded as a type of practical data collection to tackle uncertainty during the COVID-19 lockdown. The data collection was then inevitably conducted using an online survey as a surrogate approach to gain answers to certain research questions during the COVID-19 pandemic and lock down restrictions.

b) Due to experience gained through the pilot study, one important question was added and some were revised to be easier for the participants to understand based on the same topic and themes from the original ethics application, but also to ensure the collection of rich, detailed and usable data as much as possible. The added question was: *What do you think about 'data versus intuition to inform business decisions'?* This question was added because, as the research site moved towards the goal of becoming data-driven, some participants in the pilot study mentioned that there was always a back story when they drew conclusions from having data. There needs to be a balance between data and intuition. This indicates that intuition to some degree continues to play an important role. Furthermore, some questions were revised to be easier for the participants to understand and to ensure getting as much rich, detailed and usable data as possible. Examples are given below.

   - The original question was: *How does a data-driven approach help you to achieve your work?* The revised version became: *Has a data-driven approach been done in a way that you want it to be at work? Please explain how.*

   - The original question was: *Identify any limitations on a data-driven approach?* The revised version became: *Please identify any challenges arising from having or using a data-driven approach? Concerning challenges arising from a data-driven approach, what change would you suggest? In what way do you think it would be helpful?*

c) The process followed the pilot study, except for the inclusion of an online survey with open-ended questions. This meant no major changes would create a risk to the study's participants.

As agreed to and supported by the supervisor, a surrogate approach was adopted on the project to enable the researcher to continue with the research's data-gathering stage. Collecting data using online-surveys appeared to be the most advantageous approach to obtaining data associated with increasing adherence to COVID-19 guidance and rules from the Government. The online surrogate interview seemed to be safe and convenient for all participants to complete in their own time and at their own pace whilst physically distancing. In addition to participants' safety and convenience, using an online survey created significant advantages to achieving the completion of the DBA project on time throughout the pandemic. However, several limitations were identified through the online survey, compared with the traditional approach of semi-structured face-to-face interviewing as presented below.

a) There was no possibility for probing and especially immediately clarifying any ambiguous points that arose from some participants.
b) The answers/responses which the researcher received were short on details and examples as might have been seen in using semi-structured face-to-face interviews for some participants, but the data was sufficient for analysing.
c) The impact of working from home and the difficulty and delay in receiving responses. Support was needed from the supervisor with follow-up emails.

Thus, the research site evidence in this study was gained from both the one semi-structured face-to-face interview and online survey using open-ended questions to answer the two research questions.

3.9 Data Gathering Procedure

As noted, data in this study was gathered through the use of two methods a semi-structed face-to-face interview and an online survey due to the COVID-19 pandemic.

3.9.1 Gathering Data Using a Semi-Structured Face-to-face Interview

Prior to the interviews, the participants were contacted through emails to confirm the appointed time and place at their convenience, which each participant was able to arrange for themselves, but it was in a safe, quiet and private room where the interview was unlikely to be disturbed and the quality of a digital voice recorder would not be reduced (Saunders, Lewis, and Thornhill 2016). In preparation before going to conduct the interviews, the researcher, as the interviewer, familiarised herself with the interview schedule and attempted to understand how the two research questions in this study were formulated. In doing so, this increased her confidence and ability to communicate more effectively when conducting the interviews. It also helped the researcher keep on the track during the interviews. Apart from that, some paper was prepared for note-making on the emergence of any important points despite the conversation being audio-recorded.

Each interview lasted between 30-45 minutes to reflect the participants' views on the topic being studied. A digital voice recorder was used where consent was given to help the researcher as English is not their first language so as to capture all information during the interview conversation (see Appendix E). All participants who agreed to take part in the study were initially given the participant information sheet (see Appendix F) which included a brief overview of the research project, the length of an interview, the use of a digital voice recorder, their anonymity and confidentiality, and their rights as research participants. However, all this was explained again to the participants to ensure the protection of their privacy before the interviews took place and, they were offered the opportunity to ask questions (Bryman and Bell 2015) to establish credibility and gain the interviewees' confidence.

During the interviews, an online stopwatch was used to keep the interview duration on track and to ensure the study did not disrupt the participants' working environment in any way unless the participants wished to extend the time. For instance, some participants still continued the conversation even though the audio recorder was switched off after finishing the interviews. For instance, one participant expressed the view that there were not so many higher educational organisations in some countries that actually had someone specifically for the analytics side of things as compared to universities in the UK, which offered reassurance that the organisation was qualified to serve as the research site wishing to develop a data-driven approach.

Interestingly, establishing a good rapport with the participants, being an empathic listener, the act of note-taking when unexpected discoveries arose, and noticing and being curious about interesting points were also effective ways to encourage the participants to express themselves as much as they could since they assumed that their ideas were being recognised and were contributing to further knowledge to the study while simultaneously enhancing trust and intimacy with the interviewees.

When interviewing the participants, lessons learned from the pilot study and the literature were applied:

a) Showing a warm/friendly manner to put the participants at their ease and to help create rapport and trust (Braun and Clarke 2013; Bryman and Bell 2015),
b) Balancing act between attentively listen and note-taking what the participants say,
c) Being open-minded to different ideas and unexpected discoveries arising,
d) The use of open questions to encourage the participants to define and describe as they wished, including what, how, or why while simultaneously using specific and closed questions as introductory questions when a particular topic of the interview was being addressed, such as, *Could you tell me about…*? (Saunders, Lewis and Thornhill 2016),
e) The use of probing questions to follow up on initial responses and seek more explanations and meanings to clarify something from the participants, such as in *what ways? Can you give me an example, if possible?* and *what does it mean?* (Bryman and Bell 2015; Saunders, Lewis, and Thornhill 2016; Creswell and Creswell 2018),
f) Maintaining a friendly tone of voice to encourage the conversation,
g) Giving the participants time to think and respond to the questions, and
h) Avoiding leading questions and correcting the participants' responses to get a particular answer.

Since conducting an interview requires intense focus, the schedule was planned to interview only a single participant in a day (Braun and Clarke 2013). After each of the interviews had been completed, they were transcribed as soon as possible after conducting it. By doing so, it allowed the researcher to "reflect on and adjust your interviewing style and questions" (Rubin and Rubin 1995 cited in Braun and Clarke 2013, p. 91) before moving to the next interview. Through this preparation, the language barrier could also be minimised. Furthermore, mutually jotting down notes during the interview proved beneficial for cross-checking the transcription for accuracy and consistency.

Lastly, a thank you email for agreeing to take part in the study was sent to every participant soon after the interview. Those were intended to avoid any bias that may affect the reliability and validity of the data obtained.

3.9.2 Gathering Data Using an Online Survey Due to the COVID-19 Pandemic

To adapt to the COVID-19 pandemic, an online survey was used. These questions were still determined by the research questions and were carefully considered and discussed with the supervisor for polishing. However, some important questions were added, which emerged from the pilot study. There were several reasons why one important question needed to be added. First, the researcher was unable to probe and clarify the participants when they did not understand specific questions. Second, the questions were designed to maintain a meaningful answer and generate rich data for analysing based on the same topic and themes from the original ethics application, so as to keep an online survey approach similar to a face-to-face interview in the pilot study while simultaneously creating no harm to the participants. Lastly, the researcher could not trace the data back to an individual participant due to the protection of privacy through anonymity and confidentiality. Both the semi-structured face-to-face interview and an online survey were treated as similar for data analysis.

The sensitivity and appropriateness of the open-ended questions in the online survey were verified by four peers, ensuring the wordings were clear and comprehensible. Only a few wordings in some questions were ambiguous, which then were revised to be more understandable by the participants. The pilot study also allowed the researcher to obtain experience conducting in-depth interview techniques which could then be applied to amending the questions in the online survey. A short explanation was also given to some questions for clarification. For instance, a data creator means a person who produces or provides analytical reports, spreadsheets or directly interacts with a data-driven approach, while a data user refers to a person who uses data insights from analytical reports, spreadsheets or indirectly interacts with a data-driven approach to support things, such as decisions. Anonymity and confidentiality were outlined in the online survey to the participants in a summary of the research study, a commitment to anonymity and confidentiality, and the participants' rights as researcher participants. The final questions are presented in Appendix B, but some examples are below:

a) How do you use a data-driven approach to perform and support your roles and responsibilities?
b) Concerning challenges arising from a data-driven approach from question 5, what change would you suggest? In what way do you think it would be helpful?
c) What, in your opinion, are the factors contributing to a data-driven culture in an organisation?

The participants were contacted to complete the online survey through emails. Although using an online survey gave the participants the opportunity to fill out the forms at their convenience, time and place, the changes that arose due to working from home during the lockdown impacted when the researcher sent the questionnaire and the difficulty in receiving responses back. With support from the supervisor in sending follow-up emails, the subsequent response time improved.

3.10 Data Analysis

For the data analysis, both sources of data were treated as similar. The data was analysed using a thematic analysis, which is described as "a method for identifying themes and patterns of meaning across a dataset in relation to a research question" (Braun and Clarke 2006 cited in Braun and Clarke 2013, p. 175). According to Braun and Clarke, this analysis is a process of data reduction, which is distilled into meaningful patterns in order to analyse and explore the research questions. Braun and Clarke (2012) also highlight that thematic analysis is a useful approach for identifying, analysing, and interpreting patterns of meaning within qualitative data, enabling the researcher to examine the perspectives of different research participants. As a consequence of that, thematic analysis was used as a research method in the study. Following Braun and Clarke (2012), the data analysis in this study went through the six-phase approach for thematic analysis. The six steps are:

a) Familiarising oneself with the data,
b) Generating initial codes,
c) Searching for themes,
d) Reviewing potential themes,
e) Defining and naming themes,

f) Producing the report.

Before starting the actual analysis, the researcher immersed herself in the data by reading through the transcripts and all responses several times. While re-reading the entire data and cross-checking the audio-recordings, any interesting and important emerging ideas relating to the research questions in each participant's interview transcript and response excerpts, were highlighted and noted. Reflective thoughts and brief interpretations were also noted while simultaneously going deeper into its meaning by asking the question "what kind of world is revealed through their accounts?" (Braun and Clarke 2012, p. 61).

With keeping the research questions in mind, the initial codes were then identified. Multiple readings enabled the researcher to modify existing codes as well as to discover additional codes emerging while continuing to read the data. The selected codes and their supporting quotes were subsequently written down in a table which consisted of two columns as presented in Appendix C. The first column demonstrated the selected codes whereas the quotes to articulate the selected codes were illustrated in the second column. In this extract, various phrases were highlighted in different colours corresponding to different codes. Also, some supporting quotes were changed to a red font if they were interesting, surprising, or provided unexpected outcomes.

All the selected codes were reviewed several times to identify similar and overlapping issues between codes. The codes which clearly fit together were then combined to create potential themes, whilst substantial overlapping codes were merged into themes or generated into sub-themes within a theme. A table of the combination of codes was generated where codes were listed in the first column and themes were shown in the second column (see Appendix D).

The next stage was to further review, revise and refine the themes in relation to the coded data extracts and the entire data as part of the process of developing potential themes. At this stage Maguire and Delahunt's suggestions (Maguire and Delahunt 2017) were applied to develop themes, and key questions were asked during the cross-checking between the themes and the coded data extracts to obtain distinctive (having a clear focus in each theme) and coherent themes that worked with regard to the coded data extracts, as illustrated below:

a) Do the themes make sense?
b) Does the data support the themes?
c) If themes overlap, are they really separate themes?
d) Are there themes within themes (sub-themes)?
e) Are there other themes within the data?

The themes derived from the data were also revisited to verify that they captured the most important and relevant elements of the data in relation to the research questions as themes to ensure having meaningful themes. In doing so, this stage allowed the researcher to generate new emerging themes, relocate themes or remove existing themes.

Lastly, themes were refined into final themes by ensuring they had three aspects: having a singular focus, relating but not overlapping and directly addressing the research questions (Braun and Clarke 2012). Each theme was identified by either arriving at the translation of the participants' words themselves or having been influenced by relevant literature. The process of data reduction into codes and themes involved the application of both inductive and deductive reasoning to gain comprehensive themes in which the researcher selected "the "best" explanation from competing explanations or interpretations of the data" or abductive reasoning (Mantere and Ketokivi 2013 cited in Bryman and Bell 2015, p. 27). The endpoint of this phase was reporting on those comprehensive themes (see Table 7 in Chapter 4: Findings and Analysis).

These six stages for thematic analysis did not necessarily involve a simple linear process; the researcher could move forward and back between them (Maguire and Delahunt 2017). A summary of the six-phase thematic analysis approach is demonstrated in Table 6.

Table 6: A summary of the six-phase approach to conducting a thematic analysis

Phases	Conducted in each phase
(1) Familiarising oneself with the data	Repeatedly reading transcripts and carefully listening to audio-recordings to become intimately familiar with the entire data. Interesting and important ideas which are relevant to the research questions are highlighted.
(2) Generating initial codes	The initial codes are generated with collating data relevant to each initial code.

(3) Searching for themes	To shift from initial codes into potential themes, the codes clearly fitted together are combined to create potential themes whilst substantial overlapping codes are merged into themes or generated into sub-themes. Ambiguous and irrelevant codes are eliminated to make each theme internally coherent, meaningful and distinctive.
(4) Reviewing potential themes	Themes are further reviewed, revised and refined which resulted in distinctive and coherent themes with regard to the coded data extracts as well as a set of meaningful themes in relation to the research questions.
(5) Defining and naming themes	The process of data reduction into codes and themes in this study involves the application of both inductive and deductive reasoning in order to arrive at final themes.
(6) Producing the report	To create the final report by which each theme is arranged and sequenced in some logical and meaningful manner in order for telling a coherent story about the data.

Source: Table adapted from Braun and Clarke (2012)

3.11 Criteria for Ensuring Research Rigour

Lincoln and Gupta (1985) present trustworthiness as an important criterion to ensure a qualitative study's rigorous nature. Trustworthiness involves establishing the following four key components: credibility, transferability, dependability and confirmability (Bryman and Bell 2015), and these are discussed in further detail below.

3.11.1 Credibility

Credibility refers to the confidence in the quality of the research conducted and its findings which is approved by others' perspectives (Lincoln and Gupta 1985). This study established credibility of its findings through:

a) Using snowball sampling to reach and recruit the research participants who were expected to provide rich and meaningful data (Biernacki and Waldorf 1981). The initial research participants were asked to assist the researcher identify additional potential participants.

b) Setting up a detailed research site protocol and pilot study (Yin 2018).
c) Peer debriefing (Lincoln and Gupta 1985) to review interview questions, open-ended questions and establishing themes.
d) Thick descriptions to convey the findings (Creswell and Creswell 2018).

Regarding thick descriptions, the researcher provided detailed descriptions of all phases of the research process to demonstrate the transparency of this study and to facilitate readers who might desire to repeat it in their contexts (as presented in Chapter 3). Aside from this, the researcher has also presented in appendices the study's essential documents, such as interview questions and an example of the coding process.

Member checking, a technique for strengthening credibility, was not possible to perform with the participants in the main study because the use of an online survey due to COVID-19 would have undermined the privacy and anonymity of the participants.

3.11.2 Transferability

Transferability demonstrates the applicability of the research findings or empirical evidence to other contexts (Lincoln and Gupta 1985), i.e., new participants and new contexts which provide parallel external validity or generalisability for assessing a quantitative study (Bryman and Bell 2015; Saunders, Lewis and Thornhill 2016). According to Lincoln and Gupta 1985, it is essentially the responsibility of the researcher to provide thick descriptions to enable readers who might want to make the transferability judgements. Here, transferability was established by providing sufficient information concerning context, research participants and the research process.

3.11.3 Dependability

Dependability involves the extent to which the findings are coherent and can be repeated at other times (Lincoln and Gupta 1985). Since there is no credibility without dependability, according to Lincoln and Gupta, it is not necessary to separately demonstrate dependability; the showing of credibility is sufficient to establish dependability. A technique which Lincoln and Gupta suggest to enhance dependability is known as a research audit trail. The research audit trail is a thorough collection of all the relevant documents relating to the research either in report writing or audio recordings, but also the rationale for decisions, including reasons and justification which are advantageous in providing transparency and tracing the research process.

Nevertheless, as Shenton (2004) contends "in order to address the dependability issue more directly, the processes within the study should be reported in detail, thereby enabling a future researcher to repeat the work, if not necessarily to gain the same results. Thus, the research design may be viewed as a "prototype model". Such in-depth coverage also allows the reader to assess the extent to which proper research practices have been followed" (p. 71).

To ensure dependability, this study used a research audit trail and a thick description technique throughout the research report (e.g., a rationale for decisions), describing the research findings to the readers by using comprehensive themes accompanied by the participants' relevant quotes, but also by presenting supplementary study documents in appendices, which provided readers with the sufficient information to develop their thorough understanding about the research's approach and its effectiveness.

3.11.4 Confirmability

Confirmability is concerned with ensuring that the data and findings are clearly derived from the participants, rather than taken from the researcher's personal preferences and viewpoints (Lincoln and Gupta 1985), even though complete objectivity is impossible in the nature of qualitative research (Bryman and Bell 2015). According to Lincoln and Gupta, when all three criteria of rigour (i.e., credibility, transferability, and dependability) are achieved, the study's confirmability is consequently enhanced. For this study, an audit trail was employed to establish confirmability and facilitate confirmability.

3.12 Ethical Considerations

This study was concerned with ethics throughout the pilot period and the main study and adopted the University of Stirling and GDPR guidelines. Ethical approval must be reviewed and approved by the General University Ethics Panel (GUEP), prior to the fieldwork being conducted. The research project and the potential participants for the data collection were discussed with the supervisor to determine whether their jobs were relevant to a data-driven approach and would be expected to provide rich and insightful research data. These potential participants were then informally contacted. Some participants also suggested some of their colleagues to the researcher. Emails were sent to those who agreed to participate in the study. Attached to the emails were an electronic consent form and a participant information sheet:

a) An electronic consent form recorded the participants' agreement by signing a form, if they agreed to be interviewed in the study (See Appendix E).
b) An information sheet including brief and clear information of the study; the rationale covering confidentiality, anonymity, obligation to take part, audio-recorded media, dissemination and contact details (See Appendix F).

Overall, this study followed the suggestions of Braun and Clarke (2013); Bryman and Bell (2015); Saunders, Lewis and Thornhill (2016) and Creswell and Creswell (2018) regarding ethical considerations. The core ethical requirements are illustrated below:

a) Confidentiality and anonymity: All interviews were confidential. The transcribed data ensured that all identifiable data were replaced with fictitious names, such as Interviewee Number 1 and Respondent Number 2 when discussing, analysing and reporting data. If the findings were to be disseminated, the participants would not be identifiable in any publication. By doing this, the participants' confidentiality and anonymity were protected.
b) Maintain personal privacy: All electronic and audio data were securely stored on the University's server with password protection, while the hard copies of transcripts were kept in a secure and locked cabinet at all times on the campus, accessible only by a single researcher. All data will be disposed of on a date determined in accordance with University of Stirling and GDPR guidelines.
c) Responsibility: The participants were under no obligation to take part. They also had the right to withdraw at any time without providing any reason nor would there be any negative impact. Individual interviews were conducted on-site at an organisation in a safe, quiet and private room with only the researcher and the

participants. The researcher also provided all participants the opportunity to ask for any clarification. Importantly, the data collection would never be carried out disregarding the participants' approval and permission. In doing so, there was no harm to the participants.

d) Integrity: The research results were reported honestly. The sources of others' work and ideas were properly acknowledged. All information about the study were unveiled verbally and in written documents to avoid any deception.

3.13 Summary

This chapter has presented the details of the methodological components applied in this thesis, including the research paradigm, research strategy, role as a qualitative researcher, pilot study, researcher participants in the main study, challenges while doing the main study, data collection method, data gathering procedure, data analysis, accounting for the rigour of the research designs, and ethical consideration. The next chapter moves from the raw empirical data to the findings and analysis. The first and second order themes which emerged from the empirical data will be presented and discussed.

CHAPTER 4: Findings and Analysis

4.1 Introduction

Data for this research was collected using a face-to-face semi-structured interview and an online survey as a surrogate approach due to COVID-19 restrictions in conducting fieldwork. This also seemed to be safe and convenient for all participants to complete in their own time and pace while physically distancing. Apart from that, a surrogate approach allowed the researcher to develop further findings and analysis but also complete the project on time during the pandemic, as discussed in Chapter 3.

This chapter presents the two following sections: the findings and analysis from the empirical research site. The findings are explored and discussed including each theme (2nd order) and its sub-themes (1st order) that were derived from the empirical data analysis. The empirical findings highlighted the importance of technology issues, but also presented challenges about the issues impacting organisational transformation to becoming data-driven, ensuring all possibilities during the interviews/data gathering were able to participate. The empirical findings suggested the following 10 themes: (1) data insights underpin decisions and performance, (2) data insights facilitate multiple perspectives for holistic understanding, (3) the human element underpins data insights, (4) the impact of data quality and data silos, (5) distrust in data credibility, (6) a lack of harnessing multiple perspectives on data, (7) a lack of human capability to engage with data, (8) the emerging gap between data user, data provider, and the implications of being data-driven, (9) revealing the story in the data dilemma, and (10) the diverse vision and attitude of leaders and people. The empirical findings are presented subsequently and are analysed to further illustrate the 10 themes: two enablers and eight constraints of becoming a data-driven organisation underpinning the concept of sociomateriality. The overall summary themes/1st order themes and sub-themes/2nd order themes emerged from the empirical data, but enablers/constraints are also listed and summarised in Table 7.

Table 7: Overall summary sub-themes/1st order themes and 2nd order themes emerging from the empirical data as well as enablers/constraints

Sub-themes / 1st order themes	**Themes / 2nd order themes**	**Enablers/ Constraints**
- Data insights are key to inform future marketing strategic decisions (Empirical 1) - Data insights are key to improve performance (Empirical 2)	Theme 1: Data insights underpinning decisions and performance	Enabler 1
- Understanding other people's perspectives on data insights through collaborative interaction (Empirical 3) - Data insights' objectivity resolves differences between individuals (Empirical 4) - Data insights' objectivity justifies the hypotheses and support pre-decision-making proposals (Empirical 5)	Theme 2: Data insights facilitating multiple perspectives for holistic understanding	Enabler 2
- Data cannot act regardless of taking into consideration human element (Empirical 6) - Human element provides the context that gives meaning to data and transformation into value (Empirical 7)	Theme 3: The human element underpinning data insights but being ignored while implementing a more data-informed approach	Constraint 1
- Data accuracy and consistency issues (Empirical 8) - Data accessibility and exploitation issues (Empirical 9) - Data integrity and consistency in analysis and interpretation issues (Empirical 10) - Misperception of data truth issue (Empirical 11) - Data validity and its relationship with an organisation's purpose (Empirical 12)	Theme 4: Data quality and data silos	Constraint 2

- Concerning the transparency of how data is being manipulated (Empirical 13) - Dilemma that many raised such unreliable and sceptical doubts regarding data and its metrics (Empirical 14)	Theme 5: Distrust in data and data analysis credibility	Constraint 3
- Plurality of interpretation issues (Empirical 15) -Fragmented collaboration and communication cross-functional teams (Empirical 16) - Multiplicity of uses of data issues (Empirical 17)	Theme 6: Lack of harnessing multiple perspectives on data	Constraint 4
- Data inquiry capability is required (Empirical 18) - Better training in data analytical skills and updating knowledge are solutions (Empirical 19) - Adequate data analytics specialists are required (Empirical 20)	Theme 7: Lack of human capability to engage with data	Constraint 5
- Final users and their data interpretation are key to making a data-driven success (Empirical 21) - Data analysis produced is disconnected from the people who use it (Empirical 22)	Theme 8: Emerging gap between data user, data provider and implication of being data-driven	Constraint 6
- Data should be given priority over intuition (Empirical 23) - Balance is needed between data and intuition (Empirical 24)	Theme 9: Differences in people's perceptions of revealing the story in data	Constraint 7
- Senior leaders' commitment to being data-driven is key for success (Empirical 25) - Attitude towards a data-driven approach and its impact on their organisation (Empirical 26)	Theme 10: Diverse vision and attitude of leaders/people alignment on being data-driven	Constraint 8

The empirical findings elaborated and discussed in Section 4.2.1 onwards relate to sub-themes/1st order themes in Table 7 above. Section 4.2.1 first moved from the raw empirical data to develop first order analysis, and then the data analysis process moved from first order themes to second order themes as presented in Section 4.3.1 onwards.

4.2 Empirical Findings

The respondents' data on these perceptions was gathered by using a face-to-face semi-structured interview and online surveys as a surrogate approach due to COVID-19. The data of respondent numbers 1–17, 19, and 20 were collected through an online survey, while interviewee number 18 was asked questions in a face-to-face semi-structured interview which was conducted before the coronavirus crisis. In total, 28 responses and 1 interview were received. 85% are data end-users, which represented a variety of roles and responsibilities (e.g., reviewing and monitoring recruitment activity, marketing advertising, and faculties, evaluating institutional performance, suggesting future strategies and business decisions, informing financial planning and budget setting), whilst the remaining 15% are data creators whose jobs included producing reports in digital marketing, student recruitment and admission, creating and maintaining management dashboards. The respondents were asked about individual interaction around the data analytics and their interaction with others that enabled and/or constrained them in performing their roles and responsibilities. By iteratively developing themes through various stages of coding, the issues impacting organisational transformation to become a data-driven organisation were identified. The thematic analysis revealed a spectrum of perceptions supporting and struggling to embrace a data-informed approach. The empirical findings reflected the concept for which Leonardi (2012) coined the term 'sociomaterial imbrication' where multiple human (social) agencies and material agencies are imbricated by people as the interactions unfold. The findings, including empirical data, sub-themes/1st order themes and themes/2nd themes, are explored in more detail and discussed in sections 4.2.1 and 4.3.1, respectively, highlighting issues in enabling and constraining people to successfully adopt a data-driven approach.

4.2.1 Sub-themes/1st Order Themes

Empirical Finding 1: Theme 1: Data insights underpinning decisions and performance

Seven respondents highlighted that data insights were used to inform strategic decisions, particularly future marketing strategies. Data generated insights enabled them to first gain and understand customer insights including capturing customer behaviour, journey and interest. Then, they would know in which future directions to go as data insights were evident. This led them to achieve their recruitment goals and inform future marketing strategies based on these data insights, especially during the COVID-19 pandemic (Johnson 2020). As the empirical data suggests, data insights potentially allow them to analyse trends and inform and devise decisions that align with their goals, objectives and initiatives for the future strategies especially in marketing.

Interestingly, respondent number 5 mentioned that a competitive advantage would be created as long as the data was used correctly, noting: 'If used correctly data can help make smart informed business decisions that give the organisation a competitive advantage.' This excerpt is in accordance with that of Janssen, Voort and Wahyudi (2017) who argue that "the quality is not solely dependent on the data, but also on the process in which the data is collected and the way data is processed" (p. 338), but also "big data provides little value if it is not accurate and people are not able to interpret the decisions" (p. 342). Davenport (2009) also notes that correct assumptions are crucial when using data analytics to support decision making.

Through the data insights' value to marketing that the respondents mentioned, the first sub-theme was identified as *data insights are key to inform future marketing strategic decisions*. The following empirical data from an online survey revealed the role of data analytics to support marketing:

> **Respondent Number 4:** 'Provides market insights.... Feed into strategic decisions'.

> **Respondent Number 5:** 'Analyse results and put forward solutions to business problems based on the data. If used correctly data can help make smart informed business decisions that give the organisation a competitive advantage'.

Respondent Number 6: 'Understanding markets and behaviours cannot be done from an inwards point of view. Data is the most level play field to understand what is happening.... Data is necessary to understand your markets and behaviours.... Digital advertising campaigns and web page usage and interpreting them to suggest strategies or tactics, admission data and trends data…. The data help us understand the customer journey and their areas of interest in order to offer them the information they require. The data we use help us to achieve our recruitment goals and plan out our marketing strategies'.

Respondent Number 7: 'Analyse data to inform future strategies.... Use data for marketing strategies'.

Respondent Number 8: 'To inform decision making process'.

Respondent Number 9: 'Data helps us to know what direction to go in.... Analysis of student data, student numbers, new courses coming to market'.

Respondent Number 20: 'Using COVID-19 as a recent example, our advertising data spiked in certain markets because lots more people are now at home using the internet. However, we know that several factors (including financial uncertainty and/or travel restrictions) meant that it was unlikely to translate into application conversions. We adjusted our advertising accordingly and were proven correct in our assumption'.

Therefore, drawing on empirical data presented above, the diversity of the seven respondents gives confidence in the empirical finding.

Empirical Finding 2: Theme 1: Data insights underpinning decisions and performance

Empirical finding 2, the respondents' comments given below, revealed that *data insights are key to improve performance*, as **five** respondents highlighted their performance (e.g., marketing campaigns) were investigated and then improved through the data insights that their organisation produced. Through data insights, the respondents were also able to gain a better understanding of their performance. Based on evidence and insights, the respondents believed that increased efforts to perform better and outperform their competition can be a source of competitiveness. It became evident to them that they are empowered to drive decision-making with data, as stated in Except 1. As a result, data insights enabled the way their organisation operated and achieved competitiveness through continuous performance improvement. However, one respondent (Respondent Number 8) believed that their organisation had not yet created a competitive advantage from their existing data. Empirical data analysis of Respondent Number 8 indicates that obtaining data insights facilitates them to analyse performance, but is not necessary for establishing such an advantage. Without an understanding of enablers and constraints, an organisation will be unable to develop and underpin their data-driven culture and gain their desired outcomes, namely, a competitive advantage from data insights. This sub-theme is illustrated in the following excerpts:

> **Respondent Number 4:** 'Measures of efficiency and competitiveness'.
>
> **Respondent Number 6:** 'Continuing data analysis drive any changes to campaigns in order to improve performance'.
>
> **Respondent Number 7:** 'Use data for performance improvement. You can improve future strategies when you investigate your performance and external data shows you where you stand in the competition and how you can inform your strategies'.
>
> **Respondent Number 8:** 'To analyse performance against targets…. I don't think we use our data to gain a competitive advantage'.
>
> **Respondent Number 10:** 'It helps to check progress of campaigns and make changes and improve. We are able to look at data and make changes accordingly and optimise our campaigns'.

Empirical Finding 3: Theme 2: Data insights facilitating multiple perspectives for holistic understanding

The respondents not only highlighted the advantages of being data-driven, but also highlighted *understanding other people's perspectives on data insights through collaborative interaction*. According to the empirical data analysis, eight respondents mentioned that they collaborated and worked together on data insights in conversations and meetings. Through shared understanding and ideas on data insights, different people brought diverse knowledge that helped them better detect and focus on high-priority issues, e.g., identifying and addressing issues of concerns, and discussing the needs of reports and dashboards from the people who use the data—a shared understanding of data insights among individuals whose interaction helps to ensure all clarity and direction generated coherence. Such insights not only facilitate but also build up a coherent understanding through collaborative interaction and acted as another sub-theme/1st order theme. The respondents realised the significance of the culture of collaboration with data and whom they work with helps to reveal the most critical insights in their data, and therefore they are able to act.

> **Respondent Number 7:** 'Helpful as you get insights from other's point of view on the data presented'.
>
> **Respondent Number 10:** 'They help me understand the data and can drill down on specific issues'.
>
> **Respondent Number 11:** 'A shared understanding of how best to use data to improve performance and decision making'.
>
> **Respondent Number 12:** 'Often others "see" something I haven't—good to share and discuss'.\
>
> **Respondent Number 14:** 'Usually meet first to discuss their requirements from the dashboard. What questions they need to be able to answer etc.'.
>
> **Respondent Number 15:** 'Sharing outputs for some colleagues but sharing code and holding detailed collaborative meetings'.

> **Respondent Number 17:** 'We can share ideas about what the data is telling us and plan other associated activities and investment in a particular subject area or market, including recruitment events and marketing. We work closely with the Analytics and Reporting Manager to build and design the reporting we use to suit our purposes'.

> **Respondent Number 19:** 'Shared knowledge and experience allow us to spot anomalies or areas of concern. Further it helps us agree future responses and requirements from future data to check our analysis'.

Empirical Finding 4: Theme 2: Data insights facilitating multiple perspectives for holistic understanding

Another key advantage of decisions supported by data insights that the respondents indicate is that *data insights' objectivity resolves differences between individuals*. Although only one participant mentioned this aspect, it is interesting that the same data insights were perceived and used by people as the standard rational criterion and evidence to them to deal with heterogeneity when making decisions. The interviewee illustrated this in the following excerpt:

> **Interviewee Number 18:** 'So, we needed the data in order to say now we know that this one works rather than, spending weeks arguing about which one we should use. And sometimes you do just need to have the data there in order to work for everyone to agree with it'.

Empirical Finding 5: Theme 2: Data insights facilitating multiple perspectives for holistic understanding

Empirical findings 5 emerged from a participant who indicated that *data insights' objectivity obtained through analysis results was used as the evidence to justify the original hypothesis and support pre-decision-making proposals* for holistic understanding. As empirical data suggested, data insights offered solid evidence to confirm that their intuitive hypotheses, ideas and insights run in a similar direction, which would benefit more than having a conversation. Consequently, such insights regarding justifying and supporting pre-decision-making proposals was placed as the sub-theme/1st order theme, enabling people to verify and provide supporting evidence for their original hypotheses and drawing conclusions whilst discussing with their colleagues.

> **Respondent Number 12:** 'Previously we used to say, "my feeling is that..." and that was often accepted. Now we are being asked, where is the evidence. This is good when the conversation and the evidence are produced together with a common understanding'.

Empirical Finding 6: Theme 3: Human element underpinning data insights but being ignored while implementing a more data-informed approach

Even when data facilitates decision-making affordances and performance improvement as noted above in Empirical findings 1 and 2, there still exists the issue that data cannot create action. This would be ignoring the human element, as human engagement provides value throughout each step of data analytics by discovering, interpreting, and communication of meaningful data insights (Mikalef et al. 2018). As such, the human element should not be underestimated even though data analytics was implemented. It is somewhat surprising that Respondent Number 12 realised that becoming data-driven organisation created a significant problem of overlooking the human element in the drive to become data-driven (see excerpt below). Accordingly, it is evident that the human element is important but being ignored while implementing a more data-informed approach. An organisation's data analytics capability in reinforcing the potential value that comes from being more data-driven, such as better decisions, performance improvement, or/and competitiveness is incomplete without humans because the way a data-driven organisation works, the two complement each other in their entangled relationship (Orlikowski 2007; Orlikowski and Scott 2008). Humans can be overlooked in their efforts to become data-driven, and this is challenging in the research site. The empirical data below suggested that *data cannot act regardless of taking into consideration the human element* as in the following excerpts:

> **Respondent Number 3:** 'Without humans there is no data'.

> **Respondent Number 10:** 'They (human element) help you understanding data'.

Respondent Number 12: 'We forget the human element and see it is information from a system'.

Respondent Number 14: 'Humans play apart from data entry, manipulate how data is transformed and presented'.

Respondent Number 16: 'Human intervention is important to get major insight into the data'.

Empirical Finding 7: Theme 3: Human element underpinning data insights but being ignored while implementing a more data-informed approach

Having realised and claimed that being data-driven still needs humans as claimed in Excerpt 6, the respondents justified that the *human element is required to provide context that gives meaning to data and transform into value*. This is because there is a context behind data which requires humans to discover it. As Respondent Number 7 mentioned, for instance, 'The data tells us the facts, but it doesn't tell us WHY'. Moreover, the respondents explained that regarding the human dimension, it was important to ask the right questions to carry out the analysis and get exactly the right or insightful answers, which they sought. From this, uncontextualized data seemed to be pointless as it could not be transformed into actionable insight (value), which is perceived as involving humans. This is illustrated in the following excerpts:

Respondent Number 2: 'It's important as being involved in the coding/interpretation'.

Respondent Number 4: 'Analysis is carried out to answer human questions, so if questions are not asked, the data is not analysed, and there is a sense that the analysis is filtered to support the ideas and views of the analyst. Understand what questions other people want answering'.

Respondent Number 6: 'Humans have the capacity to understand nuances, take into account the context in which the data is applied to, can establish what type of information/data is required to build upon a strategy or make decisions'.

Respondent Number 7: 'Humans are vital in generating data and interpreting it. Without sound interpretation you cannot inform strategies in the best of the data potential'.

Respondent Number 8: 'It should be used to inform decision making as there is always context to the data that needs to be understood'.

Respondent Number 17: 'The data tells us the facts, but it doesn't tell us WHY. The role of humans is important. The analytics give us the information, but we need to add context to it'.

Respondent Number 19: 'The ability to understand the qualitative reasons behind data I would suggest is a human function. The wider knowledge and experience associated with learning cannot, as yet be fully codified and therefore human intervention is still required'.

Empirical Finding 8: Theme 4: Data quality and data silos

Empirical finding 8 reveals that the next barrier to empowering people with data-driven decisions which concerned the respondents is a *data accuracy and consistency issue,* apart from ignoring the value of the human element in their efforts to become data-driven as evident in Empirical findings 6. Interestingly, a respondent mentioned with special emphasis that the data produced appeared to be unreliable. The following excerpts illustrate data accuracy and consistency issues in their organisation:

Respondent Number 5: 'Having correct data sets to be able to interpret data for the purpose required. Quality control and consistency over time. Accurate'.

Respondent Number 13: 'Accuracy and consistency of data'.

Respondent Number 14: 'Quality of data'.

Respondent Number 16: 'Quality of the data and unlabelled data are the two main challenges'.

Interviewee Number 18: 'I think what we're finding more and more is that the quality of the data in the first place is unreliable. The quality of the data needs to be solid'.

Empirical Finding 9: Theme 4: Data quality and data silos

The respondents also indicated that access to good data and knowledge can increase their data quality, allowing data to be actively used. However, as Except 9 demonstrates, the *data accessibility and exploitation issue* have challenged attempts to become data-driven. Individuals and their organisations should be able to more easily access and exploit data and information. The more that is accessible and usable, the more insights will be used for enhancing and strengthening the organisation's path to becoming a data-driven organisation. These are illustrated in the following excerpts:

Respondent Number 4: 'Poor discipline in some data recording or information is requested that is not in database—e.g., sex of applicants. Result is that questions that sound simple from a management perspective can be difficult to answer—e.g., what percentage of male VS female applicants from England eventually join the course?'

Respondent Number 6: 'It's required to have access to the data and good knowledge on how to use it'.

Respondent Number 8: 'We often have to ask for bespoke reports to be run and don't have access to basic data set'.

Respondent Number 12: 'We need to have access to excellent data analytics to make much more accurate forecasting and planning'.

Respondent Number 13: 'Availability of data'.

Respondent Number 16: 'Accessibility of the data. A standard interface to access the data... Having access to more data provides insightful understanding which leads to more data analytics to the organisation'.

Empirical Finding 10: Theme 4: Data quality and data silos

Empirical finding 10 reveals the case study organisation encountered fragmented and varied data as each department created its own standard for gathering, analysing, and reporting on its unique reference information. Without a single source, the respondents encountered difficulty in *data integrity and consistency in analysis and interpretation*. This is regarded as a potentially problematic challenge to building a data-driven organisation that inhibits people from accomplishing their goals based on data analysis.

Respondent Number 4: 'Data is often complex to extract and too fragmented in different systems and time series'.

Respondent Number 5: 'Different departments can mine, report and interoperate the data differently. Often using different systems and data sets'.

Respondent Number 6: 'Reports and data bases may produce different outputs depending on software/licenses etc.'.

Respondent Number 8: 'One area should own the data and set the requirement for the source data that feeds into dashboards'.

Respondent Number 10: 'When using foreign digital media e.g., Chinese platforms not integrating with google analytics'.

Respondent Number 14: 'Multiple sources of data and variations/different terminologies within the data'.

Respondent Number 15: 'Some software works differently on different operating systems so sharing data and resources between these can be burdensome'.

Interviewee Number 18: 'Because we use a lot of different systems. Because we're using all these different systems and these different agencies. They all seem to have different ways to measure what it's happening and so the data they will get. So, there always seem to be discrepancies'.

Empirical Finding 11: Theme 4: Data quality and data silos

Even though the role of humans was realised as an important factor in becoming data-driven (Empirical findings 6 and 7), the respondents also highlighted biases in the output results that arise due to human participation. The respondents realised this issue and its possible subsequent outcomes, how human error or human intervention can affect the results of analysis being incorrectly considered as truth. These views triggered *misperception of data truth issue*. Accordingly, the underlying assumptions of data interpretation were unwittingly flawed due to human biases, human error, or human intervention that undermined the respondents' perceptions of where a data-driven approach was enhancing their ability to achieve their goals. It seems that although a data-driven approach is widely perceived to reduce the impact of human biases, the output results still appeared to be unreliable as humans are needed to interpret the analysis results. Hence, this is considered another issue impacting organisational transformation.

Respondent Number 2: 'Human biases will be introduced as they both develop the algorithms and interpret the results'.

Respondent Number 5: 'There is a room for error when humans are involved. And the data is only as good as the data you collect, capture in input. Human error'.

Respondent Number 6: 'Human participation always involves subjectivity and their way of seeing things may affect the way that data is interpreted'.

Respondent Number 9: 'Sometimes human error can happen'.

Respondent Number 10: 'Data can be misinterpreted or mishandled'.

> **Respondent Number 14:** 'Human error can happen at any stage which can affect the output results'.

> **Respondent Number 17:** 'People often make assumptions when looking at data'.

> **Respondent Number 19:** 'Human intervention can place interpretations on data based on personal bias or misinterpretation'.

Empirical Finding 12: Theme 4: Data quality and data silos

Data validity and its relationship with an organisation's purpose is another issue the respondent noted. As empirical finding 12 suggests, the data currently compiled by the case study organisation were not tied to the organisation's specific purpose. Also, the data and outputs from the data generated were not designed to address the specific questions or contain specific information but were for another purpose. The specific information that the data end-user desired was not contained. Consequently, data seemed to be invalid, had no real meaning, did not truly inform the people (data end-user), and could not lead (constrain) the data end-user into taking data-driven decisions and actions, as evidenced below.

> **Respondent Number 1:** 'The information given in terms of recruitment activity has no apparent correlation to the eventual numbers of students who turn up. Some of the data provision therefore feels more ritualistic than useful'.

Empirical Finding 13: Theme 5: Distrust in data and data analysis credibility

Empirical finding 13 *concerns the transparency of how data is being manipulated*, such as how data is being collected, analysed and interpreted. The respondents perceived that data manipulation in their organisation was sporadic. They also perceived that there was room for data to mislead the end-user by the staff who produced data and the output results (the data creator). Empirical finding 13 also illustrated that participants struggled with obtaining the right data and output results within their organisation. According to the respondents' comments below, two issues were found concerning the transparency of how data was being manipulated: distrust in data collection and interpretation as well as distrust in the data creator. They perceived the data was being manipulated and was inaccurate due to misleading sufficiently low-quality collection methods, and especially data analysis and interpretation. People were not just concerned about data being collected, but also how anecdotes were being told around the data which is made and given by the staff who produce the data (data creator). This indicates that the respondents demand more transparency of how data is being collected and made available. Lack of good data manipulation in becoming a data-driven organisation is, therefore, regarded as an impediment to people who want to operate in a data-driven manner. These are illustrated in the following excerpts:

> **Respondent Number 1:** 'I don't have confidence in the credibility of the data being collected, or its interpretation'.
>
> **Respondent Number 2:** 'Transparency about what goes into them and how to interpret'.
>
> **Respondent Number 6:** 'Data can be manipulated to extract specific results'.
>
> **Respondent Number 8:** 'Staff can produce data to show the answer they want to see—rather than what it is actually telling you'.
>
> **Respondent Number 10:** 'Data can be misinterpreted or mishandled'.
>
> **Respondent Number 13:** 'Improved trust that sensitive data will not be inappropriately used/attributed'.

Empirical Finding 14: Theme 5: Distrust in data and data analysis credibility

As a consequence of empirical finding 13, a *dilemma concerning such unreliable, sceptical doubts data and its metrics* was reflected by the respondents. They claimed that errors and mistakes regarding data analysis and the interpretation of results caused issues regarding unreliability and sceptical consequences. Empirical finding 14 reveals that inaccurate metrics caused confusion and scepticism regarding data, and thus, the results from data analysis and the metrics made a data-driven approach still not function as expected by the people who used it. As a result, people struggled to rely on data and data analysis results to improve their work.

Respondent Number 7: 'Sometimes the right metrics are not used properly'.

Respondent Number 11: 'Reliance on others using data analytics properly'.

Respondent Number 12: 'There is often doubt that it is correct or that it is still too high level or leaves you without the answer you need relying on narrative. Because of way that we change so often the way information is coded or stored. It is hard to be confident that there are credible trends. Often you are left with too many unanswered questions which would suggest a malfunction—in the set-up requirement'.

Respondent Number 15: 'It's common to see use of flawed analytical methods and of flawed data resources that impact in my institution'.

Interviewee Number 18: 'I think what we're finding more and more is that the quality of the data in the first place is unreliable.... There's always a bit of confusion around which numbers are right and it's not always easy to tell'.

Empirical Finding 15: Theme 6: Lack of harnessing multiple perspectives on data

The respondents' comments below suggest that the *plurality of interpretation issue* or having a single version of the truth from the data interpretation were currently challenged, resulting in discrepancies that constrain their ability to work with their data sources.

Respondent Number 5: 'Difficult to get a single point of truth'.

Respondent Number 13: 'Having a "single source of truth" removes inconsistencies and also helps ensure consistent expectations'.

Respondent Number 19: 'The availability of agreed relationships between areas of data and their interpretation differs and often requires revisiting and reworking of data to ensure shared understanding and agreement. Agree criteria on the use of data and its interpretation. The main challenge is in the agreement of the required data elements and the criteria used to bring them together to create information and knowledge'.

Empirical Finding 16: Theme 6: Lack of harnessing multiple perspectives on data

In addition to plurality of interpretation issue, *fragmented collaboration and communication cross-functional teams* were also perceived by the respondents, as illustrated in the excerpts given below. As the empirical finding 16 suggests, it appears that as a data-driven approach is used and perceived to offer greater insights for decision-making, people struggled not only with the *plurality of interpretation issue* (see the empirical finding 15), but also in integrating their data, resulting in claims that the less data-driven they become. Empirical findings 15 and 16 also seem to be connected to the constraints people experience in interacting and exchanging information across the organisation. Namely, data silos create further collaboration and communication fragmentation.

Respondent Number 4: 'This is a very minor activity and usually individual. Probably reasonably sophisticated in-service divisions, poorly supported in academic divisions'.

Respondent Number 5: 'This (collaboration) is lacking in our organisation. Too many systems that don't talk to each other'.

Interviewee Number 18: 'I think we just were not very good at collaboration'.

Empirical Finding 17: Theme 6: Lack of harnessing multiple perspectives on data

Next, the respondents encountered the *multiplicity of uses of data*. It appears that empirical findings 15, 16, and 17 are connected. These three issues, namely, *plurality of interpretation, fragmented collaboration and communication cross-functional teams,* *and multiplicity of uses of data* are perceived as barriers to their intentionality of working with their data sources or to actionable data insights. This is demonstrated in the following excerpts:

> **Respondent Number 6:** 'Data may be interrogated in different ways so may show different conclusions'.

> **Respondent Number 8:** 'People using the same data but running different reporting formats or using the same data but producing different results'.

Empirical Finding 18: Theme 7: Lack of human capability to engage with data

As empirical finding 18 suggests *data inquiry capability is required* in developing the data-driven organisation case study. The respondents realised that there was a problem with a lack of sufficient skills and knowledge to deal with data. Skills and knowledge were two important factors to ensure the use of data analytics efficiently and successfully. The skills mentioned included the ability to share, understand data, tell stories, provide context, and even express what was required to capture, process and interpret data. Interestingly, a respondent pointed out that knowledge about not only the data but also their sector was helpful to succeed in their data analytics efforts. It seems that having an analytical mindset and skills should be encouraged in all staff—not only in the staff involved in data. Data literacy should be in-built throughout a data-driven organisation. Nevertheless, data literacy is still lacking for the research site and is an impediment to becoming a data-driven organisation.

> **Respondent Number 4:** 'Analysis can only be carried out to the extent of the knowledge and skills of the person undertaking that analysis, unless using a template provided by others'.

> **Respondent Number 6:** 'If people dealing with data follow what is knowledgeable about their sector, having a good sense of what type of data are necessary for each type of decision and contrast the data from key information the results should be apt for building strategies, tactics, campaigns'.

Respondent Number 7: 'People think data is useful but not everyone understands how they work'.

Respondent Number 8: 'Lack of capability of staff. Lack of skills'.

Respondent Number 10: 'Understand that data is knowledge you need. Different levels of understanding/knowledge'.

Respondent Number 11: 'Shift in mindset and a strong skill set. If someone makes a mistake because they have not been inducted in the software properly, it can lead to issues further along the process. Staff having the skill set to perform and use data analytics successfully. The skills and knowledge to do so efficiently'.

Respondent Number 12: 'Staff resource has inhibited us from pursuing it. It was the driver for the installation which is a frustration. We had someone in the team who enjoyed data, but he lacked the ability to share it in a way that was meaningful for our purpose'.

Respondent Number 14: 'Being able to understand the data and tell stories from it can aid us in strategic planning'.

Respondent Number 16: 'Skilled personnel'.

Respondent Number 17: 'People wanting data but not skilling themselves to use the reporting tools themselves. The ability to provide context. If people want lots of data and they don't have the skills to generate it themselves then someone needs to do it for them'.

Respondent Number 19: 'Many people talk about the value of data and the use of analytics but do not have the ability to express what they require or what is required to capture, process and interpret data'.

Empirical Finding 19: Theme 7: Lack of human capability to engage with data

The realisation of the importance of data inquiry capability, as illustrated by empirical finding 18, led the respondents to suggest *better training in data analytical skills and updating knowledge* as a solution to the challenge of people's capability to engage with data that they are struggling with. Interestingly, one of the respondents (Respondent Number 12) pointed out that the staff engaged with a data-driven approach through their learning experiences rather than training. Lack of analytical capability could prevent people from driving their goals with data but also limit their organisation's ability from becoming more data-driven. Better training and updating knowledge at various levels subsequently emerged from the respondents as a significant solution to address this problem. Empirical finding 19 highlights *better training in data analytical skills and updating knowledge are solutions*:

> **Respondent Number 4:** 'Mostly better training. Better training in analytical tools'.
>
> **Respondent Number 6:** 'Being able to read/interpret the data is a skill necessary to draw conclusion. Key data need to be available to be able to paint a picture. Training and understanding of the systems used to provide the data. Staff with the knowledge at various levels, and potentially training when required'.
>
> **Respondent Number 7:** 'Better training and updating of knowledge'.
>
> **Respondent Number 9:** 'Training for all staff involved with data'.

.

> **Respondent Number 11:** 'Workshops in how to use data analytics properly. This would enhance the benefits of using data analytics'.
>
> **Respondent Number 12:** 'I think very few of us are experts and those who have access to these reporting tools learn by using rather than through any training'.

Empirical Finding 20: Theme 7: Lack of human capability to engage with data

Empirical finding 20 also highlights that *adequate data analytics specialists are required* within the case study organisation. As the respondents claimed, the potential value of being data-driven is currently restricted by a lack of data analysts within their organisation. For instance, Respondent Number 17 pointed out ‘that can’t just be one person in a large organisation’. This is revealed in the following excerpts given below.

> **Respondent Number 4:** ‘Limited expertise in developing more sophisticated analysis or visualisations. Experts on hand to do the analysis’.

> **Respondent Number 17:** ‘Under resourced! The manager in this area is exceptional but he doesn't have a team. That can't just be one person in a large organisation’.

> **Interviewee Number 18:** ‘We would probably have more investment and data analysts than we currently do. I think it’s useful to have the data analysts serve to analyse the data’.

Empirical Finding 21: Theme 8: Emerging gap between data users, data providers and implications of being data-driven

Interestingly, there was one respondent who indicated that the final step in the data-driven approach was decided by the final user, rather than by the data analyst or the data itself. From this, the perception and understanding of the final user regarding data was critical. It also appears to support empirical finding 18 that having an analytical mindset and skills should be encouraged in all staff—not only for staff involved in data. Empirical finding 21 claims that final *users and their data interpretation are key to data-driven success* as evidenced by the following excerpt:

> **Respondent Number 4:** ‘Even once data is analysed, the interpretation of the data is entirely dependent on the perceptions and understanding of the final user’.

Empirical Finding 22: Theme 8: Emerging gap between data users, data providers and implications of being data-driven

In addition to empirical finding 21, one respondent revealed they rarely influenced the data to be gathered or analysed, whereas another respondent admitted they did not have a clear understanding of what the data analysis reports were saying. These views echoed *the data analysis report produced is disconnected from the people who use it* (data end-user) that constrained their engagement in a data-driven approach. Empirical findings 21 and 22 indicate that unlocking the value of becoming data-driven, the importance of the data end-user, should not be overlooked (Gemignani et al. 2014). This is illustrated in the following excerpts:

> **Respondent Number 1:** 'I have very little say in the format or content of spreadsheets I receive in respect of recruitment number etc. I cannot influence the collection or dissemination of data'.

> **Respondent Number 2:** 'I don't really follow how they are created and feels like a black box at times. Not fully understanding how they are generated and what some of them mean'.

Empirical Finding 23: Theme 9: Differences in people's perceptions of revealing the story in data

When the respondents were asked about the perception of what they thought about data versus intuition to inform business decisions, as empirical finding 23 highlights, *data should outweigh intuition* to reveal the story in data. This is because personal biases will be eliminated from decision-making making the process more effective. These respondents perceived that the right data analytics were a better tool to reduce all the personal bias and outlook that could not be measured, such as intuition. Once they prioritised and trusted the data, they considered relying more on evidence-based data to reveal the story with data in this regard.

Interestingly, while Respondent Number 4 mentioned 'proper data analytics should be more transparent and reduce unidentified bias', another respondent pointed out that 'staff can produce data to show the answer they want to see—rather than what it is actually telling you'. (See empirical finding 13, Respondent Number 8.) The respondents' views are demonstrated below.

Respondent Number 4: 'Intuition can be very useful, but easily in error due to personal bias and outlook. Proper data analytics should be more transparent and reduce unidentified bias'.

Respondent Number 5: 'Data needs to be king'.

Respondent Number 6: 'Content is king, and data is necessary.... Data is necessary to inform business decisions-actions based on the data will have to take into account intelligent and creative way of implementing what the data is telling us'.

Respondent Number 10: 'Data is knowledge'.

Respondent Number 13: 'I think decisions should be evidence based. Intuition isn't valuable'.

Respondent Number 14: 'I agree that data trends to be a more reliable base to make decisions from'.

Respondent Number 16: 'Data to inform business decision is more pragmatic approach'.

Empirical Finding 24: Theme 9: Differences in people's perceptions of revealing the story in data

Some respondents hold distinctive views and argued that the use of data analytics alone was insufficient. Human intuition or gut instinct also counts in the analysis process. They argued in three main ways regarding this issue. First, data and intuition were not against each other. Rather, data and intuition should be balanced since data and its analytics could be used to present and determine as one outcome and not the whole story. Second, data is only as good as the ability to ask questions and analyse it. The right decisions with data were not subject to only having data; the ability to ask questions, analyse the data, and create stories were involved. Last, data should be presented to confirm intuition; otherwise, there was a limitation underpinning their conclusion of the story to make decisions. Therefore, they advocated for a balance between data analytics and human intuition and suggested that they should go hand in hand to facilitate creating a full picture before making decisions. For these respondents, *balance is needed between data and intuition* as the following excerpts illustrate:

> **Respondent Number 2:** ‘Better balancing of evidence, better interpretation of data and biases inherent in them. It’s not about versus, rather data PLUS analysis, interpretation and intuition.... Analytics give you one kind of measure/outcome rather than anything about why outcomes are going in the right or wrong direction or informing the strategies for how to improve’.

> **Respondent Number 3:** ‘Data is only as good as the questions asked and the competence to analyse it. Partial or naïve data will lead to poorly informed decisions. Having data doesn’t necessarily mean making the right decisions with it’.

> **Respondent Number 7:** ‘Data is a tangible factor that shows where the organisation stands but intuition should not be dismissed completely’.

> **Respondent Number 8:** ‘There needs to be a balance. There is always a story behind the data’.

> **Respondent Number 11:** ‘There needs to be a cross over. Data is useful but we need to remember that students and staff are not just data points on a graph. The human factor needs to be incorporated’.

> **Respondent Number 19:** ‘Data should confirm Intuition or at the very least support its suggestions.... There are limitations on the conclusions you can draw from analytics alone’.

> **Respondent Number 20:** ‘I think there is a need for both...The data alone was not sufficient to draw this conclusion...We do not make decisions until the data has been adequately analysed. This does not always mean we will listen to the

data; sometimes human understanding of a situation will take precedence. However, we always consider the full picture before coming to a conclusion'.

Empirical finding 25: Theme 10: Diverse vision and attitude of leaders/people alignment on being data-driven

Moreover, empirical finding 25 highlights that organisations with an established data-driven culture need to be empowered by senior management who are claimed as a critical agent of data-driven cultural change. Interestingly, one participant mentioned that they adopted a data-driven approach but were not fully supported by their leadership, resulting in a failure in their efforts to adopt a data-driven approach to their work. Due to this, they struggled to persuade the senior staff to trust the data insights they presented. As a result, the senior staff relied on the participant's opinion instead. Also, it became evident to other participants that enabling a culture change towards data-driven decision making was entirely driven by the commitment and vision of senior management. From the respondents' and interviewees' perspectives, they realised that leaders have the most powerful impact on establishing a data-driven culture; however, they struggled to get their senior executives to fully support being data-driven. Taken together, empirical finding 25 leads to *senior leaders' commitment and vision to a data-driven being key for success* as the following excerpts illustrate:

Respondent Number 9: 'Openness of senior staff'.

Respondent Number 12: 'Good leadership'.

Respondent Number 14: 'A change in culture needs to be driven by senior management'.

Interviewee Number 18: 'It seems quite difficult to for some people, some senior people to trust the data completely. They do believe the data when it suits them to believe it but sometimes their personal opinion kind of overrides what data is telling them'.

Respondent Number 20: 'It depends entirely on management in my opinion. If managers believe in a data-driven approach, then that is what is adopted'.

Empirical Finding 26: Theme 10: Diverse vision and attitude of leaders/people alignment on being data-driven

Empirical finding 26 highlights the attitude *towards a data-driven approach and its impact on the case study organisation*. The respondents were asked to explain what their organisation's data analytics capability looked like, and they described a broad range of attitudes. Some respondents claimed that their organisation increasingly favoured and better used evidence derived from data, as illustrated in the following excepts below:

Respondent Number 4: 'Better availability of analysed information and culture to use it in making management decisions'.

Respondent Number 5: 'Where decisions are made using hard facts derived from data'.

Respondent Number 7: 'Crucial for business viability'.

Respondent Number 15: 'Evidence from data has always informed my organisation'.

Respondent Number 16: 'It is increasingly relying on big data, analysis and pattern recognition'.

Although it became evident that the case study organisational culture evolved in a more data-oriented direction, other respondents argued that the organisation still struggled to capture and create value from their data. A respondent realised that they did not use data very well in the organisation, and importantly, the organisation was unable to gain competitiveness from the data they had. So, they were not competitive with their data, yet. Interestingly, another respondent pointed towards a data-driven approach and its impact on their organisation claiming that the data still did not carry considerable weight.

Respondent Number 8: 'We don't use data very well in the organisation. I don't think we use our data to gain a competitive advantage'.

Respondent Number 12: 'I think also we "use" data analytics, but we don't refer to it as that, so it doesn't carry any weight'.

In addition, a respondent perceived that the organisation was currently mandated by a data-driven approach as the respondent believed that a data-driven culture worked as, acted as, and became Big Brother. However, the respondent did not provide further clarification or point to any specific issues. However, it seems that there is complete authority in a solely a data-driven approach in the case study organisation.

Respondent Number 2: 'Big brother'.

As demonstrated by the empirical evidence, empirical finding 2 indicated that obtaining data insights facilitates an organisation to analyse its performance but it is not necessary for establishing such an advantage. This empirical data confirmed the challenges, as discussed in Chapter 2, that organisations encounter in trying to create a data-driven organisation, where a healthy data-driven culture remains elusive but also a data-driven culture barrier related to alignment and equal weighting of people, data and technology.

This research argues that without an understanding of the enablers and constraints of a data-driven organisation through the sociomateriality lens, the creation of a data-driven organisation remains challenging and limits the organisation's efforts to become data-driven. The empirical findings presented in this section will now be analysed to further illustrate the issues impacting organisational transformation.

4.3 Analysis

The analysis discussed below relates to the themes/2nd order themes in Table 7. The data analysis process, as demonstrated in this section, moves from the first order themes to second order themes. The empirical findings presented in section 4.2.1 are analysed to further illustrate the issues impacting organisational transformation to becoming data-driven concerning enablers and constraints that lead to people's interaction with technology (e.g., a data-driven approach) or the imbrication of people and technology (e.g., a data-driven approach). Drawing on the empirical evidence from section 4.2.1, 10 issues emerged to form a model of enablers and constraints towards becoming a data-drive organisation through the sociomateriality lens.

4.3.1 Themes/2nd Order Themes

The sociomaterial imbrication lens from Leonardi (2011and 2012) was adopted to develop and conceptualise enablers and constraints as demonstrated in Figure 6. As Leonardi (2012) notes:

> "Affordances and constraints are constructed in the space between social and material agencies. People's goals are formulated, to an important degree, by their perceptions of what a technology can or cannot do, just as those perceptions are shaped by people's goals. Depending on whether they perceive that a technology affords or constrains their goals, people make choices about how they will imbricate social and material agencies" (p. 38).

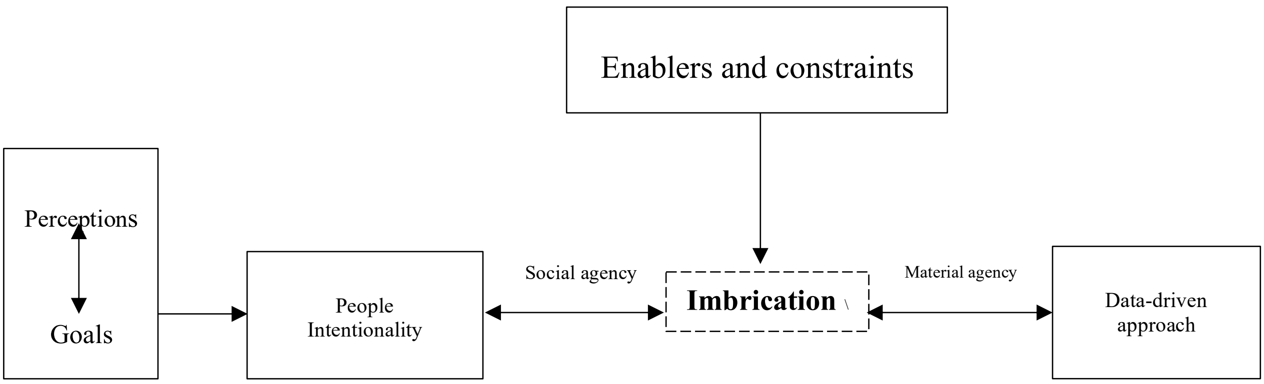

Figure 6: The sociomaterial imbrication lens from Leonardi (2011and 2012) was adopted to develop and conceptualise enablers and constraints

Imbrication is a joining together, an overlap between people and technology which brings a change in routine or a functionality in technology. Leonardi employs the metaphor of imbrication to suggest how social and material (agencies) become sociomaterial. By adopting sociomateriality: the imbrication lens, the proposed theoretical model of enablers and constraints towards becoming a data-driven organisation are as demonstrated in Figure 7. Section 5.4 was created, for the first time, to fill the research gaps by considering both humans and technology but also by extending the sociomateriality lens into the context of a data-driven organisation. Significantly, the model reveals that all elements highlighted need to work together dynamically, rather than separately. The conclusion exposes the need for holistic and dynamic change in management, which is required along with the move and development of a data-driven organisation. Through the use of this model, the intention is not only to expand the existing literature on organisations attempting to become data-driven, but also to question this model in practical ways. The original contribution this thesis has made to the field of study will be elucidated in Chapter 5.

In the following section, two enablers and eight constraints towards becoming a data-driven organisation are presented and discussed.

Enabler 1: Data insights underpinning decisions and performance

The respondents agreed that there are two main benefits of being data-driven: with regard to marketing strategies (Davenport, Mule and Lucker 2011; McAfee and Brynjolfsson 2012; Gandomi and Haider 2015; Khade 2016; Elgendy and Elragal 2016; Mela and Moorman 2018; Johnson 2020), as highlighted in the empirical finding 1; and regarding how to improve organisational work performance (Wilson 2010; LaValle et al. 2011; McAfee and Brynjolfsson 2012; Henke et al. 2016) as highlighted in empirical finding 2. Through data and its analysed results (data insights), people were able to develop and adjust their marketing strategic decisions and improve performance. By this, *the data insights underpinning decisions and performance* were perceived as a strategic and performance enabler for transforming into a data-driven organisation. This is what Leonardi (2012) describes as affordances that are constructed in the space between multiple human (social) agencies and material agencies of sociomaterial imbrication. While other people realised the advantages of being data-driven, Respondent Number 20, however, mentioned that ‘we adjusted our advertising accordingly and were proven correct in our assumption'. This indicates that their willingness to act on data and its analysed results (imbricated with a data-driven approach) tend to be where data insights support and enable their assumption. It is notable that the participants are still not fully data-driven in their manner even though they do not realise it. By using Leonardi’s (2011 and 2012) concept of imbrication, it is possible to demonstrate that there is a complex relationship between a technology's materiality and people agencies towards a data-driven organisation.

Enabler 2: Data insights facilitating multiple perspectives for holistic understanding

Although data insights refer to a deep understanding pertaining to a given topic or situation generated by analysing data and information, however, as highlighted by empirical finding 3, the respondents claimed that a shared understanding and ideas on data insights with others enables them to develop and gain more practical data insights into plans for specific issues, such as recruitment events and marketing. Also, it allowed them to capture anomalies or areas of concern together. These insights led them to move together in the same direction. Moreover, empirical finding 4 highlights that data insights were the standard rational criterion and evidence which afforded them to address heterogeneity when making decisions together. Lastly, the respondents noted that data insights offered solid evidence to confirm that their intuitive hypotheses and ideas and insights run in a similar direction. It would be a benefit to have more conversations with colleagues, according to empirical finding 5. It should be noted that while the objectivity in data facilitates organisations to measure and manage more precisely as well as justify and support pre-decision-making proposals, in turn leading to improved decision making and performance, these are similarly claimed by McAfee and Brynjolfsson (2012); Elgendy and Elragal (2016); Davenport (2013), empirical findings 3, 4 and 5 show that along with better decisions, a strengthening performance results from such dynamic interaction among individuals with data insights. Taking empirical findings 3, 4 and 5 together illustrates *data insights facilitate multiple perspectives for holistic understanding* through a collaborative interaction which affords interaction between the human and technological agencies of sociomaterial imbrication (Leonardi 2011 and 2012). Therefore, dynamic interaction creates sociomaterial imbrication, enabling an organisation to become data-driven.

Constraint 1: The Human element underpinning data insights but being ignored while implementing a more data-informed approach

Becoming data-driven an organisation requires a significant shift in people's existing mindsets and behaviours, and this significant shift is recognised as a key challenge for organisations by scholars (Lavelle et al. 2011; Ross, Beath, and Quaadgras 2013; Henke et al. 2016; Viden, Shaw and Grant 2017; Diaz and Saleh 2018; Diaz, Rowshankish and Saleh 2019; Lunde, Sjusdal and Pappas 2019; Bean and Davenport 2019; Waller 2020; Bean 2020). Empirical findings 6 and 7 show that humans and a data-driven approach are complementary in their entangled relationship (Orlikowski 2007; Orlikowski and Scott 2008), but humans are being ignored in establishing a culture of data-driven decision-making within the research site. The human element is an important part of being data-driven because there is a context behind the data that gives it meaning, can be transformed into value, and which requires humans to discover it; data is worthless without context. This is in line with Davenport and Prusak (1998): "the data tells nothing about why...data says nothing about its own importance or irrelevance. but data is important to organisations...data becomes information when its creator adds meaning" (p. 2); Chamorro-Premuzic (2020): "data without insights is meaningless, and insights without action are pointless" (p. 2); and Roberts (2015): "although explicit knowledge can be transferred in a codified form independently of humans, if organisations are to absorb and apply such knowledge, people must interpret it" (p. 78). Although, organisations attempt to treat data as an important asset, decisions are anchored in data and operate and evolve the culture in a more data-driven manner. The human component behind change remains crucial for accomplishing a data-driven organisation. Mikalef et al. 2018, Davenport and Prusak 1998, Chamorro-Premuzic 2020, Roberts 2015, and Wilson and Daugherty 2018 concurred with this view. It is important to note that the *human element underpinning data insights but being ignored while implementing a more data-informed approach* is a challenging issue to unlock the potential value of data and considered a barrier related to alignment and equal weighting of people, data and technology resulting in constraining the sociomaterial imbrication with respect to a data-driven organisation.

Constraint 2: Data quality and data silos

Empirical findings 8–12 show *data quality and data silos* which involve the five following aspects. First, the respondents prioritised *data accuracy and consistency* as being important in the first place, although they still struggled with it (see empirical finding 8). Second, the respondents realised their encounters with *data accessibility and exploitation* have challenged their attempts to become data-driven (see empirical finding 9). These two issues are included in the facets of data quality which are similarly claimed by Anderson (2015). Even though "being a data-driven organization takes more than great technology and quality data" (Nair 2020, p. 3), the data quality issue is concerned by people who use it (Shah, Horne and Capella 2012; Sidi et al. 2012; Redman 2013; Sivarajah et al. 2016; Redman 2016; Data & analytics case study roll-up report 2016; Nagle, Redman and Sammon 2017; Waller 2020; Redman 2020; Svensson and Taghavianfar 2020). Interestingly, Redman (2013) highlights the importance of data users for improving data quality. According to him, "data's credibility problem management—not technology—is the solution" (p. 84); "The solution is not better technology: It's better communication between the creators of data and the data users" (p. 86). For Redman (2013), connecting data creators with data users—their customers—is crucial while organisations struggle with the data quality challenge. Empirical findings 8 and 9 illuminate not only the challenge of data quality, but also the gap between data creators and data users in this regard.

Third, the participants raised the issue of data *integrity and consistency in analysis and interpretation*, due to the fragmented and varied data as each department created its own standard for gathering, analysing, and reporting on its unique reference information, making it difficult to find a single version (see empirical finding 10). Subsequently, it is more difficult for the participants to accomplish their goals based on the same set of data analysis to become more data-driven. Those who also concurred with the data silo issue are Gemignani et al. (2014), Wilder-James (2016), Nair (2020) O' Tools (2020). Interestingly, the participants also admitted that the quality of data could be undermined by human biases, human error, or human intervention. Their views triggered *misperception of data truth issue* (see empirical finding 11). Lastly, one participant noted data *validity and its relationship with organisation purpose as an issue*. The data currently compiled by the research site was not tied to the organisation's specific purpose which constrains efforts working on data (see empirical finding 12). Because of this, data and its results appeared meaningless to them.

The experts cite that being data-driven emphasises analytically derived insights and making decisions where data outweighs human intuition (Kiron and Shockley 2011; Kiron, Ferguson and Prentice 2013; Kiron, Prentice and Ferguson 2014; Carl 2015; Mikael et al. 2018). Accordingly, *data quality and data silos* generate sociomaterial imbrication, but in a way that constrains becoming a data-driven organisation. Data quality and data silos creating distrust *in data credibility* is claimed by Anderson (2015), Redman (2013), (Clark and Wiesenfeld (2017), Pugna, Dutescu and Stanila (2019), and Svensson and Taghavianfar (2020) and this is discussed in the following section.

Constraint 3: Distrust in data and data analysis credibility

Distrust in data and data analysis credibility was another dominant pattern detected during the iterative process of searching and analysing the empirical findings data. Empirical findings 13 and 14 highlight a *distrust in data and data analysis credibility*, relating to two issues: *concerning the transparency of how data is being manipulated* (see empirical finding 13), and *dilemmas, such as unreliable, sceptical doubts data and its metrics* (see empirical finding 14). The respondents realised that transparency is particularly important. They argued that they lacked confidence in data and the data analysis that their organisation produced. They perceived that 'data can be misinterpreted or mishandled' (Respondent Number 10), 'data can be manipulated to extract specific results' (Respondent Number 6), and 'staff can produce data to show the answer they want to see, rather than what it is actually telling you' (Respondent Number 8). This was because they often discovered the use of flawed data resources and analytical methods. They had doubts about relying on data to improve their work. In doing so, data and analysis's credibility significantly influence people's willingness to embracing a data-driven mindset, in accordance with Anderson (2015); Redman (2013); Clark and Wiesenfeld (2017); Pugna, Dutescu and Stanila (2019); and Svensson and Taghavianfar (2020). In becoming a data-driven organisation, data are not only relied on over intuition, but also become more transparent to obtain actionable insights which the organisation needs to be able to compete (Clark and Wiesenfeld 2017) as well as fully trust data and let it replace intuition (Pugna, Dutescu and Stanila 2019). Therefore, *distrust in data and data analysis credibility* creates sociomaterial imbrication, constraining an organisation from becoming data-driven.

Constraint 4: Lack of harnessing multiple perspectives on data

In spite of that related to theme 4: data quality and data silos, constraint 4: *Lack of harnessing multiple perspectives on data* should be generated into a potential additional theme which illustrates patterns in the data especially in emphasising harnessing multiple perspective on data. The respondents in this study indicated that their organisation was struggling to harness multiple perspectives on data. As empirical finding 15 demonstrates having a single source of truth is difficult for the research site. The participants also noted ‘the main challenge is in the agreement of the required data elements and the criteria used to bring them together to create information and knowledge’ (see Respondent Number 19). Empirical finding 16 shows ‘too many systems that don’t talk to each other’ (see Respondent Number 5) that allows ‘a very minor activity and usually individual’ (see Respondent Number 4). Furthermore, empirical finding 17 demonstrates that data is interrogated in different ways, resulting in different reporting formants, results, and conclusions. Namely, there are three issues the respondents encountered. (1) *plurality of interpretation*, (2) *fragmented collaboration and communication in cross-functional teams*, and (3) *multiplicity of uses of data*. From empirical findings 15, 16, and 17, it was clear that the research site lacks the capability of harnessing multiple perspectives on data, which causes chaos and confusion when operating in a data-driven manner. Therefore, *lack of harnessing multiple perspectives on data* is another potential constraint on the sociomaterial imbrication towards becoming a data-driven organisation.

Constraint 5: Lack of human capability to engage with data

The limits to the current skills and knowledge when dealing with data and analytics were mentioned by the respondents. This theme then emerged as the respondents realised that skilled and knowledgeable personnel were essential to their organisation incorporating data and analytics into their performance. Interestingly, they included not only the ability to perform in data analytics properly (hard skills) but also the ability to share it in a way that is meaningful to their purpose (soft skills). This was what Littlewood (2018) described as the data skills to turn data into insights and action, and are therefore needed in implementing a data-driven approach into a decision-making process as Barton and Court (2012) claimed. As Respondent Number 12 claimed ‘staff resource has inhibited us from pursuing it. It was the driver for the installation which is a frustration’ (see empirical finding 18). Empirical finding 18, highlighted that the research site struggles with a lack of the human capability needed to perform data-driven insights e.g., a lack of human ability to match between data collection and analysis, and specific requirements (objectives) that it serves. Accordingly, staff's lack of data skills impedes the correct use of data to extract and extend insight. To lessen skilled and knowledgeable personnel gaps, better training in data analytical skills and updating knowledge were suggested as solutions, per empirical finding 19. Moreover, the respondents indicated that their organisation is tackling a lack of sufficient data analytics specialists as empirical finding 20 illustrated. The respondents also claimed the value derived from being data-driven was restricted by being under resourced in data analysts and limited expertise in developing more sophisticated analysis or visualisations (see empirical finding 20). Taking these emerging aspects from empirical findings 18, 19, and 20 together, the triggering of a *lack of human capability to engage with data* in the research site is a challenging issue regarding developing a data-driven organisation. These are consistent with the findings of Shah, Horne, and Capella (2012) who contend that "investments in analytics can be useless, even harmful, unless employees can incorporate that data into complex decision making" (p. 23) and Basin and Zao-Sanders (2020) who state that "but while we have all this data, and it's becoming more influential than ever, there's still a big problem at hand: Most of us are not very good at interpreting and making sense of it" (p. 3). Therefore, empirical findings 18, 19, and 20 clearly indicate that a *lack of human capability to engage with data* reinforces the sociomaterial imbrication but in a way which constrains the creation of a data-driven organisation.

Constraint 6: Emerging gap between data user, data provider, and implication of being data-driven

From empirical findings 21 and 22 two issues are highlighted: (1) *final users and their data interpretation are key to make a data-driven success* and (2) *data analysis produced is disconnected from the people who use it*. These two issues reveal that the data insights generated will be worthless without the end-user and their involvement as they contribute the most to making data a success in their organisation becoming data-driven (Davenport and Prusak 1998). However, people cannot connect data insights they gained from the data reports to inform or guide their future decisions and actions which lead to better outcomes. People are then reluctant to exploit their data. According to empirical findings 21 and 22, there is an *emerging gap between data users, data providers, and implications of being data-driven*. This was what Gemignana and Gemignani (2014) describe as a 'data communication problem' as the organisation continues to distance analysis from the people who must use it in support of their decision-making process, resulting in a problem with actionable insights.

Moreover, it should be noted that constraints 2 and 6 are connected, as the research site continues to evolve and develop its data-driven organisation. Constraint 2 illustrates the gap between data creators and data users, while constraint 6 illustrates the gap between data users, data providers, and a data-driven approach. Scholars similarly regard the problem of data credibility (Redmen 2013) and the data communication problem (Gemignana and Gemignani 2014) as social problems which require better communication and interaction between the creators of data and the data users. Therefore, it is a two-way relationship which involves the data creators and the data users working together to achieve a shared aim. Distance between both is a potential constraint of the sociomaterial imbrication with respect to the movement of a data-driven organisation.

Constraint 7: Differences in people's perceptions of revealing the story in data

Empirical findings 23 and 24 illustrate that the research site is encountering a difference *in people's perceptions of revealing the story in data*, since the respondents perceived a different data-driven perspective. First, data should be prioritized over intuition because data is more reliable, important, knowledge, valuable, and pragmatic (see empirical finding 23). Second, data and intuition are complementary measures/outcomes rather than contradictory, having data alone leads to limitations to draw on the conclusion (see empirical finding 24). Intuition still has a role in interpreting the data, although data is perceived and treated as a strategic asset, as is also maintained by Shah, Horne, and Capella (2012); McAfee and Brynjolfsson (2012); and Davenport (2013). It is interesting that data can reveal significant insights and unprecedented opportunities to businesses but the difficulties of revealing the story in data remain. Regarding the concept of a data-driven organisation thus refers to an organisation that shares a pattern of behaviours and practices with respect to making evidence-based decisions rather than intuition or personal opinions spreading widely throughout the organisation (Kiron and Shockley 2011; Kiron, Ferguson and Prentice 2013; Kiron, Prentice and Ferguson 2014; Carl 2015; Mikael et al. 2018). Therefore, *differences in people's perceptions of revealing the story in data* is regarded as another potential constraint on the attempts of organisations to become data-driven.

Constraint 8: Diverse vision and attitude of leaders/people alignment on being data-driven

Empirical findings 25 and 26 highlight *diverse vision and attitude of leaders/people alignment on being data-driven*. Empirical finding 25 shows that senior leaders' commitment and vision to a data-driven organisation is critical for the change which is supported by scholars. McAfee and Brynjolfsson (2012) argue that exploiting data analytics can radically improve an organisation's performance only if decision making has been changed to lessen reliance on experience and intuition, starting with the role of the senior executive team. Brown and Gottlieb (2016) found that, according to their respondents who are defined as high-performers of analytics capabilities, senior-leadership involvement plays a critical role for organisations' effectiveness at data and analytics. A lack of communication from the top results in confusion among the groups responsible for implementing analytics and, therefore, can inhibit collaboration among functional teams in the process of creating a data-driven organisation. Pugna, Dutescu and Stanila (2019) also found that leaders committed to an embedded data-driven decision-making process is one of the critical components for success in data-driven companies, alongside technological challenges. In a similar vein, Carande, Lipinski and Gusher (2017) note that successful data analytics starts at the top. Waller (2020) held a similar idea, asserting that data-driven culture starts at the (very top). Davenport and Mittal (2020) also state that the importance of the CEO's role in an organisation becoming data-driven.

Empirical finding 26 demonstrates that the attitude towards a data-driven approach and its impact on their organisation varied even though the research site started by implementing a data-driven approach throughout. The research site increasingly relies on data, but complete power is with only a data-driven approach as Respondent Number 2 mentioned—'Big Brother'. However, the value of a data-driven approach still has not spread across the entire research site. And more importantly, some respondents perceived that they were not competing with their data yet. They did not notice that their organisation took a data-driven approach nor its potential to create value, such as achieving a competitive advantage. As Respondent Number 8 said 'I don't think we use our data to gain a competitive advantage', and Respondent Number 12 said 'I think also we "use" data analytics, but we don't refer to it as that, so it doesn't carry any weight'.

Accordingly, it seems that becoming a data-driven organisation is challenging for the research site. Incorporating data and analytics into strategies and decisions to achieve a competitive advantage without understanding enablers and constraints can also paralyse the growth of a data-driven organisation. Therefore, *diverse vision and attitude of leaders/people alignment on being data-driven* within an organisation is considered as a constraint in the aim of becoming a data-driven organisation.

A summary of enablers and constraints to be found in this study for becoming a data-driven organisation after which the findings are discussed, provides in Table 8 below.

Table 8 A summary of enablers and constraints to be found in this study for becoming a data-driven organisation

Enablers	**Significance for 'Imbrication'**	**Significance for 'A data-driven organisation'**
Data insights underpinning decisions and performance	Data insights were perceived as affording the ability to make informed decisions and performance, people in the research site are likely to adapt their work routines to align with technology's agency.	Through data and its analysed results (data insights), people are able to develop and adjust their strategic decisions and improve performance on student recruitment and marketing.
Data insights facilitating multiple perspectives for holistic understanding	Data insights were also perceived as affordances for holistic understanding, the resulting sequence of imbrications leads to changes in routine.	All key stakeholders together can build a holistic understanding on the future student recruitment and marketing they are striving towards, and the role data insights plays in this regard.
Constraints	**Significance for 'Imbrication'**	**Significance for 'A data-driven organisation'**
The Human element underpinning data insights	From the point of view of sociomaterial imbrication, it	For an organisation to be data-driven, there have to be

but being ignored while implementing a more data-informed approach	emphasises the need to be attentive to both humans and technology (a data-driven approach). Otherwise, people overlook the opportunities afforded by that technology.	humans in the loop, this is because building a data-driven organisation actually means to drive people who are data-driven across the organisation.
Data quality and data silos	Possibilities for action emerge from the interaction (or imbrication) between actors and technology are hindered by data quality and data silos issues.	Data quality is critical to facilitate decision-making with confidence across the organisation. Also, data silos isolate data within the organisation and hinders collaboration. With data quality and data silos, the organisation continues to grapple to operate in a data-driven manner.
Distrust in data and data analysis credibility	People within the research site perceived distrust in data and data analysis credibility as constraining their desired action. It is challenging for them to make choices about the way they imbricate human and material agencies which results in changing their work routines to align with technology's agency.	Data quality is key in the creation of a data-driven organisation, as it could also impact on data and the credibility of data analysis. When data quality cannot be improved, and the credibility of data analysis is still in question.
Lack of harnessing multiple perspectives on data	The perception of a lack of harnessing multiple perspectives on data produces a sequence of imbrication in the way that people realise they could be	Lack of harnessing multiple perspectives on data causes chaos and confusion for operating in such a data-driven manner. A single source of truth or

	stopped from reaching a specific goal by using a technology.	centralised data is required while the research site now strives to become data-driven.
Lack of human capability to engage with data	As there is a lack of human capability to engage with data, people make a choice to imbricate with technology in a way that they are likely to continue applying data-driven routines in unchanged ways.	Transforming an organisation to be data-driven requires developing capabilities with regard to analytical skills but also the ability to work with data, such as the ability to interpret data, to draw insights and to ask the right questions in the first place.
Emerging gap between data users, data providers and implications of being data-driven	Emerging gap between data users, data providers and implications of being data-driven hinders the two agencies (human and material agencies) becoming imbricated and working together to achieve the organisation's objectives to be data-driven.	This constraint involves connecting and collaborative work with data among groups of people, namely, data providers and users, as this has the potential to unlock the value of the data already held by an organisation.
Differences in people's perceptions of revealing the story in data	As differences in people's perceptions of revealing the story in data is regarded as constraining, human and material agencies become imbricated and results in ways that allow people to get their work done by applying their existing routines.	Concerning the concept of a data-driven organisation, thus refers to an organisation that shares a pattern of behaviours and practices in respect to making evidence-based decisions rather than intuition or personal opinions spreading widely throughout the organisation.

		Differences in people's perceptions of revealing the story in data constrains the attempts of an organisation to become data-driven.
Diverse vision and attitude of leaders/people's alignment on being data-driven	Despite a data-driven approach helping the research site to deliver their marketing and student recruitment goals, the diverse vision and attitude of leaders/people's alignment on being data-driven is regarded as constraining, and in doing so human and material agencies are imbricated in ways that people are likely to apply their existing routines.	Diverse vision and attitude of leaders/people's alignment on being data-driven results in confusing the groups responsible for implementing a data-driven approach, and therefore inhibits collaboration among functional teams in the process of creating a data-driven organisation.

4.4 Summary

According to the empirical findings and analysis, there are multifaceted, complex and interconnected issues that impact an organisation's transformation into a data-driven organisation. There are enablers and constraints that lead to people's interaction with a data-driven approach or the imbrication of people and the dimension of a data-driven approach: (1) data insights underpinning decisions and performance, (2) data insights facilitating multiple perspectives for holistic understanding, (3) the human element underpinning data insights, (4) data quality and data silos, (5) distrust in data and data analysis credibility, (6) a lack of harnessing multiple perspectives on data, (7) a lack of human capability to engage with data, (8) the emerging gap between data users, data providers, and implications of being data-driven, (9) differences in people's perceptions of revealing the story in data, and (10) the diverse vision and attitude of leaders/people.

Although a data-driven culture is critical in forging a data-driven organisation, an organisation, however, struggles to operate in a data-driven manner as they encounter the eight constraints, which mainly involved a cultural barrier. This is in line with the constraints mentioned in the literature such as Lavelle et al. (2011), Chaffey and Patron (2012), Ross, Beath, and Quaadgras (2013), Henke et al. (2016), Clark and Wiesenfeld (2017), Diaz, Rowshankish and Saleh (2018), Sejahtera et al. (2018), Bean and Davenport (2019), and Waller (2020). According to Bean and Davenport (2019), companies are failing to become data-driven due to challenges related to cultural challenges, which also support the 10 issues as presented in this study. A possible explanation for the challenges related to cultural challenges is the interdependent impacts of these enablers and constraints in the development of a data-driven culture and becoming a data-driven organisation.

In addition, these enablers and constraints also compliment the results in Sejahtera et al. (2018), but also include that enablers and constraints have an interdependent impact through the sociomaterial practice described by Leonardi (2011 and 2012). This is considered an explanation for why becoming a data-driven organisation remains a significant challenge for organisations. Consequently, the successful transformation into a data-driven organisation happens in only a few organisations (Mayhew, Saleh and Williams 2016; Henke et al. 2016); furthermore, only a small fraction of organisations are able to capture the potential value from being data-driven (Henke et al. 2016; Gupta and George 2016; Mayhew, Saleh and Williams 2016; Diaz, Rowshankish and Salen 2018; Lunde, Sjusdal and Pappas 2019; Troyanos 2020).

Subsequently these 10 issues, which have emerged to form a model of enablers and constraints, and their consequential elements in the move to becoming a data-driven organisation, have substantiated the originality of this work. The model will be elaborated and discussed further in Chapter 5, which allows the researcher to develop the theoretical model and its contributions and the implications for practice. The theoretical contribution in Chapter 5 will also provide an explanation of the movement towards being data-driven. To achieve this, an organisation has to work on their enablers to see improved results, but they also must deal with the constraints as the model significantly reveals that all the elements highlighted need to work together dynamically rather than separately in order to deliver the move and development required in a data-driven organisation.

CHAPTER 5: Discussion and Contributions

5.1 Introduction

This research contributes to the understanding of enablers and constraints and their significant impact as well as offering a theoretical model of enablers and constraints in becoming a data-driven organisation derived from the findings in this study.

In the previous chapter, the empirical evidence from the research identified that there are multifaced, complex and interconnected issues that impact organisational transformation in becoming a data-driven organisation. The findings also revealed ten factors that influence the move and development in becoming a data-driven organisation: (1) data insights underpinning decisions and performance, and (2) data insights facilitating multiple perspectives for holistic understanding both worked as enablers, whilst (3) the human element underpinning data insights but being ignored while implementing a more data-informed approach, (4) data quality and data silos, (5) distrust in data and data analysis credibility, (6) lack of harnessing multiple perspectives on data, (7) lack of human capability to engage with data, (8) the emerging gap between data users, data providers, and implications of being data-driven, (9) differences in people's perceptions of revealing the story in data, and (10) diverse vision and attitude of leaders/people's alignment on being data driven were identified as constraints. Moreover, the findings identified that these two enablers and eight constraints have an interdependent impact, relating to one another, on an organisation's move to become data-driven.

In this chapter, research questions derived from the literature and the key findings involved in identifying enablers, constraints, and their consequences all as part of the process of creating a data-driven organisation will be summarised. Developed from this, the next section presents and discusses the theoretical model and contributions. This includes a model of enablers and constraints involved in the move and development towards becoming a data-driven organisation, which forms the basis of the originality of this work. Next, this is followed by a discussion of the impacts of those enablers and constraints on becoming a data-driven organisation, practical implications, methodological contribution, limitations, and future research, and conclusion.

5.2 Research Questions

This study explored the perception of data users and technology providers to understand enablers, constraints, and their impacts on the move and development towards becoming a data-driven organisation. To carry out this exploration, the following two research questions were developed from the literature review:

1. What are enablers and constraints of becoming a data-driven organisation?
2. What are the impacts of these enablers and constraints on becoming a data-driven organisation?

These questions were derived from the literature, which highlighted a gap as organisations progress on a journey towards becoming data-driven and involved the following three challenges. First, organisations still have not allowed data-driven organisations to reach their full potential of being data-driven. Second, it has been challenging for organisations to adopt data-driven decision-making processes that overcome historically accepted decision making. Third, there is a lack of empirical research that addresses the empirical and theoretical discussion on the evolution of an organisation as it transitions to becoming a data-driven organisation. These three challenges indicate the importance of the need for a better understanding of a data-driven organisation, with the result that the movement towards becoming data-driven remains elusive, and therefore required further investigation. This research on the topic of a "Data-driven Organisation through the Sociomateriality Lens: Towards an Understanding of Enablers and Constraints" is an attempt to fill this gap as this will benefit those organisations that are struggling in their efforts, as well as dealing with the challenges and the potential value from in this regard being more data-driven.

5.3 Enablers and Constraints of Becoming a Data-driven Organisation

This section presents and discusses the findings for the first research question on what are the enablers and constraints of becoming a data-driven organisation as shown in Table 7, Section 4.1.

In this study, the analysis of the findings for the first research question shows that there are technological but also non-technological factors that enable or constrain an organisation from becoming data-driven. The empirical findings revealed that 'data insights underpinning decisions and performance' and 'data insights facilitating multiple perspectives for holistic understanding' work as enablers. However, the 'human element underpinning data insights are being ignored while implementing a more data-informed approach', 'data quality and data silos', 'distrust in data and data analysis credibility', 'lack of harnessing multiple perspectives on data', 'lack of human capability to engage with data', the 'emerging gap between data users, data providers and implications of being data-driven', 'differences in people's perceptions of revealing the story in data', and 'diverse vision and attitude of leaders/people alignment on being data-driven' constrain the development towards achieving a data-driven culture and thereby becoming a data-driven organisation. As a result, there are 10 factors that enable and constrain an organisation from becoming data-driven to be found in this study, namely, two enablers and eight constraints.

Table 9 also demonstrates the factors that enable and constrain an organisation from becoming data-driven reflected in the academic literature and research findings. The existing literature presents the main factors that enable and constrain a data-driven organisational change, and they are listed in Table 5 (see Section 2.5). The key findings of this study are consistent with the literature reviewed in terms of identifying and describing factors that achieve a data-driven organisation, while some emerging factors are discovered in this study. The similarities and differences in the main findings with other studies will be presented and discussed below; if similar things emerge, this emphasises the generalisation of the results in this study. If not, potential factors emerging and affecting the practicality can be identified.

Table 9: Factors that enable and constrain becoming a data-driven organisation in the literature review and the research findings

Factors in the literature review	**Research findings**	
Being data-driven and its potential impact on organisational	Data insights underpinning decisions and performance	Enabler 1

capabilities (i.e., marketing, decisions, performance and competitiveness)	Data insights facilitating multiple perspectives for holistic understanding	Enabler 2
The Human component in the drive to become a data-driven organisation	The Human element underpinning data insights, but which are being ignored while implementing a more data-informed approach	Constraint 1
Data silos	Data quality and data silos	Constraint 2
Data quality		
Data and data analysis credibility	Distrust in data and data analysis credibility	Constraint 3
	Lack of harnessing multiple perspectives on data	Constraint 4
Data literacy skills	Lack of human capability to engage with data	Constraint 5
Data communication to enhance data user's engagement	Emerging gap between data users, data providers and implications of being data-driven	Constraint 6
Leadership involvement	Differences in people's perceptions of revealing the story in data	Constraint 7
	Diverse vision and attitude of leaders/people's alignment on being data-driven	Constraint 8

For example, the participants highlighted the advantages of data-informed decisions and performance improvement, which is in accordance with previous studies (e.g., Davenport, Mule and Lucker 2011; Khade 2016; Gandomi and Haider 2015; McAfee and Brynjolfsson 2012). However, interestingly, one participant (Interviewee Number 18) also pointed out that the objectivity of data insights resolves differences between individuals. To paraphrase her, she claimed the data was needed in order to say now we know that this one works rather than spending weeks arguing. And the data just needs to be there for everyone to agree with it. So, this differing element was observed, and the same data insights were perceived and used by people in the case study which helped them deal with diversity when making decisions.

According to the literature (e.g., Mikalef et al. 2018; Davenport and Prusak 1998; Chamorro-Premuzic 2020), the human component behind change remains crucial for achieving a data-driven culture and becoming a data-driven organisation, which supports the findings in this study. The most surprising finding was when one participant commented that ‘we forget the human element and see it is information from a system’. Building a data-driven culture actually means to drive people who are data-driven throughout an organisation. Clearly, developing only a data-driven approach and ignoring the human element makes the dynamic work differently. As a result, if the human element underpinning data insights is ignored while implementing a more data-informed approach, this is considered to be a constraint.

This study also found that data quality issues and data silos work as a constraint on the path towards achieving a data-driven culture and creating a data-driven organisation. This corresponds to the findings of other scholars (e.g., Gemignani et al. 2014; Wilder-James 2016; Nair 2020; O’ Tools 2020; Anderson 2015; Kiron and Shockley 2011). The data quality is apparently prioritised for the participants, although they still struggle with it. Also, the fragmented and varied data as each department creates its own standard for gathering, analysing, and reporting on its unique reference information makes it difficult to find a single version. Subsequently, this creates difficulties in accomplishing their goals based on the same set of data analysis to become more data-driven. Furthermore, data quality issues enhance distrust in data credibility (e.g., Svensson and Taghavianfar 2020; Barton and Court 2012; Shah, Horne, and Capella 2012). Furthermore, data silos illuminate another potential drawback in a data-driven organisation, which lacks the harnessing of multiple perspectives on data.

Data literacy skills are claimed by Littlewood (2018); Barton and Court (2012); Shah, Horne, and Capella (2012); and Basin and Zao-Sanders (2020) as a significant factor that can produce actionable insights from data. This study found that a lack of human capability to engage with data remains a significant constraint on organisational efforts to become data-driven.

Data communication to enhance data user's engagement is mentioned in Davenport and Prusak (1998); Redman (2013); Gemignani et al. (2014). This involves connecting and collaborative work with data among groups of people, namely, data providers and data users, as this has the potential to unlock the value of the data already held by an organisation. However, a gap between data users, data providers and the implications of being data-driven emerged in the organisation chosen for this case study and thereby had to be identified as a constraint.

Finally, the literature (e.g., McAfee and Brynjolfsson 2012; Brown and Gottlieb 2016; Waller 2020) highlights the role of senior management, its commitment and communication including attitudes and skills. Leadership involvement is clearly a critical factor in shaping a data-driven organisation, and this supports the findings of this study. This study found that differences in people's perceptions of revealing the story in data as well as diverse visions and attitudes of leaders'/people's alignment on being data-driven worked as constraints.

To date, empirical research that tackles empirical discussion on the evolution of an organisation as it strives for a data-driven culture is still lacking and, as a result, the benefits gained by a data-driven approach have been limited (Vidgen, Shaw and Grant 2017; Sejahtera et al. 2018; Lunde, Sjusdal and Pappas 2019; Bean and Davenport 2019). Also, there is limited research on the factors that help or hinder organisations to become data-driven (Sejahtera et al. 2018). The model presented in this thesis (see Section 5.4) seeks to address these significant challenges.

5.4 Theoretical Model and Contributions

From the empirical evidence, the model presented in Figure 7 below links people and technology (namely, a data-driven approach) and reveals the factors that help or hinder an organisation as it moves towards becoming data-driven. The resulting insights gave rise to a model of enablers and constraints in the move and development towards becoming a data-driven organisation. Figure 7 below presents the model.

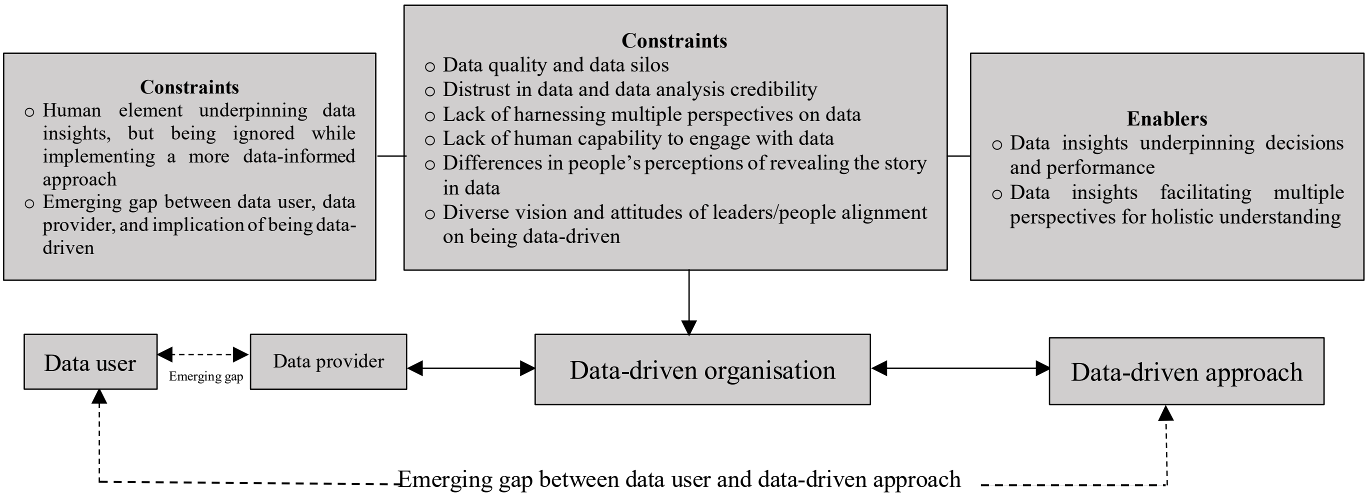

Figure 7: The proposed theoretical model of enablers and constraints towards becoming a data-driven organisation derived from the findings in this study

This model depicts the empirical findings in this study, which is grounded in a sociomaterial perspective as illustrated in Figure 6 (see Section 4.3.1) introduced by Leonardi (2011 and 2012), which emphasises the need to be attentive to both humans and a data-driven approach in the creation of a data-driven organisation. The key enablers, constraints, and their consequences have been conceptualised based on a combination of existing studies and the expanded sociomaterial lens. So, by adopting a sociomateriality lens, the model in Figure 7 was created, for the first time, to bridge the research gaps by considering both humans and a data-driven approach but also through extending the sociomateriality lens into the context of a data-driven organisation.

A data-driven approach was introduced into the model as it was perceived to support data insights, which work as enablers. However, the findings indicate that a data-driven approach alone does not make an impact on the goal of becoming a data-driven organisation. This is because humans are also important. They consist of not only data providers, but also data users, and as a result, they have been added to the model. For an organisation to be data-driven, there have to be humans in the loop; this is critical because building a data-driven culture actually means to drive people who are data-driven across the organisation. The eight constraints include six problems and two barriers to people's intentionality. Consequently, this model reveals that all the elements highlighted need to work together dynamically, rather than separately, to deliver a data-driven organisation.

The model illustrates the five most important things. First, it is crucial for an organisation to work on their enablers for improved results; but they also need to deal with the constraints. However, if they only remove one constraint, that makes no great difference. So, in total 10 things need to be done. Therefore, the movement towards being data-driven is regarded as complex and dynamic, rather than linear, and this leads to the next point: whoever is responsible for the transformation, needs to be aware of the need for holistic and dynamic change in management. Importantly, the three main elements of data users, data providers and a data driven approach need to work in harmony. However, data silos create some problems, and the dynamic interaction between these three is another point. Finally, in sociomateriality, people and technology become entangled. However, the people in the case study failed to recognise this entanglement and a gap emerged between them and a data-driven approach. In light of this, if an organisation only recognises and overcomes constraints but not enablers and vice versa, then entanglement is never going to happen. Furthermore, there will be fragmentation between humans and technology because if this is ignored, then an organisation will never become data-driven.

Therefore, the model in Figure 7 to which the enablers, constraints, and their consequential elements were added, form the basis of the originality of this work. The strength of this research lies in the model in Figure 7, which is an extension of the perspective of sociomateriality introduced by Leonardi (2011 and 2012) as illustrated in Figure 6 and applied to the field of becoming a data-driven organisation. This model is based on the organisational culture and context of the case study. As the main research findings suggest, dynamic interactions of people and technology are critical. This is connected to the hypothesis that both should be regarded as equals, which align to achieve the development of a data-driven organisation. This also echoes a sociomaterial perspective which suggest that there is no separation between the two, as all are interlinked. Otherwise, cultures evolving in a more data-driven direction and gaining potential benefits from a data-driven technology may not be fully achieved. The conclusion results in the need for holistic and dynamic change in management, which is required along with the development of a data-driven organisation.

Figure 8 below demonstrates the fragmentation between three most important elements on being data-driven: data users, data providers, and a technology (namely, a data-driven approach) within the research site. Consequently, the research site will struggle to become data-driven, unless they work harmoniously in a dynamic way.

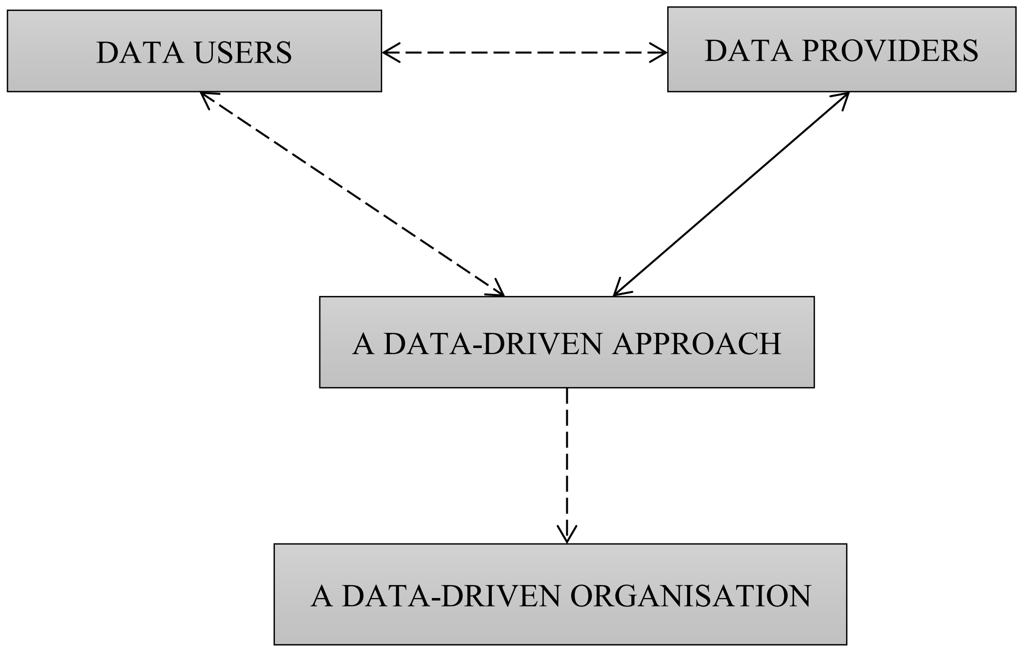

Figure 8: Fragmentation between stakeholders
on being data-driven within the research site

In addition to the theoretical model and its contributions, this study has important implications for practice. Based on the theoretical model in Figure 7, practical recommendations and methodological contributions for the development of a data-driven organisation will be discussed in Sections 5.6 and Section 5.7.

5.5 Impacts of Enablers and Constraints on Becoming a Data-driven Organisation

This section provides the analysis of the findings for the second research question on the impacts of these enablers and constraints on becoming a data-driven organisation. This study found that data-based decision making provides an organisation with the capabilities to make impactful business decisions and to optimise their performance. Also, the objectivity of data insights is used to deal with diversity when making decisions. Nevertheless, if data is siloed, it divides an organisation and hinders collaboration. As such, fragmentation between stakeholders on being data-driven will continue in an organisation. And when there is fragmentation, data quality cannot be improved, and the credibility of data analysis remains in question. Moreover, dynamic interaction between people (data users and data providers) and a data-driven approach are critical, as both need to be regarded as equals. For an organisation to be data-driven, there still has to be humans involved; this is critical because building a data-driven culture actually means to drive people who are data-driven across the organisation. Although an organisation may have invested in technologies and an analytical approach, becoming a data-driven organisation remains challenging as a lack of people with the ability to engage with data, as well as differences in people's perceptions of revealing the story in data and diverse vision and attitudes of leaders/people alignment on being data-driven, are all drawbacks

This indicates that enablers and constraints, plus their impacts on the path towards achieving a data-driven organisation, is dynamic and entangled. So, while in the past organisations have tackled enablers or constraints separately, it actually extends far beyond that. If they want to bring about a holistic and dynamic change in management, then they need to recognise and be aware that all elements highlighted in the model, need to work together. That is why it is difficult to measure their individual impacts and contributions in isolation.

This study has generated a new model depicting the development leading towards a data-driven organisation, and Figure 7 has proposed factors functioning as enablers and constraints in the process. Two key findings for the second research question on the impacts of these enablers and constraints on becoming a data-driven organisation were discovered. First, the movement towards a data-driven organisation is complex and dynamic rather than linear. Two enablers, eight constraints, and their interconnected nature were identified. Crucially, all those enablers and constraints cannot be looked at in isolation as if one moves in one direction, it impacts the other. Consequently, the organisation would be unable to become data-driven due to the sensitivity of those enablers and constraints. All of the elements or agents for change within the model must interact, co-evolve and mutually adapt to enhance the influence and impact of these enablers, and mitigate the constraints of building a data-driven organisation.

And second, the constraints which have been found in this study, reveal the fragmentation between data users, data providers and a data-driven approach. Unavoidably, the relationship between these three elements is also dynamic and entangled if an organisation is to become data-driven. Clearly, there may be a negative impact, if these three elements act in isolation. For instance, if the data users do not recognise the affordances of a data-driven approach, then they are not engaged in the data-driven projects and data analysis. Data providers may fail to provide what the data users need, and excessively focus on a data-driven approach. So, if the data providers drive the change in isolation of data users, then the data users' needs are likely to be overlooked. If any one of the three elements view any agency as independent but are also unaware of or considering the sociomateriality which is a constituent of organising,, then entanglement is never going to happen. Fragmentation among groups of people and technology agencies will continue in an organisation and therefore it will never achieve its objective of being data-driven.

Clearly, the entanglement among groups of people (data users and data providers) and a data-driven approach agencies will never occur. Hence, until the organisation can reach a level where data users, data providers, and a data-driven approach agency are mutually intertwined, it is likely that the organisation will never achieve its objective of being data-driven and becoming a data-driven organisation. As another example, if the project leaders (or the data analysts) do not consider that technology has a role, although it may appear to be a material artifact it is entangled with the other two elements. Project leaders (or data analysts) are unable to develop and build a system without considering the data users, who need data information to help them achieve their goals. If the data users do not know what the technology can do for them, but the project leaders (or the data analysts) want to do something with the technology, then the constraints noted in the theoretical model in Figure 7 will likely have a detrimental impact on the project. Moving towards a common goal as a data-driven organisation in isolation of these three stakeholders will be problematic and can lead to unintended consequences. Accordingly, their expectation of the final result to organisational change would otherwise be different from the original intent. Therefore, these need to be taken into consideration and remain consistent in a harmonious way for an organisation to move towards being data- driven.

In summary, this study identifies the factors functioning as enablers and constraints in the development of a data-driven organisation and recognises that all need to work together dynamically to work towards the strengthening of enablers and mitigation of constraints on building a data-driven organisation. Any one element cannot be considered in isolation. Otherwise, there will be frustration with the data and technological solutions, and this is where there appeared to be a gap in the knowledge, and which this study has further investigated and attempted to bridge.

5.6 Implications for Practice

In connection with practice, this study found three practical implications for the development of a data-driven organisation based on research findings. These are managerial implications, training and workshops, and improving the ability of data providers.

First, it implies managerial implications for those responsible for driving change with a view to data-driven transformation. They need to recognise and be aware that the need for holistic and dynamic change in management is of practical significance for an organisation to move towards being data-driven.

Second, organisations of all types (i.e., public/private and educational institutions) can apply the findings in this study to create or develop training and workshops on understanding the significance of dynamic interactions to foster a data-driven culture with the aim of becoming a data-driven organisation. By doing so, it is hoped that the distance between groups of people and a data-driven approach will decrease.

Third, the findings in this study can help teams of data providers to recognise and be aware that their ability to work with cross-functional silos is important, but that there is also a need to communicate with data in order to bridge the gaps between data users, data providers, and the implications of being data-driven. Thus, based on the findings in this study, it is recommended that a team of data providers should act as a go-between or mediator for the data users and technology.

5.7 Methodological Contribution

In the literature, some studies investigated this related topic using an interview method to collect the data. Likewise, at the beginning of this study, face-face interviews were intended to be used but due to COVID-19, the use of this type of interview was out of the question. Subsequently, an online survey was used to tackle this problem. Although the two types of methods can be treated as being similar for data analysis, they are not equivalent. This is because, an online survey does not give the participants opportunities to expand on their ideas and also for the researcher to ask for additional ideas or clearer statements. Therefore, it emerged that the use of an online survey could be a type of practical type of data collection and one that is useful for future research, especially one that could be used during a similar situation.

5.8 Limitations and Future Research

This study is not without limitations, similar to any other research. First, due to the COVID-19 outbreak, this study had to be conducted remotely. The participants' perceptions of their engagement with technology and other people were gathered by using one face-to-face semi-structured interview and an online survey as a surrogate approach. Although both sources of data were treated as similar, it needs to be acknowledged as a limitation of the methods used, which should be taken into consideration in future research. Second, the responses which the researcher received were not very rich in either details of description or examples as might have been the case in using semi-structured face-to-face interviews for some participants, but they were sufficient for analysis. Third, this study provided the research field with a unique site for implementing a data-driven approach. However, it should be added that this project was limited to one organisation and comprised a relatively small sample size. As a result, it may be argued that this limitation may prevent a broad generalisation of the results. Last, it should be emphasised that the theoretical model presented in this study may not be considered a universal model, since a majority of organisations are in the process of moving and developing data-driven organisations. Notwithstanding, the research site acts as a representative sample of the majority of organisations that utilise a data-driven approach for their decision making and are not yet fully integrated. In this regard, the need for better understanding of a data-driven organisation is required. It would, therefore, be interesting for future research to add insights and enhance the work demonstrated in this study.

5.9 Conclusion

While organisations are awash with data and investments in data continue to grow, the need to become a data-driven organisation is not likely to disappear (Bean and Davenport 2019). As scholars also encourage organisations to become data-driven, and it has been assumed that data creates better decisions, better performance and an improved competitive position, it needs to be stressed that, it is difficult for an organisation to achieve data-driven status and be successful. It is apparent that many organisations are struggling to become data-driven. Consequently, the number of data-driven organisations achieving their full potential value from being data-driven is insignificant.

This research project set out to answer the questions raised from the literature review on becoming a data-driven organisation from the sociomaterial perspective. The empirical evidence illustrated the dynamic relationships of enabling and constraining factors as demonstrated in Figure 7, as well as the fragmentation between three components: data users, data providers, and technology (namely, a data-driven approach) as illustrated in Figure 8. Failure in organising and overcoming such dynamic relationships and fragmentation would never result in an organisation becoming data-driven. The model in Figure 7 displays the dynamic conditions, but also reveals the critical issues for becoming a data-driven organisation. Establishing mutual understanding and shared perspectives on the practical implications of organising and entanglement are vital to addressing the current situation of the case study's organisation.

Consequently, this thesis makes three contributions from the research site to the current literature on becoming a data-driven organisation. To begin with, this is the first research study which identifies how the complexity of issues and their relationships between people and technology have a reciprocal impact as an organisation moves towards becoming a data-driven. Second, this study introduces the model of enablers and constraints involved in the move and development towards becoming a data-driven organisation and provides a comprehensive roadmap showing how an organisation can overcome a limited understanding of how they can improve their current data-driven capability, so as to strive towards its goals of becoming data-driven. This model, which has been supplied, also extends Leonardi's conceptualisation, namely, the sociomaterial perspective to the research and literature on a data-driven organisation and the context, where the two enablers and eights constraints as well as the three elements: data users, data providers, and technology need to work in harmony in a dynamic way. Third, the theoretical model also contributes and expands the mutual understanding of the importance and the complexity of the entanglement between the social world and materiality in moving towards becoming a data-driven organisation. Otherwise, the organisation will continue to experience fragmentation among data users, data providers, and technology (namely, a data-driven approach) as well as the interconnected issues affecting decisions while they are striving towards a data-driven organisation.

In addition to the three theoretical contributions, this study recognises that future research is required regarding the need for better understanding of a data-driven organization. Nevertheless, this study confidently contends that its findings are robust enough to make a worthwhile contribution to management scholars, and the development of a data-driven organisation which has a similar context and does not yet recognise the complex interrelationships and entanglements between issues impacting the organisational transformation required in becoming a data-driven organisation and the three elements: namely, data users, data providers and technology.

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APPENDICES

Appendix A: Interview Schedule for Semi-structured Interviews

Interview Schedule for the thesis: Data-driven organisation through the sociomateriality lens: Towards an understanding of Enablers and Constraints

Section 1. Introduction and background questions

1. Could you please describe your role and responsibilities?

Section 2. Perceptions of a data-driven approach (data technological driven or reports) and organising questions

2. How a data-driven approach (data technological driven or reports) help you to achieve your work? Why is it important?
3. Has it done what you want it to do?
4. Identify any benefits/limitations on a data-driven approach (data technological driven or reports)? If limitations, what change would you like to see? Why do you think they would help?
5. Who do you interact with when you adopt a data-driven approach (data technological driven or reports)?
6. How do you work with them?
7. How does the interaction with them help you to get successful to you work?
8. How do the benefits/limitations that you get from the interaction with others?
9. How does a data-driven approach (data technological driven or reports) help you to create a competitive advantage?

Section 3. Perceptions of a data-driven organisation questions

10. What do you think about what a data-driven organisation would look like? (How does it look like?)
11. What do you think how a data-driven organisation in your organisation look like?

Appendix B: Open-ended Questions for an Online Survey as a Surrogate Approach
(Due to the Spread of COVID-19)

Data-driven organisation through the sociomateriality lens:
Towards an understanding of Enablers and Constraints

Please answer the following open-ended questions. It may take approximately 20 minutes to finish these. The information will be kept confidential, and results anonymised. The sections cover individual's working with a data-driven approach, as well as working with others with a data-driven approach

Section 1: Introduction and background questions

1. Could you please describe your roles and responsibilities as a data analytics creator or as a data analytics user?

Your answer

*Note:
Data creator refers to a person who produces or provides data analytical reports or data spreadsheets or directly interacts with a technology (namely, a data-driven approach).
Data user refers to a person who uses data insights from data analytical reports or data spreadsheets or indirectly interacts with a technology (namely, a data-driven approach).

2. What types of a data-driven approach do you have or use to perform and support your roles and responsibilities?

Your answer

*Note:
The types of a data-driven approach e.g., data analytics applications/software (such as Google Analytics), Dashboard, Data analytics reports in digital marketing, and student recruitment and admissions or Data spreadsheets.

Section 2: Perceptions of a data-driven approach (data technological driven or reports) and organising questions

3. How do you use a data-driven approach to perform and support your roles and responsibilities?
Your answer

4. Has a data-driven approach been done in a way that you want it to be at work as a data analytics creator or a data analytics user? e.g., in decision making, developing marketing strategies, performance improvements and so on. (Has using a data-driven approach help you to achieve your goals at work in a way as you want it to be?) Please explain how.
Your answer

5. Please identify any challenges arising from having or using a data-driven approach?
Your answer

6. Concerning challenges arising from a data-driven approach from question 5, what change would you suggest? In what way do you think it would be helpful?

7. What do you think about the role of humans throughout a data-driven approach? Why do you think so?
Your answer

8. Please identify any challenges arising from human participation in a data-driven approach?
Your answer

9. Concerning challenges arising from human elements from question 8, what change would you suggest? In what way do you think it would be helpful?
Your answer

10. Who do you interact with when you use a data-driven approach to perform and support your work?
Your answer

11. How do you work with others when you use a data-driven approach to perform and support your work?
Your answer

12. How do the interactions with others help you when you use a data-driven approach to perform and support your work?
Your answer

13. Please identify any challenges arising from the collaborative use of a data-driven approach across functions?
Your answer

14. Concerning challenges arising from the collaborative use of a data-driven approach across functions from question 13, what change would you suggest? In what way do you think it would be helpful?

Your answer

Section 3: Perceptions of a data-driven organisation questions

15. What does 'a data driven organisation' in your organisation look like?

Your answer

17. What do you think about 'data versus intuition to inform business decisions'?

Your answer

Thank you very much for your time spent taking this questionnaire and your information

Appendix C: Example of Codes and their Supporting Quotes

Codes	Quotes
Marketing strategic decision	-If used correctly data can help make smart informed business decisions that give the organisation a competitive advantage. (5) -Provides market insights...Feed into strategic decisions. (4) -Understanding markets and behaviours cannot be done from an inwards point of view. Data is the most level play field to understand what is happening...Data is necessary to understand your markets and behaviours...Digital advertising campaigns and web page usage and interpret them to suggest strategies or tactics, admission data and trends data... The data help us understand the customer journey and their areas of interest in order to offer them the information they require. The data we use help us to achieve our recruitment goals and plan out our marketing strategies. (6) -Analyse data to inform future strategies... Use data for marketing strategies. (7) -To inform decision making process. (8) -Data helps us to know what direction to go in... Analysis of student data, student numbers, new courses coming to market. (9) -Using COVID-19 as a recent example, our advertising data spiked in certain markets because lots more people are now at home using the internet. However, we know that several factors (including financial uncertainty and/or travel restrictions) meant that it was unlikely to translate into application conversions. We adjusted our advertising accordingly and were proven correct in our assumption. (20)

Improve performance	-Measures of efficiency and competitiveness. (4) -Continuing data analysis drive any changes to campaigns in order to improve performance. (6) -Use data for performance improvement. You can improve future strategies when you investigate your performance and external data shows you where you stand in the competition and how you can inform your strategies. (7) -To analyse performance against targets. I don't think we use our data to gain a competitive advantage. (8) -It helps to check progress of campaigns and make changes and improve. We are able to look at data and make changes accordingly and optimise our campaigns. (10)
Data accuracy and consistency issue	-Having correct data sets to be able to interpret data for purpose required. Quality control and consistency over time. Accurate. (5) Accuracy and consistency of data. (13) Quality of data. (14) Quality of the data and unlabelled data are the two main challenges. (16) I think what we're finding more and more is that the quality of the data in the first place is unreliable. The quality of the data needs to be solid. (18)
Role of human element in data-driven	Without humans there is no data. (3) They (human element) help you understanding data. (10) We forget the human element and see it is information from a system. (12) Humans play a part from data entry, manipulate how data is transformed and presented. (14) Human intervention is important to get major insight in the data. (16)

Appendix D: Example of Combining Codes into Themes

Codes	Themes
- Marketing strategic decisions - Improve performance	Data insights, and decisions and performance
- Data insights and collaborative interaction - Data insights and resolving differences - Data insights and justifying the hypotheses and support pre-decision-making proposals	Data insights, and holistic understanding
- Data cannot action regardless people - People gives meaning to data and transform into value	People element underpinning data insights
- Data accuracy and consistency issue - Data accessibility and exploitation issue - Data integrity and consistency in analysis and interpretation issue - Mis-perception of data truth issue - Data validity and its relationship with organisation purpose issue	Data quality and data silos
- Concerning the transparency of how data being manipulated - Dilemma that many raised such unreliable and sceptical doubts data and its metrics	Distrust in data and data analysis
- Plurality of interpretation issue -Fragmented collaboration and communication cross-functional teams - Multiplicity of uses of data issue	Lacking harnessing multiple perspectives on data
- Data inquiry capability is required - Better training in data analytical skills and updating knowledge are solution - Adequate data analytics specialists are required	Lack of human capability
- Final users are key - Disconnection between data analysis and people	Gap between data user, data provider and implication of being data-driven
- Prioritising data, rather than intuition - Balancing between data and intuition	Differences in people's perceptions
- Senior leaders' commitment - Attitude towards a data-driven approach and its impact on their organisation	Diverse vision and attitude of leaders/people

Appendix E: Electronic Consent Form for Studies

Electronic Consent Form for studies

Research Project Title: Data-driven Organisation through the Sociomateriality Lens: Towards an Understanding of Enablers and Constraints

GUEP Approval Number:

	Please tick box
I confirm that I have read and understood the information sheet explaining the research project and I have had the opportunity to ask questions about the project.	
I understand that my participation is voluntary and that I am free to withdraw at any time during the study without giving a reason, and without any penalty. I understand that if I withdraw no more data will be collected from me. However, any data collected up until the point that I withdraw may be kept and used in the data analysis.	
I understand that my responses will be kept anonymous.	
I agree to take part in this study	

Appendix F: Participant Information Sheet

Participant Information Sheet

1. **Research Project Title**

   Data-driven Organisation through the Sociomateriality Lens: Towards an Understanding of Enablers and Constraints

2. **Background, aims of project**

   I am Parnchit Wattansaruch, a full-time Doctor of Business Administration student at University of Stirling in Scotland, UK. I am undertaking a research entitled 'Data-driven Organisation through the Sociomateriality Lens: Towards an Understanding of Enablers and Constraints', which aims to understand affordances constraints and inter-relationships. I would like to invite you to take part in this research study and I would be very grateful.

3. **Why have I been invited to take part?**

   You have been invited because you are heavily involved with data and analytics by using it and its insights to perform and support your roles and responsibilities. You may also have experience, insight and information, which are able to provide and contribute to further knowledge to the study.

4. **Do I have to take part?**

   No. You do not have to take part. You are under no obligation to take part. If you do decide to take part, you can withdraw your participation at any time without needing to explain any reason. If you withdraw I will not collect any more data from you. However, any data collected up until the point that you withdraw will be kept and used in the data analysis. You will be given this information sheet to keep and be asked to complete an electronic consent form.

5. **What will happen if I take part?**

   You will participate in short interviews. Your interviews will be audio-recorded if you give your consent. Audio-recording is to help me as English is not my first language. Each interview will last between 30-45 minutes on-site at an organization in a safe, quiet and private room. You will not be asked to follow up visits.

6. Are there any potential risks in taking part?

There are no foreseeable risks in taking part. There are no financial or health and safety issues involved in this project.

7. Are there any benefits in taking part?

There will be no payment for taking part in this project. By participating, you will contribute towards the development of analytical capabilities within the organization.

8. What happens to the data I provide?

I am carrying out this study as part of my personal studies towards the completion of my doctoral degree. The information will be stored anonymously using fictitious names such as Interviewee 1 and Interviewee 2. All electronic data and audio data will be securely restored on the University server with password protection while the hard copies of transcripts will be kept in a secure and locked cabinet at all time on the campus accessible only by the researcher. All data will be disposed when reaching the determined date in accordance with University of Stirling and GDPR guidelines.

9. Recorded media

The interviews will be audio-recorded through voice recorder application and recording device, if consent is given. Using the audio-recording during the interview will help grasp all information provided. The audio data and the transcribed data in forms of electronic data will be stored confidential and secure on the University's server with password protection. Such data will only be accessible by the researcher. When discussing the data analysis with my supervisor, I will use the transcribed data in which all identifiable data are already replaced with fictitious names. By this the confidentiality of the audio data will be protected. Importantly, the data will never be carried out without the participants' approval and permission.

10. Will the research be published?

This research will be used for my postgraduate doctoral project. The findings may also be presented at conferences or published in academic journal. You will not be identifiable in any publication. The University of Stirling is committed to making the outputs of research publicly accessible and supports this commitment through our online open access repository STORRE. Unless funder/publisher requirements prevent us, this research will be publicly disseminated through our open access repository.

11. Who has reviewed this research project?

The ethical approaches of this project have been approved via The University of Stirling [General University Ethics Panel].

12. Who do I contact if I have concerns about this study or I wish to complain?

If you would like to discuss the research with someone. Please contact either of these persons.

1. Parnchit Wattanasaruch, Researcher
   Email: parnchit.wattanasaruch1@stir.ac.uk
2. George Burt, Supervisor
   Email: george.burt@stir.ac.uk
3. Kevin Grant, Dean of Stirling Management School
   Email: kevin.grant@stir.ac.uk

You will be given a copy of this information sheet to keep. **Thank you for your participation.**