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Leveraging big data
the development of new dynamic capabilities

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Leveraging big data: the development of new dynamic capabilities

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Abstract

Radical technological development over the last thirty years has disrupted the ways that firms operate. The widespread take-up of technological devices has led to a proliferation in rich data capturing every human-computer interaction. Established firms are being challenged by digitally-born competitors using big data-led business models.

Big data brings huge opportunities in terms of market intelligence, the identification of new development prospects, and market insights that can inform firms' strategic marketing choices. Although there is evidence that firms can improve their performance and competitiveness by adopting big data, many are failing to exploit this new data resource. There is limited understanding of how the firms that are benefitting from big data are achieving these improvements. The research uses a dynamic capabilities lens to investigate the capabilities that established firms use to make efficient and effective use of the big data resource in a turbulent environment. Reflecting the lack of knowledge and limited theory development in this domain, the research uses a qualitative, inductive approach. Interviews in four case study firms, capture the voices of experience of twenty-one senior managers in established firms, who have used big data in strategic marketing projects. Using the Gioia Methodology, their insights into the value of big data in these marketing projects and the capabilities needed to use the new resource, provide the basis for two new theoretical models.

The New Data Value Wheel records the five characteristics of big data being used by the case study firms and identifies the value-creating potential of each characteristic. The Big Data-Driven Capabilities Model presents the five dynamic capabilities that the firms are using to leverage the big data resource in their strategic marketing. The approaches used by the firms to cons the five capabilities are provided in a supporting framework.

The research bridges management and information systems (IS) literature, contributing to theory by using a dynamic capabilities lens from management to investigate the IS, big data phenomenon. The research also makes a methodological contribution through adaptation of the Gioia Methodology to add granularity to the process of analysis. Furthermore, the two new models make a timely contribution to marketing practice by

providing frameworks, based on practical experience, for organisations seeking to leverage value from big data.

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- Editor-in-Chief, John
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You make me laugh and proud every day.

Candidate Declaration

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Certificate of Ethical Approval

Certificate of Ethical Approval

Applicant:

Claire Brewis

Project Title:

How is Big Data impacting on the way in which organisations manage their customer relationships?

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Medium Risk

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Chapter 1 Introduction

1.1 Introduction

This research investigates the capabilities that established firms have developed in order to use big data within their strategic marketing activity. This introductory chapter is divided into five sections. Section 1.1 provides the research context; Section 1.2 explains the choice of the dynamic capabilities lens to frame the research thinking; Section1.3 outlines the research opportunity, the research questions and the chosen methodology; Section 1.4 identifies the research outcomes and contributions, and Section 1.5 presents the structure of the thesis.

1.1.1 The research context

Since the technological 'big bang' in 1990 (Bughin 2016), which saw the arrival of the internet and digitisation of data, established firms which were operating prior to that, have seen dramatic changes in their operating environments. These changes include the emergence of new digitally-born competitors, increases in web-based customer transactions, online channels of goods purchase and distribution, the arrival of social networks, and a panoply of new data sources (Chen, Drennan, and Andrews 2012). The effects of the new technologies, and the scale and scope of the resulting data, have been described as "the motherlode of disruptive change" (Baesens et al. 2014: 629).

Big data has increasingly been described in terms of five 'V' characteristics: volume, variety, velocity, veracity, and value (Wamba et al. 2015). These descriptors reveal the features which, in combination, make big data more complex than the 'small' data (Mayer-Schonberger and Cukier 2013) previously available to organisations. Big data brings particular challenges in terms of new forms of data storage, data management, and big data analytics, in order to generate insights that can assist firms in establishing their competitive advantage (Wamba et al. 2015). The resulting insights can be used to enhance firms' vision of their operations and markets, allowing managers to make decisions based on data and rigour, rather than intuition (McAfee and Brynjolfsson 2012).

The extant information systems literature uses hyperbole regarding the potential of big data, describing it as "digital oil" (Yi et al. 2014: 6), and the "new raw material of the 21st Century" (Berners-Lee and Shadbolt 2011: 1). Firms that adopt data-driven decision-making can record increased output and productivity (Brynjolfsson, Hitt, and Kim 2011). Others have found a positive correlation between the use of data analytics and organisations' annual growth rate (Davenport and Harris 2007). Big data may also prove valuable to firms in improving their competitiveness in the marketplace. As Quinn et al. (2016) observe, the proliferation in data and developments in data analytics bring huge opportunities in terms of market insights, the identification of new target markets and providing broader insights which can inform marketing strategy.

However, there is a disconnect between the potential offered by new technologies, generating more robust and granular data, and firms' readiness to engage with it (SAS 2012; Stone and Woodcock 2014). Many firms are failing to exploit the benefits of the new resource (Mithas, Tafti, and Mitchell 2013) and much data in the marketplace is discarded, ignored or analysed in a cursory way (Perrons and Jensen 2015). A 2019 executive survey of large American corporations identified that 53% of firms did not treat big data as an asset, with 72% reporting that they had not yet forged a data culture (Bean and Davenport 2019). From a UK perspective, there are claims that fifty-three per cent of firms are not engaged with big data at all (Whishworks 2018).

Aligning an organisation's response to changes in its external environment is a function of strategic marketing (Varadarajan 2015). Marketers are the firm's 'radar' to identify competitor activity, changes in customer behaviour, recognise threats and opportunities, and to develop value-enhancing propositions (Dibb et al. 2019). They are being challenged by the deluge of data beyond the capabilities of their organisations to comprehend and use (Day 2011). However, failing to engage with big data constrains the firm's market intelligence and its ability to develop a marketing strategy that can respond to the accelerated rates of change in the market. The growing marketing capability gap is, unquestionably, costly to the firms' current profitability, as well as their future competitiveness (Stone and Woodcock 2014).

1.1.2 The dynamic capabilities lens

Firms are able to respond to turbulence in their operating environments, particularly rapid technological changes, by adopting dynamic capabilities (Teece 2014). Dynamic capabilities are competences firms use to alter the combination of resources they are employing, in order to respond to the external turbulence. These resources comprise the financial, physical, human and intellectual assets which are held by, or accessible to, the organisation. In a stable environment, such as day-to-day business operations, an organisation is focused on providing consistent support to delivering its existing products and services (Helfat and Winter 2011).

In conditions of rapid environmental change, dynamic capabilities enable firms to alter their resource base, modifying their ordinary capabilities and directing change in response to the organisation's external environment (Helfat and Winter 2011). The radical technological changes associated with big data highlight the kinds of environmental changes that would stimulate an established firm to apply dynamic capabilities. The new technologies associated with these environmental changes, also make available the new big data resource. Through their dynamic capabilities, firms can introduce big data into their resource base (Ambrosini and Bowman 2009). By combining and reconfiguring their resources, they are able to constantly and systematically, improve their ordinary capabilities and build new capabilities. In doing so, firms can improve their competitiveness and match the context in which they operate, a concept known as evolutionary fitness (Helfat 2007).

However, there is relatively little understanding of the mechanisms that determine the origin and evolution of dynamic capabilities (Abell, Felin, and Foss 2008; Eisenhardt, Furr, and Bingham 2010; Fallon-Byrne and Harney 2017; Felin and Foss 2009). As a result, the fundamental question of "how the enterprise can keep renewing its resource base and create new capabilities" (Al-Aali and Teece 2014: 103) remains unanswered.

Abell, Felin, and Foss (2008) observe that when firms can understand the capability building process it is easier for them to construct the dynamic capabilities they require.

1.2 The research opportunity

The weight of current big data research is in information systems (IS) literature, particularly in the growing body of technologically-oriented research on big data analytics (Wang, Kung, and Byrd 2018). However, big data is also relevant to management theory. As new technology, including big data analytics, becomes ever more influential in strategy work, it is increasingly important for information systems and strategy experts to work together to develop technology-mediated strategy practices (Whittington 2014). Whilst studies indicate that firms which are adopting big data can improve their performance and their competitiveness (McAfee and Brynjolfsson 2012; Wang, Kung, and Byrd 2018), there is limited understanding of how they are achieving these improvements, and the development of theory is at an early stage (Rialti et al. 2019).

Furthermore, there are very few empirical studies on big data's application from a management and marketing perspective (Barrales-Molina, Bustinza, and Gutierrez-Guttierez 2014; Wamba et al. 2015). This has led to a number of calls for research, for example, Phillips-Wren et al. (2015: 465) challenged researchers to investigate, commenting that "One of the most interesting questions in the field of big data research today is 'What capabilities can organisations acquire to succeed in big data efforts?'". Rialti et al. (2019) invited researchers to use dynamic capabilities to explore the relationship between big data, analytics and dynamic marketing strategies.

In response to these highlighted research opportunities, the research question posed for this study is:

> How is big data changing organisations' strategic marketing capabilities?

Reflecting the lack of knowledge and limited theory development in this domain, the research uses a qualitative, inductive approach. Data are gathered from senior managers in established firms, which have applied big data to their strategic marketing activity. Interviewees from four case study firms provided insights relating to the research sub-questions:

1. What are the characteristics of big data that make it a valuable strategic marketing resource for established firms?
2. What dynamic capabilities are established firms using to leverage big data for strategic marketing?
3. How are established firms constructing the dynamic capabilities that they are using to leverage big data for strategic marketing?

The research process utilises the Gioia Methodology; "a systematic approach to new concept development and grounded theory articulation that is designed to bring 'qualitative rigor' to the conduct and presentation of inductive research" (Gioia, Corley, and Hamilton 2012: 15). A feature of the Gioia approach is that participant narratives are featured without being condensed. So, the 'voices of experience' are referred to throughout the analysis and provide the basis of new theoretical models. The analysed data are interpreted in relation to IS, dynamic capabilities and management literature to ensure its grounding in extant theory.

1.3 The research outcomes

Distillation of the insights from the four case study firms resulted in two new theoretical models. The first model, the **New Data Value Wheel** (NDV Wheel), extends Wamba et al.'s (2015) '5V' framework. Each big data capability is described in terms of the value that established firms are extracting from it. The theory clarifies big data's position as an intangible, intellectual resource. The second model, the **Big Data-Driven Capabilities Model** (BD-DC Model), identifies five new dynamic capabilities that incumbent firms are using to leverage the big data resource in their strategic marketing. The theory highlights the importance of the reconfiguration capabilities (Teece 2007) in enabling firms to assimilate the new resource. The second model is supported by the big data-driven capabilities mesofoundations framework, which identifies how the case study firms created the new data-driven capabilities. It describes the firms' approaches to reconfiguring their resource base.

The research uses original integrations of existing theories and in-depth empirical evidence to determine how big data is changing firms' strategic marketing capabilities. The results contribute to two theoretical domains; they bridge IS and management literature and extend dynamic capabilities theory. The research also makes a timely contribution to the practice of marketing, by providing frameworks based on the practical experience of case study firms, which will be of value to organisations seeking to get greater value from big data.

1.4 The structure of the thesis

The thesis is presented in eight chapters, and following this introduction (*Chapter 1*) is structured as follows:

Chapter 2: Big data – the research context, explains the origins of big data and describes its five key characteristics. The chapter proposes that big data may be viewed as a useful resource that can be used in strategic marketing to improve organisations' competitiveness. However, gaining usable insights from the complex resource requires specific capabilities, and the chapter concludes by identifying the emergence of a growing marketing capabilities gap.

Chapter 3: Dynamic capabilities – the research lens, starts by describing the resource-based view of the firm and the background to dynamic capabilities theory. The narrative explains the role of dynamic capabilities in enabling firms to respond to environmental turbulence and to maintaining evolutionary fitness. The seminal works in dynamic capabilities literature are discussed to explain how firms construct new capabilities by allocating and reconfiguring their resource base. To understand the detail of how dynamic capabilities are created, the chapter concludes by considering a microfoundations level explanation of their construction.

Chapter 4: Research methodology, begins by reiterating the research questions and aims that will direct the methodology. The chapter addresses the choice of the qualitative, Gioia Methodology, as a mechanism for developing new theory. The research design is explained, including justifying the use of case study and elite interviews as sources of data, and explaining the selection of the cases. The chapter explains how the systematic, Gioia data-to-theory process was applied to the participant narratives, to produce new theory.

Chapter 5: Findings – a fundamentally different resource, highlights the value that the case study firms ascribed to the different big data characteristics. The findings show that the firms viewed each characteristic as contributing to the value of big data in their strategic marketing. The rich interview data reinforces big data's position as a new, intangible and intellectual resource which can enhance a firm's resource base. In line with the Gioia Methodology, the chapter contains extensive use of participant narratives and descriptions.

Chapter 6: Findings – data-driven dynamic capabilities, identifies the five new dynamic capabilities that firms have developed, to leverage value from big data. Through these capabilities the firms are able to change their resource base and improve their competitiveness. Each capability is considered in turn, providing detailed descriptions of the firms' tactics in developing their capabilities. Their narratives provide insights into how the firms construct their dynamic capabilities. As in Chapter 5, extensive use of participant 'voices' are provided as supporting evidence.

Chapter 7: Discussion and conclusions, draws together the primary research findings with extant IS and management literature. This chapter has two elements. Firstly, the findings from Chapter 5 are reviewed, and Wamba et al.'s (2015) '5V' framework is extended to produce the **New Data Value Wheel** (NDV Wheel). The NDV Wheel clarifies big data potential as a resource of value in strategic marketing. Secondly, the findings from Chapter 6 are reviewed in relation to extant theory. The resulting **Big Data-Driven Capabilities Model** (BD-DC Model) positions the findings in the context of Teece's (2007) sensing, reconfiguring and seizing dynamic capability framework. It highlights the importance of the reconfiguration capabilities for established firms. The research responds to the paucity of knowledge of how dynamic capabilities are constructed, and confirms the need for further research between the macro dynamic capabilities level and the microfoundations.

Chapter 8: Conclusion, contribution and autobiographical reflections, concludes the thesis by responding to the research questions and aims. The contributions to knowledge that are achieved through the research are then highlighted. Notably, these include the development of new theoretical models which bridge IS and management literature. Furthermore, they highlight the huge opportunity that exists to apply the new models in practice, with firms which are not yet using big data to inform their strategic marketing. The limitations of the study are noted and a future research agenda is proposed. Finally, as the doctoral process aims to develop knowledge and skills in research, the thesis concludes with the researcher's autobiographical reflections.

Chapter 2 Strategic marketing and the new big data resource

2.1 Introduction

The technological innovations of the last three decades have created a turbulent operating environment for firms. The availability of portable devices, the internet and social media have made interactions with customers more complex. Points of firm-to-customer contact have increased exponentially, with each contact recorded digitally in the form of 'big data'. Firms' understanding of their customers and markets can be transformed by the detailed information available within big data. Benefitting from this new market intelligence requires strategic marketing capabilities which can direct the firm to make data-led decisions that are competitively advantageous. This chapter aims to explain what big data is and how it can contribute to improving firms' competitiveness.

The chapter is broken down into eight sections. Section 2.2 explains the vital role that strategic marketing plays in enabling firms to respond to changes in their external environment. This provides the context for the research, which is investigating the applicability of big data in relation to strategic marketing. Section 2.3 explains how technological turbulence in firms' operating environments has generated new data sources, referred to as big data. Section 2.4 highlights the recent proposition that big data is an organisational resource which can contribute to firms' competitiveness. Section 2.5 explains the characteristics of big data in the form of a '5V' framework. Section 2.6 discusses the transformation of big data into insights that can inform strategic marketing decision-making. Section 2.7 highlights why firms may be resisting the use of big data and the emergence of a growing marketing capabilities gap. Section 2.8 provides a chapter summary which highlights the challenges of using big data in strategic marketing.

2.2 Strategic marketing and the corporate strategy

Since the technological 'big bang' in 1990 (Bughin 2016), which saw the arrival of the internet and digitisation of data, incumbent firms have seen dramatic changes in their operating environments. These changes include new digitally-born competitors, web-based customer transactions, on-line channels of goods purchase and distribution, the arrival of social networks and a panoply of new data sources (Chen, Chiang, and Storey 2012). The new big data sources include customer feedback and transaction details which may enable firms to improve their market intelligence, identify new development opportunities and, as a result, define a differential advantage over their competitors. Aligning the organisation's response to changes in its external environment is a function of strategic marketing (Varadarajan 2015).

Strategic marketing is a long-term perspective on how firms create, communicate and deliver products that offer value to customers, through interactions with their consumers, competitors and other parties, such as suppliers and partners (Varadarajan 2010). There is compelling evidence that 'a critical determinant in the success and survival of the firm lies in the successful implementation of marketing strategies' (Thorpe and Morgan 2007: 660).Strategic marketing is not a tactical, functional approach; it is an executive-level responsibility, enabling a firm to secure competitive advantage and growth (Hunt 2018). Strategic marketing requires a holistic view of the firm's external trading environment including an understanding of customer behaviours, sentiments and expectations as well as knowledge of competitor propositions and intentions. Starting with a market-orientated perspective expands the firm's strategic dialogues beyond its current activities, introducing more opportunities for securing competitive advantage and growth (Day 2011). At the same time, strategic marketing calls for knowledge of the internal qualities of the firm, such as how it is currently performing, the elements which make it successful, as well as the organisational capabilities and resource base (Dibb et al. 2019). Bringing together the external and internal perspectives allows firms to develop a well-informed marketing strategy.

There is a close alignment between a firm’s strategic marketing activity and its overarching mission, goals and corporate strategy. The corporate strategy provides the direction and scope of the organisation in the long-term, in response to the needs and dynamics of the market and the firm’s stakeholders (Whittington et al. 2019). Strategic marketing contributes to the wider corporate strategy by identifying potential opportunities to pursue, which activities to target, and the type of competitive advantage to be developed and exploited (Day, Weitz and Wensley 1990). A core component of strategic marketing is the creation of a competitive advantage, through which a firm achieves superior performance relative to its rivals (Hunt and Derozier 2004). A competitive advantage can be achieved through product or service differentiation, brand identity or the provision of customer value through low cost offers or focus on product or market niches (Porter 1985; Porter 2008). Competitive advantage strategies are not mutually exclusive, and a firm’s product portfolio may incorporate a number of different approaches. For example, a media company may have high profile, differentiated, news brands and at the same time be targeting its digital products at niche markets such as sport or healthcare.

Strategic marketing activity is documented in a firm’s marketing strategy, which records the marketing planning and decision-making for communication within the organisation. The strategy explains how a firm will compete in its markets, identifying how marketing effort should be allocated. It is distinct from a market strategy which identifies the target markets in which the firms will compete (Hunt 2018). The marketing strategy provides the direction for tactical marketing programmes and elements, such as pricing and promotion in the marketing mix. Quality data on market activity provides a robust basis for the development of marketing strategies.

2.2.1 The contribution of strategic marketing

Marketers are the firm’s ‘radar’ to understand competitors, identify threats and opportunities, develop value-enhancing propositions and satisfy ever-changing customer buying behaviours (Dibb et al. 2019). They do so through two distinct but interconnected strategic marketing activities: market orientation which informs market intelligence; and identifying opportunities for differential competitive advantage.

2.2.1.1 Market orientation and market intelligence

Market orientation involves firms in environmental scanning to collect information about their operating environment. This provides market intelligence which supports marketers in identifying opportunities and threats to assist in planning (Dibb et al. 2019). As well as supporting strategic marketing decisions, the data collected also provides business intelligence. At a corporate level, this enables firms to construct better informed strategies and plans and, as a result, implement better tactics and decisions (Ramesh, Dursan, and Efraim 2010).

There are three components to market orientation: customer orientation, competitor orientation and interfunctional co-ordination (Slater and Narver 1994). Customer orientation involves awareness and anticipation of current and future customer needs and behaviours. The intelligence generated from customer orientation can improve customer segmentation and inform marketing programmes, such as targeted advertising campaigns (Stone and Woodcock 2014). Competitor orientation allows firms to use knowledge of competitor strategies, strengths, weaknesses and their differential advantage, to anticipate competitors' activity in different markets and within customer segments. The knowledge arising from competitor orientation supports the firm's effective prioritisation and targeting of markets and customers segments (Hunt 2019).

The third component of market orientation is interfunctional co-ordination. Market orientation is not limited to the marketing function, it is a general management responsibility, involving multiple business functions (Day 1994). Knowledge of customers and competitors may come from sources such as sales, suppliers or partners. Internal insights on current performance and capabilities may include IT, finance, manufacturing, quality assurance, service delivery, order fulfilment and customer service staff, as well as marketing personnel. The outcome of this organisation-wide generation of information is reflected in the third component of market orientation; a need for dissemination of knowledge across departments (Kohli and Jaworksi 1990). The dissemination may be through the corporate or marketing plan or internal communications which articulate, to internal audiences, the planned, targeted opportunities and the organisational alignment to the target markets (Dibb et al. 2019).

Firms that are market-orientated are alert to changes in their external marketplace. As a result they have better market intelligence, on which to base their planning and decision-making. With the changes in technology and the consequent availability of big data, market-orientated firms will be aware of sources of big data, their potential for the firm; what big data offers them in terms of customer knowledge; how their competitors are using it; and the arrival of new competitors. It will also identify their own abilities to work with the data, and the availability of resources and partners outside the firm which can help overcome capability gaps. Capability gaps will be discussed further in section 2.7.

2.2.1.2 Identifying opportunities for differential or competitive advantage

Market intelligence allows firms to identify the ways in which they are or could be distinct from their rivals; their differential advantage. A differential advantage is the attribute of a brand, product, service or marketing mix which is desired by customers and only provided by one supplier (Doyle 1994). This type of advantage offers an edge over rival firms, although the benefits may only be short-lived, because it is likely to be emulated by rivals seeking value enhancing propositions for their customers. The nature of the advantage depends on the offers of competing firms and brands, and whether targeted customers are substituting the firm's products with a competitor's alternative solution. Firms need to take a broad view of this competitive activity and recognise new, as well as established, market opportunities arising within their changing operating environment. If firms apply too narrow a competitive set, they are not optimising their market intelligence (Aaker 2009).

By having a strong knowledge of their market, firms can identify market opportunities which are the circumstances and timing that will allow the organisation to reach a target market. Market opportunities have features which will be more or less attractive to the firm, including market size and growth, and whether or not there are already competitors operating in that market. As well as market attractiveness, there are only temporary periods of 'optimum fit' between the requirements of the market and the capabilities of the firms competing in that market (Abell 1978). A firm may view a market opportunity as attractive but not be adequately resourced within the timing constraints of the strategic window to take advantage of the opportunity. Influential factors in the timing of market opportunities include changes in technology, the availability of new markets and new distribution channels (Dibb et al. 2019).

In summary, strategic marketing has a key role to play in ensuring that firms maintain a differential advantage over their rivals, in the face of technological turbulence. Market orientation ensures that organisations are aware of changes in the market including knowledge of competitor activity and changes in customer needs or behaviours. This provides market intelligence on which to base planning and decision-making. The resulting decisions may include clarifying a firm's differential advantage over their rivals and the market opportunities within their preferred target markets. Firms with access to detailed, current, and extensive customer and market data are likely to be in a stronger position than their competitors. The next section will identify how technological turbulence has introduced new data sources with the potential to radically impact organisations' strategic marketing.

2.3 Technological innovation and the emergence of big data

This section explains how technological developments led to the generation of big data. It explains how big data has evolved from website content to include social media platforms and the Internet of Things. The technological and mathematical events, which have enabled big data to become a valuable source of market intelligence for firms, are also identified.

Environmental and specifically, technological, turbulence is changing the markets in which firms operate. One change is the availability of big data, which provides firms with a different type of market intelligence and highlights new opportunities for differential advantage, than were available previously. Big data is a recent phenomenon which emerged in the last decade alongside the development of new technologies (Chen, Chiang, and Storey 2012). These technological innovations began in earnest with the creation of the internet and the World Wide Web (Web) in the late 1980s and early 1990s. Uptake of technology has grown exponentially and now encompasses mobile telephones and portable computing devices; websites and social network platforms; and the Internet of Things (IoT), which provides internet connectivity between objects (Sebastian et al. 2017). These technologies allow virtually anything and everything to be documented, measured, captured and recorded digitally as data. This 'datafication' process (Mayer-Shonberger and Cukier 2013) has led to a transformation in data storage, using 'the cloud' and to advances in analytics and visualisation software. As technology continues to progress in areas such as robotics and artificial intelligence, machine-to-machine communications are having a further impact on data collection and use. However, there is a view in information systems literature that technology refers to both technology-as-artifact and technology-in-practice (Leonardi, Nardi and Kallinikos 2012). Taking this broader perspective focuses attention on what people actually do with particular technology in their ongoing and situated activity (Orlikowski 2000). The authors' emphases on technology's practical application highlight its relevance for organisations.

The new technologies and the scope of the resulting data are significantly changing the nature of firms' operating environments, to the extent that big data has been described as "the motherlode of disruptive change" (Baesens et al. 2014: 629). The disruption has brought new competition but has also provided firms with the potential to improve their competitiveness, innovation and efficiency (Braganza et al. 2017).

2.3.1 The evolution of big data

Each step change in technological evolution has resulted in changes to the types and formats of data output, providing business and market intelligence. To understand the scope of technological change and the breadth and variety of data sources available to inform and direct strategic marketing, it is useful to recognise the web development stages over the last thirty years.

Since the ‘data big bang’ (Bughin 2016) in 1990, the stages of technological and data evolution have been described in extant literature in terms of Web 1.0 – Web 5.0 (Trunfio and Della Lucia 2016). The current stage of technological development is the Web of Context or Semantic Web (Web 3.0) and the Web of Things (Web 4.0). The future Web of Thought (5.0), involves human emotional interaction between humans and computers, in which the Web can recognise users’ emotions and reactions (Trunfio and Della Lucia 2016). With each progression in Web development, established firms had to add a new generation of materials and related new processes to their existing data processes.

As research in big data is at an early stage (Chen and Zhang 2014), it is necessary to briefly describe the stages of the big data evolution to provide context for the subsequent discussion. Before Web 1.0, organisations collected and owned their own data. Sources included customer transaction logs, contact information databases, market research reports and industry data. Data were analysed through data samples, using statistical analysis, to predict future patterns and inform marketing decisions (Elgendy and Elragal 2014).

The Web originated as a static format of linked websites with firms producing site content to engage with customers (Web 1.0). Web 1.0 introduced business intelligence from web-site engagement and enabled customer transaction records to be stored using relational databases, such as customer relationship management (CRM) and enterprise resource planning (ERP) databases, and data warehousing. Drawing information out from Web 1.0 data required data-mining and more complex statistical analysis and presentation than previously, using dashboards and scorecards; referred to as Business Intelligence and Analytics (BIA). The sources of data were fragmented in origin, which required cumbersome data warehousing and analytics. In addition, because of inadequate computing power to use whole samples of high-volume large variety data, only samples of data could be used to predict behaviour and preference (Mayer-Schonberger and Cukier 2013). Web 1.0 information could be batch processed and the variety of sources was limited, so was not as capital intensive as later generations of more complex Web-based data (Kitchin and McArdle 2016). Web 1.0 data, and its precursors, have subsequently been referred to as “small data” (Mayer-Schonberger and Cukier 2013).

At the end of the 1990s, the Web developed into a more social, dynamic format (Web 2.0), where both individuals and organisations published user-generated content through social networking platforms, such as Facebook, Twitter, YouTube and Wikipedia. The ‘social web’ brought with it the emergence of real-time information flows of big data, of customer behaviour and sentiments (Rajendra Prasad et al. 2013). This required firms to adapt to a high velocity of information, rather than the slow-bundled data they had been working with previously. Where previously data had been structured, this new format meant that ninety per cent of data was unstructured and complex to interpret (Dobre and Xhafa 2014). For firms to benefit from these fast information flows and the new forms of unstructured data from social media, business intelligence needed to be web-based, and to use web analytics and opinion-mining software. As with small data, market analysis was the domain of the marketing function, supported by information technology technicians. However, the novel, web-based technologies demanded data scientists (McAfee and Brynjolfsson 2012), business analysts and marketers to work together to transform the data into useful insight for decision-making and marketing action.

The next incarnation (Web 3.0), known as the ‘semantic web’, reflected the emergent mobile and sensor-based technologies, using location and person-centred analysis. These represented a further shift in the form of big data and its analysis, allowing a personalisation of marketing activity, responding to customer needs, behaviours and geography. The IoT and the evolution of human-computer communications are now bringing the next incarnations of Web 4.0 and Web 5.0.
Table 2-1 highlights the range of data, resulting from the different web phases, which now inform individuals’ and organisations’ digital footprint (Blasquez and Domenech 2018).

Table 2-1 Big data source examples

Static Web Static or 1:1 sources (Web 1.0)	***Web of Communication Web-based data (Web 2.0)***	***Web of Context Environmental data (Web 3.0)***	***Web of Things sources (Web 4.0)***
Read-only websites Emails SMS text messages Call centre logs Client chats	Web clickstream/ Website links Online purchase information Social media e.g. Facebook, Twitter feeds Product reviews Blogs Pictures e.g. Instagram	CCTV Radio Frequency Identifiers Barcode scanners Geographic information systems (GIS) Satellite data	Internet of Things (IoT)
Source: Collated from Chen et al. (2012), Moorthy et al. (2014), Trunfio and Della Lucia (2016)			

The increased global uptake of mobile technologies and the concomitant growth in data promises a doubling of the digital universe of data every two years between 2012-2020 (Cheah and Wang 2017). As a result, big data will have an increasingly significant role to play in firms' knowledge of their customers, their customers' opinions and behaviours.

2.3.2 Improving engagement with big data

Technology-generated data, produced in real–time, are too large and complex for traditional software and storage systems to capture, store, manage and process in a practicable amount of time (Kubrick 2012). However, four events have improved firms' engagement with the new, large, fast-moving data. Firstly, the significant decline in storage costs (Komorowski 2014). Secondly, the ongoing growth in computing device processing speeds. Thirdly, the analysis of unstructured data resulting from breakthroughs in mathematics; and fourthly, the development of software platforms, like Hadoop, which allow massive datasets to be broken down and manipulated (Perrons and Jensen 2015). These technological advances in storage and computation, have enabled the timely and cost-effective capture of big data, which was not feasible before the big data era (Gandomi and Haider 2015).

In summary, the transformation of technology in the last thirty years has resulted in the extensive digital capture of technology-human interactions, described by the term 'big data'. Information systems literature records the evolution in phases from Web 0.0 to Web 5.0, combining structured, unstructured and as yet unreadable data. This evolution continues so that firms are witnessing and experiencing ongoing technological and data change. A coincidence of developments in data storage and mathematical computation means that the data can be efficiently stored and analysed with a view to securing business benefits. Although big data did not originate primarily as a marketing resource, it has the potential to inform and support firms' strategic marketing decisions. The next section will investigate how big data may be viewed as a strategic marketing resource.

2.4 Big data as a resource

This section explains that big data is a valuable resource which can inform a firm's differential advantage and improve its competitive position. It considers the effects of technological changes at a macro and business level. With reference to the resource-based view of the firm, the section then addresses the potential contribution of big data for incumbent businesses.

The extant information systems literature uses hyperbole regarding the potential of big data. Big data's perceived importance as a resource is alluded to in the references to big data as "digital oil" (Yi et al. 2014: 6) and "the new raw material of the 21st Century" (Berners-Lee and Shadbolt 2011: 1). It is worthwhile for firms to engage with big data as there is evidence that it can improve operational performance. Brynjolfsson, Hitt, and Kim (2011) find that firms adopting data-driven decision-making, have output and productivity levels that are five to six per cent higher than would be expected given their investments and technology usage. The authors argue that this is because these firms are making decisions based on data-driven mathematical models rather than intuition. Davenport and Harris (2007) also find a positive correlation between firms' use of data analytics and five-year annual growth rate. Big data's potential to improve organisational performance has led to it being described as the next frontier for innovation, productivity and competition (Jagadish et al. 2014).

2.4.1 New competition and new business models

The new technologies and the resulting big data are providing a catalyst for the development of entirely new business models (Hagen et al. 2013).

These changes are "transforming processes, altering corporate ecosystems and facilitating innovations" (Wamba et al. 2015: 234), which are adding competitive turbulence and challenge to the operating environment. Table 2-2 presents three examples of pre-digital services and the new technological devices and big data sources which have resulted from their digitization. These examples highlight industries where new digital-born competitors have entered established markets, emphasising the dramatic effect of the new innovations. In addition, Trip Advisor and Uber represent an entirely new 'sharing economy' business model, which uses on-line platforms to support peer-to-peer interactions and transactions (Borodo, Shamsuddin, and Hasan 2016). This sharing approach side-steps the traditional business model, as the firm is the facilitator of services, rather than the provider.

The digital-born firms are using big data to provide more immediate, detailed, personalised, customer-orientated products and services than the approaches used previously. Market-orientated, incumbent firms may use this awareness of new competitor activity and sources of new intelligence to review their competitive position or their differential advantages. This critique may direct them to change business model, follow new innovation paths, or possibly to collaborate with those in emerging industries (Cheah 2016) to improve their customer propositions. Not all firms will take a long-term approach to achieving competitive advantage. Where a firm is striving for competitive survival in a hyper-competitive setting, it may choose instead to take a leading position in a series of short-lived competitively advantageous solutions (D'Aveni 1994). Alternatively, the firm may focus on using resources which can contribute to organisational competitiveness.

Table 2-2 Data-led business models, devices and big data sources

	Old system (1990)	New technology devices/big data sources	Big data generated
Taxi service (pre-Uber 2009)	Phone call Taxi rank Map or 'The Knowledge' training Cash payment to driver	Mobile phones GPS Satellite navigation Online platform Payment portal	Location of customer Departure/destination/distance of journey Cost of journey
Retail (pre- Amazon 1994)	Retail outlet Payment to retailer/bank	Retailer or Intermediary websites Online platform Access from desktop/mobile device Payment portal Scanning technologies including QR or bar coding/microchip of items and packaging Storecard	Product range (images, prices) Customer reviews / recommendations Customer location and purchase records Parcel tracking Payment information Other purchases from retailer
Holiday accommodation (pre-Trip Advisor 2000)	Travel agent Tourist information Star ratings Guest book	Website or intermediary website Online platform Access from desktop/mobile device Payment portal Electronic reservations and payment	Product range (including images, description, prices, competitor prices) Customer reviews Occupation and availability rates Payment information

2.4.2 A resource for improved competitiveness

In the management literature, firms are viewed as portfolios of homogeneous, idiosyncratic and difficult-to-trade assets and competencies (Rumelt 1974; Teece 2007; Wernerfelt 1984), which set them apart from their competitors. These assets include tangible resources such as financial, physical and human; as well as intangible resources such as knowledge, brand, intellectual property and reputation (Cheah and Wang 2017). Firms striving for competitive advantage need to use those resources which are valuable and rare, inimitable and organised (Barney 2007; Hunt and Morgan 1995). The ownership of these difficult-to-replicate assets is not sufficient to ensure sustainable competitive advantage. To be sustainable, firms need to continually adapt their asset base in response to their external environment (Teece 2007). The allocation of resources enables the assets to be deployed advantageously to maintain competitive advantage over competitors (Peteraf and Barney 2003). It can lead to improved decision-making regarding resources allocated in response to customer and competitor actions, which in turn can improve firm performance. Resource allocation is however subject to the constraints of strategic priority, investment limitations and internal conflicts including uncertainty, complexity and intra-organisational conflict (Amit and Schoemaker 1993).

References to resources often identify brands, patents and intellectual property as intellectual organisational resources (Cheah and Wang 2017; Hunt 2018; Fahy 2002). Historically small data has not been explicitly identified as a resource. Despite Fahy's (2002) suggestion that big data should be viewed as an intangible, firm-specific asset, similar to registered brands, designs and patents, it has only recently been considered as an intangible, intellectual resource (Gupta and George 2016).

Cheah and Wang (2017) propose that big data is an intangible, intellectual resource, as it provides firms with more comprehensive knowledge of their customers, their markets and their industry. Knowledge which may spur them to create marketing offerings with superior value or lower production costs than their competitors. The recognition of big data as a resource provides firms with an additional element to inform their strategic decision-making. Despite its potential, however, many firms are failing to exploit the benefits of the new resource (Mithas, Tafti, and Mitchell 2013), and much marketplace data is discarded, ignored or analysed only in a cursory way (Perrons and Jensen 2015). Bean and Davenport (2019) note that in a 2019 survey of very large American corporations, more than half state they are not treating data as a business asset. Whilst a UK-based study suggests that fifty-three per cent of UK firms are not engaged with big data at all (Whishworks 2018).

However, firms which are actively engaged in using big data analytics are starting to recognise big data as an asset to the firm (Perrons and Jensen 2015). These firms are actively and deliberately investing in data collection which can contribute to their organisational performance. Recognition of big data as an asset, which can offer a return on business investment, increases its value to shareholders and the organisation. A stumbling block to organisational stakeholders recognising big data as an asset, is that it is not yet valued in company balance sheets (Lam and Tan 2019). Where it is being measured, the metrics are significantly different from the familiar terms, such as return on investment. Instead, a language of 'reach' 'acquisition' and 'conversion targets' is being used (Han, Kamber, and Pei 2012). It is predicted that by 2021, increased investment and return from big data and related algorithms will result in a formal mechanism to value big data (Laney 2016). Recognising the balance sheet value of the big data asset will increase its importance to stakeholders and is likely to improve their understanding and willingness to invest in big data infrastructure. Management literature suggests that the new resource could change the way the business operates, as: "big data has the potential to transform the entire business process" (Wamba et al. 2015: 234). It could also change the strategic direction of the organisation as big data is "the next frontier for innovation, competitiveness and productivity" (Manyika et al. 2011: 1).

In summary, the experience of firms which have engaged with big data is that it has the potential to transform a firm's competitive position. Big data has altered the operating environment of established firms, bringing in digital–born competitors but also new forms of data to inform their business strategies. The acknowledgement of big data as an intangible, intellectual resource will raise its value and relevance to stakeholders, who play a vital role in supporting decisions regarding big data infrastructure investment. The contribution of better market intelligence to a firm's competitiveness may also be better understood. The next section defines big data and the characteristics it offers which alter the nature of market intelligence and have the potential to improve strategic marketing decision-making.

2.5 Defining big data

This section considers how big data is defined. Big data has different characteristics from small data, and it is these features which impact on organisations' strategic marketing capabilities. Both the information systems and management literature have adopted a descriptive framework for big data. This framework provides an understanding of big data's potential to improve firms' market intelligence and their potential for competitive advantage. This section of the research context identifies the five characteristics of big data which have been widely adopted as the current descriptive framework. The characteristics are: volume, variety, velocity, veracity and value. Each one is defined and the benefits and challenges are explained. Finally, it considers the issues arising for firms from the lack of a clear definition.

2.5.1 The elusive definition of big data

Although the term 'big data' started to appear in management publications in 2006, a precise definition continues to be elusive (Chen, Chiang and Storey 2012). The emphasis in the information systems and management literature has been on the features of big data (Jansen, Vera, and Crossan 2016; Erevelles, Fukawa, and Swayne 2016; Chen and Zhang

2014) or the authors assume that the definition is widely understood and do not provide a specific explanation (Braganza et al. 2017; Xu, Frankwick, and Ramirez 2016).

Until recently, the predominant framework for big data was Laney's three Vs (Chen, Chiang, and Storey 2012). Laney described big data as: "high volume, high velocity and or high variety information assets that require new forms of processing to enable enhanced decision-making, insight discovery and process optimisation" (Laney 2001: 75). According to Laney's description, *volume* refers to the enormous quantities of data, *variety* reflects the different structures of the data and *velocity* means the creation of the data in real time. Laney's terms have subsequently come to have different interpretations (Kitchin and McArdle 2016). For example, volume now refers to the number of records, or the volume of information per record, or volume in storage requirements in bytes. Similarly, the term velocity refers to rapidity of change, frequency of data generation and also frequency of handling, recording or publishing. To make greater sense of the new phenomenon, researchers sought to expand on Laney's (2001) '3Vs' of big data.

Subsequent research aimed to provide greater detail and to address areas not specifically highlighted by Laney. These studies refined the big data description and clarified the distinction with earlier data forms. These traits included *indexicality*, where data can be attributed to an individual or individual device (Dodge and Kitchin 2005); *exhaustivity*, whereby an entire system is captured, rather than a sample (Mayer-Schonberger and Cukier 2013); and *scalability,* when datasets can be readily increased or reduced in size (Marz and Warren 2012). However, it was Marr's (2014) study which introduced two further 'Vs', veracity and value which have been absorbed into the current '5V'definition of big data.

Marr's two additional 'V's are different to Laney's '3V's, as they relate to the big data process rather than to the data itself. They require the alteration of big data from its original form. *Value* refers to the transformation of data for insight within the big data process, while *veracity* of big data requires an element of transformation to convert what might be messy and incomplete data, into reliable data (Marr 2014).

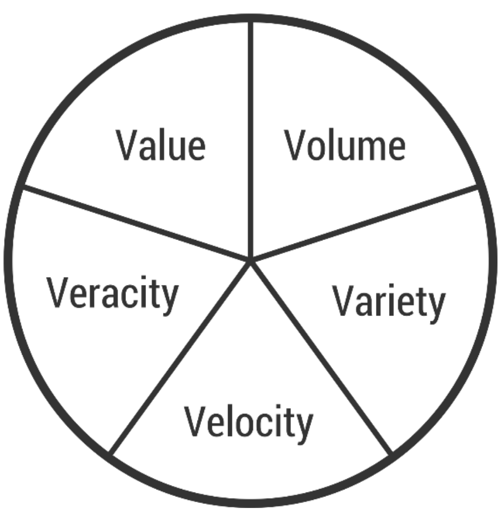
2.5.2 The big data '5V' framework

Two recent systematic literature reviews on big data (Wamba et al. 2015 and Fiorini, Seles, and Jabbour 2018) have noted that the '5V's are widely adopted in current management and information systems literature. Wamba et al. (2015: 235) define big data as "a holistic approach to manage, process and analyse '5V's (volume, variety, velocity, veracity and value) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantage".

Big data's '5V' characteristics make it fundamentally different to its small data antecedents, (Wamba et al. 2015) although the dividing line remains somewhat nebulous. Figure 2-1 offers a representation of the '5V' descriptors which will be then be discussed in more detail.

Figure 2-1 The '5V' characteristics of big data

(Source: adapted from Wamba, Akter, Edwards and Guanzou 2015)



Volume

The significance of the volume characteristic is alluded to in the term 'big' data and relates to the large volume of data that either requires extensive amounts of storage capacity or consist of large numbers of records (Russom 2011). The starting point for the 'big data' term was the information systems literature, and referred to the handling and analysis of massive datasets (Diebold 2012). It observed that technology-generated data produced in real-time was too large and complex for traditional software and storage systems to capture, store, manage and process in a practicable amount of time (Kubrick 2012). Other technology-centric definitions (Kaisler et al. 2013) also emphasise the storage of data. Kaisler et al. (2013: 1) define it as "the amount of data just beyond technologies ability to store, manage and process efficiently". This definition ignores the pace of change in computing and the evolution of technologies to cope with the new data, such as Hadoop and i-cloud storage technologies and related analytical software. These ongoing developments mean that because storage capacities are allowing bigger datasets to be captured, what may be defined as big data today may not meet the threshold in future (Gandomi and Haider 2015).

The volume characteristic of big data introduces technological challenges in relation to data storage. Previously, small data could be stored in relational databases and spreadsheets, but big data requires large scale storage facilities. New forms of data repository are required, known as 'data pools' or 'data lakes', which can hold large volumes of data in multiple forms. This pooling of data allows a wider variety of data sources to be aggregated, then accessed and analysed through data warehouse systems. The magnitude of big data impacts on more than storage requirements, it also encompasses management, analysis and visualisations technologies (Chen, Chiang, and Storey 2012).

Variety

Another cornerstone of the big data definition is its 'variety' (Laney 2001), which refers to the range of data sources used. Having a variety of big data sources in different formats results in a complex and multi-dimensional dataset (Russom 2011). Big data sources range from structured data, including tabular data in relational databases and spreadsheets, to unstructured datasets. Unstructured datasets are in themselves diverse and still evolving, including 'social big data' generated by social networking sites and multi-media data such as videos, images and audio files, which currently lack the structure to be machine read.

Having a variety of data sources allows the firm to bring together different viewpoints on a customer or phenomena. For example, quantitative and qualitative insights into a customer's purchasing experience are available by combining purchase transaction data and product review data. Using a variety of data may not appear to differ significantly from small data (Kitchin and McArdle 2016). However, in conjunction with the characteristic of volume, the firm is receiving richer information from different perspectives. This combination provides a broader picture of the customer, through more comprehensive data which allows the firm to anticipate customer behaviour and respond with new products or internal efficiencies.

Five per cent of big data is considered to be structured (Cukier 2010; Gandomi and Haider 2015), which suggests that popular discourse focuses on structured data and predictive analysis. The remaining ninety-five percent, in the form of unstructured data, is largely ignored by firms (Gandomi and Haider 2015). This may be due in part to a dearth of software capable of analysing unstructured data. The increased uptake and engagement with social media presents a huge source of big data (Stone and Woodcock 2014), which is likely to drive technological developments to bridge this gap in the near future.

There is likely to be continued growth in structured data, as a result of progressive innovations in machine-to-machine data sources. Urban and mobiles sensors, such as credit card readers, smart grid, Wi-Fi access points, GPS sensors within mobile phones, and the Internet of Things (IoT), generate new forms of high volume, ordered data (Blasquez and Domenech 2018; Sivarajah et al. 2017). These add a further structured variant to the range of big data firms may utilise to inform their market intelligence and business strategies.

Velocity

As with the volume and variety characteristics, 'velocity' and the speed of available data has been viewed as a central element since early in the conceptualisation of big data (Laney 2001). The proliferation of digital devices, such as mobile phones and GPS sensors, are generating real-time data at a rate that was not possible in the pre-digital era. "Big data technologies enable firms to create real-time intelligence from high volumes of perishable data" (Gandomi and Haider 2015: 139) in ways that could not have been handled by traditional data management.

In Laney's definition, 'velocity' refers to data being available in real time. Kitchen and McArdle (2016) subsequently revised the definition to reflect the frequency of data availability, either through frequency of generation or handling, recording or publishing of big data. Kitchen and McArdle's theory proposes that data velocity may be high frequency but not necessarily in real time. To benefit from the velocity of available data, firms need to be able to analyse and act on the data swiftly (Gandomi and Haider 2015).

Veracity

'Veracity' is recognised as a big data characteristic in more recent information systems and management literature (Wamba et al. 2015; Ferraris et al. 2018). Veracity refers to the quality and level of trust of the data sources (White 2012). If big data is of a poor quality and unreliable, the decision-making on which it is based, will have unreliable foundations. White (2012: 211), who was the original proponent of veracity as a key element of big data, commented that "if data is not of sufficient quality by the time it has been integrated with other data and information, a false correlation could result in the organization making an incorrect analysis of a business opportunity".

Veracity of data requires processing to become reliable and trustworthy. Through the data management process, the data becomes less messy, noisy, error-strewn and uncertain (Kitchin and McArdle 2016). For some industries, veracity is a critical data characteristic. In healthcare, customers or users require medical information to be accurate, consistent and traceable (Wang, Kung, and Byrd 2018). In banking and finance, consumers' expect that the collected and held transaction and personal data will be accurate and trustworthy. Once the data is accurate and transparent, it can be used as a robust basis for prediction, forecasting, decision-making and defining competitive strategies.

Value

‘Value’ is also a more recent addition to the five ‘Vs’ characteristics of big data (Wamba et al. 2015). It is described in extant literature in three different ways. Kitchin and McArdle (2016: 1) defined value as “many insights being extracted and the data repurposed”. The ‘reuse’ maximises the value of each dataset to the firm, improving operating efficiency and increasing return on data investment.

Gandomi and Haider (2015) went on to present two descriptions of ‘value’. Firstly, value arising from combining the characteristics of big data, for example, combining individual low value density elements of big data to generate high value density. Gandomi and Haider’s (2015) second description relates to value generated from leveraging big data, and is more prevalent in the management literature (Wamba et al. 2017). They observed that “big data is worth less in a vacuum” and that value results when it is leveraged to drive evidence-based decision-making (Gandomi and Haider 2015: 140). Examples of value creation using big data include Amazon using textual content from consumer reviews to forecast consumer product demand. They also include mobile phone companies personalising their services in response to the evidence of mobility patterns and phone use generated by smart grid, Wi-Fi access points and GPS sensors contained inside mobile phones (Blasquez and Domenech 2018).

The inclusion of value amongst the characteristics of big data does not sit neatly with the original ‘3Vs’ because the data requires processing to deliver value. However, its inclusion does emphasise the essential relationship between big data and business strategy (Akter et al. 2016).

2.5.3 An amorphous term

In their ontological study of datasets, and the sets’ fit with recognised big data traits, Kitchin and McArdle (2016: 9), concluded that the term ‘big data’ is a “catch-all amorphous term that assumes that all big data share a set of general traits”. Their analysis showed that only a handful of datasets had all the traits, and that the qualifying criteria were velocity and exhaustivity, rather than volume and variety. They concluded that the "3Vs meme is actually false and misleading and along with the term itself is partially to blame for the confusion over the definitional boundaries of big data" (Kitchin and McArdle 2016: 9). But the lack of a precise definition may be the result of ongoing changes to big data, as new technologies continue to evolve. Because of the dynamics of their changing context, definitions risk being seen as outdated, incomplete or function-specific. Whatever the cause, the lack of clarity impedes firms' engagement with and understanding of the value of using big data (Kitchin and McArdle 2016).

In summary, to explain big data, management and information systems literature has adopted a descriptive framework rather than a precise definition. This format may be the result of the pace of evolution of the big data phenomenon or the recognition of firm's big data application within the literature. Unlike previous incarnations, the current '5V' framework introduces characteristics which connect the data with business management. Each of the five current characteristics of big data have implications for the firm in terms of potential added value, whilst simultaneously requiring changes in investment and infrastructure. Volume of big data gives firms access to larger datasets but at the same time demands investment in new forms of data storage capacity. Data variety involves a more comprehensive dataset, but necessitates investment in continuously innovating technologies. Velocity in big data secures high speed data capture and analysis, whilst demanding infrastructure investment to support faster decision-making. Veracity of data provides an accurate basis for quality decision-making but requires processing to ensure data reliability. Finally, data value requires data transformation to create value and business benefit. The characteristics of big data, which are continuing to evolve, have the potential to impact on a firm's resource base and to inform strategic marketing direction. The next section will show how those data characteristics are transformed into insight and data-driven decision-making.

2.6 Transforming data into data-driven decision-making

This section of the chapter discusses the transformation of big data for data-driven decision-making through big data analytics (BDA) and insight extraction. The role of BDA, and whether its prioritisation in extant literature is justified, are considered. The contribution of different types of analytics and the insights that they generate are then discussed. The section concludes by explaining the relationship between data insight and data-driven decision-making.

2.6.1 Analytics and the wider issue of insight extraction

The availability of big data can offer firms improved market intelligence, but as discussed in Section 2.4, big data has a complex combination of characteristics. Data must be analysed if it is to be translated into insights that can be used to improve firms' strategic decision-making. As Ferraris et al. (2018: 8) note: "One of the most powerful aspects of the big data revolution is the unification of large datasets with advanced analytics for problem solving". BDA describes "a new generation of technology and architectures designed to economically extract value from large volumes of a wide variety of data by enabling high velocity capture, discovery and or analysis" (Chen, Chiang, and Storey 2012). Extant information systems and management literature on big data focuses on the technical aspects of BDA (Wamba et al. 2015), which are the techniques used to analyse and acquire intelligence from big data (Gandomi and Haider 2015). At the start of 2009, significant changes in cloud storage and analytics software led to a 'revolution' in BDA (Bryant et al. 2008). Banks and e-commerce pioneered BDA to improve organisational effectiveness, drive new revenue streams and gain competitive advantage (Sivarajah et al. 2017). Since then, BDA has been viewed as an 'added value' activity, capable of protecting a firm's market position and transforming the way in which firms do business, which may explain its status in big data-related literature (Akter et al. 2016).

The focus on BDA is understandable given its technical role in analysing and acquiring intelligence from big data (Gandomi and Haider 2015) and in securing insights that drive decision-making. However, BDA is only a sub-process in the overall process of insight extraction from big data (Sivarajah et al. 2017). The focus on analytics tends to eclipse the importance of the wider business intelligence perspective and the relationship between the data and business strategy. The business intelligence concept emerged following the rapid innovation and technology developments of the 1990s, where large amounts of data were generated, but little of it was being used (Wang, Kung, and Byrd 2018). Business intelligence embraced the collection, interpretation and the analysis of business information, as well as the processes required to obtain a better understanding of market trends and improve decision-making. This wider perspective recognises that to leverage BDA, organisations must do the following: address managerial issues (McAfee and Brynjolfsson 2012); orchestrate strategy choices and resource configuration (Xu, Frankwick and Ramirez 2016); and understand the managerial, economic and strategic impact of BDA (Raghupathi and Raghupathi 2014). Addressing these broader issues requires organisational big data architecture which reflects the purpose and strategy of the organisations, and which supports the process of generating value (Blasquez and Domenech 2018).

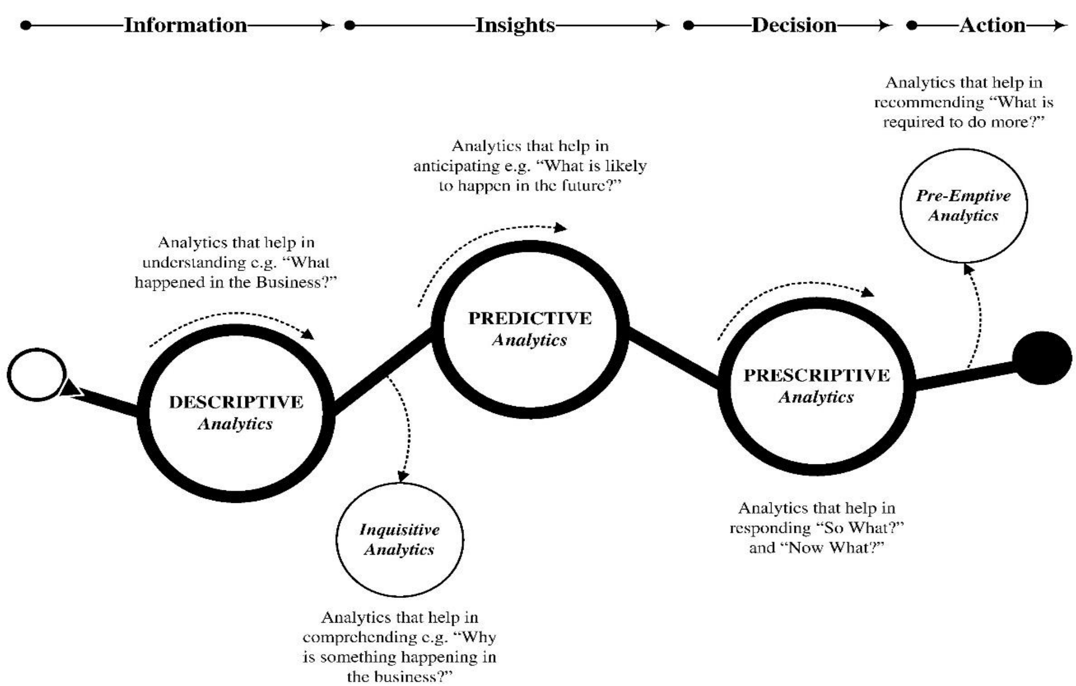
An organisation's BDA capabilities involve the management of high volumes of disparate data and are influenced by the speed of transformation of new data into insight (Wixom et al. 2011). Different types of data analytics are required, depending on the purpose of the analysis. Sivarajah et al.'s (2017) classification of big data analytical methods explains the function and relationships between the different methods (see Figure 2-2).

Firms select the appropriate analytics method to generate the insights they require. Descriptive analytics investigate data and information to determine the current state of a business situation by identifying developments, patterns and exceptions. They are pertinent early in the data lifecycle as they establish a baseline for subsequent forms of analytics. Inquisitive analytics probe data using statistical analyses to test business propositions and accept or reject them. Predictive analytics determine future possibilities, using forecasting and statistical modelling.

Prescriptive analytics use optimisation and randomized testing to assess the impact of changes in business activities. Pre-emptive analytics provide the firm with the potential to take precautionary actions against damaging situations by identifying hazards and informing mitigating strategies. Like big data, analytics is continuously evolving; for example, the growth in location-aware social media and mobile applications is likely to result in the proliferation of real time analytics, and the increase in user-generated content will change the nature of descriptive analytics.

Figure 2-2 Classification of big data analytical methods

(Source: Sivarajah et al. 2017: 266)



2.6.2 Insight extraction

The proliferation of data from electronic sources and advanced analytics (Brady et al. 2002) is providing the opportunity to enrich market insights. These insights can improve the breadth and depth of market intelligence, which may improve strategic marketing through approaches such as enhanced strategic planning forecasts and operational efficiencies (Srinivasan, Rangaswamy, and Lilien 2005).

A central feature of BDA is the capacity to 'fish' for insights from voluminous, big 'data lakes'. Where small data can only address specific questions, BDA can both answer questions and pattern–spot in the large volumes of data. Pattern-spotting allows connections to be made within data which could not be identified in more compartmentalised data storage arrangements. As Mayer-Schonberger and Cukier (2013: 14) observe; "When we let the data speak, we can make connections that we had never through existed". Blasquez and Domenech (2018) describe this as 'modelling' data, which they divide into supervised, question answering and unsupervised, pattern-spotting paradigms for modelling. Modelling enables firms to experiment with data, discover customer needs, expose variability and test performance improvements. The firms leading the big data charge are applying both supervised and unsupervised modelling paradigms to create value (Perrons and Jensen 2015). By modelling the data, their enhanced market intelligence and insight may alert the firm to new development opportunities.

As BDA models are built within the information systems domain, they focus mainly on the technological processing of data (Blasquez and Domenech 2018; Wang and Hajli 2017). Models such as CRISP-DM, which is the industry standard for data mining, include discovery and planning; however, the focus is on sourcing and processing data, and not on its impact on the business. Labrinidis and Jagadish (2012) suggest a five-stage process for data insight extraction, which usefully separates data management from analytics, but again focuses only on technological processes. Figure 2-3 identifies their key stages.

Figure 2-3 Big Data Analytics – the five stages of insight extraction

(Source: Labrinidis and Jagadish 2012: 89)

Data management	Acquisition and recording Extraction, cleaning and annotating Data integration, aggregation and representation
Analytics	Modelling and analysis Interpretation and visualisation

These technology-focused approaches to BDA do not take into consideration how an organisation engages data with its strategy, to secure value for the firm. To secure value from data insights requires an interaction between the technological aspects of insight extraction and business insights into the application of the data (Alvarez 2016).

Data analytics can be harnessed to analyse customer needs and behaviours and to better understand customer value. This more refined marketing intelligence can inform strategic marketing decisions, by enabling firms to manage churn and loyalty. As an example, the discovery of buying preferences can be used to inform precision marketing (Provost and Fawcett 2013). Alternatively, BDA may inform business efficiencies in related areas; for example, by informing supply chain management, which can lead to increased revenue (Cheah and Wang 2017). As well as directing organisational change, BDA can also identify market trends for new business ideas, and generate creative and innovative thinking (Wang, Kung, and Byrd 2018). Analysis and insight extraction have a strongly technical orientation; however, to secure value from those insights requires the insights to be aligned to corporate strategy.

2.6.3 Data-driven decision-making

The insights from big data can enhance firms' vision of their operations and markets, allowing managers to make decisions based on data and rigour rather than intuition (McAfee and Brynjolfsson 2012). Ferraris et al. (2018: 86) observe that: ”decisions that previously were based on guesswork, or on painstakingly hand-crafted models of reality, can now be made using data-driven mathematical models”. The resulting transparency facilitates improved data-driven decision-making processes, which are at the core of the hype around big data (Erevelles, Fukawa, and Swayne 2016; Wamba et al. 2015).

The translation of data-led insights into value involves firms in innovative behaviours. These behaviours include new business models, different approaches to target markets and customer segments, and market-responsive product development and upgrading. They can also inform marketing programmes, such as improved product or delivery processes and marketing mix innovations (Cheah and Wang 2017).The effects of data-driven decision-making can also be reflected in greater innovation in internal business processes, such as more efficient production and operational business practices (Yiu 2012), and new working relationships and alliances (Cheah and Wang 2017). The innovations can also include the commercialisation of data and data processes to generate new revenue streams (Cheah and Wang 2017). In their study of the energy sector, Perrons and Jensen (2015: 120) view the innovation-data process-commercialisation triumvirate as a virtuous circle: "The digital revolution will be complete when the sector figures out how to monetise the data that it is now capable of collecting and then uses it to create all the data it can".

As well as directing changes in behaviour, data-driven decision-making enables better informed strategies that can lead to improved business performance (Constantinou and Kallinikos 2015). These changes encourage increase organisational agility and responsiveness to the external operating environment (Chen and Zhang 2014; Corte-Real, Oliviera, and Ruivo 2017).

Data-driven innovation in decision-making is not limited to emerging high-tech industries or start-ups. Firms operating in traditional manufacturing industries are also able to harness the power of big data and i-cloud storage and transform the way they conduct business (Cheah and Wang 2017). Although Cheah and Wang's study (2017: 245) investigates a relatively small number of cases, it shows that "tolerating ambiguity" and encouraging risk-taking in established firms, provides a conducive environment for breakthrough ideas and radical innovation.

In summary, BDA is positioned in information systems and management literature as the main generator of value from big data. The importance of garnering insights from ever-changing data sources, makes the need to understand the potential of BDA from a technical perspective inevitable. However, without reference to organisational goals and strategy, BDA can only be viewed as a sub-process of insight extraction. Organisational focus on the technical analytics, neglects engagement with the corporate strategy, which constrains big data's contribution to the wider business. Big data insights provide the opportunity for firms to base their decisions on data, rather than on intuition. The adoption of data-driven decision-making is reflected in more innovative behaviours and better informed strategies. The next section will consider the challenges for firms' engagement with big data.

2.7 The challenges of big data

Although the opportunity to use big data exists, it does not necessarily mean that firms are automatically able to engage with and apply it. This section addresses the challenges for firms in using big data. These include the effects of organisational rigidities, capability constraints and the need for organisational ambidexterity to manage the existing operations, whilst also engaging with new business opportunities. The section identifies the existence of a data-related strategic marketing capabilities gap.

The "proliferation in data and developments in data analytics brings huge opportunities in relation to market insights and the identification of target markets as well as providing broader insights which can inform marketing strategy" (Quinn et al. 2016: 2122). However, there is a disconnect between the potential offered by new technologies generating more robust and granular data, and firms' readiness to engage with it (SAS 2012; Stone and Woodcock 2014). Marketers are being challenged by the deluge of data beyond the capabilities of their organisations to comprehend and use (Day 2011). This constrains their market intelligence and their ability to develop a marketing strategy that can respond to the accelerated rates of change in the market.

There are a number of reasons why firms have trouble keeping pace with the technological changes. Day (2011) identifies these as resulting from organisational rigidities, and lagging reactions between the availability of new information and the firm's action in response. Organisational rigidities which may hold the organisation back include path dependence, organisational complacency and structural insularity (Day 2011). Path dependence arises where firms have experiences of operating in a particular way, which is reinforced by business success (Leibowitz and Margulies 1994). These experiences may constrain their willingness to embrace an alternative approach. Organisational inertia and complacency may result from firms successfully following a particular path, such as exploiting existing resources and capabilities, and consequently, being less open to experimental and exploitative activities (March 1991). A third cause of organisational rigidity occurs in firms where departments function independently of one another, and are reluctant to work co-operatively (Aaker 2009). This structural insularity is a problem for engaging with big data, which requires multifunctional involvement throughout the process of transforming big data into strategic marketing decision-making.

In order to adopt new data-driven business models, established firms have to diverge from their existing operating methods and traditional culture (Sivarajah et al. 2018). Overcoming organisational rigidities may involve new capabilities and skills, new partnerships and changes in organisational processes. There are global shortages in many data-related skill-sets, including expertise in data science, customer analytics, social networks and digital media (Ready and Conger 2007). The skill shortages are leading firms to seek alternative ways to address the data-related capability gaps. Where organisations are unable to develop or recruit big data-related capabilities, they may partner with external organisations (Jagadish et al. 2014). The forms of partnerships vary in relation to the nature of the firm's competences, the company strategy and other resource availability. For example, there may be a contractual relationship, or an acquisition of a data-driven organisation, to integrate it into their own business (Fogarty and Bell 2014). The approach adopted to meeting the skills gap may have other implications for the firm (Gunther et al. 2017). Outsourcing can create intellectual property and data ownership challenges. Mergers and acquisition can also be demanding because of the impact of cultural changes (Weber et al. 1996), variability in partner agility, and different managerial approaches (Sebastian et al. 2017).

A further challenge to established firms using big data is that they already have a market position, existing business processes, and a defined market strategy. Rather than abandoning their original strategy and taking up another, the firms may find that they are operating two different approaches in parallel (Rezazade Mehrizi and Lashkovbolouki 2016). The challenge is how to exploit their own resources enough to maintain current viability, whilst exploring sufficiently to secure their future viability (March 1991). To do so, firms have to prioritise and allocate resources between exploration and exploitation (Gupta, Smith and Shelley 2006), determining how to manage the tension between the two (He and Wong 2004). Through this divergent approach, the organisation manages the existing business and engages with new business opportunities, a phenomenon called ambidexterity.

With reference to extant theory, Prange and Schlegelmilch's model (2009:219) (see Figure 2-4) summarises how firms manage their ambidexterity by using simultaneous or sequential timing of activities, and organisational or individual levels of activity. Their model indicates four modes of ambidexterity. Structural ambidexterity involves management of the conflicting demands of exploitation and exploration, by allocating different activities to different business functions (O'Reilly and Tushman 2004). Temporal ambidexterity combines long periods of incremental data exploitation, punctuated with significant exploration projects (Tushman and O'Reilly 1996).

Figure 2-4 Prange and Schlegelmilch's ambidexterity model

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Timing of activity</td></tr>
<tr><td>SIMULTANEOUS</td><td>SEQUENTIAL</td></tr>
<tr><td rowspan="2">Level of activity</td><td>ORGANISATIONAL</td><td>STRUCTURAL AMBIDEXTERITY</td><td>TEMPORAL AMBIDEXTERITY</td></tr>
<tr><td>INDIVIDUAL</td><td>CONTEXTUAL AMBIDEXTERITY</td><td>PERIPATETIC AMBIDEXTERITY</td></tr>
</table>

Source: Prange and Schlegelmilch (2009: 219)

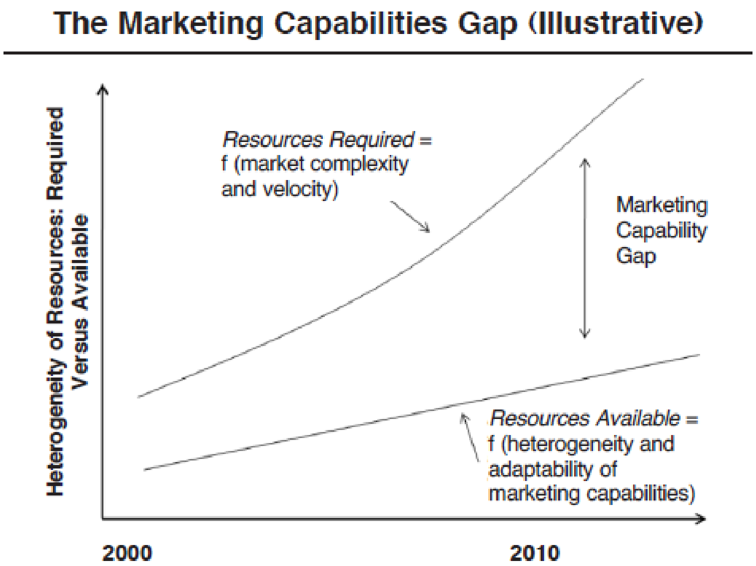
Contextual ambidexterity delegates decision-making through the organisations' structures and routines, giving employees the autonomy to make their own judgments on how to divide their time between the conflicting exploitation / exploration demands (Birkinshaw and Gibson 2004). The fourth peripatetic ambidexterity mode, proposed by Prange and Schlegelmilch (2009) involves changes to the top management team at key times.The ambidexterity modes are complementary, and firms apply different combinations depending on their strategy (Jansen 2015).

2.7.1 The strategic marketing capabilities gap

As well as organisational obstacles to engaging with big data, there are also capability constraints. The World Federation of Advertisers (2013) has identified their members' biggest challenges for working with big data and the percentage of firms identifying those challenges as a significant problem. These challenges may be viewed strategically and operationally. Firms are dealing with the huge array of data sources (54%); finding business analysts good enough to produce insights (49%); deploying insights practically in the business (49%); getting marketers to understanding how to use big data (45%) and measuring the impact and return on investment (42%). These issues highlight the emergence of a strategic marketing capability gap in relation to big data.

The challenges are widening the marketing capability gap between the marketing capabilities available to react to the changes in the market, and those required by firms to respond to the increasingly complex and technologically turbulent markets. The growing gap is unquestionable costly to firms' current profitability and their future competitiveness (Stone and Woodcock 2014). The nature of the gap is illustrated in Figure 2-5.

Figure 2.5 The Marketing Capabilities Gap



Source: Day 2011: 185

Firms are struggling to handle the challenges of big data in strategic marketing and addressing the capability gaps. At the same time, within academia, there is a dearth of research on the impact of advanced technology and data proliferation, as well as on how strategic marketing opportunities are being shaped or challenged in the digital era (Dibb et al. 2019; Quinn et al. 2016). As a result, there is a poor understanding of how big data is changing strategic marketing capabilities. The next chapter will investigate the dynamic capabilities needed to respond to market changes, to provide a lens through which to view the experiences of those who are using big data for strategic marketing.

In summary, despite the benefits of engaging with big data there is evidence that not all firms are adopting this new resource. This may be as a result of being overwhelmed by the scale and scope of the data and the implications of changing organisational capabilities to secure value from the new resource. Alternatively, their reluctance may be the result of organisational rigidities based on past experience. The result can be a growing marketing capability gap, which affects firms' profitability and competitiveness. There is a paucity of academic research in this area which has provided the catalyst for this study.

2.8 Chapter summary

Firms are operating in technologically turbulent environments, which bring challenges in the form of new competition with data-led business models. It also brings opportunities, such as improved understanding of customers and markets and the identification of prospects for differential advantage, through the new big data resource. Big data is complex; it has multiple characteristics which increase the detail of information captured. It is resource intensive and challenging for firms to draw insights from the data, on which to base their decision-making. While the transformation to becoming a data-led organisation requires technical competence, it also needs wider business engagement to leverage value from the data. Established firms have to embrace the technical changes and overcome organisational rigidities to work with big data. There are challenges in running the existing business, whilst exploring new market opportunities. In addition, the global nature of the technological changes is causing capability constraints, such as skills shortages. Each of these elements is adding to the data-related marketing capabilities gap. Firms that are using big data within their strategic marketing activity have overcome the capability gap to use the new resource.

Leveraging the big data resource for strategic marketing purposes, requires new capabilities to scan the external operating environment, develop market intelligence and respond to new market opportunities. The next chapter introduces dynamic capabilities theory which offers a lens to examine the capabilities needed to leverage big data for strategic marketing.

Chapter 3 Dynamic Capabilities – the research lens

3.1 Introduction

Chapter 2 explained how technological turbulence has changed the market environment for many firms, bringing in different, digitally-born competition and new market opportunities. It has also introduced a new resource in the form of big data, which has fundamentally different characteristics to the data sources used previously. Big data has the potential to enhance the firm's resource base by improving the detail and quality of the firms' customer and market intelligence. In order to maintain their evolutionary fitness, market-orientated firms need to use as comprehensive a resource base as possible, to identify and respond to the new market opportunities.

Firms deploy their resources using capabilities, of which their operational capabilities are used to execute day-to-day operations. However, dynamic capabilities are required to modify the resource base in response to the changing environment. In order to use big data to inform strategic marketing decisions that will maintain and improve firms' competitiveness, new dynamic capabilities may be required.

This chapter reviews the literature on dynamic capabilities theory, through seven sections. Section 3.2 explains the choice of dynamic capabilities research lens. Section 3.3 outlines the origins of dynamic capabilities and their relationship to competitive advantage. Section 3.4 explains the construction of dynamic capabilities, including considering the resources and the organisational capabilities used to allocate and reconfigure resources. Section 3.5 explains Teece, Pisano, and Shuen's (1997) concept of dynamic capabilities and introduces a number of alternative dynamic capabilities theories. Section 3.6 outlines the three-component conceptualisation Teece (2007) subsequently developed and explains the choice of Teece's (2007) model as a suitable basis for the research discussion. Section 3.7 identifies the role and importance of microfoundations in the construction of dynamic capabilities. It also notes the absence of theory regarding the mesofoundations, which reflect the group, team and departmental contributions to the development of dynamic capabilities. Section 3.8 provides a chapter summary, explaining where this study fits within dynamic capabilities literature.

3.2 Choosing the research lens

In choosing a research lens to focus the study, a number of theories were considered that reflected the research context of strategic marketing. These included Customer Relationship Management, which was deemed to be too technically-orientated, and Strategy-in-Practice, which was thought to be too broad in scope to highlight the issues relating to the technological resource in a marketing context. However, investigation of these theoretical domains provided useful sources of literature on the applied practices of managers and individual employees (Helfat 2007a; Schilke, Hu and Helfat 2018).

The literature review on big data emphasised that technology was radically changing firms' operating environments, with the emergence of new competition, business models and ways of engaging customers (Wamba et al. 2015). At the same time, the literature showed that new sources of data were being generated that could provide a resource to improve the competitiveness of firms (Braganza et al. 2017). As an evolution of the resource-based view, dynamic capabilities theory considers both the resources and the capabilities that firms need to adapt their resource base when operating in a dynamic environment.

Dynamic capabilities theory includes a number of functional viewpoints, such as dynamic management capabilities and dynamic marketing capabilities, each of which was also considered as a possible research lens. However, based on the early interview content these were considered to be too narrow to address the research question. Because the research was grounded in the experiences of knowledgeable agents, it was appropriate that insights emerging from their inputs should inform the choice of theoretical lens. Appendix 1 offers a brief synopsis of these potential lenses and the reasons they were not adopted in this instance.

The overarching, dynamic capabilities view of the firm was therefore chosen as the most appropriate lens because it accommodated the changing operating environment, the adaptation of the firms' resource bases, and was broad enough to accommodate the multiple domains of big data, strategy and marketing, that were reflected in the big data initiatives.

3.3 Dynamic capabilities and competitive advantage

This section discusses the significance of competitive advantage to firms, and explains how the RBV was viewed as a way of achieving it. The transition of the RBV into the dynamic capabilities view (DCV) is described. The DCV proposes that for firms to achieve or sustain competitive advantage in a changing market environment, dynamic capabilities are required to reconfigure the resource base. Finally, the section highlights the shift of focus within competitive advantage theory from a long-term view towards a short-term aim of evolutionary fitness for organisational survival and growth.

The research investigates how big data is impacting strategic marketing capabilities, which are an important driving factor in firms' competitive positioning (Munuera and Rodriguez 1998). Commercial organisations strive to position themselves favourably compared to their competitors through achieving a market orientation and developing differential advantage. They do so through improving their business performance by developing strategies, which reflect external factors (Porter 1985) such as changes in the operating environment or the behaviour of their competition. In the 1980s and early 1990s, the view was that these strategies could deliver sustainable competitive advantage, and that firms could take a long-term view of staying ahead of their competitors (Porter 1985; Porter

1996). This Porterian viewpoint assumed stable market conditions and ignored the heterogeneity of firms in the marketplace (Fisk 2016).

In the 1990s, the RBV provided the dominant explanation for firms securing competitive advantage (Wernerfelt 1984). The essence of RBV lies in the emphasis on resources and capabilities as the origin of competitive advantage and superior performance (Collis 1994; Penrose 1959; Wernerfelt 1984; Parente et al. 2011). The theory proposes that firms are an aggregation of resources, such as finance, staff, and branding, which are allocated to deliver products and services to customers more efficiently and effectively than their competitors. Firms can maintain long-term competitive advantage based on the successful creation, extension, addition or protection of their valuable, rare, inimitable and organised (VRIO) resources (Parente et al. 2011). Individual firms are heterogenous, with unique collections of resources that are often not easily adapted, added to, or discarded. As a result, it is not easy for them to change in response to new competition or a new market opportunity (Wang and Ahmed 2007).

The emergent dynamic capabilities view of the firm is built on the RBV and the idea of resource-based, sustainable competitive advantage. This viewpoint emphasises the importance of capabilities to make efficient and effective use of firms' resources in a changing operating environment (Teece, Pisano, and Shuen 1997). As well as the changing emphasis from resources to capabilities seen in the 1990s, the idea of achieving sustained competitive advantage started to be viewed as unlikely in dynamic environments (D'Aveni 1994; Eisenhardt and Martin 2000). Instead of seeking long-term competitive advantage, firms chose to take leading positions in a series of short-lived, competitively advantageous solutions (D'Aveni 1994); or focused on using resources which were rare and valuable, and therefore resistant to imitation or substitution (Barney 2007). Rather than stressing competitive advantage, literature emphasised relative competitive positioning (D'Aveni 2007); and how well the organisations matched the context in which they operated - a concept described as evolutionary fitness (Helfat 2007a). Decisions regarding which strategy to adopt to achieve differential advantage or evolutionary fitness, are determined through strategic marketing.

The DCV has become “one of the leading frameworks aimed at drivers of long-term survival and growth” (Wilden, Devinney, and Dowling 2016: 997). From a theoretical perspective, competitive advantage continues to be core to DCV, and something which “might well be characterized as the Holy Grail of strategic management” (Helfat and Peteraf 2009: 91). Wilden, Devinney, and Dowling (2016) note that over eighty per cent of dynamic capabilities authors still emphasise competitive advantage. However, the theoretical focus has moved from finding the dominant dynamic capabilities, to investigating the processes relating to sensing, shaping and seizing opportunities, and reconfiguring the firms’ resource bases to achieve organisational survival and growth. High evolutionary fitness involves close alignment between the firm’s capabilities and the demands of their operating environment, with the aim of supporting organisational survival and growth. Organisations that are capable of adapting to their external environment can achieve organisational survival; whereas those that thrive and increase in size in response to the changing external environment can achieve organisational growth (Helfat 2007a). The result of this shift in competitive approach is that firms are seeking shorter-term advantage in response to changes in the marketplace. This is evident in their identification and calibration of opportunities, the judicious selection of technologies and product attributes, design of business models and commitment of resources to investment opportunities, which can lead to enterprise growth and profitability (Inan and Bititci 2015).

Securing competitive advantage relies on firms adapting to changes in their operating environment by adjusting their resource base (Teece, Pisano, and Shuen 1997). Technological turbulence over the last three decades has introduced a new resource in the form of big data, which is the digital capture of human/technology interactions (as described in Chapter 2). New data-driven competitors with significantly different business models and strategies, such as sharing communities and online customer engagement, are challenging established firms. As well as contesting the status quo for existing firms, big data provides them with new opportunities for competitiveness, innovation and efficiency (Braganza et al. 2017; Jagadish et al. 2014; Manyika et al. 2011). Studies show that this resource has the potential to increase firms’ outputs, productivity and growth (Brynjolfsson et al. 2011; Davenport and Harris 2007), and contribute to improving their competitive positioning. For firms striving for competitive advantage, the big data resource provides a catalyst for improving evolutionary fitness. However, the context of a technological dynamic industry does not necessarily result in enhanced value from dynamic capabilities (Fainshmidt et al. 2016). Achieving enhanced value is subject to the firm changing its resource base to accommodate big data, through the application of dynamic capabilities.

In summary, the research uses a dynamic capabilities lens to address the research question. The DCV has emerged as an important framework aimed at drivers of firms' long-term survival and growth. Within the DCV, firms respond to turbulence in their operating environment by using their capabilities to make efficient and effective use of their resources. The aim is to achieve evolutionary fitness, to match their external environment, with a view to securing competitive advantage. For firms to use dynamic capabilities they need to understand how dynamic capabilities are constructed, their relationship to the firm's resource base, and to the ordinary capabilities used to run the business when conditions are stable. The construction of dynamic capabilities is explored in the next section.

3.4 The construction of dynamic capabilities

This section of the chapter outlines the construction of dynamic capabilities. It starts by explaining the form that organisational resources take, and how they contribute to competitive advantage. It goes on to describe organisational capabilities and their role in the deployment of resources. The composition of organisational capabilities is discussed, to explain the hierarchy of dynamic capabilities. Finally, the distinction between day-to-day operating capabilities and environmentally-responsive dynamic capabilities is presented.

3.4.1 Resources and resource allocation

In the RBV, organisations are presented as portfolios of idiosyncratic and difficult-to-trade, firm-specific assets (Teece 2007: 1319). The assets are controlled by the firm, enabling it to conceive of and implement strategies that improve its efficiency and effectiveness (Barney 1991). In striving for competitive advantage or evolutionary fitness, firms must select or emphasise the use of those advantage-creating resources that are valuable and rare, inimitable or organised (VRIO) (Barney 2007). This approach aims to makes it difficult for competitors to emulate the firm's strategy.

Within the firm's assets, resources are the cornerstone of dynamic capabilities theory, underpinning all the other elements. They can be consolidated into groups, such as shown in Cheah and Wang's (2017) four categories:

- Financial: sources of funding to support the operational growth of the company;
- Physical: such as raw materials, products, tools, plant, hardware and premises;
- Human: including individuals who make up workforce; their skills, commitment, capabilities, as well as organisation structures;
- Intellectual: intangible assets including knowledge, reputation, brand awareness, goodwill, intellectual property and big data.

Numerous other resource groupings have been proposed that extend Cheah and Wang's (2017) categories. These include organisational resources such as quality control, corporate culture and networks (Mahoney and Pandian 1992; Hofer and Schendel 1980); and others which present business resources as also being economic resources (Ng 2014). However, Cheah and Wang's four groups provide a succinct way to describe the breadth of resources within a firm and identify a clear position for big data as an intellectual, intangible resource. Intangible resources are more difficult to replicate and therefore provide a more meaningful basis for strategic marketing development (Fahy and Smithee 1999).

Teece (2007) observed that competitive advantage flowed from changes in the ownership of these scarce and difficult-to-imitate assets, rather than from product-market positioning.

However, ownership of these difficult-to-replicate assets is not on its own sufficient for sustainable competitive advantage. To be sustainable, firms need to continually adapt their asset base in response to their external environment (Teece 2007). Resource allocation or reallocation is subject to the constraints of the organisation's strategic priority, investment limitations and internal conflicts; including uncertainty, complexity and intra-organisational conflict (Amit and Schoemaker 1993). It relies on capabilities which enable the assets to be deployed advantageously (Day 1994). In their broadest form, these capabilities are described as organisational capabilities.

Big data has started to become recognised as an intellectual resource, which can sit alongside other intangible resources such as brand awareness, intellectual property and knowledge (Cheah and Wang 2017). This new resource combines the volume, variety, velocity, veracity and value characteristics of data, which can provide actionable insights to contribute to competitive advantage (Wamba et al. 2015). Big data has the potential to be a valuable, rare and hard to imitate resource for the firm (Prange and Schlegelmilch 2009), if aspects of the data are selected and emphasised in a manner that is difficult for competitors to emulate. To give an example, where a retail organisation can draw on high-velocity big data on customer transactions, it can provide prompts for additional, related items to increase the total value of the customer's purchases. In this case, the retailer is using the VRIO characteristics of the data to secure competitive advantage over other retailers. Prioritising the use of big data to drive sales activity, rather than using marketing promotions capability, requires changes in the organisational capabilities. By emphasising the VRIO qualities of the resource, particularly where they are internal and non-tradable, big data may be viewed as an asset as well as a resource (Fahy 2002).

In summary, to secure competitive advantage, firms must select those resources which will improve their evolutionary fitness, allowing them to adapt their asset base in response to the changing environment. VRIO resources (Barney 2007) are most likely to deliver competitive advantage, requiring organisational capabilities to prioritise their use in the most beneficial way for the firm. The use of an intellectual resource, such as big data, is likely to facilitate organisational responsiveness to technological changes in the operating environment.

3.4.2 Organisational capabilities

Organisational capabilities can be described as the firm's capacity to deploy its resources to perform a task or activity, to improve organisational performance (Amit and Schoemaker 1993; O'Regan and Ghobadian 2004; Teece, Pisano, and Shuen 1997). Capabilities include methods, roles and routines. Methods are formal descriptions of objectives and tasks, whereas roles are social structures and responsibilities, and organizational routines are the activities that enable firms to develop through exploratory or exploitative learning (Fillipini, Guttel, and Nosella 2012). Zollo and Winter (2002) suggest two different types of organisational capabilities; operational capabilities and dynamic capabilities, which emerge from firms developing learning processes over time. Within strategic management, the function of these capabilities is to adapt, integrate and configure the firm's resources, to make incremental changes in line with the requirements of the changing environment.

There is a view within the management literature that capabilities are hierarchically ordered (Ambrosini and Bowman 2009). Each level of the hierarchy effects change on the levels below, such that operational routines bring about change in the resource base; lower order capabilities inform changes in ordinary capabilities; and higher order meta-capabilities on lower order, and so on. The two-classification theory proposed by Zollo and Winter (2002), and subsequently referred to in other studies (e.g. Inan and Bititci 2015), is not the only way in which the hierarchy of organisational capabilities is presented. Table 3-1 describes five different approaches to dividing organisational capabilities, based on Inan and Bititci's (2015) research. Looking in more detail at the different approaches provides a more nuanced understanding of how the construction of organisational capabilities is viewed, which may prove valuable in analysing the research findings.

Table 3-1 Alternative views on the hierarchy of organisational capabilities

Collis 1994	Collis description	Winter 2003	Zahra et al. 2006	Ambrosini & Bowman 2009	Inan & Bitici 2015	Wang & Ahmed 2007
First category	Basic functional activities	Zero level capabilities		Resource base		Resources (zero-order)
Second category	Continuous improvement	First order capabilities	Substantive capabilities	Incremental dynamic capabilities	Operational capabilities	Capabilities (1st order)
Third category	Novel strategies pre-competitors			Renewing dynamic capabilities	Dynamic capabilities	Core capabilities (2nd order)
Fourth category	Higher order/ meta-capabilities	Higher order capabilities	Dynamic capabilities	Regenerative dynamic capabilities		Dynamic capabilities (3rd order)

(Source: adapted from Inan and Bititci (2015: 312)

Collis's (1994) early work divides organisational capabilities into four categories, ranging from basic functional activities, through continuous improvement, into a more externally-responsive category involving implementing novel strategies before competitors; and finally, the meta-capabilities used to adapt and reconfigure established capabilities. Winter's (2003) categorisation is aligned to Zollo and Winter's (2002) proposition. It reflects the RBV, starting with resources, otherwise known as zero-level capabilities, and adds to those first order and then to the higher order capabilities. Inan and Bititci (2015) follow a similar approach, although they treat resources as a given but emphasise the operational and dynamic capabilities split. Ambrosini and Bowman (2009) and Wang and Ahmed (2007) each present four-step categorisations, originating with resources, then building up to dynamic capabilities. Ambrosini and Bowman's four steps describe different functions of dynamic capabilities, whereas Wang and Ahmed highlight the role of core capabilities, which are used to deliver the firm's usual, routine business. The different categorisations are useful to note because they identify the relationships between different levels of capability. The categories clarify that firms hold resources (zero-order capabilities), as well as first order capabilities, which ensure they can operate their day-to-day business, while including a capability for continuous improvement. In addition, firms have the capacity to change, by developing higher order dynamic capabilities which allow them to be market-driven or market-driving (Carrillat, Jamarillo, and Locander 2004).

As an example of the hierarchy of dynamic capabilities, a firm operating in a competitively turbulent environment may have resources such as a corporate plan, skilled marketing personnel and limited funding. It may use the ordinary capabilities of its marketing personnel to scan the external environment and identify competitor activity. The senior marketing personnel may use higher order dynamic capabilities to exploit the potential of the firm's products and processes through improved efficiency. Alternatively, managers may decide on a strategy of exploration, responding to the competitor offerings through higher order dynamic capabilities of new product development or strategic alliances for new methods of delivery. If the firm pursues both exploitative and explorative strategies at the same time, then the firm's ambidexterity would be described as a meta-capability.

Higher order capabilities are those resulting from organisational responsiveness to external stimuli. The organisation's superior, higher order dynamic capabilities enable it to craft and modify lower order capabilities, rules and processes (Pisano, Di Stefano, and Verona 2013; Winter 2011). This allows the organisation to adapt and evolve in response to the changing operational environment, seeking out new business opportunities, whilst using ordinary capabilities to manage day-to-day business (Newey and Zahra 2009). Examples of higher order capabilities are new product development, mergers and acquisitions and networking.

There are benefits to firms of having higher level capabilities (Fainshmidt et al. 2016). Firstly, higher order dynamic capabilities are valuable and harder to imitate than those that are lower order. Secondly, the increased complexity of higher order capabilities maintains a performance differential and is likely to secure a greater return on investment (Crook et al. 2008). This perspective is not universally accepted; Rahmandad (2012) counters that the capabilities needed to cope with increased complexity are costly, which may neutralise the performance outcome benefit. Fainshmidt's third benefit is that higher order dynamic capabilities are more transformational, because they change the way that a firm solves its problems through generating new, low order dynamic capabilities. These higher order capabilities may also be more impactful because firms that invest in them are able to secure competitive advantage through their investment flexibility. Dynamic capabilities may also help firms to overcome core rigidities, which can result when an organisation is competent in a set of processes, which become less relevant when the operating environment changes (Leonard-Barton 1972). Competence traps may also arise where organisations focus on maintaining their core competence, ignoring shifts in the market (Arndt 2011), then finding themselves without the capabilities to be market-responsive. Higher order capabilities allow firms to overcome the competence trap.

As well as the hierarchy of capabilities, current theory in the digital transformation literature highlights the role of integrative capabilities (Helfat and Raubitschek 2018). Integrative capabilities provide the reliable and repeatable co-ordination capacity needed to introduce and modify resources, processes and business models to capture value for the firm. The notion of integrative capabilities and the importance of co-ordinating actions is novel in dynamic capabilities theory. This idea may be useful in big data initiatives where a variety of specialist skills are required but are in short supply (see Section 2.7.1).

In summary, organisational capabilities represent a portfolio of capabilities that firms can use to reconfigure their resource base. There is a hierarchy from resources, at zero level, through operating capabilities to higher order dynamic and meta capabilities. Each level drafts and modifies the lower capability levels. Higher level dynamic capabilities are beneficial to firms because they are harder to imitate and impactful, but also because they can help firms overcome organisational rigidities, in order to respond to the changing market environment.

3.4.3 Operating capabilities

Operating capabilities, also known as ordinary capabilities (Helfat and Winter 2011), are the routines or collection of routines which enable a firm to execute its main operating activities

(Newey and Zahra 2009). These operating capabilities provide the interdependent infrastructure of operational and administrative routines that underpin business operations. This might include day-to-day operational routines such as strategic development and implementation, product manufacturing, distribution, budgeting, or customer enquiry handling. Their role is to sustain business performance through the ongoing execution of activities, using more or less the same techniques on the same scale to support existing products and services (Inan and Bititci 2015). The emphasis is on stable, routine and repetitive patterns of activity (Nelson and Winter 1982), which deliver the core business consistently over time, with incremental changes made through continuous improvement (Bessant et al. 2003).

Operational capabilities are introspective and do not address changes in the market place or deal with one-off problems (Helfat and Winter 2011). For a firm to redirect and reposition itself in a way that can lead to sustained competitive advantage, it must be able to respond to changes in its external, operating environment. The notion that resources could be adapted in response to environmental change led to the theory of dynamic capabilities (Teece, Pisano, and Shuen 1997). In reality, the distinction between operational and dynamic capabilities is not always clearly defined. Some capabilities, such as new product development, may be used for both operational and dynamic purposes (Helfat and Winter 2011).

In summary, the role of organisational capabilities is to deploy organisational resources. They are hierarchically ordered, with a range of classifications originating with resources, also known as zero capabilities. Ordinary capabilities, which allocate resources in day-to-day operations are next in the hierarchy. Dynamic capabilities allow organisations to respond to changes in their external environment, modifying lower order capabilities, and thus resources. At the top of the hierarchy are meta-capabilities, higher order capabilities, which modify other level capabilities to achieve differential advantage and contribute to firms' evolutionary fitness. Understanding this hierarchy provides valuable context in which to consider how big data is changing firms' strategic marketing capabilities. The next section outlines the role that dynamic capabilities play in strategic marketing.

3.5 Dynamic capabilities: a variety of perspectives

This section of the chapter outlines the role that dynamic capabilities play in strategic marketing, by improving firms' evolutionary fitness in the face of changing operating environments. Teece, Pisano, and Shuen's (1997) theory is the seminal work in dynamic capabilities literature and underpins much of the theory in the subsequent two decades.

Based on his earlier study, Teece developed a widely-used model, which proposes that dynamic capabilities have three components, sensing, seizing and reconfiguring. Their role is "to sense and seize opportunities, as well as reconfigure when change occurs, which requires the allocation, reallocation combination and recombination of resources and assets" (Teece 2007: 1341). His theory offers a dynamic capabilities structure which may provide a useful framework for this research.

Dynamic capabilities involve a firm altering its resource base, modifying its ordinary capabilities and directing change in response to the organisation's external environment (Helfat and Winter 2011). Through their dynamic capabilities, firms can introduce novelty into their resource base (Ambrosini and Bowman 2009) in the form of new, valuable, rare and hard-to-imitate resource configurations (Schilke, Hu and Helfat 2018). By making these adaptations, they are able to constantly and systematically improve their lower-order capabilities, and build new resources and capabilities. Where changes are able to take place continuously, the firm is better able to adapt to a turbulent environment (Girod and Whittington 2017). This adaptation can give them competitive advantage in a changing environment and contribute to improved organisational performance (Teece, Pisano, and Shuen 1997).

The theoretical work on dynamic capabilities focuses on two tenets, both of which are relevant to big data. Firstly, that dynamic capabilities contribute to organisational performance (Helfat 2007) and innovation, in defining differential advantage through "the ability of a firm to recognise the value of new, external information, assimilate it and apply it to commercial ends" (Cohen and Levinthal 1990: 128). Secondly, that the value of dynamic capabilities is more pronounced in environments characterised by rapid change, particularly in response to technology (Girod and Whittington 2017; Teece 2014). In stable environments, the consistency of existing capabilities reflects low rates of predictable and incremental external change (Duncan 1972; Leonard-Barton 1992; Teece 2007). Environmental dynamism negatively affects the contribution of ordinary capabilities and positively affects the contribution of dynamic capabilities to relative firm performance (Drnevich and Kriauciunas 2011). Radical changes in the environment are likely to require radical changes in dynamic capabilities (Pisano, Di Stefano, and Shuen 2013). The effect of environmental turbulence will be discussed later in the chapter (see Section 3.4.3).

The key feature of any dynamic capability is alteration and change. Dynamic capabilities are rooted in firms' abilities to acquire, integrate and shed resources and to reconfigure internal and external competences to address the rapidly changing environment (Augier and Teece 2007; Teece, Pisano, and Shuen 1997). Firms transform their capabilities by using their organisational processes to "integrate, reconfigure, gain and release resources – to match and even create market change" (Eisenhardt and Martin 2000: 1107). Extant theory proposes that dynamic capabilities create and shape firms in a variety of ways including their resource position (Eisenhardt and Martin 2000); mediating their ordinary capabilities (Kogut and Zander 1992), and directing operational routines (Nelson and Winter 1982; Wilden at al. 2013, Zahra, Sapienza, and Davidsson 2006). The effects of these changes can be resource synthesis and reconfiguration (Eisenhardt and Martin 2000) but also more extensive corporate renewal (Danneels 2002, Verona and Ravasi 2003). The changing characteristics of the market lead to altered operating practices and new methods for creating value (Wilden and Gudergan 2015). To do this involves a variety of types of capability; including emulating best practice, using an experiential process, or the aggregation of a complex bundle of resource and routines (Pisano, Di Stefano, and Verona 2013).

The DCV theory is underpinned by two seminal works, those of Eisenhardt and Martin (2000) and Teece, Pisano, and Shuen (1997). Teece at al.'s work incorporates a framework for understanding the role that dynamic capabilities carry out, which underpins an extensive body of subsequent dynamic capabilities research. In their seminal work, Teece, Pisano, and Shuen (1997) identify dynamic capability as the firms' ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments.

3.5.1 Teece's sensing, seizing and reconfiguring model of dynamic capabilities

According to Teece (2007), dynamic capabilities can be defined in terms of sensing, seizing and reconfiguring. Sensing comprises "analytical systems to learn and to sense, filter, shape, and calibrate opportunities" (p.1326). Thus, sensing includes all processes that help an organisation collect and analyse market information to learn about customers, competitors and channel members. Seizing relates to addressing sensed opportunities "through new products, processes, or services" (p.1326). For firms seeking differential or competitive advantage, there is a strong alignment between seizing new opportunities and doing so in line with the firm's business strategy. Aligning the two may involve investment in increased research and development activities, changes in the business model, or mergers, acquisitions or divestments (Teece 2010). Reconfiguring refers to an "ability to recombine and to reconfigure assets and organizational structures" (p.1326). The purpose of the reconfiguration is to align the organization's internal processes with opportunities that it senses and those that it proposes to seize. Teece's (2007) three-part categorisation provides a way of seeing the different contributions which dynamic capabilities can make to firms' competitiveness.

To some degree, Eisenhardt and Martin's (2000) theory is positioned in relation to Teece, Pisano, and Shuen's (1997) work, taking a contrasting view on some elements. As an example, they contradict Teece, Pisano, and Shuen's emphasis on market dynamism as a factor in dynamic capabilities, as they do not view achievement of sustainable competitive advantage as significant. They see dynamic capabilities as being best practice; simple, experimental rules which result in unpredictable outcomes. As the capabilities are unstable, Eisenhardt and Martin propose that they cannot deliver sustainable advantage. This has been addressed in subsequent theory, by changes in the expectation of sustainable competitive advantage towards short-term, evolutionary fitness (Helfat et al. 2007). An interesting aspect to Eisenhardt and Martin's theory is their accent on rules and processes, which emphasise individual and group level contributions to dynamic capabilities. For this study, the choice of dynamic capabilities as a lens relates directly to the view that big data is accessible to firms because of market turbulence, and that its use supports firms' competitive advantage. As such, Teece , Pisano, and Shuen's theory is more pertinent to this study, although the micro-level aspects of Eisenhardt and Martin's research remain relevant, and will be discussed in Section 3.5.

3.5.2 Alternative dynamic capabilities models

Since the seminal works of Teece , Pisano, and Shuen (1997) and Eisenhardt and Martin (2000), a number of other conceptualisations of dynamic capabilities have emerged. Some of these involve small changes to established models, adding additional factors to Teece's (2007) sensing, seizing and transforming capacities. One example is the addition of 'leveraging', whereby resources are extended by deployment in a new domain (Ambrosini and Bowman 2009). A variation on applying an established resource in new domains could be used to leverage the benefits of a new resource, such as big data.

Other conceptualisations of dynamic capabilities emphasise function, such as Barreto's (2010) focus on dynamic capabilities to deliver improved performance. Barreto (2010: 271) positions dynamic capabilities as a "firm's potential to systematically solve problems, formed by its propensity to sense opportunities and threats, to make timely and market-orientated decisions and to change its resource base". Building on the studies of others, he notes three ways in which dynamic capabilities and performance are linked. Firstly, through a direct effect on performance outcomes (Teece, Pisano, and Shuen 1997; Zollo and Winter 2002). Secondly, where performance is a product of resource-based reconfigurations and managerial decision-making (Eisenhardt and Martin 2000, Helfat et al. 2007). Thirdly, where dynamic capabilities operate indirectly, mediating their effect on performance via changes to the firm's resource base (Protogerou, Caloghirou, and Lioukas 2012; Zahra, Sapienza, and Davidsson 2006; Zott 2003). Barreto's (2010) approach provides a valuable perspective on the purposefulness of dynamic capabilities. It suggests that the impact of dynamic capabilities can be evidenced, so their contribution to achieving evolutionary fitness or competitive advantage can be measured.

3.5.2.1 An alternative categorisation of adaptive, absorptive and innovative dimensions

An alternative categorisation, developed from an empirical study, is proffered by Wang and Ahmed (2007). Their model reflects Teece's description of dynamic capabilities (2007: 35) as "a firm's behavioural orientation constantly to integrate, reconfigure, renew and recreate its resources and capabilities and most importantly to upgrade and reconstruct its core capabilities in response to the changing environment to attain and sustain competitive advantage". However, Wang and Ahmed (2007) address issues in the definitional characteristics of sensing, seizing and transforming, through three dimensions:

1. Adaptive capability – an organisation's capacity to capitalise on opportunities;
2. Absorptive capability – an organisation's skill to identify, assimilate and apply new information;
3. Innovative capability – an organisation's capacity to create new products and markets.

Like Teece's model, each category is conceptually distinct, with different emphases. Using the three dimensions together explains the firm's mechanisms for linking internal resource advantage with external, marketplace competitive advantage.

Adaptive capability relates to the organisation's flexibility in identifying and capitalising on emerging market opportunities (Chakravathy 1986). Unlike Teece's (2007) theory, where the focus is on sensing and spotting new opportunities, Wang and Ahmed (2007) position the organisational response at a strategic level. Their categorisation includes the effective searching and balancing of exploration and exploitation strategies (Staber and Sydow 2002).

Wang and Ahmed's model suggests that firms with higher adaptive capability have a stronger ability to learn from partners, integrate external information and transform it into firm-embedded knowledge (Wang and Ahmed 2007). These activities are delivered through strategic flexibility in the selection of available resources, and also flexibility in applying them (Sanchez 1995). Adaptive capability is evident in firms' management systems, where outmoded traditions, practices and sacred cows are challenged; changes in the marketplace are responded to swiftly; and shifts in business practice are reflected in rapid evolutions in capabilities (Gibson and Birkinshaw 2004).

Absorptive capability is the ability of a firm to recognise and assimilate the value of new external information and apply it to commercial ends (Cohen and Levinthal 1990). The purpose is to align organisational factors with external changes. The 'absorptive' terminology indicates more clearly than Teece's (2007) reconfiguring descriptor that dynamic capabilities require firms to adapt internally to use the new information.

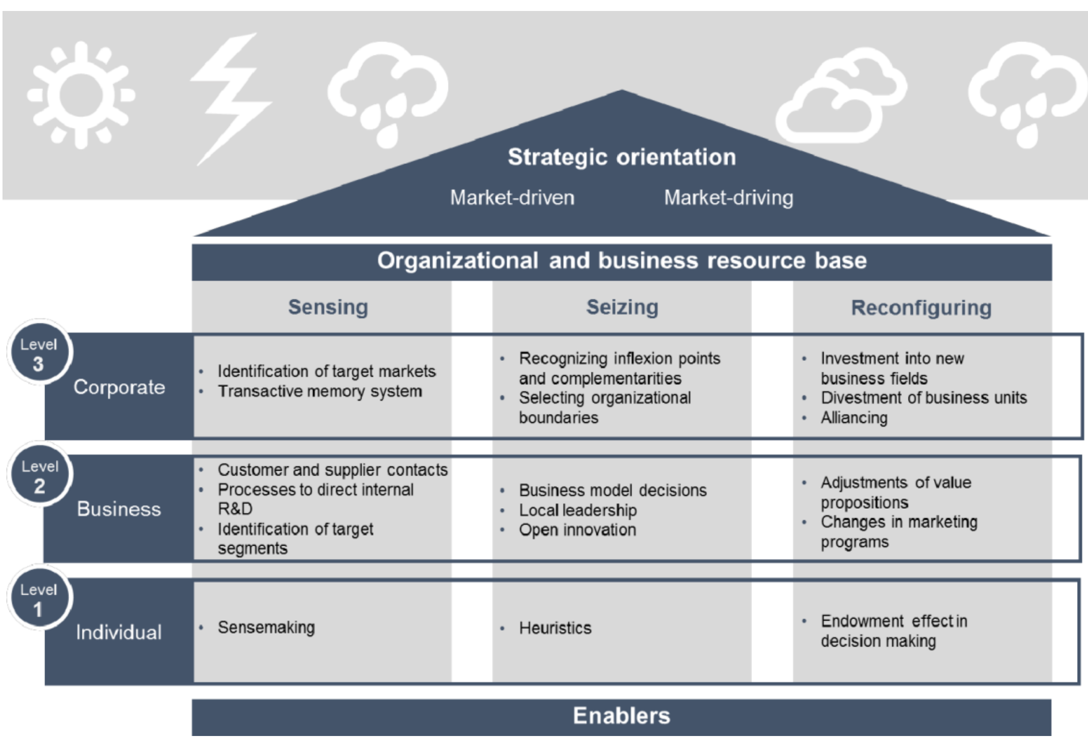
The third factor in Wang and Ahmed's (2007) categorisation is innovative capability, which links firms' innovativeness to marketplace-based advantage. Wang and Ahmed describe it as the ability to develop new products and markets through aligning strategic innovative behaviours and process. Innovative capabilities includes several dimensions, such as: new product and service innovation; methods of production or rendering of services; risk taking by key executives; and seeking unusual and novel solutions (Miller and Friesen 1983). Wang and Ahmed's product-focused approach is more narrowly market-focused than Teece's (2007), which accommodates market-responsive and internal efficiencies in support of competitive advantage.

In short, Wang and Ahmed's (2007) categories are similar to those of Teece, but expand the sensing and reconfiguring components and narrow the seizing element. The change from reconfiguring to absorptive is important, as it indicates the organisational changes required to make use of new information. Wang and Ahmed's innovative capability is ostensibly more focused on product-based responses than Teece's seizing capability. The differences between the models are subtle but distinct, and each may add value to the findings in the empirical elements of this study. Wang and Ahmed's approach to the range of mechanisms, which link internal resource allocation with external marketplace advantage, are reflected in Teece's (2009; 2010; 2014; 2018) later work on dynamic capabilities.

3.5.2.2 The House of Dynamic Capabilities

Another alternative view of the construction of dynamic capabilities is the House of Capabilities concept, proposed by Wilden, Devinney, and Dowling (2016). They suggest that dynamic capabilities are a portfolio of capabilities, none of which can be separated from the whole. An important factor in the portfolio is the relationships among the organisational capabilities and other structural components. The House brings together the elements which contribute to dynamic capabilities theory in a single model, in which the specific and separate attributes have collective meaning.

Figure 3-1 The House of Dynamic Capabilities



Source: Wilden, Devinney, and Dowling (2016: 1031)

Figure 3-1 presents Wilden, Devinney, and Dowling's (2016) House, showing that each element has a role to play in improving the firms competitive positioning, and explaining the relationships between them. The content of the House of Dynamic Capabilities portfolio includes the changes occurring in the external environment, such as the industry the firm is operating in. The chosen organisational strategy, comprising the long-term managerial plans that are put in place to adapt to internal and external changes, are included (Day, Weitz, and Wensley 1990). The portfolio also encompasses the firm's resource base; operating and dynamic capabilities (Eisenhardt and Martin 2000; Zahra, Sapienza, and Davidsson 2006); the levels of analysis - whether stakeholder, managerial or operational - and the enablers of dynamic capabilities such as investment and skills (Wilden, Devinney, and Dowling 2016: 1031).

The holistic House model presented visually in this way is useful in showing the connections between the different aspects of dynamic capabilities that are reflected in extant theory. The model could be particularly valuable in studying a single dynamic capability, because it addresses the wider factors from the capabilities literature. Wilden, Devinney and Dowling's (2016) House introduces the idea that capabilities apply at corporate, business and individual levels. Wilden, Devinney, and Dowling's (2016) House of Dynamic Capabilities offers a useful perspective on the different factors influencing the construction of dynamic capabiliies. These factors are not as clearly or comprehensively defined in other theories. However, the model does not address the microfoundations such as organisational path, processes, routines, culture or leadership, which also contribute to the construction of dynamic capabilities. The microfoundations will be considered in more detail in Section 3.6.

3.5.2.3 Dynamic capabilities: generalisable aligning actions

Like Wilden, Devinney and Dowling (2016), Yeow, Soh and Hansen (2018) also propose a view of dynamic capabilities, which is aligned to Teece's (2007) sensing, seizing and reconfiguring categories. Yeow, Soh and Hansen (2018)'s perspective on dynamic capabilities is informed by paradox theory, which identifies that firms experience paradoxical tensions between their established operating positions, structures, processes and resources, and their planned strategy to respond to the changing environment. The theory notes that it is critical to address these tensions for organisations to survive and thrive (Smith and Lewis 2011). Paradox literature emphasises the contribution of individual and organisational actions and activities in changing the resource base, aligning it to emergent strategy, in order to effect organisational change.

To realign their resources and processes to support changes in strategy, firms need dynamic capabilities (Daniel, Ward and Franken 2014; Yeow, Soh and Hansen 2018). Based on their empirical study in digital strategy, Yeow, Soh and Hansen suggest that these capabilities comprise three core capacities: exploring; building; and extending, which they identify as broadly reflecting Teece's (2007) sensing, transformation and seizing capacities. It is noteworthy that Yeow, Soh and Hansen's study, shows a sequential connection between the capacities which position the transforming/reconfiguring capacity between sensing and seizing; suggesting that seizing is only possible once the firm has reconfigured its resource base.

The sensing, transforming and seizing capacities are used purposefully by firms to adapt to the changing environment, through specific actions which work together to effect change. A cluster of specific organisational actions work in conjunction with one another to effect this change (Eisenhardt and Martin 2000; DiStefano et al 2014). The sensing capacity is divided into the scanning, learning and calibrating actions that are taken by individuals and organisations. The transforming capacity is divided into leveraging, creating, accessing and releasing actions. Seizing is divided into designing, selecting and committing to actions. In comparison to other views of dynamic capabilities, this approach endeavours to identify the actions firms take to modify their resources. The approach is valuable in describing how the dynamic capabilities enable the firm to respond to the changing environment through actions, rather than identifying the elements that change, which tends to be the approach in microfoundations literature (see Section 3.5).

In referring to resources, routines and processes, Yeow, Soh and Hansen's (2018) aligning action approach complements microfoundations theory. However, it is distinct from the microfoundational approach because it emphasises the contribution of individual and organisational actions in aligning the resources with the emergent strategy that is designed to respond to the changing environment.

These alternative models to Teece, Pisano and Shuen's (1997) dynamic capabilities theory and Teece's (2007) conceptualisation, are helpful in confirming the appropriateness of Teece's model as the main influence on this study. Teece's theory focuses on the capabilities firms need to respond to a changing environment, which is the subject of the research question. Teece's theory has become the seminal work on dynamic capabilities with subsequent models often being adaptations of his three categorisation of dynamic capabilities (Wilden, Devinney and Dowling 2016; Yeow, Soh and Hansen 2018). However, features from these subsequent theories may still be valuable in informing the analysis and discussion in this study. Wilden, Devinney and Dowling's (2016) House of Dynamic Capabilities, is of interest because it brings together different influencing factors on capability development, including the importance of the levels of activity. Wang and Ahmed's (2007) three dimensions suggest that the internal adaptation of processes or systems has to take place before the firm can apply its new capabilities to value-creating activities. Yeow, Soh and Hansen (2018) propose a breakdown of the sensing, seizing and reconfiguring capabilities, into clusters of organisational and individual actions, which can adapt resources, processes and structures to respond to the changing environment.

In summary, a review of big data and resource-based literature resulted in the choice of dynamic capabilities theory as the lens for investigating how big data is changing firms' strategic marketing capabilities. The predominant theory in dynamic capabilities literature is that of Teece, Pisano, and Shuen (1997). Other theories have been considered to ensure than an open mind to the literature has been retained, which is a requirement of the chosen Gioia Methodology, as will be discussed in Chapter 4. These other theories have a close relationship to Teece , Pisano, and Shuen's original work and Teece's subsequent research (2007; 2009). Each has aspects that are relevant to this research. The next section will consider Teece's (2007) work in more detail.

3.6 Dynamic capabilities: sensing, seizing and reconfiguring

The elements of sensing, seizing and reconfiguring (Teece 2007) make different contributions to the development of dynamic capabilities. To understand the potential of each, it is useful to provide more detailed explanation of the roles they perform.

3.6.1 The sensing component of dynamic capabilities

Dynamic capabilities theory emerged in recognition of the changes that firms were making in response to sensing turbulence in their operating environments. The sensing capability is a strategic, competitive response capability, which firms use to learn about the characteristics of their environment and related opportunities and threats (Daft, Sormunen, and Parks (1988). The resulting knowledge informs and directs the firm's market orientation and has the potential to change its market dynamics (Zhou and Li 2010).

Sensing is externally-facing, and involves constant environmental scanning for changes in market stability and for development opportunities, methods, and internal and external innovations (Katkalo, Pitelis, and Teece 2010). Sensing includes search and exploration across markets, reflecting the organisation's capability to learn about its customers, its competitors and the broader market environment (Day 1994). The outcome is increased knowledge and understanding of market segments (Slater and Narver 2000), the existing customer base (Morgan, Anderson, and Mittal 2005), and competitors (Teece 2018). It is suggested that firms which sense opportunities with higher added value than their rivals can secure competitive advantage (Peteraf and Barney 2003).

3.6.1.1 Sensing capabilities and environmental turbulence

Firms are operating in increasingly turbulent environments, whether in response to changes in their markets, competitor activity or technological developments (Wilden and Gudergan 2015). These increasingly dynamic environments incorporate destabilising forces such as technical innovation, globalised competition and highly entrepreneurial actions (Schreyogg and Sydow 2010). In a highly turbulent market, firms need to sense what is changing in their environment and reconfigure their marketing and technology capabilities to satisfy the altered customer needs (Jaworski and Kohli 1993). Based on their path, position, existing processes and the nature of the turbulence, firms take different actions to protect and improve their competitive position. According to extant theory, those that possess dynamic capabilities can effectively enhance their competitive advantages, despite facing highly volatile environments (Wu 2010).

Environmental dynamism is a multidimensional construct with dimensions that uniquely influence the importance and ease of firms' balance of efficiency and flexibility (Eisenhardt, Furr, and Bingham 2010). The response to sensing different forms of turbulence, such as the arrival of new competition or technology, requires different forms of firm adaptation.

Over the last thirty years, the technologically turbulent environment has introduced new technological devices, new technology-led business models and also new data sources, as discussed in Chapter 2. Technologically turbulent business circumstances require greater levels of scanning of customer demands, competitor actions and the identification of technological advances which can drive changes in the product and process technologies in the firm (Wilden and Gudergan 2015). The availability of new, technology-based data sources provides an opportunity to secure perfect information about the firm, market and competitor activity, allowing decision-making which secures the greatest value (Blackwell 1953). The technology-enabled, big data resource has the potential to increase economic returns by gathering deeper market insights from the oceans of newly available data (Braganza et al. 2017). Improvements in the technologies that collect and analyse data, reduce the errors and eliminate noise in the information, making it easier to optimise decision-making. Thus, more precise and accurate information from big data, on customers, their expectations, behaviours, preferences, as well as knowledge of competitors' offers and performance, should secure higher performance (Brynjolfsson, Hitt, and Kim 2011). So whilst technological turbulence introduces change into operating environments, the changes also provide new market and development opportunities for the firm.

Environmental turbulence may also be the result of new competitors joining the market. When the business environment is competitively turbulent, the firm is at risk of losing the resource advantages which have been critical to its business operations (Ferrier, Smith, and Grimm 1999; Sirmon et al. 2010).The firm needs to adapt its resources, processes and systems to take advantage of emerging opportunities or deal with threats from competitors. There is a view that competitive turbulence has the most critical impact on firms because failing to sense and reconfigure in response to competitor activities prevents them from achieving parity, let alone advantage (Wilden and Gudergan 2015). However, it is also argued that the goals that are most closely associated with firm survival have greatest priority for the firm, so that managers will give those closest attention (Greve 2008). In which case, a firm will prioritise addressing technological or competitor turbulence, depending on which it views as more threatening.

Greater technological turbulence increases the importance of scanning as a strategic marketing capability, because it improves market knowledge and reduces uncertainty of technological turbulence (Calantone, Garcia, and Droge 2003). Frequent scanning for customer actions, competitor activity and technological advances (Li and Calantone 1998) provides insight, which triggers the reconfiguration of capabilities. This modification of processes, routines and resources, reduces organisational inertia and enables technologies to be exploited efficiently (Levinthal 1991).

Teece's (2009) later research presents the sensing element of the capability as more than scanning the environment. He extends the remit to include the shaping of new opportunities through creation, learning and interpretation activity. This indicates a process of engaging with the new knowledge. Sensing and shaping new opportunities are represented by scanning, creation, learning and interpretation activities (Teece 2009). Some research suggests that firms which direct their sensing capability externally, produce more radical solutions for advantage, than the more incremental solutions of those relying on internal sources (Chiu, Hsu and Wang 2006). Other research emphasises internal efficiency and proposes that internal sensing captures opportunities, which are more likely to be proprietary to the firm, thus resistant to imitation and more likely to achieve sustainable competitive advantage (Peteraf and Barney 2003).

In summary, firms that are operating in turbulent technological environments need to apply sensing capabilities if they are to ensure their evolutionary fitness (Calantone, Garcia, and Droge 2003). In the first instance, scanning the environs identifies technological advances, such as the availability of big data. More in-depth sensing activity exposes the data characteristics, the range of possible sources and their potential for the firm. As well as sensing the technological developments, the scanning process highlights how big data is being used by competitors, both digitally-born and established. These may be market-driven in the same market segments, threatening the existing business or marketing strategy, or stimulating market-driven change. Alternatively, they may be in different segments or industries, prompting the firm to innovate, using big data for market-driving activity.

3.6.2 The seizing component of dynamic capabilities

The second category of dynamic capabilities, as proposed by Teece (2007), is seizing. Seizing, refers to how the firm acts on the information received from the sensing activities, to capture value from new market opportunities.

Different studies emphasise different outcomes of the seizing process which may be internally or externally focused. Big data can enhance firms' visions of their opportunities and markets by providing more detailed information (McAfee and Brynjolfsson 2013). This knowledge allows the organisation to modify its asset base to respond more effectively to its customers. These modifications may include internally-focused, data-led changes such as improved process efficiency, new practices and alliances. They may also stimulate the upgrading and reconstructing of core capabilities (Lin, Wu, and Lin 2008), because of the differences in big data characteristics and of a data-driven approach to strategic marketing. Examples of seizing capabilities in extant literature include: alliancing (Eisenhardt and Martin 2000; Gassmann and Enkel 2004); mergers and acquisitions (Teece 2007); networking; knowledge brokering (Easterby-Smith et al. 2009); marketing (Bruni and Verona 2009); and knowledge transfer to exploit knowledge outside the organisation (Eisenhardt and Martin 2000; Teece 2007). If a new technological opportunity is sensed, such as the availability of big data, it may be assimilated through technology-driven changes such as digital delivery, the adoption of data-driven decision-making, and new product development. These types of radical change nearly always require stakeholder buy-in and investment in development and commercialisation activity (Teece 2018).

Seizing new opportunities may also involve customer-focused outcomes, such as the commercialisation of ideas and processes to generate new products and services (Adler and Shenhar 1990). It might include innovation (Easterby-Smith et al. 2009) through, for instance, digital new product development or enhancement. Another more radical approach is to seize new opportunities through new business model development. One option is to emulate competitors' models, although extreme business models transitions, such as those involving adopting new technologies in an existing business, are unlikely to succeed without major financial investment (Teece 2018). Models that can be comfortably aligned to the existing business are both easier to implement and can still add value. The firm may also adopt a complementary, strategic business model to seize a new customer base. A firm with a big data resource may choose to commercialise the data or the data system. There are legislative constraints to selling personal customer data, but firms may commercialise their data analysis or visualisation systems. Alternatively, other proprietary data sources, such as Internet of Things (IoT) sensor data, create a "new kind of intellectual capital that can be sold or used as the basis for either internal innovation or an external collaboration" (Teece 2018: 45). The process of delivering data-led, customer-focused change may involve the firm in restructuring its core organisational principles (Girod and Whittington 2017). Aligning the business to the new strategy may require the organisation to add, split, transfer, merge or delete established business activities, in order to transform (Karim 2006). The data-led organisational transformation of business models, strategy, processes, product development or decision-making are relevant to both established and digitally-born firms (Cheah and Wang 2017), and play an important role in seizing new market opportunities.

Seizing these new opportunities, at pace, in order to respond swiftly and appropriately to the changing environment, has challenges. These include shortage of expertise and skillsets (Ready and Conger 2007), and the new opportunities are financially resource-intensive (Teece 2018). As a result, the outcomes of the seizing process may need to be performed outside the firm's main business through subsidiary organisations, partnerships or suppliers (Rice et al. 2001). Cooper et al. (1997) observed that activities that could be competitively provided by external providers, without loss of knowledge to the firm, should generally be outsourced, provided that there was sufficient in-house resource to effectively manage the contractual relationship. The co-ordination of these new relationships might in themselves require reconfiguration of dynamic or operational capabilities.

As discussed in Section 2.2, there is a close alignment between a firm's strategic marketing activity, and the direction and scope of the organisation in the long-term. As such, an important consideration in relation to seizing opportunities is alignment to other organisational elements. The chosen approach must be internally coherent (Ritter 2014), and aligned with the internal structure and overall management approach of the company (Birkinshaw and Ansari 2015). Furthermore, where seizing opportunities involve changes to the business model, the altered business model must be aligned to the firm's strategy (Rumelt 2011). So a strategic marketing choice for the firm to become data-driven, cannot be made in isolation, but involves coherent decision-making across the organisation.

3.6.3 The reconfiguring component of dynamic capabilities

Teece's (2007) third category of dynamic capabilities, is reconfiguration. Reconfiguration is the responsive capability which enables firms to renew and modify their assets to maintain competitiveness, as markets and technologies change, over time (Katkalo, Pitelis, and Teece 2010). The activities involve "asset realignment, co-alignment, realignment and redeployment", to minimise internal conflict and maximise the resource exchanges within the organisation (Teece 2007: 1336). Following subsequent work by Teece and others (Augier and Teece 2014; Teece 2018), Teece's three categories have come to be known as 'sensing, seizing and transforming'. In Teece's 2018 work he includes a model which describes transformation as the realignment of structure and culture through "existing capabilities" and "investing in additional capabilities". For this study, the earlier term 'reconfiguring' has been adopted, as it describes the reconfiguration activities with reference to the firms' resource base, and in a level of detail that is useful to support the research.

3.6.3.1 Position, paths and processes

Established firms have a defined market position. Whether firms can seize the new market opportunities resulting from the changing environment, depends on the assets they hold, including their intellectual property, technology, customer base and reputation (Teece 2007). Firms have to choose which of their internal and external competencies are most likely to support their products and services, and invest in the competencies which are critical to delivering their strategy (Dierickx and Cool 1989). The firm can develop in particular directions, depending on its resource position and what it views as the possible paths ahead. The choice of development paths is limited by those chosen previously by the firm, their available assets, as well as the potential returns from the chosen path. A further consideration is the managerial and organisational processes, which are the routines, patterns of learning and practice the firm uses to carry out its business (Teece, Pisano, and Shuen 1997).

The firm is both enabled and constrained in developing dynamic capabilities by its position, the potential paths it can move in and its internal processes (Teece, Pisano, and Shuen 1997). If an organisation is evolutionarily fit, then it will be market-orientated and responsive to the environmental changes, such as technological and competitive turbulence and the potential of its resources. The established firm's position, processes and planned paths may inhibit its speed of uptake of a different resource and the required capabilities because of previous commitments of investment or infrastructure, custom and practice, and employee resistance to change. The gap in what the firm is doing and wants to do in using the new resource as part of its asset base, is highlighted in its capability gaps.

Turbulent operating environments may change the competitors in the market place, introducing new players with new business models and business processes. Unlike established firms, when confronted with new resources, new firms are unhindered by an existing position, paths and processes, and can be more imaginative in their solution-making (Braganza et al. 2017). The new style competition is evident in the big data-driven, disruptive business models of new start-ups such as Uber and AirBnB, whose businesses originate with new technologies and use an entirely different market system than existed previously. Existing firms need to respond from an established operational position, so are constrained by existing operational capabilities. Changing their capabilities requires a revised vision and strategy for the firm, the defining of a revised trajectory and operational plans (Inan and Bitici 2015), as well as the discarding of original paths and established processes.

To select which elements of sensed opportunities and threats, and which resources may provide competitive advantage, requires entrepreneurial vision and intuition (Conner 1991). In stable environments, the seizing capability may be viewed as a co-ordination activity involving the firm in defining organisational strategy, and in establishing infrastructures and procedures to absorb and integrate resources, in order to create and capture value from opportunities (Katkalo, Pitelis, and Teece; Pisano, Di Stefano, and Verona 2013). It also involves capabilities relating to adaptation of the resource base, including resource imitation or replication (Zott 2003) and reconfiguration (Ambrosini, Bowman, and Collier 2009).

In volatile or technologically turbulent environments, capability gaps emerge when there is a disparity between the actual configurations of a firm's operating capabilities and the value maximising configuration. As a result, firms need to develop novel capability configurations to bridge the capability gap (Wilden and Gudergan 2015).

3.6.3.2 Capability gaps

In a stable business environment, the firm's capability to adapt and maximise value requires only small changes. In fast-paced, unpredictable turbulent environments, there is a risk of obsolescence of operational capabilities (D'Aveni 1994). The capability gap to maximising value can be dramatic, and firms' ability to close the gap by sensing the threats and opportunities and reconfiguring, is vital (Lavie 2006). This process requires them to "engage in market-based learning and use the resulting insight to reconfigure the firm's resources and enhance its capabilities, in ways that reflect the firm's market environment" (Morgan 2012: 108). Chapter 2 (see Section 2.7.1) indicated how this capability gap may arise in strategic marketing in relation to big data, which will be further explained within this section.

High velocity markets are non-linear and involve unpredictable change, so existing knowledge is less relevant and the challenge is to develop new knowledge and innovate quickly, abandoning ineffectual ideas (Eisenhardt and Martin 2000). Two difficulties arise from the new developments. Firstly, the new capability configurations are fundamentally unstable and experiential processes with unpredictable outcomes (Pisano, Di Stefano, and Verona 2013). Secondly, established firms have developed rewarding capabilities to achieve and exploit their existing competitive position (Leonard- Barton 1992; Teece 2007). In the face of environmental turbulence, they can struggle to adapt to fill the gaps because of their emphasis on exploitation, rather than exploration. As a result, existing capabilities become liabilities (Leonard-Barton 1992; Day 2011), which constrains the potential to maximise value and limits firm growth.

A critical success factor of the reconfiguring and transforming capability is in supporting organisational flexibility. Teece (2007) argues that flexibility allows firms to move quickly to take advantage of new opportunities, to see which resource configuration emerges as dominant, and change in response to competitors' innovations. There is a tension between flexibility and efficiency. On one hand, organisations need to be flexible to adjust fluidly to unanticipated situations. On the other, organisations need to be efficient to gain traction, create direction and avoid mistakes. High performance in dynamic environments relies on leaders resolving the tensions of flexibility and efficiency for their organisations (Brown and Eisenhardt 1997; Tushman and O'Reilly 1996), and overcoming the organisational rigidities.

Studies have highlighted a variety of higher order capabilities which are pertinent to the assimilation of big data for strategic marketing. These include internally-orientated capabilities such as knowledge creation (Braganza et al. 2017); knowledge development/learning (Teece, Pisano, and Shuen 1997); decision-making; Research and Development (Easterby-Smith et al. 2009); and responsive team building with expert input.

In response to the availability of the big data resource, firms can act on new information to select the opportunities and threats that will secure or undermine their differential advantage. Extant literature highlights three considerations in making these selections: Board and stakeholder vision; the allocation of human resources; and securing value from the data. Engaging with big data requires entrepreneurial vision by the Board and stakeholders, to respond through changing strategy and investment in new resources (Xu, Frankwick, and Ramirez 2016). To give an example, the arrival of a new data-driven competitor in the Fast Moving Consumer Goods (FMCG) market, such as Alibaba[1], may drive incumbent firms to exploit their established data resources, to improve business efficiency,

[1] Alibaba, also known as Alibaba Group Holding Limited, is a Chinese multinational technology company, founded in 1999, specializing in e-commerce, retail, Internet, and technology.

and to improve customer responsiveness. Alternatively, these circumstances may lead to more innovative, exploratory actions, such as new product development. Balancing the ambidexterity (Duncan 1976) of the organisation between these divergent approaches is critical in effectively directing resource allocation within the firm.

Another consideration within the reconfiguring capabilities, is the appropriate allocation of human resources. A firm's decision to engage with the new data resource may cause capability gaps, such as lack of skills and expertise to select, process and secure insight from the data. Given global engagement with new technologies, there are worldwide skills shortages in some big data-related roles, such as data scientists (McAfee and Brynjolfsson 2012). Where recruitment of skills is constrained, firms may need to establish new alliances and partnerships to address the skills deficit.

A third factor in the impact of big data on firms' reconfiguring capabilities is the importance of securing value from the data. In Barney's (1991) theory of VRIO resources being advantage creating, he notes that if resources are not creating value, then they are not a source of advantage. Extant management and information systems literature emphasises the role of big data analytics (BDA) in enabling firms to draw value from data. BDA is the technical process of extracting insight from data (Wixom et al. 2011), but this is only part of the wider reconfiguring capability. The broader capability involves connecting the data, in the form of business intelligence, to the firm's business strategy (Sivarajah et al. 2017). The reconfiguring capabilities allow big data to be absorbed into the firm, facilitating big data-led organisational transformations.

In summary, reconfiguration capabilities have an important role to play in helping established firms overcome organisational rigidities, and respond to environmental changes. Reconfiguring capabilities involve the orchestration of other capabilities and resources. Extant research has identified higher order capabilities such as knowledge creation, and research and development, which are relevant to firms' strategic marketing competences. For big data to add value in strategic marketing, firms are likely to need dynamic capabilities which include Board and stakeholder visions, the allocation of human resources and an emphasis on securing value from the data.

3.6.4 Securing value from dynamic capabilities

Competitive advantage was discussed in Section 3.3, in relation to the resource-based view of the firm and the development of dynamic capabilities. There is some dispute as to whether dynamic capabilities are, in themselves, able to offer competitive advantage. Barney's (1991) early work suggested that VRIO resources are advantage-creating resources which provide an opportunity for sustained competitive advantage. However, Teece, Pisano, and Shuen (1997) propose that organisational competitiveness relies on dynamic capabilities to orchestrate the resources through co-ordination, integration, learning and reconfiguration.

Eisenhardt and Martin's (2000) later work implies that dynamic capabilities cannot be the source of sustained competitive advantage, because the gaining, integration, release and reconfiguration of resources, makes them rare and valuable but not inimitable. Both propositions have been overtaken by the turbulence-responsive shift, towards short-term solutions and evolutionary fitness (Helfat et al. 2007), which suggest that firms are looking for dynamic capabilities to offer temporary, rather than sustainable solutions.

There is, however, evidence in more recent studies that the frequent reconfiguration of capabilities, to respond to sensing, seizing and reconfiguring opportunities, increases the likelihood of the firm securing sustainable competitive advantage (Braganza et al. 2017; Pisano, Di Stefano, and Verona 2013). The three different elements of dynamic capabilities, proposed by Teece (2007), make distinct contributions to improving the evolutionary fitness and competitive positioning of the firm.

One view is that seizing and reconfiguring have the greatest value to the firm. Firstly, because the combination makes it difficult for firms to imitate the same outcomes (Helfat and Winter 2007). However, they are challenging to deliver, because they rely on the firm overcoming the constraints of its established position, paths and processes and of their absorptive capacity (Cohen and Levinthal 1990). To avoid inertia, firms have to overcome organisational rigidities, and the lag between information and action. Organisational rigidities can include path dependency where the firm's successful experience of a capability limits their path choices to what has succeeded previously (Liebowitz and Margolis 1994). Another rigidity, the complacency that arises from focusing on mastering one capability, can inhibit the firm's awareness of the opportunities for dynamic and higher order capability development (March 1991).

Droge, Calantone, and Harmancioglu (2008) suggest that sensing and seizing are more important components because they reflect the organisations' externally focused activities. Makadok (2001) concurs, suggesting that sensing and seizing capabilities enable the firm to take advantage of opportunities and deal with threats when facing strong competition.

Other studies suggest that the more that firms engage in sensing and reconfiguring, the more dynamic capabilities improve and are embedded in organisational memory (George 2005; Braganza et al. 2017; Cohen and Levinthal 1990). Furthermore, that organisational improvement, through learning from repeated trials, results in self-reinforced use of dynamic capabilities and decreases variability and instability in outcomes (Zollo and Winter 2002). By constantly realigning assets and processes, firms' enhance their reconfiguration capabilities, enabling them to become more adaptive to their changing environment (Chui et al. 2006).

A final view, reflects Eisenhardt and Martin's (2000) proposal of equifinality, which states that a different model will be delivered by each firm. Even when the dynamic capabilities are ostensibly homogeneous, the firm-specific decisions and investments affecting costs and timings, lead to variation in transforming capability and performance difference between firms (Pisano, Di Stefano, and Verona 2013; Schilke et al. 2018). Equifinality suggests that companies will compete using different configurations, some of which will be more effective than others. The different sets of viable configurations explain the heterogeneity in performance, with each configuration being unique to that environment and that firm.

The literature review undertaken in this research has identified no evidence that any particular configuration of sensing, seizing and reconfiguring capabilities associated with big data, offers an increased likelihood of securing competitive advantage. However, this literature review highlights that the sensing capability is critical for firms to identify the availability of the new resource and its potential for firms. The seizing capability has an important role to play within big data dynamic capabilities, enabling firms to improve their competitive positioning, by taking actions that deliver their business strategy. Consideration of the reconfiguring capabilities identifies several areas where big data can have an impact. These include: strategic decision-making on exploration or exploitation; addressing capability gaps; and extracting value, as well as insight, from processing data in relation to business strategy. The reconfiguring capability also appears to play an important role in overcoming organisational rigidities and enabling firms to behave more flexibly.

In summary, Teece, Pisano, and Shuen's (1997) seminal dynamic capabilities theory is relevant in the technologically turbulent environment that has generated the big data resource, which offers the potential for differential advantage. Teece (2007) conceptualised dynamic capabilities in three categories: sensing, seizing and reconfiguring. The original focus on sensing as a market scanning activity has subsequently been adapted to include shaping of new competitive opportunities, which may support exploration or exploitation activities (Teece 2009). These sensing activities are vital if established firms are to improve their big data-led market intelligence and take advantage of data-driven opportunities. Organisations renew their assets and direct their market and competitive positioning, by seizing opportunities to change strategic direction through data-led decision-making, changes in business model and the commercialisation of ideas, processes, data or data-related systems. Reconfiguring capabilities involves the assimilation and integration of resources to capture value from new resources, which may include co-ordinating activities, such as redefining strategy and revising processes. In volatile environments, these reconfigured capabilities may make organisations more flexible and market responsive.

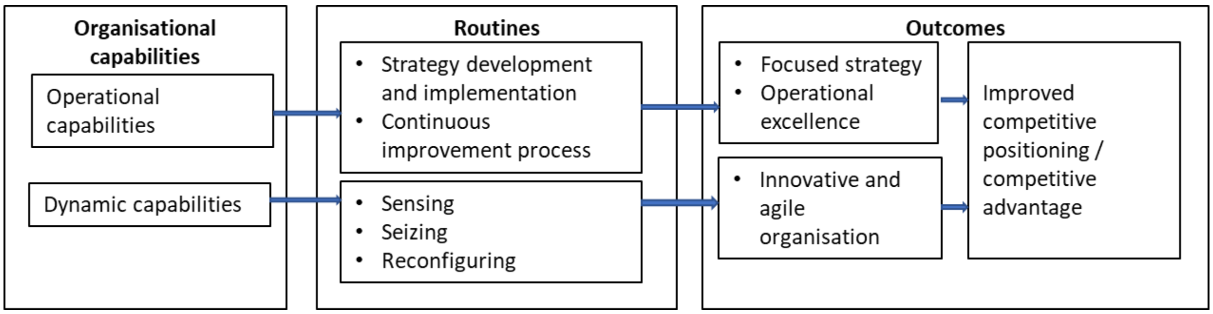
A viewpoint has emerged from the empirical, dynamic capabilities studies that there is more significance to the order of the sensing, seizing and reconfiguring categories than is apparent in Teece's (2007) model. Two empirical studies, Wang and Ahmed (2007) and Yeow, Soh and Hansen (2018) propose that the categories are part of an internal process. In the process, the reconfiguration of the organisation's routines and systems is central to the model, and has to take place before customer-responsive, value-added activities can occur. This viewpoint is valuable because it indicates a difference between Teece's conceptual model and the application of dynamic capabilities in practice, which may be relevant to this study.

Each firm will use its dynamic capabilities with equifinality, achieving a different outcome from its competitors, based on its market position, previous paths and processes. Despite differing views in the literature, there is extensive support for the notion that sensing, seizing and reconfiguring capabilities contribute to firms' short-term competitive advantage. For this reason, Teece's (2007) theory is the base theoretical framework being used in this research. The next section considers whether alternative views of dynamic capabilities can provide additional insights to the research process.

Chapter 2 highlighted the dramatic technological innovations which firms have experienced since the 1980s. Baesens et al (2014: 629) described the impact of these new technologies and the resulting data as the "motherlode of disruptive change". The technologies allow the datafication of virtually any information, with implications for data storage and management, analysis and visualisation. Big data can endow organisations with the potential for competitive survival or advantage, subject to them having the capabilities to handle the new big data resource (Wilden, Devinney, and Dowling 2016). The decision to engage with big data effects change across all the related organisational capabilities. Using an example from Table 3-1, the addition of a new intangible, intellectual resource at the zero capabilities level (Wang and Ahmed 2007) will necessitate changes in the subsequent higher order capabilities. As the new resource is novel, the capabilities required to engage directly with it are novel, so the operational methods, roles and routines which applied prior to big data will be changed. This highlights the critical contribution of dynamic capabilities in relation to the new ‘digital oil’ (Yi et al. 2014).

Organisational capabilities can be divided into at least two categories, operational and dynamic, which contribute differently to the firms’ operations and competitive outcomes.

Table 3-2 The journey from capabilities to improved competitive positioning



(Source: adapted from Inan and Bitici 2015: 315)

Operational capabilities deliver the routine allocation of resources within the day-to-day business, aiming at continuous improvement in business effectiveness and efficiency. The dynamic capabilities comprise the sensing, seizing and reconfiguring activities which enable the organisation to respond innovatively and flexibly to data-led market intelligence. The combination of operational and dynamic capabilities allows the organisation to manage its existing market positioning and simultaneously to seek competitive advantage, through improved evolutionary fitness. Table 3-2 provides a visual summary of the link between capabilities, organisational routines and outcomes.

There is a growing recognition that further advancement in clarifying dynamic capabilities will come from a more micro understanding of the formation and transformation of capabilities. These capability microfoundations will be discussed in the next section.

3.7 Microfoundations of dynamic capabilities

Dynamic capabilities represent a macro perspective on how firms reconfigure their resources. A criticism of dynamic capabilities literature has been a poor understanding of the detail of the capabilities and how they are constructed. Dynamic capabilities theory has directed attention to the processes of future resource-creation in line with changes in the environment (Bowman and Ambrosini 2003; Teece, Pisano, and Shuen 1997). There is little understanding of the mechanisms determining the origin and evolution of dynamic capabilities (Abell et al. 2008; Eisenhardt, Furr and Bingham 2010; Fallon-Byrne and Harney 2017; Felin and Foss 2009). As a result, a fundamental question remains in precisely "how the enterprise can keep renewing its resource base and create new capabilities" (Al-Aali and Teece 2014: 103).

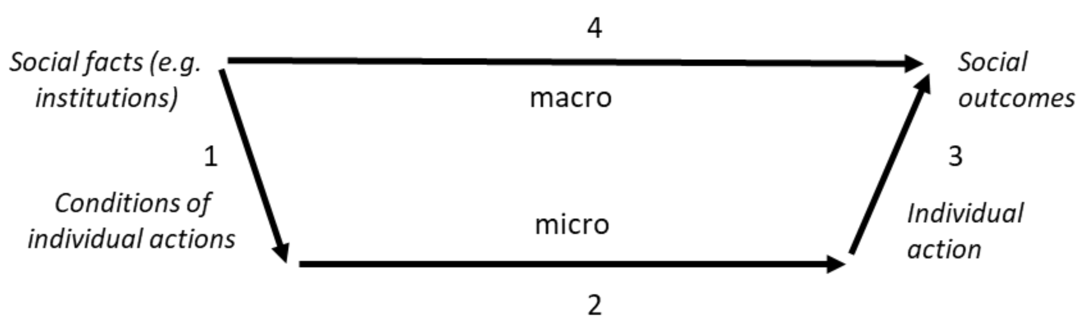
Teece (2007) describes dynamic capabilities as being "undergirded by microfoundations that are composed of distinct skills, processes, and organizational activities". This section addresses the origins of the microfoundations movement in dynamic capabilities literature. It explains their role and their importance in strategic management. Felin and Foss (2015: 601) observe that dynamic capabilities literature tends to focus on the macro level issues at "the strategic business unit, firm, market, industry cluster, or competitive group levels. While they differ in their specific fields, they all share a common focus on outcomes at the level above the individual". By focusing at this level, the detail of the mechanisms which can deliver competitive advantage are not apparent. Where dynamic capabilities describe organisational-level actions and outcomes, the micro foundations movement aims to deconstruct capabilities into contributions at an individual level (Abell, Felin, and Foss 2008; Felin, Foss, and Ployhart 2015; Kleinbaum and Stuart 2014; Wilden, Devinney, and Dowling 2016). Understanding the deconstruction of capabilities may assist in the construction of new capabilities, such as those needed to use big data for strategic marketing purposes.

In the next section the elements of microfoundations are presented, highlighting the importance of the individual and therefore human behaviour and motivation, in dynamic capabilities. The section ends by considering whether viewing dynamic capabilities at a macrolevel is sufficient, for firms needing to develop or design new capabilities, to respond to changes in their market and changes in their resource base.

3.7.1 Understanding microfoundations

There is a growing recognition that further advancement in explicating dynamic capabilities and the heterogeneity of competitive positioning (Felin, Foss, and Ployhart 2015) will come from more micro understanding of the formation and transformation of capabilities (Barney and Felin 2013; Wei and Lau 2010). Microfoundations explain the origin and development of dynamic capabilities, that is “the underlying individual-level and group actions that shape strategy, organisations and more broadly dynamic capabilities” (Eisenhardt, Furr, and Bingham 2010: 1263). Microfoundations theory builds on Coleman’s (1990) social science work, explaining the relationship between macro social elements and outcomes, and individual contributions to achieving those outcomes. This is explained in Coleman’s model, otherwise known as Coleman’s Bathtub (Figure 3-2).

Figure 3-2 Coleman’s Bathtub
A general model of social science explanation by Coleman (1990)



(Source: Abell, Felin, and Foss 2008: 491)

The logic of microfoundations exposes the limitations of an exclusive, macro higher order focus within dynamic capabilities theory, and instead invokes that “individuals and their interactions are central for understanding organisations and social systems" (Barney and Felin 2013: 145).

To understand how a collective phenomenon at the organisational level, such as sustainability or digitisation, is achieved, requires an understanding of "the constituent parts that make it up: individuals and their social interaction" (Barney and Felin 2013: 139). This requires analysis which looks "inwards and downwards" (Ployhart and Hale 2014: 152). A microfoundational approach is not solely about individuals but also requires consideration of how these components are aggregated (Barney and Felin 2013). Microfoundations refer to individuals, processes and interactions, as well as structures that influence the development and enactment of a capability (Felin et al. 2012).

Strategic marketing mandates managers to gain and sustain competitive advantage (West, Ford and Ibrahim 2015). This cannot be accomplished if managers do not understand the mechanisms which deliver this, which supports the argument for a better understanding of micro-foundations of dynamic capabilities. Routines and capabilities are often used as a useful shorthand for the complicated patterns of individual action and interaction (Teece, Pisano, and Shuen 1997; Eisenhardt and Martin 2000), but there are no mechanisms that work solely on the macro-level, directly connecting routines and capabilities to firm level outcomes. They are ultimately, best understood at the microlevel (Abell, Felin, and Foss 2008).

3.7.2 Microfoundation elements

In research such as Teece, Pisano, and Shuen (1997) and Eisenhardt and Martin (2000), it is asserted that routines and capabilities cause firm level outcomes, for example, innovation and boundaries of the firm. However, there is little explanation of the origins of routines and capabilities, and of how they are related to firm outcomes, which means that a crucial explanatory mechanism for dynamic capabilities is under-developed. The microfoundation movement questions the emphasis placed on routines and capabilities as key constructs in much of strategic management research (Abell, Felin, and Foss 2008). They also challenge the central argument that routines and capabilities are fundamental units of analysis, with organisations acting as repositories of routines and capabilities (Nelson and Winter 1982; Kogut and Zander 1992).

Microfoundations theory proposes that while routines minimise human agency, dynamic capabilities are founded on the concept of human agency, as a means of transforming existing routines and even disrupting order and stability (Katkalo, Pitelis, and Teece 2010). The literature suggests that as well as considering operational constructs for building dynamic capabilities, such as resources, routines and competences (Teece, Pisano, and Shuen 1997), firms need to consider individual and organisational constructs. At an individual level these include human resource-related activities including employee competences, individual agency, motivations, behaviours, rules and guidelines, decision-making and co-ordination of teams of individuals. Building dynamic capabilities also needs to recognise organisational-level constructs which direct employee actions, such as: the firm’s culture; position; leadership (Strauss, Lepoutre, and Wood 2016); path dependencies (Barney and Felin 2013; Barreto 2010); processes; employee obligations, expectation and behaviour (Strauss, Lepoutre, and Wood 2016); learning (Barney and Felin 2013; Barreto 2010); and organisation structures (Strauss, Lepoutre, and Wood 2016). Although these theories present a piecemeal approach to the microfoundations of dynamic capabilities, they highlight the human resource orientation of the construction of capabilities.

Strauss, Lepoutre, and Wood (2016) highlight the importance of organisational processes and practices such as organisation structures, leadership, and employee behaviour as dynamic capability microfoundations. The contribution of individual managers and employees in the construction and delivery of dynamic capabilities is an area of increasing interest in dynamic capabilities literature (Schilke, Hu and Helfat 2018; Vial 2019; Yeow, Soh and Hansen 2018). It is through individual and organisational actions that the firm’s resource base can be aligned to deliver new strategies that respond to changes in the external environment.

Organisation structures provide important, structural microfoundations for co-ordination and communication, across and beyond business functions. In highly dynamic contexts, intensive communication capabilities are required within and across functions, as well as with customers, suppliers and competitors. Cross functional interfaces, such as temporary ad hoc teams, are particularly important for dynamic capabilities, as they provide platforms for generation and reorganisation of knowledge resources (Jansen, Vera, and Crossan 2009) and knowledge exchange (Eisenhardt and Martin 2000). These types of ad hoc teams will play an important role in the inter-functional activity required to garner value from big data. Literature on cross-functional teams suggests that the empowerment of a team and the engagement of individual contributions of knowledge and understanding, are strong predictors of success in managing change (Majchrzak, More, and Faraj 2012; McDonough 2000). They help build a strong innovative dynamic characterised by innovation and affective behaviours, such as knowledge sharing, co-working and committing (Takeuchi et al. 2009), which support the firms' capabilities.

Leadership plays an important role in directing the actions of individuals and team-level activities. In the first instance, senior managers are aware and responsive to the firm operating in multiple environmental realities (Eisenhardt, Furr, and Bingham 2010).They use higher order thinking and expertise abstraction to direct firm-related decision-making choices on flexibility over efficiency (Eisenhardt and Martin 2010). Managers do this, to some degree, in defining business strategies but also in heuristic-based plans, which provide practical, short-term problem-solving techniques. While these short-term solutions do not necessarily provide optimal solutions, they offer flexibility in decision-making in response to the changing external environment (Eisenhardt, Furr, and Bingham 2010).

Employee behaviours are factors in developing capabilities, but they may impede rather than progress development. At the individual level, employees are highly constrained by social structures, goals, resources, obligations and expectations, and the implications of these are not well understood (Eisenhardt, Furr, and Bingham 2010). There is a view that employees' habitual routines provide a strong anchor for delivering consistent and efficient outcomes, leading them to resist and abandon creative actions in favour of predictable routines. These habits make reconfiguring resources towards more innovative approaches a more difficult task (Cavagnou 2011). To overcome this resistance, firms may choose to reframe a large problem into smaller, less controversial problems and secure smaller wins. This approach allows the organisation to take quick and tangible steps to generate new knowledge, acting “like miniature experiments that test implicit theories about resistance and opportunities and uncover both resources and barriers that were invisible before the situation was stirred up” (Weick 1984: 44). In this way, leaders and employees “can identify a series of controllable opportunities of modest size that produce visible results and that can be gathered into synoptic solutions” (Weick 1984: 40). In spite of this work, there remains a considerable gap in understanding the significance of employee innovative behaviours (Montage et al. 2012; Schilke, Hu and Helfat 2018).

Microfoundation level solutions provide more stable solutions than dynamic capabilities at the macro-level, for a number of reasons. Firstly, there is a view that capabilities cannot be bought, rather they have to be built up (Teece, Pisano, and Shuen 1997). Where the organisation has control over the capability building process, it may result in better strategic value and organisational performance (Wang and Hajli 2017). Secondly, the organisation’s behaviour is the result of actions of individual parts, combined to produce systematic behaviours. As a result, knowledge of individual actions may be expected to have greater predictability than the macro overview of the firm. Microfoundations are therefore an important part of strategic management as a prescriptive enterprise. Coleman (1990) argues that explanations of social activities that involve the micro level have properties of being more stable, fundamental and generally applicable, than macro level explanations.

In summary, for firms to develop responses to changing market conditions requires a detailed understanding of the capabilities needed. A view of dynamic capabilities at a macro level does not provide this detail. The macro level view highlights operational constructs such as resources and routines as the cornerstone of dynamic capabilities. The microfoundational approach challenges this view, emphasising the importance of the individual and organisation-level constructs which direct individual actions. The micro level approach may be supplemented by knowledge of capabilities at the meso group, team or department level. The big data literature (see Chapter 2) suggests multifunctional involvement with big data, which may make the mesofoundations concept relevant to this study.

3.7.3 The mesofoundations of dynamic capabilities

This section proposes that whilst Coleman's bathtub highlights macro and micro level constructs, much of organisational activity takes place at a group, department or team level. There is a lack of existing theory at this level.

Much existing empirical research has focused on investigating dynamic capabilities at the business unit or corporate level of single-business firms (Drnevich and Kriauciunas 2011; Protogerou, Caloghirou, and Lioukas 2012). The logic of microfoundations addresses the key questions that lie at the interface of individuals and organisations, with a particular focus on relationships and interactions (Ployhart and Hale 2013). A source of confusion in the literature is the level at which dynamic capabilities reside. Wilden, Devinney, and Dowling (2016: 1027) propose that these capabilities span "individuals, groups, business units, organisation and alliances and that much of the definitional confusions arises from a failure to account for the interactions across levels and between contexts". This differs from the main thrust of dynamic capabilities theory, which is positioned at the higher macro level of the business unit, company and market.

To understand the aggregation and integration of the micro and macro levels, multiple levels of analysis must be considered, including market, business and individual levels (Ployhart and Hale 2014). A microfoundations approach makes it possible to move beyond single levels of analysis to explore how theories at different levels relate to each other (Devinney 2013). The different levels of analysis impact one another and "research that focuses on only one level of analysis explicitly assumes that the chosen level of analysis is independent of other levels of organisations' activity" (Wilden, Devinney, and Dowling 2016: 1027).

An interesting observation of microfoundations theory is that it distinguishes between macro level activity, at the market, corporate and business unit positions, and micro-level activity operating at individual level. Many of the qualities raised in relation to the extant research are neither corporate nor individual but instead sit at a group, team or departmental level. References to group level contributions to dynamic capabilities are made in Eisenhardt and Martin's (2000) description of microfoundations, but are not broadly used within the wider literature. The main body of work influenced by Felin (Abell, Felin, and Foss 2008; Barney and Felin 2013; Felin, Foss, and Ployhart 2015) emphasises the role of the individual, such as the employee.

Currently, the interaction between micro and macro levels are poorly described and under researched (Fallon-Byrne and Harney 2017), which highlights a weakness in microfoundations research. This suggests that the dynamic capabilities and microfoundation literatures are missing a meso-level of analysis, at the group, team or departmental levels. The notion of a mesofoundational level of analysis (Nonaka, Hirose, and Takeda 2016) has been proposed in previous dynamic capabilities literature, but is not widely observed or adopted. In the absence of an extensive mesofoundation literature, for the purpose of this study, Eisenhardt and Martins' definition is espoused, and microfoundations are taken to encompass both individual and group-level activity.

Big data is a novel phenomenon and empirical studies on its application in management and marketing are limited (Barrales-Molina Bustinza, and Gutierrez-Guttierez 2014; Wamba et al. 2015). At this point, the microfoundations of the dynamic capabilities related to big data in these domains are not clear. This theoretical constraint makes it difficult for managers to emulate the experience of others in the use of big data for competitive advantage. Abell, Felin, and Foss (2008) observe that when firms understand the capability building process, then it is easier to comprehend the nature of the dynamic capabilities required to improve competitive positioning. Whilst neither big data nor dynamic capabilities literature talk explicitly of the microfoundations of dynamic capabilities, they do identify elements of importance. These include the leadership role of the Board and stakeholders in changing strategy and investing in data-related resources; the aggregated competences, capabilities and behaviours of employees; organisation structures, rules and guidelines; and the established routines of incumbent firms.

In summary, micro foundations research has added an extra dimension to dynamic capabilities literature, by highlighting the importance of the individual in delivering evolutionary fitness and competitive advantage. The microfoundations literature suggests that dynamic capabilities are fundamentally about human agency, and the decisions of organisation leaders and employees in the reconfiguration of resources. This perspective challenges the predominant view in dynamic capabilities theory that resources and capabilities are the key construct in strategic management. Although the research suggests that microfoundations offer a more useful approach to understanding dynamic capabilities, the studies are relatively new and still piecemeal. The inter-relationship between the micro and macro levels, at the team and department meso levels may provide further explanation.

3.8 Chapter summary

The research uses a dynamic capabilities lens to investigate how big data is changing firms' strategic marketing capabilities. Technological turbulence in firms' operating environments has brought with it challenges, in the form of new competitors with data-led business models. In addition, the web-based technologies are generating an intellectual resource which may provide new forms of market intelligence and market opportunities.

Dynamic capabilities are important to organisational competitiveness as they enable firms to reconfigure their resource base to respond to a changing environment. Teece (2007) describes dynamic capabilities as having three components: sensing, seizing and reconfiguring. Sensing involves market orientation and scanning external environments to gather marketing intelligence. Sensing is challenging but vital in turbulent conditions, if firms are going to see the potential of big data to maintain parity or differential advantage over their competitors. Reconfiguring capabilities relate to the assimilation of resources, and firms' internal and external response to changes in their resource base. For established firms, their reconfiguring capabilities are influenced by their market position, the paths they have previously followed and the processes they have in place. Firms with constrained reconfiguring capabilities may not be able to respond to the market opportunities they sense. Seizing activities may involve strategic marketing choices regarding internal processes, alliances or customer-facing activities such as the commoditisation of the firm's big data resource or systems. The outcomes of a disconnect, between the market and the firm, are capability gaps which may, in themselves, require new dynamic capabilities to resolve.

Teece's (2007) theory is extensively cited in dynamic capabilities literature and provides a useful framework for this study. Other concepts have also been considered. Three, in particular, make useful contributions to explaining dynamic capabilities. Wilden, Devinney, and Dowling's (2016) House of Capabilities, extends Teece's three components by incorporating other influencing factors. Wang and Ahmed (2007) emphasise the delivery of dynamic capabilities as a process with internal reconfiguration needed before value-creating actions can be taken. Yeow, Soh and Hansen (2018) identify the importance of individual and organisational actions to modify the firm's resource base in order to address changes in strategy. Under the Gioia Methodology (Gioia, Corley, and Hamilton), researchers are directed to remain open to different theories until after the primary research is completed; the theory then informs the grounded theory model (see Chapter 4). The effects of these other theories will be considered within the Discussion in Chapter 7.

The extant theory omits detail on how dynamic capabilities are constructed, described in the literature as their microfoundations. For firms needing to develop new capabilities to engage big data for their strategic marketing, an understanding of dynamic capabilities at the macro level is insufficient. A breakdown of activity at an individual or team level is important. There is an opportunity for this study to provide a microfoundational description of firms' strategic marketing dynamic capabilities in relation to big data.

This chapter and Chapter 2 have provided the research context and the theoretical lens for this study. The literature review led to the choice of research question: ' How is big data changing organisations' strategic marketing capabilities?', which will be addressed by this research. The next chapter presents the research methodology, firstly, by introducing the research question, sub-questions and research aims and then by explaining the chosen methodology, including the research paradigm, research design and the use of the Gioia Methodology for data analysis.

Chapter 4 Research methodology

4.1 Introduction

This chapter explains the chosen research methodology, from the interpretivist paradigm through to the process used to generate new grounded theory models. Details concerning the research design, data collection and analysis are also provided, so that the origins of the theoretical models that are generated can be clearly understood.

The chapter is divided into seven sections. Within this Section, 4.1.1 presents the main research question, the sub-questions and the research aims. Sub-section 4.1.2 outlines the proposed methodology. Section 4.2 positions the study within the interpretivist research paradigm and the social constructionist and phenomenological epistemologies. Section 4.3 explains the choice of the qualitative, Gioia Methodology as a mechanism for developing new grounded theory models. Section 4.4 explains the research approach, including the case study and interview research design and the data collection. Section 4.5 describes the ethical considerations of the research approach. Section 4.6 provides a step-by-step description of the of the participant data analysis, using the Gioia Methodology. Section 4.7 provides a chapter summary, which sets the scene for the two subsequent Findings chapters.

4.1.1 Research questions

In response to the paucity of research regarding big data and strategic marketing identified in Chapters 2, this study seeks to address the main research question:

> How is big data changing organisations' strategic marketing capabilities?

It does so by considering three sub-questions:

1. What are the characteristics of big data that make it a valuable strategic marketing resource for established firms?
2. What dynamic capabilities are established firms using to leverage big data for strategic marketing?
3. How are established firms constructing the dynamic capabilities that they are using to leverage big data for strategic marketing?

The aims of the research are to:

- Address the lack of empirically-based, academic research on big data within the marketing discipline,
- Investigate big data initiatives in several organisations to support the credibility and trustworthiness of the emergent theory,
- Collect rich, qualitative data from knowledgeable agents on their experiences of using big data within a strategic marketing initiative,
- Generate an inductive, conceptual framework which addresses the research questions, is grounded in empirical data and presents the informants' experiences in theoretical terms,
- Develop a new theoretical model which is valuable to academia, as well as practitioners, by identifying the capabilities required to engage with and leverage big data for strategic marketing activity.

The research conclusions will add to the existing management and marketing literature, by providing an empirical study of firms with experience of using big data for strategic marketing purposes. The research will also provide a practical contribution to firms by providing tools for the application of big data in strategic marketing, based on the experience of knowledgeable senior managers.

4.1.2 The research approach

The specific approach used to address the research questions is summarised in Table 4-1. The chosen Gioia Methodology requires a detailed description of the process taken to transform the research data into theory. As a result, the chapter gives an in-depth account of the processes followed. To guide the reader, an overview is provided in Table 4-1 below, with further details concerning each element of the approach provided in subsequent sections.

Table 4-1 The chosen research approach

	Level		**Research approach**
Research paradigm	**Ontology**		Interpretivism
	Epistemology		Social constructionism Phenomenological
	Methodology		Qualitative Inductive, generating grounded theory
Approach	**Methodology**		The Gioia Methodology
	Design		Overarching strategy for collecting data: Case studies Interviews
	Emphasises:		Inductive reasoning
	Data	**Methods**	Techniques for collecting data: Elite interviews with knowledgeable agents
		Instruments	Specific data collection tools: Interview structure Participant information sheet Participant consent form Interview recording and transcription

		Analysis	NVivo analytical software Iterative coding and thematic analysis Generation of data structure Review data structure in light of extant theory
		Conclusions	Generate theoretical concept based on analysis

Source: Adapted from a structure produced by Twining 2010: 155

The next section describes the chosen research paradigm and its appropriateness for this study.

4.2 The research paradigm

The research approach is a product of the chosen research paradigm (Goulding 1999) and of the research question that is being investigated (Henninck, Hutter, and Bailey 2011). The research paradigm can be described in three dimensions; ontology, epistemology and methodology. This section of the chapter considers the ontology and epistemology of this study. The third dimension, methodology, will be considered in Section 4.3.

4.2.1 Ontology

Ontology is determined by our comprehension of ‘what is’ and how we understand the nature of reality or being. Saunders, Lewis and Thornhill (2012) identify four philosophies which present contrasting views about how reality exists. These are positivism, realism, interpretivism and pragmatism, of which the first three are most typically observed in management and information systems literature (Akpobi 2017). Each takes a different perspective on the researcher’s view of reality, and determines what constitutes knowledge (epistemology) and the most appropriate types of data collection techniques. For research to be credible there must be alignment and consistency between the underlying ontology, the epistemological position, the research aims, the methods of data collection and analysis, and the research claims that can be made (Avenier and Thomas 2015; Braun and Clarke 2006; Twining 2017). Therefore, the philosophy underpinning the research needs to be made explicit (O'Brien et al. 2014).

The positivist stance originates from the natural sciences and adheres to the viewpoint that the nature of reality can be defined in a single, objective way (Saunders, Lewis, and Thornhill 2012). What is observed is independent of social actors; the researcher "observes and measures the reality that exists out there" (Creswell 2014: 7). Because the knowledge comes from observable data and facts, it relies on a deductivist approach to interpreting existing theories, to explain and understand social phenomena. This approach is ideal for studies of big data which require an objective perspective, such as assessing data impact.

Realism is also objective, and views reality as being independent of human thought or belief. It proposes that the nature of 'being' is interpreted through social conditioning and as a consequence can be evaluated by assessing social practices against existing theory (Orlikowski & Baroudi 1991). This is suitable where evaluation can take place against extensive theory, but it is inappropriate in a novel area, such as big data, where there is limited theory.

This research adopts the interpretivist philosophical approach, the primary goal of which is to generate 'understanding' (Hudson and Ozanne 1988: 510). Drawing on Weber's 'Verstehen' technique, interpretivism is rooted in the analysis of social action, the explanation of participants' underlying motives and the meaning they attach to their actions (Parkin 2002). Knowledge of the phenomena under investigation is formed by uncovering the meanings and actions behind the phenomena. Interpretivism proposes that interpretations and understandings are constructed jointly by the researcher and the participant (Thompson, Pollio and Locander 1994), without the initial constraints of using theory as recommended in the positivist and realist approaches (Orlikowski & Baroudi 1991;

Weber 2004). As such, interpretivism suits a qualitative approach to data collection, subjectively exploring social phenomena with a view to gaining insights from relatively small samples and in-depth investigation.

This interpretivist ontology is appropriate when the research deals with problems involving interactions in what appear to be complex contexts (Lakoju 2017). This study focuses on the evolving and imprecisely-defined phenomena of big data (see Section 2.5.1) and uses a socially-constructed, dynamic capabilities theoretical lens. Dynamic capabilities theory, whilst extensively explored at the macro-level, lacks literature at the detailed microfoundational level (see Section 3.5). As such, both the interaction of dynamic capabilities in relation to big data and the theoretical contexts are complex, making interpretivism a suitable research ontology.

4.2.2 Epistemology

The epistemology of research relates to what constitutes the "way of understanding and explaining what we know" and to the processes through which that knowledge is created (Crotty 2006: 2). As such, there may be more than one particular epistemology to explain the phenomenon. The close alignment between what knowledge is and what reality is, means that it can be difficult to "keep ontology and epistemology apart conceptually" (Crotty 2006: 10).

Positivist ontology is aligned to objectivist epistemologies, where knowledge and facts are derived through rigorous, controlled and planned investigations and precise measurements (Thompson 1991). In objectivist epistemology, the objects themselves are viewed as holding meaning, with objective truths awaiting discovery (Easterby-Smith et al. 2002). In this situation, the researcher's role is to reveal the object's 'true' meaning (Hudson and Ozanne 1988). In contrast, a researcher adopting a realist ontology is likely to take a subjectivist epistemology. This proposes that all meaning is created by the researcher and imposed on the object under study (Thompson 1991).

This research uses two subjectivist epistemologies to understand the big data phenomenon in the strategic marketing context. The first, the social constructionist approach, emphasises context, which in this case is the use of big data by a firm. The second, the phenomenological epistemology, considers the experiences of those with knowledge of the phenomenon, such as managers of the big data initiatives within the firm.

4.2.2.1 Social constructionist epistemology

In line with its interpretivist ontology, this study adopts a social constructionist perspective, which asserts that meaning is made in, and through, social interaction (Berger and Luckmann 1971). In this way, knowledge is constructed and not simply discovered (Pidgeon 1996). Multiple perspectives and realities are formed as “people actively create and interact” with the world (Hudson and Ozanne 1988: 510), shaping and being shaped by the backdrop of their socio-cultural context.

The social constructionist approach aims to increase understanding of the phenomena under investigation through the induction of new ideas and perspectives from rich data. Studies into the processes through which knowledge is created (Aram and Salipante 2003; Tsoukas 1994) identify that intepretivist studies emphasise contextual knowledge. This involves understanding the interplay between the setting and events in which knowledge is generated, and the understanding of the narratives of the social actors in those settings (Tsoukas 1994). In contextualism, there is a strong emphasis on the importance of language in capturing and storing experiences and meanings, and in identifying social realities through interactions with others (Berger and Luckmann 1967). Contextual knowledge contrasts with the general knowledge approach of the positivist ontology. General knowledge is garnered from the identification of patterns in social phenomena which can be measured and quantified. These patterns form the basis of universal principles that are designed to predict the behaviour of social phenomena (Aram and Salipante 2003). The limited knowledge concerning the big data phenomenon means that, at this time, there is insufficient theory for the development of universal principles. The emphasis of this study is therefore on contextual knowledge.

The social constructivist paradigm is considered particularly relevant when research aims to provide insights regarding a specific context, and how it will affect a particular phenomenon (Gephart 2004). In this case, the study aims to provide insights into specific big data initiatives and how they will shape the development of strategic marketing dynamic capabilities in established firms. Research conducted from the social constructionist position does not seek to demonstrate statistical causality, but rather to develop and extend theoretical concepts and ideas (Pratt 2009). The aim is to uncover a plausible version of reality, rather than a definitive account (Bryman 2008). In line with this epistemology, the study adopts a case study research design (see Section 4.4.1).

4.2.2.2 Phenomenological epistemology

In addition to following a social constructionist epistemology, the study adopts a phenomenological approach to understand "the way things present themselves to us in and through experience" (Sokolowski 2000: 2). In this case, the focus of interest is the experience of big data being used for strategic marketing purposes. A key concept in phenomenology is that of 'Lebenswelt', "the world in which we are always, already living" (Moran 2000: 12), which provides the context for all experiences (Cope 2005). In a phenomenological approach, participants' descriptions and interpretations are the main focus of study with these participants regarded as experts on their own lives (Thompson, Pollio, and Locander 1990). First-hand accounts of their experiences are captured carefully in a thick description (Gioia, Corley, and Hamilton 2012) which provides the basis of new theoretical development. In this study, these individual accounts are captured through semi-structured interviews. As the study is investigating experiences at a strategic level, the participants are knowledgeable agents operating at a senior management level (see interview research design, Section 4.4.3).

4.2.2.3 The role of the researcher

In both epistemologies, the researcher acts as a tool, interacting with participants to enable them to make sense of their 'lived experiences' (Thompson, Locander, and Pollio 1989). They are not a dispassionate observer but an integral part of what is being observed (Easterby-Smith et al. 2002), playing a role in forming and shaping the evidence (Stake 2005). The resulting knowledge is created using the evidence to continuously develop and modify concepts and models (De Massis and Kotlar 2014).

The researcher serves as an instrument of data collection, analysis and interpretation (Denzin and Lincoln 2005); as such, there is an inevitability of their own values influencing the process. Within both epistemologies, the bias can be addressed by the researcher 'suspending' any pre-existing knowledge of the phenomenon, known as bracketing, to enable the possibilities of new meaning to emerge (Crotty 2006). By isolating themselves from the 'life-world' under investigation, researchers may offer a thorough description of the participants' experiences (Moran 2000). Knowledge is constructed through making sense of participants' interpretations (Thompson 2007). In this study, the potential for bracketing the researcher's pre-existing knowledge is straightforward, as she has a background in strategic project management but does not have experience of delivering a big data initiative (see the researcher's background, Section 8.4.1). This makes it possible for new knowledge to be developed.

In summary, in order to answer the research question, the study adopts an interpretivist ontology which is appropriate because of the complex nature of the phenomenon and research context, as well as the limited availability of theory in this domain. The study adopts two epistemologies. The social constructionist epistemology supports generation of theory relating to the use of big data within an organisational context. Whereas, the phenomenological epistemology seeks to generate new theory based on the experiences of those with knowledge of the big data phenomenon. In both approaches, the researcher has a key role in making sense of the data and creating new knowledge. The exploratory nature of the study makes a qualitative methodology appropriate for conducting the research (Thompson, Keifer and York 2011). The next section considers the choice of research methodology.

4.3 The methodology

The methodology starts by introducing quantitative and qualitative methods. The rationale for choosing a qualitative approach is explained, with reference to the approaches to reasoning and the ways that qualitative research can contribute to knowledge. The section explains why a grounded theory approach was considered, and how that led to the selection of the Gioia Methodology as the basis for developing new grounded theory models.

Research methodology refers to the strategy or design used for conducting the research (Bryman 2016). The two main methodological approaches, quantitative and qualitative, can be considered as two ends of a continuum (Johnson and Harris 2003). A quantitative methodology is most appropriate when research is structured, uses measurable data and tests theoretical constructs. Qualitative methodologies are aligned to an interpretivist ontology, and are more appropriate when the study is exploratory and the emerging knowledge is being developed into new concepts. A concept captures qualities that describe or explain a phenomenon of theoretical interest (Gioia, Corley, and Hamliton 2012: 2). The generation of concepts is central to the theory building that can guide the creation and validation of constructs.

Qualitative research has been defined as ”at best an umbrella term covering an array of techniques which seek to describe, code, translate, and otherwise come to terms with the meaning, not the frequency, of certain more or less naturally occurring phenomena in the social world” (Van Mannen 1983: 9). The related methods are “the techniques associated with the gathering, analysis, interpretation, and presentation of narrative information” (Teddlie and Tashakkori 2009: 6). These contrast to the systematic, quantitative methods which are allied with numerical information.

Qualitative methodology allows the analysis of complicated environments through the capture of a wealth of in-depth data (Corbin and Strauss 2014), and “thorough descriptions of actual actions in real-life contexts” (Gephart 2004: 455). The intention is to use induction “to allow meanings to emerge from data as you collect them in order to identify patterns and relationships to build a theory” (Saunders, Lewis, and Thornhill 2012: 48). The empirical analysis is linked through iterative review to “a flexible literature review and theories” (Eriksson and Kovalainen 2008: 32). The outcome of the process is the development of a concept which explains the phenomenon, rather than the predictive, generalisable knowledge which might be expected in a quantitative approach (Schwandt 2003).

Quantitative methodologies, which emerge from a positivist ontology, rely on comparisons of new, highly structured, measurable data with established theory (Saunders, Lewis, and Thornhill 2012). The outcomes are rooted in deducing theory from what we already know, which discourages originality in theorizing (Corley and Gioia 2011). The quantitative approach focuses on the development of constructs which are abstract, theoretical formulations about phenomena of interest (Edwards and Bagozzi 2000). An important function of quantitative methodology is to define measurable attributes that can be operationalized and preferably quantified as variables. This approach relies on ‘theory testing’ through comparison of new data with established theory and is not suitable to the development of new concepts. As the big data phenomenon is a novel concept, it is well-suited to the use of a qualitative research methodology.

4.3.1 Reasoning

Theory testing and building rely on different approaches to reasoning. The inductive approach begins with the empirical environment and generates a context-specific theory (Hudson and Ozanne 1988). The phenomenon becomes better understood in a wider social context, as it is viewed from more perspectives (Cayla and Arnould 2008). In contrast, deductive reasoning tends to be theory-driven, with the theory being applied generally, within a number of environments. Deductive reasoning is useful in complicated empirical settings because the robust, theoretical framework can guide the research (Burawoy 1998). The drawback of this approach is that it does not necessarily adapt to different empirical circumstances.

There is a view that, rather than adopting either inductive or deductive reasoning, qualitative researchers alternate between the two approaches; through a process of abductive reasoning (Cresswell 2014). This viewpoint acknowledges that researchers need to be theoretically informed, to ensure a strong connection between the new data and extant theory (Hay 2002). Abductive reasoning tends to be viewed as a circular process where either existing literature is considered in an empirical setting to generate context-specific theory; or theory is sought to fit the empirical setting (Dubois and Gadde 2002); or researchers may use their study to extend and innovate established theory (Saunders, Lewis, and Thornhill 2012). This study is designed to use abductive reasoning, to develop theory based on experiences of interviewees from case study firms, and to ensure that the new theory sits within the context of existing knowledge.

4.3.2 Contributions to knowledge

Qualitative methodologies have been widely used and have made useful contributions in business and management research. They have been criticised by some because of ‘misunderstandings’ about their ability to produce generalizable, reliable and theoretical contributions to knowledge (Flyvbjerg 2011). This concern is largely based on positivist criticism about using interpretive, qualitative research, including about how the research design criteria, of reliability, replicability, and validity, can be satisfactorily met through qualitative approaches.

Such criticism is becoming less common as the value of interpretivism and qualitative and mixed methods research is more widely recognised (Flyvbjerg 2011). Interpretivist researchers work inductively, analysing their data, identifying themes and patterns within the data, and then contextualising them in existing literature, in order to define, extend or generate theory (Ridder et al. 2014). The primary aim of their approach is to develop rich, detailed, nuanced descriptions and understanding of their qualitative research, as is the case in this doctoral study.

Instead of the qualitative criterion of replicability, qualitative research can contribute to knowledge through generalisability (Yin 2014). The emergent theory can be generalised by its relationship with existing theoretical concepts. Furthermore, instead of emphasising validity, qualitative contributions to knowledge may be assessed by ‘fittingness’ (Sarantakos 2005) or ‘convincingness’ (Stewart 2012). These measures aim to ensure the alignment of the research findings with the research objectives, design and method. An important part of convincingness, is the researcher’s ability to describe the process, contingency and context (Stewart 2012). Contributions to knowledge through fittingness and convincingness require a reliable and trustworthy process and data. Trustworthy research should be credible, dependable, transferable and confirmable (Lincoln & Guba 1985).

Credible research benefits from evidence that the researcher and the participants have both engaged with the research process. This might be achieved through demonstration that the findings accurately represent the participants’ words, through extensive use of quotations. It might also be evident if the method incorporates both parties’ reflections on their interaction and shows the evolution in their understandings (Giddens 1984). Credible research might also be demonstrated by securing approval of the final research from the participants (Lincoln and Guba 1985).

Dependable research can be explained as the extent to which research can be replicated within the same context and with the same respondents. Dependability replaces the concept of reliability, used within quantitative research. A research study is dependable if there is a clear audit trail between the researcher's observations and recorded data and the findings (Lincoln & Guba 1985). This can be achieved through recording and transcription of raw data and ensuring a high level of documentation of the data collection and analysis processes.

Interpretivist research is transferable if the research finding can be applied to another context or set of respondents. Interpretivist research takes the view that the uniqueness of individual phenomenon and contexts could prevent a direct transfer of the findings. However, the development of theoretical frameworks that can be transferred to other settings, is both possible and achievable. Transferability requires close consideration of the contextualisation of the research, to ensure the intended audience can comprehend how the specific situation under investigation emerges (Klein & Myers 1999) and how it might apply to them.

Confirmable research requires a well-documented narration of how the data was collected and interpreted. This documentation may satisfy the need for replication by other researchers (Lincoln & Guba 1985), but it also provides reassurance of the care applied to the research process to avoid bias or systematic distortion in data collection (Klein & Myers 1999). Section 4.4. provides a detailed description of the research design and data collection process used in this research. Section 4.6 explains how the Gioia Methodology (Gioia et al. 2012) provides a systematic and rigorous approach to data collection, analysis and new theory building.

The next section considers grounded theory and the selection of the Gioia Methodology.

4.3.3 Grounded theory

The research data collection focuses on capturing the views of those with experience of the big data phenomenon, and analysing those views in relation to existing literature, to build new theory. A grounded theory methodology is appropriate for this type of interpretivist approach.

Grounded theory provides a “set of systematic procedures extending and significantly supplementing the practices long associated with participant observations in order to achieve their purpose of developing theories of action in context” (Locke 2002: 19). The underpinning methodology of grounded theory has five elements. Firstly, the constant comparative method which involves simultaneous coding and analysis of the data and comparison to existing theory; secondly, data categorizing and grouping; thirdly, analysis to devise and control an emergent theory; fourthly, responsiveness to the research context; and finally, the recognition of the completeness of the research process (O’Reilly, Paper and Marx 2012). The method is non-linear, with theory developed by cycling between the elements (Glaser and Strauss 1967).

Grounded theory aligns participant inputs and theory, through constant comparison between the two (O’Reilly, Paper and Marx 2012), but it is open to criticism because of its reliance on established theory. It has been suggested that grounded theory minimises the revelatory potential of the theory-building activity, by progressively extending existing theory, rather than generating new theory (Morse 2016). Big data is a novel phenomenon and there is limited literature on its application in strategic marketing, so it provides a real opportunity for developing persuasive new theory. In selecting an appropriate methodology for the study, a variation on grounded theory was identified; the Gioia Methodology (Gioia, Corley, and Hamilton 2012). The Gioia Methodology takes a systematic approach to data collection and analysis, and to the development of grounded theory. At the same time, its emphasis on theory originating with empirical evidence allows for the innovation that is required for new theory building.

The next section explains the Gioia data-to-theory process.

4.3.4 The Gioia Methodology

As well as encouraging greater innovation in theory-building, the Gioia Methodology (Gioia et al. 2012) benefits from the strong, social scientific tradition of using qualitative data to inductively develop grounded theory (Glaser and Strauss 1967; Lincoln and Guba 1985; Strauss and Corbin 1998) on the basis of rich, theoretical descriptions of the organisational phenomena.

The Gioia Methodology provides “a systematic approach to new concept development and grounded theory articulation that is designed to bring ‘qualitative rigor’ to the conduct and presentation of inductive research” (Gioia et al. 2012: 15). Gioia et al.’s approach aims to enable inductive researchers to apply a methodical conceptual and analytical discipline, more commonly used in quantitative, scientific research.

The chosen methodology (Gioia et al. 2012) has similarities to Glaser and Strauss’s (1967) grounded theory approach, particularly in bringing together the voices of those with practical experience of the phenomenon with theoretical analysis. The Gioia approach retains participant narratives without condensing them, reporting the voices and theory in tandem, identifying areas where supporting theory is missing and generating new theory in that void. The emphasis on language to present reality positions Gioia’s approach as social constructivist, which is fully compatible with grounded theory (Runfola 2012). Gioia et al. (2012: 2) propose that at this theory-building stage, the researcher’s emphasis is on concept development, that captures the “qualities that describe or explain a phenomenon of theoretical interest”, rather than on construct development which can be quantified and tested. In line with the research question, the concept development addresses the ‘how’ of the phenomenon, rather than the ‘what’.

There are five steps within the Gioia Methodology; thick description, first order analysis (informant centric); second order analysis (researcher centric), data structure and grounded theory. The authors stress that they have designed a ‘‘methodology,’’ rather than a ‘‘method’’. It offers a flexible orientation toward qualitative, inductive research that is “neither template nor formula”, being open to innovation, rather than a ‘‘cookbook’’ (Gioia et al. 2012: 26).

In this case, a seven-step approach has been adopted (see Figure 4-1). The data analysis process involves data reduction that “sharpens, sorts, focuses, discards and organises data in such a way that the final conclusions can be drawn and verified” (Miles and Huberman 1994:11), a process also described as data condensation by Miles and Huberman (1994). During the analysis, two additional steps were added to assist with data reduction, and with the categorisation and theming of the analysis (see Section 4.5). These steps are identified in Figure 4-1 with an asterisk. The first additional step is First Order Distillation, which involves grouping interviewee statements into categories and discarding any interview materials that are not relevant to the research question (see Section 4.6.3). The second additional step is Second Order Aggregation, which involves condensing the second order themes into the aggregate dimensions, that were interpreted by the researcher as dynamic capabilities (see Section 4.6.5). The dynamic capabilities aggregate dimensions represent the aggregation of participant contributions, to the point that each dimension describes a distinct modification of the organisation in relation to its changing environment.This more finely-tuned approach clarifies the conversion process of data-to-theory, adding rigour to the qualitative research process, to ensure that the conclusions are viewed as plausible and defensible.

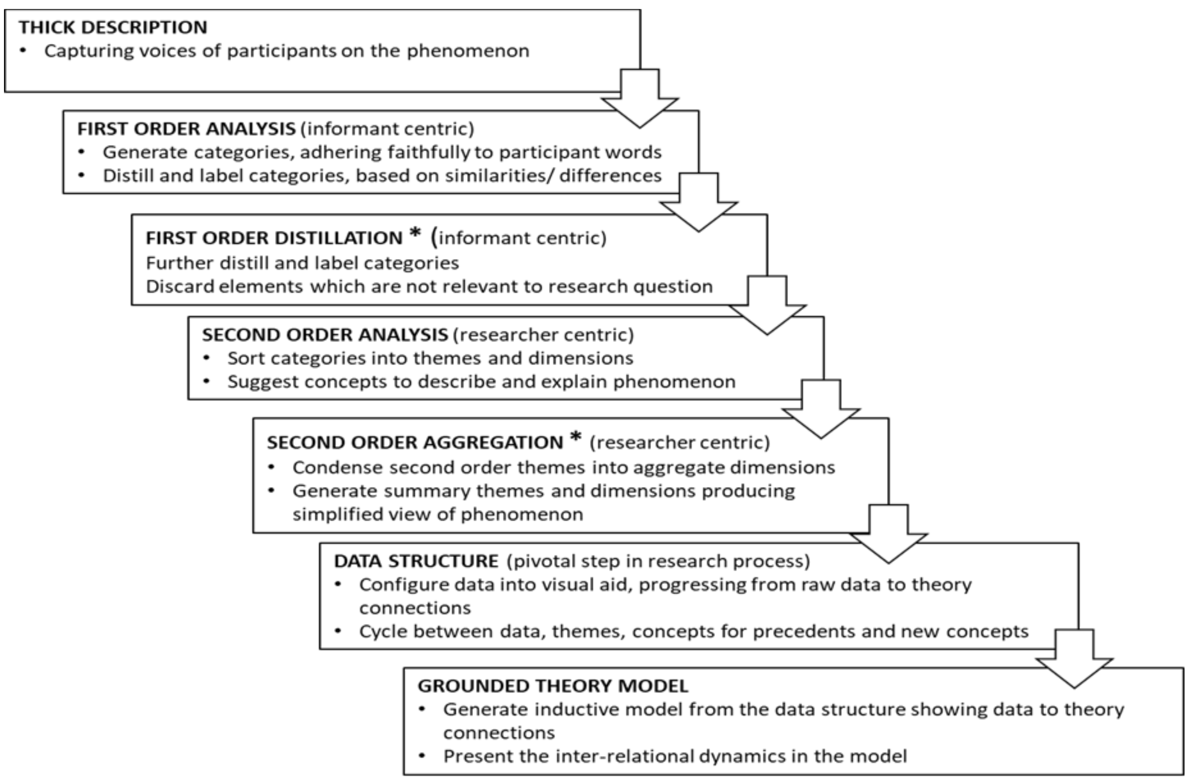
The seven-step data analysis process, set out in Figure 4-1, is used to provide the structure for the data analysis described in Section 4.6.

The analytical process begins with the verbatim accounts from the interviews of those with experiences of the phenomenon, which provides a robust basis for the thematic analysis. The analysis moves from descriptive information to patterns and abstractions (Baskarada

2014). The abstraction, in the form of the overarching themes, is supported with extracts from the data, to elucidate how the researcher has made sense of the firms' activities (Braun and Clarke 2006). A high-quality analysis is achieved through balancing the data extracts and providing a convincing, well-ordered story (Braun and Clarke 2006), to enable a clear link between the data, analysis and conclusions (Avenier and Thomas 2015).

Two key assumptions are made in using this methodology. The first is that the participants are knowledgeable agents with experience of the phenomenon and the capacity to comment about it.

Figure 4-1 The Gioia Methodology data-to-theory process



(Source: Author, adapted from Gioia, Corley, and Hamilton 2012)

* the two asterisked steps represent additions to the five-step Gioia Methodology, which are explained further in Sections 4.6.3 and 4.6.5.

The second assumption is that the researcher is also a knowledgeable agent, capable of identifying patterns in the participant commentary and framing those in relation to existing theory (see the researcher's background, Section 8.4.1). They also need to be able to highlight areas where no current explanation exists in the subject being researched. The Gioia Methodology achieves a simultaneous reporting of participant and researcher voices, with a qualitatively rigorous explanation that makes sense of the links between the data and the new concept generation. The aim of the data interpretation is to create persuasive new theories which will be viewed as plausible and defensible (Gioia and Pitre 1990).

In summary, a qualitative methodology was selected for this study because its exploratory nature is appropriate given the novelty of the big data phenomenon. The study adopts the Gioia Methodology, which offers a systematic approach to concept development, designed to bring rigour to the research. The aim is to generate new theoretical concepts to explain how big data is changing firms' strategic marketing capabilities. By using abductive reasoning, the study focuses on the empirical evidence, whilst positioning the emerging concepts within the context of existing theory. The qualitative research contributes to knowledge through convincing and trustworthy processes and data.

The next section considers the research approach to design and data collection.

4.4 The research approach

This section discusses the chosen research design and the data collection for both the case study and interview research methods.

The research design is "the way research questions and objectives are operationalized into a research project" (Saunders, Lewis, and Thornhill 2012: 196). The main issue of contention in research design stems from the different philosophical perspectives (Piekkari, Welch and Paavilainen 2009). Scholars who adopt a positivistic stance tend to favour a rigid design.

Scholars who adopt an interpretivist perspective tend to make decisions about chosen cases and units of analysis during data collection, as access is gained and empirical evidence collected (Ragin 1992). This more flexible and iterative approach allows for "interplay between data collection, analysis and analytical framework" (Eriksson and Kovalainen 2008: 129), encouraging innovation in the understanding of the specific phenomenon.

In line with the qualitative interpretivist epistemologies discussed in Section 4.2.2, this study is using case study and interview approaches for data collection. An explicit description of how data is collected is a pre-requisite in quality reporting of qualitative research (Avenier and Thomas 2015). In this section, the research design for both case study and interviews is discussed, followed by a description of the data collection carried out in this study. Section 4.4.1 explains the choice of a case study approach. Section 4.4.2 describes the case study research design, including the unit of analysis, the research context and the number of case study firms. Section 4.4.3 explains the recruitment of the four case study firms and the adaptation of the sampling strategy. Section 4.4.4 describes the interview research design, including the sample size and strategy and the use of elite interviewing. Section 4.4.5 describes the interview process and identifies the supporting documentation.

4.4.1 The choice of a case study approach

The case study approach was chosen for this research because it is an appropriate method with which to explore contemporary phenomena, such as the capabilities needed to leverage big data, in a real-world organisational context (Yin 2018) and in a real-time dimension (Runifola et al. 2018). Case study method is also appropriate because it can accommodate blurred boundaries (Yin 2018) between firms' use of big data and their organisational settings.

Other qualitative modes of inquiry were also considered including experimental, action-based and ethnographic research. Experimental research would have required the phenomenon to be separate from the context (Yin 2018), which was not feasible given the nature of the research question. Other inductive reasoning approaches were also discounted, either because they would not be able to address the research question or because they required a level of intensive access to firms that the researcher did not consider possible. An action-based research approach was considered as a way of exploring a single firm's transformation, from not using big data fully into being data-led. This approach required real-time recording of the transformation to inform the research process (Twining et al. 2017). The researcher considered that identification and recruitment of a participant firm would be difficult to achieve. The intensity of action-based research also limited the study to a single case, whereas the researcher considered that a multiple case study would provide a broader context for theory building (Pauwels and Mattyssens 2004).

Ethnography was also considered to investigate how capabilities were developed in an organisational context. However, as ethnography focuses on the behaviours of participants (Dewan 2018), an ethnographic approach would have shown how the capabilities were developed, rather than identifying the range of capabilities required to leverage big data.

The case study approach was chosen because it provided the best research method to address the research question. It also had the potential to incorporate more than one case and thus to broaden the research context. Case study also required a level of participant access which the researcher believe could be secured, which would make it possible to focus on investigating the novel, big data phenomenon, in a real-world organisational context, and in real-time. Criticisms of case study research, such as a lack of scientific rigour (Crowe et al. 2011) were addressed through the choice of the systematic Gioia Methodology (see Section 4.3.4) to direct data collection and analysis. The Gioia Methodology provided discipline and transparency through the research process. Case study research is also criticised for its limitations for generalisation in other settings (see Section 4.3.2).

4.4.2 Case study research design

This section outlines the case study research design and is followed by an explanation of the case study firm recruitment (see Section 4.4.3). This research design has been widely adopted in business and management research. This may be because the case study theory-building process is so closely aligned to empirical evidence that the resulting theory is viewed as highly plausible (Eisenhardt 1989).

A case study is an “an in-depth exploration from multiple perspectives of the complexity and uniqueness of a particular project, policy, institution, program or system in a real life context” (Simons 2009: 21). The case study may be viewed as a data collection technique, or as “a research strategy that is used to study one or more selected, social phenomena and to understand or to explain the phenomena placing them in their wider context” (Whitfield and Strauss 1998: 103). This study is adopting the latter perspective.

The aim of case study research strategy is to develop theory, whilst studying a phenomenon in context, based on insights from intensive and in-depth research (Eisenhardt 1989; Eisenhardt and Graebner 2007; Yin 2014). A case study design has the advantage of addressing ‘how’ and ‘why’ questions, in circumstances where the researcher has very little or no control (Yin 2014). It is also a useful design when there is a lack of information on the focal phenomena (Stake 2005). Case studies are often used when the boundaries between the study phenomenon and its context are indistinct (Yin 2014), as applies in the current study.

As the big data phenomenon is a novel concept, this study adopts an exploratory research approach (Yin 2014). Exploratory studies aim to discover *how* a phenomenon occurs; while explanatory studies explain and validate *why* a phenomenon takes place; and descriptive studies aim to underline its *importance*. In this study, the emphasis is exploratory, because of the novelty of the research context. In line with the interpretivist ontology and the choice of Gioia Methodology, a flexible research design was chosen. Rather than starting the research with a formal, theoretical framework, this approach originates with participant experiences of their organisation's big data initiative (Yin 2014). Other elements of research design, including the research question and aims, the analytical process and resulting themes emerged during the case study process.

A key factor in determining case study design is the choice of a single case study or multi-cases and determining the case study boundaries (Flyvbjerg 2011). Once these are defined, the researcher sets out to understand the dynamics of the topic being studied within its setting or context (Eisenhardt and Graebner 2007). Yin (1984) identifies three necessary elements in defining case study boundaries: the case, the context, and the participants.

The case and context will now be discussed. This section identifies the theory behind case study design choices, with reference to this study. Further detail on the case study participant recruitment is provided in Section 4.4.3.

4.4.2.1 The case

The research design sets out the nature of the case, the unit of analysis and determines whether the research question is best answered through single or multiple cases.

A case study is a research approach that is used to 'generate an in-depth, multi-faceted understanding of a complex issue in a real-life context' (Crowe et al. 2011:1). This study takes the form of a collective case study (Stake 1995), where multiple cases are studied simultaneously, with a view to gaining a broad appreciation of the way in which big data is changing firms' strategic marketing capabilities.

In the context of this research, the cases are all large, UK-based firms, from a variety of sectors. Each firm has implemented a big data initiative in strategic marketing, which provides the unit of analysis. The participants are senior managers in the case study firms, with knowledge of the big data initiative. It is through interviewing these knowledgeable agents that an in-depth understanding of the case firms' activities and capabilities is captured. The multi-faceted understanding of the capabilities needed to leverage big data emerges as a result of a cross-case synthesis of the cases (Yin 2018), rather than from a comparison between the participating firms' activities.

4.4.2.2 Unit of analysis

The 'case' is the phenomenon to be studied. Having a clear understanding of the case is important because it governs the type of data that will be collected (Yin 2013). Multiple entities can constitute a case, including organizations, societies or associations, cultures, incidents or events, a change process, and projects (Lincoln 1985). Within this study, the case phenomenon - or unit of analysis - is a big data initiative that is being used for strategic marketing purposes within a specific firm setting. By referring to a strategic marketing application, the firms' operational big data initiatives are excluded, ensuring the relevance of the data collected. This specific choice of case study phenomenon ensures that the research question is addressed.

Defining the unit of analysis is a key element in recruitment of case study firms because it provides a purposive criterion for sampling. Purposive sampling selects participants "in a strategic way, so that those sampled are relevant to the research questions that are being posed" (Bryman 2008: 415). Within the purposive approach, criterion sampling determines that only participants who meet pre-determined criteria are eligible to take part in the research. Criterion sampling differs from convenience sampling, where the participants are selected on the basis of accessibility to the researcher (Patton 2001). In this case, the sampling criterion is a big data initiative being used for strategic marketing purposes, within a specific firm setting.

4.4.2.3 Single or multiple cases

Having identified the unit of analysis to underpin the research design, a decision is required on the number of cases required to address the research question. Yin (2014: 92) argues that any finding or conclusion in a case study is likely to be “much more convincing and accurate if it is based on several different sources of information following a corroborative mode”. Different sources of information can be defined in a number of ways. They may include inputs from multiple organisations, multiple participants in a single organisation, or from “multiple methods of data collection to gather information from one or a few entities (people, groups, or organisations)” (Benbasat, Goldstein, and Mead 1987: 370). Eisenhardt (1989) argues that multiple data sources allow the drawing together of a wealth of complex data (Eisenhardt and Graebner 2007; Gillham 2000), offering both methodological and source triangulation.

Having determined that multiple data sources are beneficial to understanding the big data phenomenon in context, a decision is required as to whether the sources are from a single firm or multiple firms (Myers 2009). A single case study approach, which comprises an in-depth analysis of a single case (Mason 1996), can be adopted if it is representative of a research topic (Strauss and Corbin 1990), or if it provides an opportunity to observe and analyse a phenomenon that few have done before (Saunders, Lewis, and Thornhill 2016). Alternatively, it is suitable when the case is “critical, unusual, common, revelatory or longitudinal” (Yin 2014: 51). The advantage of single case study design is that the findings may be extrapolated to other settings (Orlikowski & Baroudi 1991). The drawback is that it requires an extraordinary level of access (Herriot and Firestone 1983) to participants, to secure the breadth of data on the focal phenomenon. This may be particularly difficult where the case is unusual or critical or, as in this case, relates to the competitiveness of the organisation. The single case study approach was eliminated for this research, because of the anticipated difficulties of being able to access sufficient elite, knowledgeable participants with strategic insights (see Section 4.4.4.4).

According to Dubois and Gadde (2002), multiple case studies allow researchers to cover a greater breadth of experience of a phenomenon, but may be more limited in terms of their depth. Yin (2009) views multiple case studies as separate experiments with a replication of logic across separate instances. However, Stake (2005) sees cases as determined by the purpose of the study, where the multiple case study aims to examine a phenomenon with lots of cases, parts or members. This study follows Stake's approach and defines multiple cases as investigations of the big data phenomenon in a number of different firms. There are no guidelines as to the number of case studies that should be carried out. An estimate was made to recruit three or four firms depending on the success of the snowballing recruitment of interviewees, discussed in Section 4.4.3. If fewer interviewees were recruited within a firm, then more case study firms would be required, to meet guidelines for number of interviews. Four case study firms were recruited, details of which are provided in Section 4.4.3.

All multi-case studies are in essence comparative. In exploratory case studies, the cases are chosen for their similarities through meeting the case phenomenon, rather than their differences (Stewart 2012). The research then investigates the contrasts or variances in the examples of the phenomenon under study. The strength of the approach is that it maintains the focus on the dependent variable, in this case the big data initiative, while searching for the factors that seem to explain or illuminate those differences (Stewart 2012). The outcome of exploratory case studies may not be definitive; instead, the study may generate a conceptual framework illustrated by examples from several case studies. This study is designed to generate an example-giving theory, from the multiple case study approach.

4.4.2.4 The context

An understanding of the research context is also fundamental to case study research design, as "the interaction between a phenomenon and its context is best understood through in-depth case studies" (Dubois and Gadde 2002: 554). Using real-life settings or contexts distinguishes the case study from other forms of research strategy, such as experimental and survey research. The importance of context in this research, is that it positions the phenomenon under investigation in a particular organizational setting.

Chapter 2 describes how firms are operating in technologically turbulent environments. New firms are entering the market which are digitally-born and have “operating models and capabilities are based on exploiting internet-era information and digital technologies as a core competency” (Gartner 2016: 1). Extant research indicates that while these firms are already data–driven, capability gaps are growing for those established firms which were not initially set up to use big data (see Section 2.7.1). This study has the potential to contribute to knowledge in practice by investigating the experiences of established firms which have engaged with big data. As such, the research context is established organisations which have implemented big data initiatives for strategic marketing purposes. These firms have experience, which can contribute to empirically-based theory, that may be valuable in addressing the data-driven capability gaps which may face established firms.

To minimise extraneous variation in the research context, the case study firms are all large organisations and all UK-based. No restriction was placed on which sectors were approached to participate, although the researcher was interested in achieving a spread of industries. Large firms were chosen because they are more likely to innovate, and to invest in their human and physical capital than small to medium-sized firms (Ciani et al. 2020). Furthermore, large firms influence the behaviours of other firms by spreading their ‘know-how in ways that benefit other companies of all sizes’ (Ciani et al. 2020: xx), including their supply chain and their competitors. The researcher anticipated that these qualities of large firms would be reflected in the breadth of big data-driven capabilities identified by the firms. UK-based firms were chosen because, based on employment history, the researcher was confident of access to these firms (see Section 8.4.1). A range of sectors was selected because it provided the potential for variance and divergence in the data, which literature suggested could strengthen the emergent theory (Yin 1994). For the purpose of the thesis the cases are being analysed within a cross-case synthesis, however by having data from different sectors, such as public and private, comparative analysis of the data (Yin 2018) could also be carried out in subsequent research.

The case study research design is summarised in Table 4-2.

Table 4-2 The case study research design summary

Design consideration	**Chosen research design**
Case phenomenon (unit of analysis)	A big data initiative, used for strategic marketing purposes, within a specific firm setting.
Sampling strategy	Criterion sampling using use case phenomenon as criteria.
Context	Established organisations, which meet the sampling criteria.
Participant firms	A multiple case study approach.
Case study numbers	3-4 case study firms.

The next section provides more details on the recruitment of case study firms in this study.

4.4.3 Case study firm recruitment

Using the case study research design summarised in Table 4-2, four case study firms were recruited. The four firms were drawn from a shortlist of ten that met the criteria of being large, UK-based firms, which reflected a spread of industries. All shortlisted firms exemplified the case phenomenon, in that they had implemented a big data initiative for strategic marketing purposes. This section identifies the four case study firms and explains the circumstances in which the more extensive EducationCo case study arose.

Participant recruitment commenced with opportunity sampling of possible key informants at marketing conferences, and searching the internet for relevant firms. Relevant firms were those who were self-promoting their firms' use of big data in strategic marketing. A shortlist of six organisational contacts was produced, which represented a variety of sectors including charity, finance and food manufacturing. The researcher also used convenience sampling and talked directly to contacts and colleagues from industry. This generated four further informants, whose firms met the sampling criteria. The recruitment process to engage these firms took place over eleven months, whilst the literature review was carried out.

As described above, there were clear criteria for the participating firms. Each of the ten shortlisted firms that met these criteria were contacted, through email to a known key informant. Four firms from the shortlist self-selected to participate in the research, which was an acceptable number of cases for multiple case research (Eisenhardt 1991). Access to participants varied across the case firms, ranging from one company offering meetings with multiple senior staff across the organisation, whilst other access was limited to one or two executive-level employees. In their interaction with the key informants the researcher sought to optimise access to more research participants, however, it was necessary to take a pragmatic approach to access given the commercially sensitive nature of the interview content and the challenges in securing elite interviews.

The approach to case firm recruitment taken in this study is aligned to a constructionist viewpoint (Stake 1998). Yin's (2014) positivist approach to multiple case study selection relies on a tight and structured design for research, where data sampling is closely related to theoretical sampling, and cases are selected to address the research question. In contrast, Stake (1998:22) proposes that 'the course of study cannot be charted in advance' and argues for flexible design that allows researchers to make changes after they proceed from design to research. By building a shortlist of firms that met the sampling criteria, the research design used in this study, allowed for any of the ten firms to participate and accommodated the self-selection of the final group of participant firms.

In order to manage the data collection process, firms were contacted in clusters rather than in unison, which resulted in firms confirming involvement over several months. Rather than being from the purposive sampled firms, it transpired that the key informants for the participating firms had all been convenience sampled from the researcher's and colleagues' business contacts. Given the commercial sensitivities relating to big data as a source of competitive advantage, it may be that participants required a level of trust with the researcher. This was possible where a pre-existing relationship provided reassurance to the key informant.

The four firms were an FMCG organisation, which will be referred to as FMCGCo; a media organisation (MediaCo); an automotive organisation (AutoCo) and an educational organisation (EducationCo). Table 4-3 provides summaries of each case study firm, and of the strategic marketing big data initiative that was the subject of data collection.

A further opportunity arose from the contact with the EducationCo's Head of Strategy, which allowed greater access to the case study firm. Their Business Intelligence Project (BIP), the big data initiative they were using in their strategic marketing, was due to be evaluated. This evaluation sought to identify the elements of project success, and those requiring improvement, by collecting the views of their big data users. As the purpose of this review aligned closely with the objectives of the doctoral study, the researcher offered to carry out the evaluation. This required separate consent documents and management and ethics approvals (see Section 4.5). A separate research report and presentation of findings were provided to the BIP senior project team. Each EducationCo participant also received a summary of the BIP evaluation report.

Table 4-3 Details of the case study firms

	FMCGCo	**EducationCo**
Company position and paths	Leading global FMCG firm with 400 brands in 190 countries. Strategic aim: to achieve green credentials – business efficiency and effectiveness. Pre-big data initiative: processes fragmented by different sub-companies, brands and divisions.	A fast growing, modern university providing high quality higher education and applied research, supporting 29,000 learners across three campuses. It is recognised in the top 20 UK Universities for teaching quality and student experience. Pre- big data processes: data held on multiplicity of databases.
Big Data Initiative (BDI)	Single repository of 'recipes' of global product range; AI[2] to improve efficiency, aligning packaging to international legislation and achieving faster product-to-market.	Single repository of student data: to improve internal efficiency and improve customer responsive services, e.g. retention project.
Strategic aim	Increased business efficiency to improve customer experience e.g. with faster product-to-market.	Embrace digital as a tool in delivering mission of being a leading provider of innovative learning and impactful research.
Resources	Finance – investment in cloud-based infrastructure, transition of data base contents to single repository; machine learning technology. Human – competence in data potential; AI related skills Physical – offsite repository of data. Intellectual – security of brand IP[3], maintenance of knowledge, access to open source legislative data.	Finance – investment in data warehouse and cloud-based data storage, investment in technical partners to support initiative. Human – competence to establish project; train existing staff in new system. Physical –visualisation systems (dashboards) hardware. Intellectual – knowledge of students (customers) from comprehensive dataset; goodwill of staff to engage.
Operating capabilities	Employees accessing data from individual databases by product and by company.	Specific employees accessing data from individual databases, in response to specific student-related query.
Microfoundations of big data initiative (BDI)	***Process based constructs*** Routines: abandonment of old data processing, adopting new system, maintenance of existing data systems. Competence: to establish new system, technically and operationally; contracting with new high-risk partners. ***Organisation level constructs*** Leadership: choice of strategy, observation of benefits; Culture change: adopt new pattern-spotting potential of big data and work with different partners. Structures: technical structures, new teams.	***Process based constructs*** Routines: changed from central and local data storage to single repository of data and analysis delegated to administrative end users. Competence: to establish new system – technically, operationally and responsive to business strategy; to operate new system. ***Organisation level constructs*** Leadership: choice of strategy; observed data opportunity Culture change: shift in analytical emphasis. Organisational structures: overcoming departmental silos. Employee engagement - critical for improved customer responsiveness.

[2] AI – artificial intelligence

[3] IP – intellectual property

	MediaCo	AutoCo
Company position and paths	One of top 20 largest UK Media companies; expanding into digital media, from its origins as a newspaper publisher. Pre-big data initiative: processes fragmented by different divisions; data used for operations management.	Largest UK-based physical and digital vehicle marketplace (auction site), operating across Europe. Includes vehicle logistics, auctions, finance and remarketing. Pre-big data initiative - product reliance on multiple databases and print based data visualisation.
Big Data Initiative (BDI)	To devise and launch an online local news, information and community platform using data from its own regional journalistic content, news sites, blogs and social networks, combined with open source data on crime, property, health. Starting with UK focus.	Development of an app to support the part-exchange process between vehicle dealers and customers. Combines biggest dataset in vehicle industry with machine learning techniques, to provide appraisals, valuations, stock management and facilitate vehicles going to auction. App was subsequently commoditised to serve a different market.
Strategic aim	To move its product base from publishing based into digital, building on its existing resource base.	To support their supply chain by using cutting-edge technology to improve vehicle sales and profitability.
Resources	Finance – investment in cloud-based technologies, hardware and software for digital development. Human – skills base of data scientists, software engineers. Physical – physical location for new skills base, hardware. Intellectual – consistency with brand IP, access to other social networks and open source data.	Finance – investment in cloud-based technologies, hardware and software for digital developments, machine learning technologies. Human – AI related skills, software engineers. Physical – hardware. Intellectual – security of brand IP, maintenance of VRIO knowledge from owned dataset, access to open source legislative data. Access to purchased data from external partners and others in supply chain.
Operating capabilities	Day-to-day publication of local news and community information through paper-based products.	Providing European supply chain with vehicle-related data to provide prompt and accurate vehicle pricing.
Microfoundations of big data initiative (BDI)	***Process based constructs*** Routines – establishment of new digital product development routines, new partnerships. Competence – digital product developers and software engineers. ***Organisation level constructs*** Leadership – choice of strategy. Stakeholder investment in new digital division. Culture change – addition of new divisions. Technical structures – digital divisions with technical infrastructure. Organisation structures – new teams.	***Process based constructs*** Routines – changing delivery models from book-based vehicle pricing to app-based delivery, same partners, new technologies. Competence – maintaining comprehensive and responsive data store. ***Organisation level constructs*** Leadership - choice of strategy, BDI is a core product in firm’s digital services strategy; willingness to commercialise big data system. Technical structures – predominantly in-house development, engagement with expert partners. Organisation structures – dedicated product team.

Undertaking the EducationCo's evaluation improved the researcher's depth of knowledge of big data initiatives, which contributed to a more robust understanding of the research context. It also increased the number of EducationCo interview participants, which provided more perspectives on their big data initiative, and provided detailed micro-cases that were incorporated within the Findings (see Chapters 5 and 6). Although the number of interviewees was highest for EducationCo, the volume of interview material per capita was higher for other case study firms, such as MediaCo. The longer interviews provided in-depth content which also allowed for detailed micro-cases.

The next sections describe the study's data collection, with reference to the interview research design, participant recruitment and the interview process.

4.4.4 Interview research design

This section identifies the theory behind the interview research design choices, with reference to this study. The key to successful data collection is to collect the data appropriately and systematically, and supply sufficient contextual information "to give readers a sense of what it was like to have been in the research setting" (Kuper et al. 2008: 687). In line with the phenomenological epistemology, the chosen data collection method was to provide this contextual information through interviewing.

Interviews involve one-to-one interactions between a researcher and participant (Orlikowski and Gash 1994) that are viewed as "targeted, insightful and highly efficient means by which to collect rich, empirical data" (De Massis and Kotlar 2014: 19). They are a valuable source of primary data for case studies, because they provide detailed and unique data (Ghauri and Grønhaug 2005). In-depth interviews are "a powerful – if not the most powerful tool" for capturing an understanding of the insider's perspective of the phenomena (Moisander et al. 2009: 333). This understanding is achieved by accurately recording the interviewee's description and interpretation of the phenomenon in context. The primacy of the reporting is given to the participant's account of their experiences (Thompson, Locander, and Pollio 1990). The researcher's role is to interpret these experiences in relation to others accounts of the same phenomena, and to report that interpretation.

There is a high expectation of trust in the interviewing relationship (Daniels and Cannice 2004). The researcher expects the interviewee to report their experiences and insights accurately, and the interviewee expects the researcher to collect and present their data in a way that does not compromise them. Trust can be built with enduring relationships between the interviewee and the researcher, coupled with the familiarity of the case study organisation and the manager's situation within it (Zaltman and Moorman 1988). This is difficult to achieve in a one-off interaction but can be assisted if the familiarity can be increased. Trust-building interactions include knowledge of the other party, communication between the two parties over time, and managing expectations of the interview through preparatory briefing. Section 4.4.4 and 4.5 identify the actions taken in this study to increase interview trust.

4.4.4.1 The choice of interviews as the sole data source

In line with the study's phenomenological epistemology (see Section 4.2.2.2) interviews were selected as the primary source of data, to capture the experiences of those with knowledge of the big data phenomenon. At the outset of the study, the researcher intended to follow Eisenhardt's (1998) guidance that multiple data sources provide a more complete picture, by adding in information from documentary sources.

Additional data sources were considered, such as the FMCGCo Chief Marketing Officer's publication on the firm's strategic responses to digital technologies. The document included information on the organisation's strategy, including examples of innovative partnerships. However, the participating case firms were all large and high profile in their industries. While supplementary documentary sources were readily accessible from the internet, the firms were identifiable from these sources. Referencing the documents or social media sources would have directly identified the firms. Firm identification would have compromised their anonymity and that of the interviewees, contradicting the researcher's ethical responsibility, and risking the firm's commercial wellbeing and the participants' job security.

Other qualitative sources were considered for inclusion, such as project and Board meeting minutes relating to the big data initiative or alternatively, observations of these meetings. These sources might have identified challenges, opportunities or other perspectives on how dynamic capabilities were constructed not highlighted in the interviews. However, access to these meetings was not available to the researcher during the data collection.

At the same time that issues of anonymity and access were arising, the researcher was mindful of the emphasis on the 'voices of experience' of the chosen Gioia Methodology. The researcher chose to forfeit the additional detail on the big data phenomenon that might risk participant wellbeing, and to focus solely on the rich data emanating from interviews.

To ensure that the interview data is sufficient and pertinent to the research question, the research design addresses the sample size, sampling strategy, the nature of the participants and the interview structure. This section is followed by an explanation of the data collection carried out in this study, including the interview participant recruitment and the interview process (see Section 4.4.5).

4.4.4.2 Sample size and saturation

A qualitative study of the type undertaken here, aims to answer the research question using data collected from a sample of sufficient size, depth and relevance. From Yin's (2014) positivist perspective, replication logic across cases is a necessary ingredient in any attempt at theory development, as it is argued that a larger number of cases results in a more externally valid outcome (Leonard-Barton 1990). There are different views as to the number of interviews required to demonstrate rigour in qualitative research. Becker and Bryman (2012) argue that the sample size depends on the nature of the study being conducted. Some suggest that the researcher should aim for thirty interviews (Alder & Alder 2012), whereas others propose forty (Brannen 2012). Warren

(2001: 99) suggest that “to have a non-ethnographic qualitative interview study published, the minimum number of interviews seems to fall in the range twenty to thirty”.

A crucial issue to applying numerical measures to qualitative research is that sample saturation point needs to be achieved, at which no additional data are being found, and the data properties can be developed into categories (Glaser and Strauss 1967). The point of saturation can be difficult to pinpoint, and some themes may have scope for generating apparently limitless data (O’Reilly and Parker 2013). This may be the circumstance in this study because of the novelty of the case phenomenon under investigation.

However, as the study is a qualitative one, based on multiple cases, measurement of the number of participants might be viewed as an inappropriate quality criteria for the study (Dubois and Gadde 2002). Instead, the emphasis should be on the richness of data. In this study, practical triangulation of data is achieved by interviewing various participants, across the firms, on the same topic, which Pauwels and Matthyssens (2004) describe as synchronic primary data triangulation.

However, within doctoral research it is practical to have a rough target for the desired size of sample, due to resource and time constraints. As such, this study acknowledges the statistical guidance provided regarding qualitative, interview studies. Patton (1990: 186) recommends that qualitative studies should have “minimum samples based on expected reasonable coverage of the phenomenon given the purpose of the study and stakeholders interests.” A sample size of twenty to thirty interviews was planned in line with Warren’s proposition. In the event, twenty-two interviews were carried out; a sample size which complies with Warren’s (2001) parameters. These interviews generated thirty-five hours of data. Table 4-4 details the volume of interview material relating to each case.

Table 4-4 Volume of interview material

Automotive company (AutoCo)	FMCG company (FMCGCo)	Media company (MediaCo)	Education company (EducationCo)	Total
1 participant	2 participants	4 participants	14 participants [4]	21 participants
2 interviews	2 interviews	4 interviews	14 interviews	22 interviews
3.5 hours of data	3.25 hours of data	9.25 hours of data	19 hours of data	35 hours of data

The planned interview length was sixty to ninety minutes. The researcher offered to stop the interviews after 60 minutes, and then at 75 minutes, to minimise inconvenience to the participants. However, one interviewee offered a second interview and others gave more than two hours of their time. Excluding the initial introduction research and consent and briefing, almost all of the interview data was highly relevant and usable.

Interviews that lasted an hour or less were associated with the EducationCo Business Intelligence Project (BIP). This was because some of these interviews related to the evaluation of the organisational project, which participants tended to view as part of their job. Consequently, they were not intrinsically interested in discussing the big data phenomenon in ways that the other interviewees seemed to be. As such, the time guideline provided in the introductory email (Appendix 2) may have been viewed by these interviewees more literally. The longer interviews took place at either end of the core working day and were with participants known to, or directly referred to the researcher by other participants. These factors may have influenced their willingness to speak for longer. Familiarity between the researcher and key informants will be discussed further in relation to sampling strategy.

[4] Three additional interviews were carried out; the data from which were not used in this study because they were only relevant to the BIP evaluation. In these cases, the participants were data users and not elite interviewees.

4.4.4.3 Sampling strategy

When undertaking qualitative, interview-based research, it is imperative to include informants whose background and knowledge is pertinent to the study. Deciding on the most appropriate sampling method can be challenging. Unlike in quantitative studies, where the chosen sample is required to be representative of the population being studied, in qualitative studies there is no clear-cut guidance about how to select participants (Trost 1986). In a qualitative approach, the study may benefit from incorporating samples that reveal outlying views or more interesting theoretical insights into the phenomenon (Glaser and Strauss 1967).

In this study, the interview sample was closely aligned to the case study sample, because the initial case study contacts acted as the first key informant interviewees for each firm. As with the case study research design (see Section 4.4.2), non-probability sampling was selected to deliver rich insights, rather than statistically reliable generalisations from the defined population (Ritchie et al. 2003). Criterion sampling was also used to further narrow the selection by identifying and selecting participants with specific characteristics, such as those with experience of implementing big data initiatives within strategic marketing. In order to gather a range of perspectives, the interviewee's role in relation to the big data initiative was not specified. Table 4-5 identifies the participants' job roles. Although the research design involved criterion sampling, the case study and the key informant interview recruitment relied on convenience sampling of the researcher's and business colleagues' contacts. This could be a factor in helping explain the length and frankness of these interviews.

Snowball sampling is a type of purposive sampling, whereby the initial research participant acts as a key informant and stimulates involvement of colleagues or contacts to participate in the study (Bryman 2008). The approach is often deployed in cases where accessing the sample presents problems, for instance, if the participants are likely to be difficult to find and approach. As this study involves the strategic use of big data, the knowledge and insights of senior management are valuable to the study. Because of the nature of their jobs, senior managers may be difficult to access, so the identification of initial key informants and then the use of snowballing recruitment represents a valuable strategy to engage interviewees. In addition to facilitating access, snowballing also helps to overcome issues of trust and ethical concerns between participant and researcher, including concerns about the confidentiality of data. Snowballing recruitment is therefore a suitable strategy for this research.

The success of snowballing recruitment was variable. The numbers of snowballed introductions were not defined in the research design. The actual numbers varied between one and fourteen participants per firm. In AutoCo, the key informant gave two interviews which provided three and a half hours of interview material. However, no further contacts were introduced. In contrast, EducationCo's Head of Strategy introduced sixteen other participants, thirteen of whom met the sampling criterion. The benefit of the increased number of participants was the variety of perspectives it was possible to gather and the potential provided for developing detailed, firm-specific micro-cases within the research findings.

The researcher was surprised at the openness of the research participants, perhaps resulting from them knowing or having a personal association with the researcher. As a result, the participants appeared to trust the researcher to protect their interests and minimise risks to their employment and their firm's wellbeing. Some of the content of the interviews included material the researcher thought should be treated as commercially sensitive, which was therefore excluded from the coding process. This included information on new product development, plans for strategic acquisitions, and intra-firm cultural clashes.

Despite the volume of interview material, the researcher did not feel that saturation point was reached. Each interview continued to introduce new materials, which O'Reilly and Parker (2013) note can be the case in novel research areas. Even so, the analysis generated robust aggregate dimensions, in the form of big data-driven dynamic capabilities (see Section 4.6.6). Further interviews might only add additional 'examples' or microfoundations to these capabilities. As will be explained in Section 8.3.5, further research beyond what is possible within the limits of this doctoral thesis, is needed to test these assumptions.

4.4.4.4 Elite interviews

To address the research questions, a broad range of potential interviewees was considered, including those from operational and managerial levels in information systems, marketing and management. The research focus is on strategic marketing, which takes place at a senior level within the organisation (Smith 1999). As a result, executive or elite interviewees are the preferred participants. Elites interviewees are those holding senior management or board level positions within firms which have "significant decision-making influence within and outside of the firm and therefore present a unique challenge to interview" (Harvey 2011: 433).

The greatest challenge of elite interviewing is gaining access to the participants and opportunities for lengthy interviews with business leaders are rare (Maclean, Harvey, and Chia 2012). The interviews are designed to use a semi-structured format that adopts open questions.

Table 4-5 Participant job titles and codes

MediaCo	01	Managing Director
	02	Chief Innovation Officer
	03	Director of Innovation
	04	Head of (digital) Product Development
FMCGCo	01	Project Leader Digital Research and Development
	02	Head of Data (R&D)
AutoCo	01	Project lead, business insight (Head of Business Insight)
EducationCo	01	Head of Strategy
	02	Manager Business Intelligence Project (BIP)
	03	Vice Chancellor (Director) Teaching and Learning
	04	Quality and Accreditation Manager
	05	Associate Dean Recruitment and Marketing (1)
	06	Dean PGR studies

07	Associate Dean Recruitment and Marketing (2)
08	Admissions Manager
09	Academic Data Manager
10	Data Insight and Compliance Manager
11	Data Insight Manager
12	Head of School
13	Associate Dean Recruitment and Marketing (3)
14	Associate Dean Recruitment and Marketing (4)

The decision to adopt open questions reflects that "elites especially – but other highly educated people as well – do not like being put in the straightjacket of close-ended questions. They prefer to articulate their views, explaining why they think what they think" (Aberbach and Rockman 2002: 674).

In this study, elite interviewees included those from senior positions in any department which was involved in, and therefore knowledgeable about, the firm's big data initiative. The snowballing sampling strategy made it difficult to define precisely which personnel should be involved. However, allowing representation from a variety of departments provided a range of perspectives on the research phenomenon.

In line with the interview research design (see Section 4.4.4), twenty-one interviewees were recruited. The recruitment of interviewees began with key informant interviews. The key informants were elite interviewees who held positions at senior level in different departments that had an association with the big data initiative. Table 4-5 identifies the interviewees by organisation code, individual code and job title. The coding relates to the need for anonymity of participants in commercially sensitive interviews (see Section 4.5 Ethical Considerations).

Of the interviewees, six were at a senior management but not at executive level. These were still deemed eligible as elite interviews, since senior managers in this case were in g203

positions of influence (Harvey 2011). Contributions from three of EducationCo's BIP interviewees, who operated at managerial level but were not in senior roles, were excluded from the data analysis in the thesis, although their insights were reflected in the BIP evaluation.

In summary, as mentioned previously, because interviews need to be contextually-sensitive and flexible (Holloway and Todres 2003), variations can arise between what is intended at the research design stage and what actually happens during data collection. The variations in this study between research design and data collection are discussed in each section and are summarised in Table 4-6.

Table 4-6 Variations between research design and data collection

Activity	Designed data collection	Actual data collection
Sample size	20-30 interviews.	22 interviews, with 35 hours of interview material.
Interview length	60-90 minutes.	Average 140 minutes (EducationCo were each 60 minutes).
Sampling strategy	Criterion sampling.	Opportunity and convenience sampling.
Snowballing recruitment	-	A range of 1-14 recruits per firm.
Recording interviews	-	6/22 used note taking, instead of audio recording and transcription.
Workplace venue	All to take place in office.	5/22 took place outside the office.

Although there were variations between the designed and actual data collection, the primary research was effective in collecting rich data from knowledgeable agents in multiple case study firms. The quality of the research data ensured that the research questions could be addressed, as is evident in the Findings (see Chapters 5 and 6).

The next section describes the interview data collection process.

4.4.5 The interview process

This section identifies the choice of interview structure and explains the interview process used, including pre-briefing of participants; the venue; the interview; recording and transcription; and the codifying and storing of participant details.

When undertaking case study interviews, the choice of interview structure is crucial to ensure that the data collected addresses the research question. Interviews can be classified according to the degree to which they are structured (Fontana and Frey 1994). Structured interviews have been criticised for constraining participants to the specific question asked, preventing them from expressing their own views (Patton 2002). In contrast, the lack of focus in unstructured interviews risks inadequately capturing relevant material.

Semi-structured interviews, which were used in this study, are commonly used in qualitative data collection, sit centrally in this range. These interviews use a more conversational approach, relying on a pre-determined interview structure of open-ended topic or questions, allowing participants to answer with in-depth responses. An important feature of this technique is that the openness and flexibility of response may reveal information that was not previously known. There is also an evolutionary nature to semi-structured interviews; the researcher is gathering additional insights into the phenomenon with each interview, which may in turn influence the direction of the research (Farquhar 2012).

The key informants were contacted by the researcher, face to face, by telephone or email to invite their participation. This was followed by a pack being sent to them including the Research Information Sheet (Appendix 3) and the Participant Consent Form (Appendix 4). The participants then contacted the researcher to confirm, or otherwise, their participation. As the researcher provided information beforehand, the interview participants understood the parameters of the study and the interview. This understanding meant that non-attendance and withdrawal of consent by interviewees were minimised. In addition, it made for efficient use of interview time, as the within-interview briefing could be short.

The interviews were carried out solely by the researcher, meeting on a one-to one basis with the interviewee. The research design had determined the interview venue as the participant's work location, in line with the University ethics application. This was intended for the safety of both the participant and the researcher; however, at the request and for the convenience of the interviewees, six out of the twenty-two interviews took place outside the office. These interviews were held in social locations such as cafes, and in two cases in the researcher's home, as the participants were well known to the researcher and it was suggested as a convenient location for them to meet. The ethical considerations associated with the change of venue are discussed in Section 4.5.

In advance of the interviews the participant received the Research Information Sheet (see Appendix 3) outlining the project and the purpose of the interview, as well as the Participant Consent Form (see Appendix 4). The contents of the Information Sheet and the Consent Form were verbally outlined at the start of the interviews, and the Consent Forms were signed and collected at the end of the interview.

The interviews were semi-structured using a prepared Interview Structure (see Appendix 5). The interview structure was visible only to the researcher. Each interview was expected to last for sixty to ninety minutes to avoid inconveniencing the interviewee during work hours. The interview covered the research project background; the interviewee's background and the identification of a big data initiative used in their firm's strategic marketing. It investigated the forms of big data that were used; how big data was used and analysed and the competences, resources and capabilities involved in using the data for strategic marketing.

The interview closed with the reiteration of consent or withdrawal; the collection of the signed Participant Consent Form; the researcher's response to any participant questions;

and identification of other potential research participants. The interview structure dictated the shape of the interview, but the interviewer accommodated the interviewee's train of thought within the parameters of the broad research question. This maintained the interview momentum and aimed to capture data that were as rich as possible.

To ensure that the views captured were in the participants' own words, the interviews were recorded using Voice Pro software. They were transcribed so that precise wording was captured for analysis. Where audio-recording was inappropriate, or not consented to, the researcher took detailed notes as close to verbatim as possible. Because of the importance of capturing the 'voices of experience' within the chosen Gioia Methodology, paraphrasing was resisted in favour of precise reproduction of the expressions used. Of the twenty-two interviews, six required manual note-taking of the interview either in response to the interviewees request or as a result of noise or lack of privacy in the interview location. The researcher took comprehensive notes; however, possible avenues of conversation may have been missed in the effort to focus on recording the words accurately.

At the point of transcription, case study firms and participants identities were anonymised using codes (see Table 4-5 for details of the coding used). The codes were used to protect the identity of the firms and interviewees, because of the commercial sensitivities of the topic under discussion. Section 4.5 provides more detail on the ethical approach to anonymisation. These codes were maintained throughout the data collection, analysis and the drafting of the thesis. The identities were stored separately, from the coded data, in line with the University's ethical research guidelines, and will be disposed of with the interview contents in July 2021.

The next section describes the ethical considerations for the research approach.

4.5 Ethical considerations

This section of the chapter considers ethics in the research process, an important part of any research design (Twining et al. 2017). This is because "qualitative research ethics are not only a question of procedures and protocols to follow for the researcher's legal protection, but also reflect a researcher's position with regards to his/her commitment towards his/her subjects" (Santiago-Delefosse et al. 2016: 148). Where human subjects are involved, researchers must gain informed consent and behave in an ethical manner (Elliot 2014), respecting the rights of participants such as confidentiality and data protection (O'Brien et al. 2014).

In planning the research, the ethical considerations were submitted to Coventry University's Ethics Committee, to ensure full consideration was given to the sensitivities of the study and the safety of the researcher, the participants and their employers. There were four main ethical considerations for this research: informed consent; confidentiality and anonymity; researcher/participant safety and data governance. Researcher practices were guided by the University's ethics guidance.

To address the ethical considerations for the research design, each participant was required to give informed consent. This was achieved by fully briefing each participant in advance of, and at the start of the interview (see Section 4.4.5). Interviewees were asked to give written consent to participate in the study before it began; and they were fully informed about which data would be collected and how it would be handled, during and after the study's completion. They were also advised that the interview would be audio-recorded, unless they did not consent, in which case the researcher would take a manual record of the conversation. Their rights to withdraw, or remove their data from the study, were clearly stated in the Information Sheet and Consent Form, giving guidance on the latest withdrawal date.

The research was potentially commercially sensitive, as the strategic marketing initiatives may be viewed as sources of competitive advantage. Two approaches were implemented to manage the risks associated with the commercial sensitivity. The primary method was through ensuring firm anonymity. The researcher anonymised the case study firms, using terms intended to obfuscate firm recognition, as might be achieved through describing a bank as 'financial services', or a supermarket as a ‘retailer’. In addition, a coding abbreviation was used, for example ‘EducationCo’, instead of the organisation’s name. Care was also be taken in the anonymisation of participants, using a numerical coding abbreviation, so the source was not recognisable, such as EducationCo02. If the researcher wished to attribute a specific quote to a department to support an argument, the participant planned to ask for their permission. If permission was not granted the quote would remain anonymous.

Another ethical consideration was the risk to the safety of the researcher and the participant, in off-campus interviews. To accommodate the seniority, work-demands and convenience of the participants, all interviews were planned to be carried out during normal working hours, at the premises of the case study firms. The researcher’s presence on site was recorded in the sign-in book and the presence of other employees at the premises would help assure their safety. As the case study firms were large organisations, the locations were major UK cities, in central, well-populated locations. The researcher travelled independently, by car, to all interviews, taking a mobile phone to all meetings, which could be used in an emergency. Research supervisors were advised of the scheduled meetings, including participants and location, at fortnightly meetings. A diary of meetings, venues and contacts were held in the researcher’s lockable filing cabinet. A significant variation from research design arose during data collection. Sixteen out of twenty-two interviews were held in the workplace. Whilst the ethics applications stipulated the interviews being held in the participant offices, six interviews were in fact held outside of work, in social locations such as cafes and in the researcher’s home. These were for the convenience of the participants, for example, because of proximity to their workplace. Any risks to safety were managed by the researcher and participant, acknowledging their knowledge of one another.

In line with data protection legislation and the University’s data management policy, the participants’ interview contributions were stored on the researcher’s university computer using the code names described previously (see Section 4.4.5). Data on the identity of participants were stored separately from the interview data, unless additional consent for disclosure were received. The separate store was a manual record, in a locked filing cabinet, at the researcher’s home. The participant contributions were password-protected with a password known to the researcher and supervisor. The researcher carried out the coding and the password protection. Only the disposal date for the data, laid out in the ethics applications, remains outstanding.

A final variation in the research process was in the submission of two ethics applications. One application addressed the main doctoral research. The second application was for the EducationCo Business Intelligence Project (BIP) as the participants were being asked to contribute evidence that could be used for both the doctoral research and their BIP evaluation. Appendices 6 and 7 are the Certificates of Ethical Approval for the main research study and the EducationCo Business Intelligence Project, respectively. The BIP also required a separate Participant Information Sheet, Participant Consent Forms and Interview Structure (see Appendices 8, 9 and 10, respectively).

An unexpected ethical dilemma arose in the elite interviews, as a result of the freedom with which the participants spoke about their company's big data initiatives. Some of the interviewees identified strategic marketing activities which, on reflection during the analysis, the researcher considered to be commercially confidential. These included describing planned big data-led, strategic marketing partnerships, which were intended to facilitate entry into new market segments. Interviewees also identified culture clashes and funding shortages for data-led developments, which could undermine the participant's personal job security if communicated outside of the interview. Although the comments were pertinent to the research question, the researcher recognised that the need to protect the wellbeing of the participants and their employers outweighed the need to include the comments. One of the reasons for the open and frank communication may have been that some of the participants were already known to the researcher, blurring the line between interviewer and friend. As such, the participants may have expected that the interviewer would apply their integrity in sharing the interview contents.

In summary, to protect the researcher, case study firms and participants the research was carried out with close adherence to Coventry University's ethical guidelines. There were some variations to the ethical research design. These were managed by the researcher with reference to the guidelines and personal judgment, maintaining the wellbeing of all those involved in the research.

The next section describes the data analysis process used within this study, based on the Gioia Methodology.

4.6 Data analysis

The data analysis follows the Gioia Methodology seven step, data-to-theory process, described in Section 4.3.4. Gioia, Corley, and Hamilton's (2012) terminology such as 'data structure' and 'grounded theory models', which may have other definitions and interpretations, are used throughout this section as they are integral to the chosen methodology.

This section provides a detailed description of all the operations performed in relation to the empirical material (Avenier and Thomas 2015). Yin (2009: 126) observed that "data analysis consists of examining, categorising, tabulating, testing or otherwise re-combining evidence to draw empirically-based conclusions". This process involves interpretation of the data, which might culminate in the development of a theory or model (O'Brien et al. 2014). It also allows the reader to follow every step of the analysis and provides an "auditable chain of evidence" (Baskarada 2014: 10). In line with the fundamental premise of the Gioia Methodology, in order to keep the voices of experience at the forefront of the research, the participants' own terms and verbal expressions are retained through the analytical process. Researcher observations on the data analysis process are included in the autobiographical reflections (see Section 8.4).

Within quantitative methodologies and those qualitative methods using deductive approaches, the data analysis process is defined by prior theory (Baskarada 2014). Using the Gioia Methodology is in this qualitative study, involves limited reference to theory at the outset of the data analysis. Instead, the relationship with extant theory emerges after the data structure has been developed. In this section, the focus is on the empirical research analysis, whilst the combining of theory and findings is addressed in Chapter 7 (Discussion).

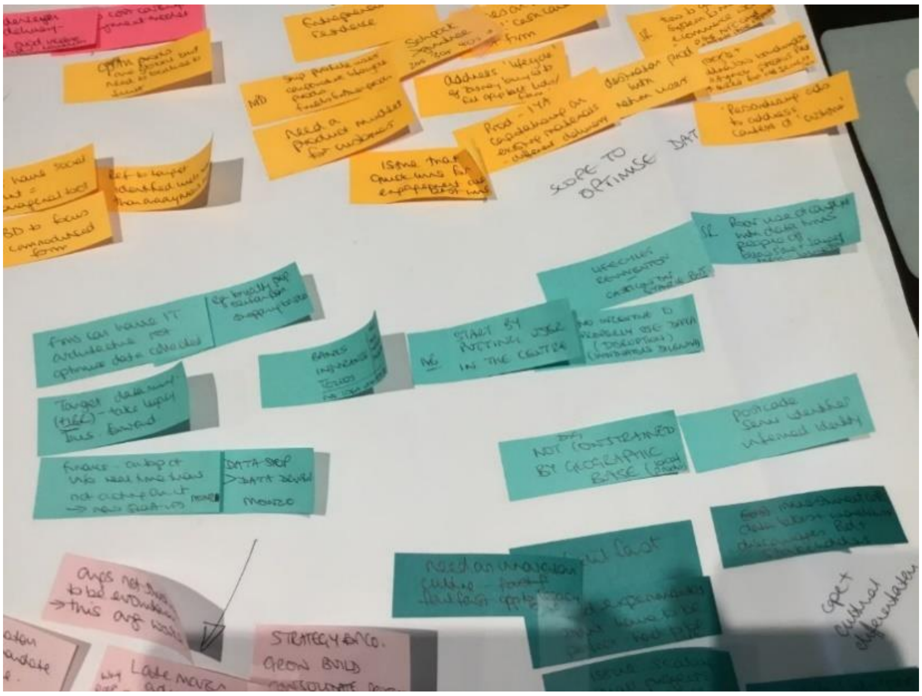
The data analysis section of the chapter is divided into seven parts. In Section 4.6.1, the thick description starts with the interview transcripts, which use the interviewee's own words to provide rich descriptions of the big data initiative at the heart of the case study. In Section 4.6.2, in the first order analysis the researcher identifies key participant terms and expressions from the thick description, and generates categories, with little attempt at distillation. In Section 4.6.3, the first order distillation involves further distillation of the categories and discarding of elements which are not relevant to the research question. In Section 4.6.4, the second order analysis emphasises the researcher's role in sorting the interview material into themes and dimensions. In Section 4.6.5, the second order aggregation condenses the themes into aggregate dimensions, such as dynamic capabilities. In Section 4.6.6, data structures are generated which present the emergent theory in a visual way. Section 4.6.7 explains the development of a grounded theory model, by contextualising the data structure in relation to extant management and information systems theory.

4.6.1 Thick description

Following the Gioia Methodology (Gioia, Corley, and Hamilton 2012), the *thick description* is the first step in the data-to-theory process, with the focus on capturing the voices of participants on the case phenomenon.

From the semi-structured interviews, the researcher collected a detailed description of the 'who, what, where, why and how' of the organisation's engagement with big data. The data analysis started with the interview transcripts, which provided rich descriptions of the big data initiative being undertaken, in the interviewee's own words. The semi-structured interview (see Appendix 5) included prompts, such as the type of data being used, its purpose, the role of stakeholders, the skills and other resources needed and the value of big data for the firm's strategic marketing activity. Whilst the participant firms all had data-led, strategic marketing initiatives, they took different approaches to engaging with big data.

Figure 4-2 Informal manual coding of thick descriptions



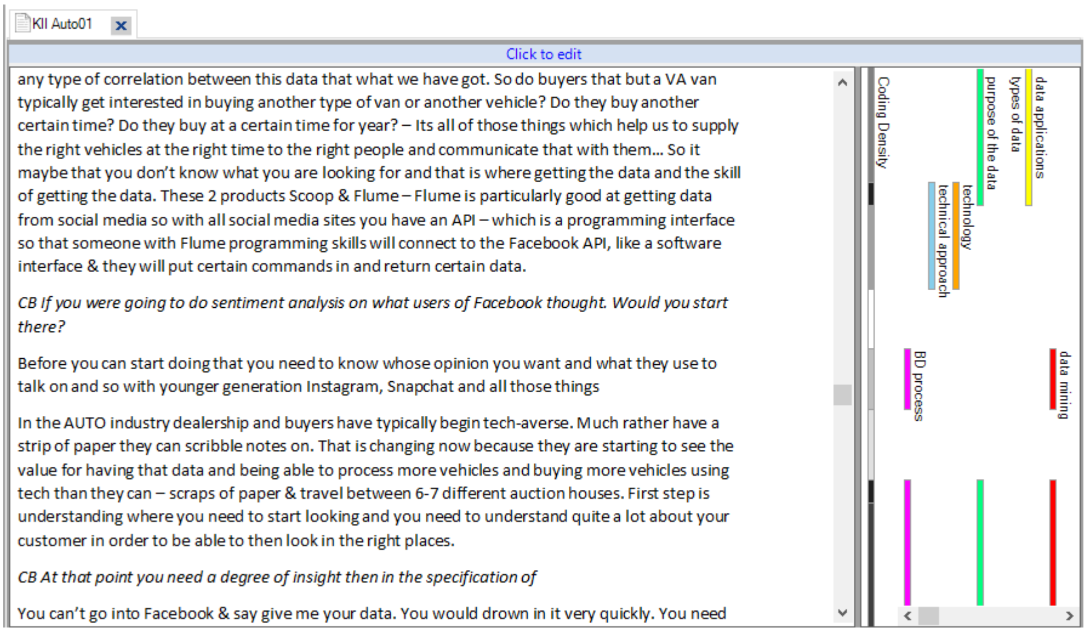
The interview transcripts provided detailed descriptions of the participant’s knowledge and experience of the big data initiative. In their combined form they presented a ‘thick description’ of the use of big data in strategic marketing. The researcher repeatedly read these descriptions, building up knowledge of the interview content and drawing out key phrases, shared characteristics and points of interest, which might represent data categories or groupings. This process was done informally, with participant expressions written on Post-its, and assembled in a mind-map configuration (Figure 4-2).

4.6.2 First order analysis

First order analysis, the next step of the Gioia Methodology (Gioia, Corley, and Hamilton 2012), involves the start of the categorisation of the interview material, adhering closely to participants’ own words.

In the first order analysis, the researcher identified key participant terms and expressions from the thick description, and generated categories, with little attempt at distillation. The researcher made two attempts to carry out the first order analysis appropriately. The first attempt involved the use of NVivo software. Each transcript was coded and grouped using terms and topics raised by the participants (see Figure 4-3). On completion of the coding and grouping the researcher was disappointed to find that the results felt flat and uninteresting, despite the interviews being dynamic and provocative. As an example, EducationCo's Head of Strategy described the challenge of engaging staff in the big data initiative, with the highly evocative description; "we were asking them to move from comfy slippers to running shoes". Using the initial NVivo coding process this came under a code of 'organisational engagement'. Another example was MediaCo's Chief Innovation Officer describing meeting skills gaps with "Google capability talent" which translated in the NVivo coding to 'high level recruitment'.

Figure 4-3 Using NVivo coding for first order analysis



A review of the coding process highlighted that, to some extent, the coding followed the questions outlined in the interview structure. The researcher decided that insufficient abstraction had been applied in thinking about categorisation and grouping, so a second attempt at coding was undertaken. As coding and analysis are iterative and influential on one another, a process of analysis frequently leads to recoding (Twining et al. 2017).

The second attempt at first order analysis was carried out manually (Figure 4-4). The content of the interview transcripts was aggregated into a single document. Each statement was numbered and the participant code recorded with it. This ensured the original source of the statement could be found again. By separating the participant statements, a more messy and innovative way to view the content was produced. Instead of being part of a flow of narrative, this made individual statements appear more independent, focused and vivid as can be seen in Figure 4-4.

Figure 4-4 Manual coding for first order analysis

… the likes of Facebook, Twitter, the online systems where everything goes through. The amount of information from Google through searches, or through Amazon, there's huge volumes of data that can be farmed to make connections	AUTO01	4.
I just have this picture of, you know, the, the King Canute sitting on the beach trying to push the tide back. It's like actually embrace the tide and let's see what power it can bring to us	ED03	5.
You benefit from tapping into a small crisis, because otherwise it's frictionless. You need to build in friction which doesn't exist when the business is stable. It is difficult to achieve transformation with stability and without friction	MED02	6.
It's an opportunity right now that fits. It's not an opportunity which will exist for a long time. Not wanting to be dramatic but in about 5-10 years' time that opportunity will have gone. If we don't manage to create a thriving industry for local journalism now in 5/10 years' time it won't be a question of saving something, it will be a question of building something from scratch. It will have gone.	MED02	7.
Company is under siege from digital supply of traditional(ly printed) product. Long-established product income is being dramatically eroded by different product delivery technology & shift in (advertising) revenues to digital.	MED01	8.
we're quite big in the UK context but we can't do any of the, Amazon or Apple or people like that could take over right now, they can, all they need is a degree of warning powers and they could become a university. They've got the AI and they've got the content and they've got, they've got system, they've got money.	ED03	9.
We all sniff out what the competition is doing – there is information on product launches & early ideas are published. There are papers at conferences. There are patent publications but not much	FMCG02	10.

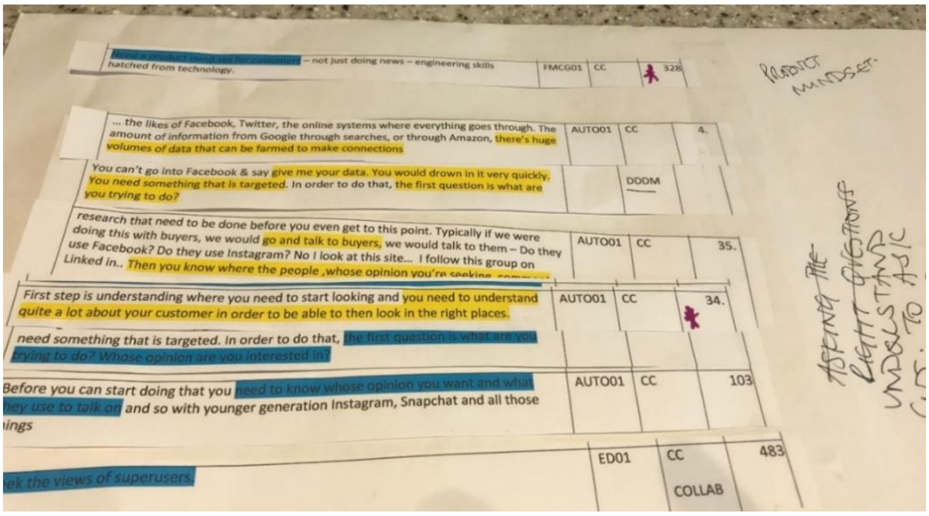
Gioia et al. (2012) suggested that up to one hundred categories might be generated from ten interviews. In this study there were over two hundred initial categories, which led to the inclusion of an additional step, the first order distillation.

4.6.3 First order distillation

Unlike Gioia's methodology (Gioia, Corley, and Hamilton 2012) guidance, *first order distillation* in this study was added as a separate step from first order analysis. It was also informant-centric. The two-step separation helped to maintain clarity between participants' terms and the researcher's judgements, concerning which statements should be amalgamated, and which terms or phrases should be selected to describe the category. Distillation involved grouping statements together into categories, which described the same issues relating to the phenomenon.

Each individually coded and numbered statement was recorded on a separate slip of paper. The categorisation started without any pre-structure, with a clear focus on the research question. The quotes were grouped together under a suggested category title, which used a particular term from one of the interviews; for example, ‘customer centric’ (CC) or ‘collaboration’ (collab). Figure 4-5 provides an example of this step of the process; the categories were abbreviated, as shown in the brackets above. Naming the categories using participant terms ensured that the interviewees’ words were retained between the original data and first order coding. There were multiple iterations of the categorisation, which often moved away from the initial categories. The categories were finalised when the researcher considered that a category, which grouped a number of statements, could contribute to addressing the research question.

Figure 4-5 First order distillation of statements to categories



One outcome of the first order distillation process was the exclusion of data which did not specifically address the research question. The nature of the data collection process provided some interesting material, including information on the big data-driven service developments of Google; the big data activities of firms outside the scope of the case study firm parameters; and the political and cultural challenges affecting firms’ digital strategies. The distillation of the participant narratives into statements of direct relevance to the research question, narrowed the focus of the research investigation. The distillation also reduced the volume of categories to ninety-seven, closer to Gioia’s guidance of one hundred (Gioia, Corley, and Hamilton 2012).

4.6.4 Second order analysis

In the Gioia Methodology (Gioia, Corley, and Hamilton 2012), the *second order analysis* is researcher-centric and involves the researcher in sorting categories and suggesting concepts to describe the phenomenon.

Figure 4-6 An example of the anatomy of the coding process

Key participant phrase	***Category***	***Theme***
Horizon scanning	**Horizon scanning**	***Looking for and liberating opportunities***
Margins are under fire		
Income is being eroded		
Monitoring everything		
Who is at the forefront?		
Observing other industries		
Understanding the competition		
Level of knowledge sets you aside	Level of knowledge sets you aside	
Identifying opportunities		
Opportunities to capitalise on		
What to offer in the next five years		
Market intelligence		
Looking for and liberating opportunities[5]		
Generating opportunities		
Audience potential		
Informing market positioning		
Identifying threats		
Exploiting our big data asset	***Exploiting the big data asset***	
Data informs every angle, opportunity and user		
Big data disrupts the entire business		
Not structured to be evolutionary		
What power data can bring		
Benefit from friction		
Seeing the value of data		
No incentive to use data		
No idea how to use data		
Not optimised data		

[5] Phrases shown in bold and italic evidence that the names of the themes and categories originate from the words of the case study interviewees.

At this analytic stage, the researcher reviewed the categories iteratively, considering the participant terms and phrases and progressing these into second order theoretical level themes and dimensions. The thematic analysis involved considering the appropriate grouping from the categories, defining how they fitted together into themes, and the relationship of the themes to one another. This process involved brainstorming and iterations of different groupings over a period of several months (see Figure 4-6 for an illustration of this process). In line with theoretical sampling in grounded theory research, throughout the analysis, there was an increased focus on the concepts and tentative relationships which were emerging (Glaser and Strauss 1967).

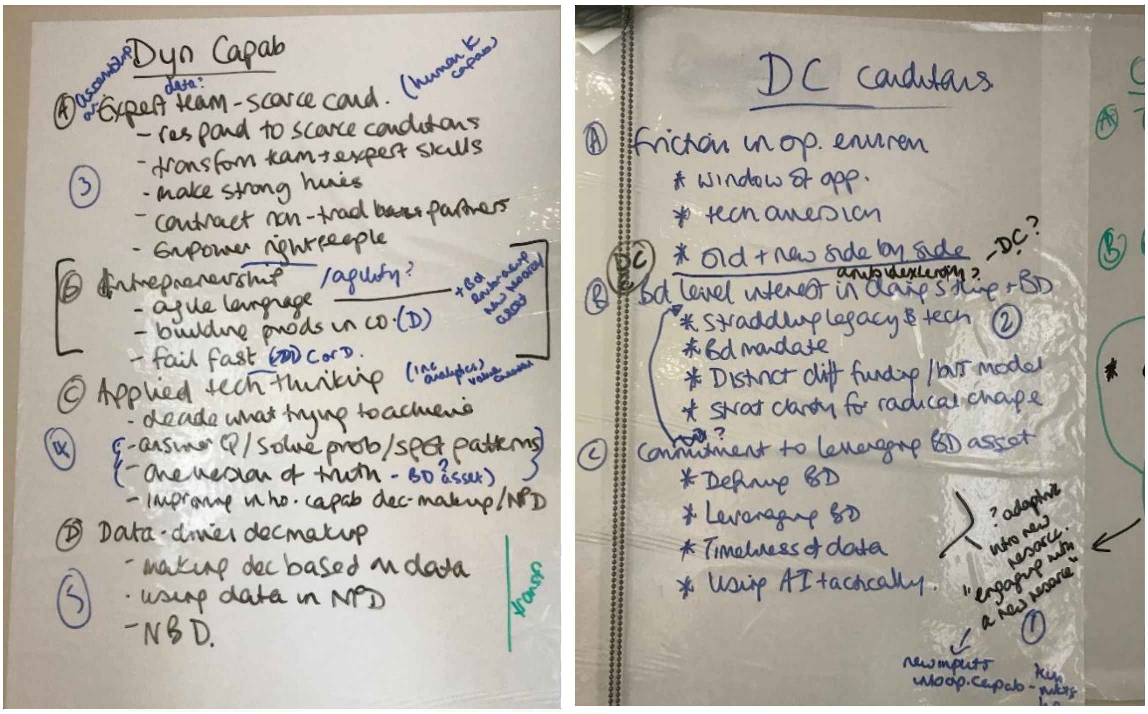
4.6.5 Second order aggregation

In this study, an additional step was added to the Gioia Methodology (Gioia, Corley, and Hamilton 2012). The *second order aggregation* enabled the researcher to condense the second order themes into aggregate dimensions.

These aggregate dimensions represented dynamic capabilities. Through the first and second order analytical stages, thematic analysis was used to group participants descriptions into categories and then into themes. This involved the researcher abstracting her view to conceptualise what she had learned from the analyses. The aggregate dimensions were reached when the categories could not be aggregated further, so each dimension had a distinct theme. This process took place iteratively, over months, as the descriptions, categories and themes were considered and reconsidered. As can be seen in Figure 4-7, not all of the themes identified became aggregate dimensions. In the aggregation process the thousands of interviewee statements, which had been distilled into hundreds and then tens of themes during the analysis, were reduced to five key dimensions. The way in which the categories and dimensions emerged is indicated in Figure 4-7.

The second order aggregation also highlighted themes with 'identity ambiguity' that were not being addressed by existing literature (Corley and Gioia 2004), such as *applied technological thinking* (see Section 6.5). The aggregation also identified those that stood out because of their ‘optimal distinctiveness’ in a new domain (Gioia, Corley, and Hamilton 2010). For example, *straddling legacy and tech* was specific to the established firms’ engagement with big data (see Section 6.3).

Figure 4-7 Second order aggregation of emerging categories and themes



In the process of aggregation, it became apparent that the category ‘*engaging with a new resource*’ was not in fact addressing *how* big data is changing organisations’ strategic marketing capabilities. Instead it highlighted *which* big data characteristics were being applied in the firm’s strategic marketing and what benefit the data was offering to the firm’s strategic marketing. This led to a decision to develop two data structures[6]; one related to the value of big data in strategic marketing (see Chapter 5); and one related to the dynamic capabilities required to use big data in strategic marketing and their construction (see Chapter 6).

4.6.6 Data structure

[6] The term data structure as used here is Gioia et al.’s (2012) term for these analytical outputs

The penultimate step of the data-to-theory process is the generation of the *data structures*, which represents a pivotal step in the Gioia Methodology (Gioia, Corley, and Hamilton 2012). They provide sense-making devices, which enable the participant and researcher contributions to be brought together, and provide the basis for the development of grounded theory models. The data structures offer graphical representations of the process by which the original theory was generated and show the rigour of the research process (Tracy 2010).

The development of the data structures involved repeatedly cycling between data, categories, concepts and themes and, to a degree, existing literature, to identify precedents and also new concepts. Gioia, Corley, and Hamilton (2012) suggest that, to avoid confirmation bias, it is best not to explore the literature too intimately. A balance is needed, whereby the researcher needs sufficient knowledge to know if they are generating new theory, understanding that it is genuinely new and not a reinvention of existing theory.

Using the analytical process described in this chapter, two data structures were generated.

The first, the new data value wheel data structure, relates to big data as a valuable resource. During the interviews, the participants described the types and nature of the big data they were using. They also highlighted the value which the new big data resource added to their strategic marketing. The points raised in the interviews did not align to the discussion on capabilities in existing literature, yet offered rich insights in explaining why the firms had chosen to engage with big data. As a result, 'Recognising big data as a fundamentally different resource' is explored in its own right in the findings, discussion and conclusions of the research. The related new data value wheel data structure originated from the primary data analysis but is closely aligned to Wamba et al.'s (2015) '5V' characteristics of big data (see Chapter 5).

The 'big data-driven capabilities data structure' represents the main body of the research and provides the basis of the new theoretical model. It is built from the inductive research, starting with the insights from the participants' experiences. The first and second order analytical steps identified five dynamic capabilities. Participants' expressions and phrases were retained to describe the dynamic capabilities (the aggregate dimensions). At the data structure level, the insight into the firms' use of these capabilities represents new knowledge. The five capabilities provide the structure for the Findings chapter (Chapter 6).

The big data-driven mesofoundations framework is a product of the BD-DC data structure. The framework emerged directly as a result of the dynamic capabilities literature review, which provided an understanding of microfoundations theory. The review identifies a shortage of literature between the micro level of resources and routines, and the macro dynamic capabilities level, described by Nonaka, Hirose and Takeda (2016) as the mesofoundations level. During the development of the data structures it became apparent that the activities identified by the participants, and subsequently categorised and grouped into dynamic capabilities during the data-to-theory process, were mesofoundations of these capabilities. The mesofoundations of the big data-driven capabilities data structure are identified in the Findings chapter (Section 6.7.2) and in Chapter 7.

4.6.7 Developing a grounded theory model

Gioia, Corley, and Hamilton's (2012) final step in the data-to-theory process is the development of *grounded theory models*. The models are developed by contextualising the inductive findings, epitomised in the data structure, in extant theory. A key part of developing the model is the relationship between the research outcome and the literature (Baskarada 2014).

In this study, the outcome/literature relationship was formed through an iterative process of cycling between the empirical findings and the related marketing, management and information systems theory. Developing the models involved shifts in emphasis between the priority of the participants' words and the researcher's analytical perspective. The process accommodated the individual contributions, the total body of empirical evidence, the relevant theoretical concepts, and the abstraction of all those elements to develop new theoretical concepts.

The findings from the participant narratives, analysed using the seven-step Gioia Methodology, are presented in Chapters 5 and 6. The inductive nature of this study involved locating the research in the domain of dynamic capabilities theory early in the research process (Eliot et al. 1999). However, in line with the Gioia Methodology, in-depth investigation of the dynamic capabilities body of literature was not carried out until after inductive analysis of the primary research (Twining et al. 2017). By taking this approach, themes emerged which might not have been obvious in a more deductive approach. By referring to existing theory at the later stage, the emerging themes were referenced against existing concepts that described and explained the research phenomenon. They also highlighted themes that were not addressed by existing literature (Corley and Gioia 2004) and those which stood out because they were distinctive (Gioia, Corley, and Hamilton 2012).

The relevant theory was outlined in earlier chapters. As big data is a relatively novel research topic in management literature, the study considered a number of bodies of literature including information systems, strategy and strategic marketing theory (as discussed in Chapter 2). The key body of theory was the dynamic capabilities literature, which provided the theoretical lens for the research (as discussed in Chapter 3).

In summary, using the Gioia Methodology enabled a systematic data-to-theory process. This approach resulted in two data structures. These structures are clearly aligned to the research question and to words of the case study firm interviewees. Chapter 7 brings together the data structure from the Findings Chapter with management and information systems theory. The research outcomes are grounded theory models, which explain how big data is changing firms' strategic marketing capabilities.

4.7 Chapter summary

The research methodology is a product of the chosen research question and the research paradigm. An interpretivist ontology is used to address the research question 'How is big data changing organisations strategic marketing capabilities?' Social constructionist and phenomenological epistemologies are combined to capture the experiences of senior managers in four established firms, which have implemented a strategic marketing big data initiative. A systematic research approach was designed and applied throughout the research process, to ensure the research was carried out reliably and rigorously.

The study uses the Gioia Methodology (Gioia, Corley, and Hamilton 2012) to develop new, grounded theory models. The structured approach of the Gioia Methodology ensures that the research outcomes are convincing and trustworthy contributions to knowledge. The voices of experience are retained throughout the analysis, from the interview narratives, through the categorisation and theming, and culminating with the labels for the dynamic capabilities. The detailed descriptions of the data analysis provide the backdrop to the development of the data structures in the Findings (Chapters 5 and 6). The final step in the data analysis, the development of the models, arises in the Discussion chapter (Chapter 7) when the findings and literature review come together.

The next chapter presents the research findings regarding the participant firms' applications of big data in strategic marketing, and how the data added value to their organisations.

Chapter 5 Findings - a fundamentally different resource

5.1 Introduction

This research investigates how big data is changing firms' strategic marketing capabilities. As a precursor to explaining how this change has occurred, the chapter highlights what the case study firms were using big data for within their strategic marketing, and how the new resource added value to their organisations. In doing so, it responds to calls for research on the potential of big data to translate into economic value (see Section 2.7.1), by addressing the sub question: 'What are the characteristics of big data that make it a valuable strategic marketing resource for established firms?'.

Technological innovations over the last thirty years have resulted in widespread uptake of technology including the internet, portable computing devices, social network platforms and the Internet of Things (IoT). The result is the capture of virtually every digital interaction, in the form of big data (see Section 2.3). Big data is described as having five characteristics (See Figure 2-1), which potentially offer firms added value, whilst also making demands on their human and financial resources, and infrastructure. This chapter presents case study participants' perceptions of the value of big data in strategic marketing, whilst Chapter 6 will focus on the capability demands of the new resource.

As detailed in Chapter 4, the data were collected from four case studies of established firms. Semi-structured, elite interviews were carried out with those with experience of implementing big data initiatives in strategic marketing. In line with the Gioia Methodology (Gioia, Corley, and Hamilton 2012), the findings include extensive use of participant quotations, to provide a rich description of their experiences. The analysis used an abductive approach, moving iteratively between the words of participants, emergent concepts and themes, informed by Wamba et al.'s (2015) '5V's descriptive framework of big data. Through the analysis, it became apparent that the participants viewed big data as being fundamentally different to their established resource base, and saw it as contributing towards their competitiveness. The findings informed a data structure, which provides the basis of a grounded theory model, which will be discussed in Chapter 7.

The chapter is divided into seven sections. Each '5V' big data characteristic is considered, with reference to the strategic marketing value that the case study firms ascribe to it. Each characteristic is supplemented with a micro-case which presents more detail from one of the case study firms. The sections conclude with reference to the emerging data structure, which later will be the basis for the grounded theory model. Section 5.2 presents findings on big data 'volume' and the richer, more granular customer intelligence which it can provide. Section 5.3 explains how big data 'variety' gives a broader scope of customer, market and product intelligence from a range of perspectives. Section 5.4 presents findings on big data 'velocity' and the potential for firms to have more immediate data offering more complete and current knowledge. In Section 5.5, big data 'veracity' is discussed in relation to the benefits of more accurate and consistent data. Section 5.6 considers big data 'value' and participants' experiences of the organisational benefits in terms of securing a return on big data investment. Section 5.7 identifies participants' insights into the effects of the continued evolution of the big data concept. Finally, Section 5.8 provides a chapter summary, positioning big data as a value-creating resource and a legitimate part of a firm's resource base.

5.2 Volume

The term 'volume' which refers to the scale of big data, is classified in a number of different ways, all relating to the storage of the data (Kitchin and McArdle 2016). Big data's scale requires it to be stored in data warehouses and data lakes[7], rather than in databases. This changes the technological requirements for storing and analysing the big

[7] The difference between a data lake and a data warehouse is that in a data warehouse, the data is pre-categorized at the point of entry, which may pre-determine how it is analysed. Whereas, a data lake is a single repository for all data, in an unstructured form, so it might be analysed at any point in time.

data because the scale exceeds what can be processed by traditional methods. As the Head of Business Insight at AutoCo confirmed:

> It’s where the storage capability and tools you are using at the moment are no longer capable of doing what you need to do... It’s generally only when using huge volumes of information. *AutoCo01*

Participants from all of the case study firms identified volume as a feature of big data. They used terms such as; “billion data points” (AutoCo01) and “large volumes” (EducationCo11). For the Data Manager of EducationCo (EducationCo11), the large volumes of student data offered a more detailed picture of individual student engagement and of the customer’s journey throughout their studies:

> It’s like a one-stop-shop, it’s a whole array of stuff, you’ve got student numbers, league tables, student satisfaction, module performance, the whole lot. *EducationCo04*

As well as providing granular, customer intelligence of single customers, big data also provided rich intelligence on the whole student body. Increasing the volume of data relating to a single phenomenon, such as a single customer or the concept of pricing, enables firms to make connections between the different elements of big data. Making these connections increases their understanding of customers or the phenomena being considered, and may improve their strategic decision-making. An example of this is EducationCo’s use of “an algorithm that sits behind student data that brings together and creates an engagement score” (EducationCo03) including details of individual students’ attendance, assessment scores and contact information.

FMCGCo initially focused on using product intelligence from organisation-held and curated volumes of data, to increase the effectiveness of getting products to market. As their Head of Big Data (FMCGCo02) observed; “We are using predominantly internal data, the sort of information we use mostly isn’t available externally”. The Project Leader for Digital Research and development (FMCGCo01) identified that the organisation’s aggregation of global product ‘recipes’ into a single repository of high-volume data allowed them to increase efficiencies in new product development. MediaCo also used big data volume to secure internal efficiencies and improve the speed of delivering new products to market. They amalgamated large volumes of photographic stock, owned and stored in different business units, into one data repository. A search of the pooled data, for example all photographs of a single television star, meant every image was available to every journalist and editor. This reduced the cost of buying stock the firm already owned and allowed for commercialisation of their pictorial assets. They carried out a similar data pooling initiative with journalistic content, ensuring a comprehensive record of their stories. This improved the records of reported material, improving the ease of research and reducing legal costs, for example, in libel claims. Their Chief Innovation Officer described the effect of collating big data in a single data repository; "We can now bulk analyse content including metadata of articles and pictures, to reduce agency fees and support legal arguments" (MediaCo02). At the same time, the metadata of local and national news content provided the basis for new online products (see the micro-case study in Section 5.3).

In the case description below, a more detailed description is drawn from AutoCo's Head of Business Insight's explanation of how the firm capitalised on the volume characteristic of big data.

Micro-case study: AutoCo and the volume characteristic of big data

The Head of Business Insight (AutoCo01) described two different strategic marketing approaches the firm took in relation to volumes of big data. Firstly, using the granularity of big data to deliver a business-to-business pricing service; and secondly, improving customer knowledge through the richness of data available from unstructured sources. Because of the scale of the data, these were "fundamentally different" to the data used previously.

He explained that, to develop their pricing service, they used "huge volumes of information", sourced from the firm's supply chain including manufacturers, dealerships and face-to-face contact with consumers: "We are purely looking at our own data, data from our other providers and information available within our network" (AutoCo01). He quantified the volume by saying:

> … we are talking about a billion data points we are using to get that information together. So …yes I think that classes as big data. *AutoCo01*

The scale of the available structured data was the catalyst to transform AutoCo into a data-led firm. The high volume of structured, big data provided granular detail specific to the product pricing phenomena, as he went on to explain:

> … you are taking into account tax, import and export. Every single make, model, derivative of a car with mileage; year when they were manufactured. You look up vehicle, look up the age, mileage, then on top of that option, any damage the vehicle has sustained, and it will give you a price. Then you look at what channel that vehicle is going to be sold in. If it's going to be sold in a retail environment. *AutoCo01*

However, the Head of Business Insight viewed organisation-curated data as only the start of the firm's engagement with big data: "I think unstructured data is the key to big data" (AutoCo01). When investigating a phenomenon such as customer opinions about products, the firm used different sources of high-volume data, including unstructured, social media platform commentary. He went on to explain:

> … if you're using your own data which you have freely available, it's in a structured… environment. You understand all the bits of data, you know how they are linked to the process. You can gain a lot of insight in there but when you start looking at unstructured data such as Facebook and social media – then you're looking at text. Text containing words, symbols, emoji's all sorts of stuff. *AutoCo01*

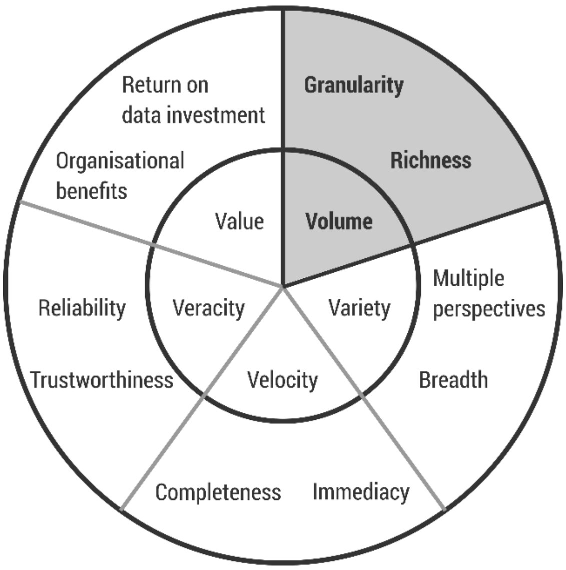
Social media offers high volumes of data with rich detail on customer interactions. This has the potential to affect data-led decision-making, by making connections which might not otherwise be visible:

> The likes of Facebook, Twitter, the online systems where everything goes through… there's huge volumes of data that can be farmed to make connections and help make decisions. *AutoCo01*

With the exponential growth of social media (see Section 2.3.1), there is likely to be a significant increase in the volume of unstructured data, capturing customer opinion and behaviour and making it available to inform firms' strategic marketing decisions. As a result, big data volume is likely to become a more significant source of potential competitive advantage.

In summary, big data is a fundamentally different resource to small data (Mayer-Schonberger and Cukier 2013), because the volume of big data can provide a **richer**, more **granular** picture of a customer or a phenomenon, captured from a single perspective (See Figure 5-1). This more detailed image is valuable because it improves customer and market intelligence, and the identification of market development opportunities.

Figure 5-1 Outcomes of big data volume



The case study firms used voluminous data, originating with internal sources, making it difficult for competitors to replicate or imitate. If the data is inimitable, then big data may be viewed as valuable and having competitive advantage-creating characteristics (Barney 2001). For market-orientated firms, the availability of a new intellectual resource that can improve market intelligence, is likely to effect the firm's sensing capabilities. In addition, the technological challenges of big data storage and retrieval solutions are likely to affect their reconfiguring capabilities (see Section 3.4.3). The experiences of the case study firms regarding data-led dynamic capabilities are discussed in Chapter 6.

5.3 Variety

Another cornerstone of the big data definition is its 'variety' (Laney 2001), which refers to the range of data sources used. Having a variety of big data sources allows the firm to bring together different viewpoints on a customer or phenomena. For example, combining purchase transaction data and product review data, provides both quantitative and qualitative insights into a customer's purchasing experience. Using a variety of data may not appear to differ significantly from 'small data' (Kitchin and McArdle 2016); however, in conjunction with the characteristic of volume, the firm receives richer and more granular information, from different sources; and therefore, different perspectives. The combination provides a more comprehensive picture of the customer, through a broader range of data allowing the firm to anticipate customer behaviour and respond with new products or internal efficiencies.

As with the volume characteristic, participants from all four case study firms talked about amalgamating a variety of sources. The Head of Business Insight from AutoCo (AutoCo01) described starting with their own data, then amalgamating internal data sources to improve business efficiencies:

> Even within a company, different areas of the business have their own datasets. Sometimes it's joining those up in-company. You have the purchasing area. Purchasing may have a certain amount of info but never linked to a stock system, or a servicing system or anything like that. By joining those up you are starting to gain insight and you can affect all the different processes. *AutoCo01*

Like AutoCo, FMCGCo also brought together previously disconnected internal resources, including global product ‘recipes’ and clinical trial data, into a single data repository. FMCGCo’s Project Leader for Digital Research and development (R&D) noted; “Largely, these give us efficiency, but they can also give new knowledge and insights” (FMCGCo01). The organisation then combined the internal, structured, big data with social data to secure; “better insights on consumers and why they like the properties of the product, so we can optimise product and the packaging” (FMCGCo02). Using a variety of data improved their customer intelligence and responsiveness.

EducationCo, however, combined their own student data with externally sourced data, such as data purchased from the centralised Universities and Colleges Admission Service (UCAS), and open source data from the destination of Higher Education leavers’ survey. The external data gave them additional information on competitor activity and capacity (EducationCo11), and market opportunity which directed their student recruitment activity.

The case study below draws together MediaCo interviewees’ descriptions of the variety of big data they were using and their application to strategic marketing activity.

Micro-case study: MediaCo and the variety characteristic of big data

Initially, MediaCo focused their big data efforts on using internal data sources, in the form of digital content on news articles and photographs. By “bulk analys(ing) content including metadata of articles and pictures“ they could improve organisational efficiencies by reducing agency fees and supporting legal arguments (MediaCo01). However, for commercial developments they also looked to incorporate external data sources. MediaCo’s Head of Digital Product Development summarised the diverse variety of data sources the firm incorporated within their data lake:

> It brings together different types of data – imported big data, smaller data, 70% external and 30% internal sources. Some from users and some from content pipelines. *MediaCo04*

MediaCo added variety to its internally-curated data lake, with “42% of data coming from Google, 20% from social media and the rest from our own sites” to “optimise digital content provision” (MediaCo02). The Head of Digital Product Development explained that by combining a variety of sources they were able to change the way articles were written to reflect customers’ reading behaviours:

> … using article word counts on site and those of competitors. We can see what in articles sells; what competitors are writing about; how much space they are giving. Previous (journalists) were writing blind. The dynamics are changing. The old style made sense but couldn’t support operational efficiencies. *MediaCo04*

Bringing together varieties of data sources, which would not have interacted previously, allowed for patterns and opportunities to be spotted in the aggregated data and provided a basis for new, differentiated product development. The Head of Digital Product Development gave the example of designing:

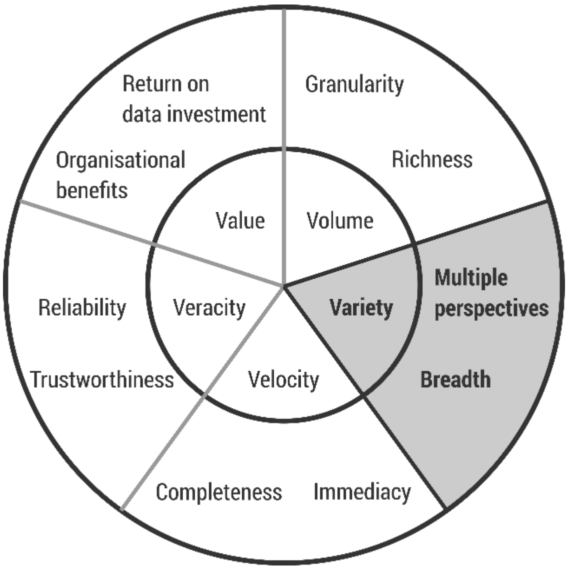
> … a neural network that writes its own articles – like local sports pages - it has a feed of scores - structured data. This data can be brought together with an article and who wrote it and it can use that authors expressions and terms, so it has the voice of the local writer. *MediaCo04*

He went on to explain that amalgamating the sources improved the organisational understanding of its data asset; “previously these have been in siloes so no-one has understood the whole business” (MediaCo04). Better intelligence led to improved product development.

In summary, the ‘variety’ characteristic of big data enables organisations to view their customers from **multiple perspectives**, which provides a **broader** vision of the firm, and its relationship to its customers and users (See Figure 5-2). A more comprehensive picture is valuable because it allows the firms to implement efficiencies and innovations which can strengthen their evolutionary fitness.

Small data can offer variety, but in conjunction with high data volume, the scale and scope of big data is fundamentally different. The complexity of the combined data sources provides a barrier to competitors accessing the same data, making big data valuable and inimitable (Barney 2001).

Figure 5-2 Outcomes of big data variety



Big data variety may be viewed as organised, as it may be structured to address a specific question. On the other hand, the aggregated data provides a basis for a haphazard process of pattern-spotting, whereby patterns and opportunities to add value to customers are sought, leading to a more novel product development process.

Choosing which types and sources of data, and which approach to decision-making will best suit their marketing strategy, and having the internal mechanisms in place to support these choices, has implications for the firm's dynamic sensing and reconfiguring capabilities (see Chapter 6).

5.4 Velocity

Since the early conceptualisations of big data, the 'velocity', or speed, of available data has been a key characteristic (Laney 2001). In Laney's definition, 'velocity' refers to big data being available immediately, in real time. Kitchen and McArdle (2016) subsequently revised the definition to reflect the frequency of data availability, either through frequency of generation, handling, recording, or publishing of data. This subtle difference in definition, lifted the requirement for big data velocity to take place in real time.

Fast-moving data has the potential for improving response times to customers, with a view to increasing customer satisfaction. From a marketing perspective, it also provides the firm with a more immediate and complete view of the relationship between the customer and the firm, regarding the touch points of purchasing transactions, product movement and customer opinion. Where volume provides increased richness and granularity, and variety adds different perspectives for a more rounded customer picture, velocity can increase the currency of the firm's knowledge of their customers.

The case study interviewees talked in less detail about velocity than volume and variety. They commented on other firms and industries such as retail, which were using big data in real time, to make "second-by-second decisions. If something trends and there is something going on the web, then Amazon want to be aware of it so they're presenting the products that match that trend" (AutoCo01). In relation to their own firms, their references to velocity tended to be in relation to automated processes. EducationCo's Business Intelligence Project Manager explained that adapting to big data velocity had streamlined their processes, as previously their data was "was siloed and on hard drives, fragmented. Now data is drawn out overnight and it's an automated process". In contrast, FMCGCo were improving the speed of their customer reactivity by using "intelligent blog reading using programmed semantic language to identify trends such as youth, anti-corporate views" (FMCGCo01).

The velocity of big data may provide an increased speed of service delivery to customers, and thus offers a tool for a firm's focus and differentiation strategies. The Project Leader for Digital R&D commented; "Our margins on products are under fire which is why … our ability to respond quickly is even more critical" (FMCGCo01). However, when the case study interviewees described how big data velocity helped them in relation to their customers, the immediacy of the data was reduced to more sporadic timeframes, such as; "multiple times a day" (AutoCo01) or "run reports when they are needed" (EducationCo01). Consequently, although the velocity of big data improved their competitive positioning by allowing faster customer response times, the interviews indicated firms were not comprehensively adopting this data characteristic.

What was less apparent was why the case study firms were not adopting real time data (see research limitations in Section 8.3.3). It may be that the practical adaptations needed to capitalise velocity required too much investment or that the firms did not have the data management capacity to cope with the additional data speed. By being limited to a fragmented approach to querying data, the potential for these firms to spot new opportunities or respond to customers promptly, may be being lost, possibly impeding their competitiveness.

The case study below explains how data velocity was used by EducationCo to improve customer service and support student recruitment decision-making:

Micro-case study: EducationCo and the velocity characteristic of big data

A number of the EducationCo participants referred to the speed of the data. The organisation's ability to respond to the velocity of big data is an issue for internal business functions as well as for customers. EducationCo's Dean (EducationCo06) emphasised the importance of velocity in providing immediate data access for customers looking for Higher Education places; "… when the clearing hotline goes red on that Thursday, you know, it's there all the time and people keep clicking it and are seen to be looking at it". In this way, big data facilitates improved customer service.

The organisation's Registry Manager (EducationCo08) explained how velocity of data was also significant for the organisational decision-making on student recruitment:

> … once you get into confirmation and clearing, actually you're going in and checking bits of it hourly to see where we are and to make decisions, 'Do we take some more students on that course because that one really isn't coming along as well as we expected?'. *EducationCo08*

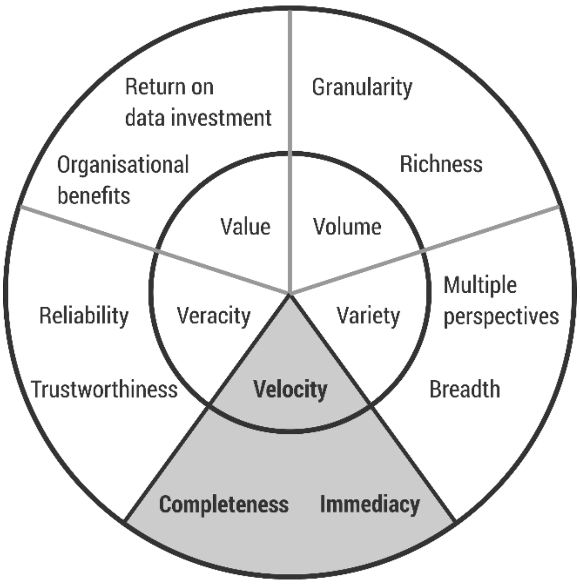
Both perspectives highlight the importance of fast and accessible processing of big data to optimise the benefit to the organisation. However, the Business Intelligence Project

Manager indicated that increased responsiveness to the speed of big data could further improve business competitiveness:

> On things like student numbers and applications, we should be as real time as we possibly can afford to be, because it's amazing what sort of differences you can make if you know how to act promptly. *EducationCo02*

In summary, big data differs from small data through data velocity, which allows firms to have a more **immediate** and **complete** picture of what could be achieved with their customer interactions (See Figure 5-3). Despite their enthusiasm for the potential of 'real time' data for the customers and the organisation, the interview participants indicated that they were applying a more episodic approach to big data velocity. However, their market orientation meant they were aware of examples of other firms using real time data. Therefore, the competitive advantage that might be achieved from this real time customer and market intelligence, was not available to the case study firms.

Figure 5-3 Outcomes of big data velocity



However, it is possible that the complexity and technicality of the speed of big data make it challenging for firms to put into practice. The demands of addressing data speed are likely to have implications for firms reconfiguring and seizing capabilities (see Chapter 6).

5.5 Veracity

The ‘veracity’ of data has only been recognised as a characteristic of big data in recent literature (Wamba et al. 2015). Veracity in big data is how accurate or truthful a data set is (Bello-Orgaz, Jung and Camacho 2016), and refers to the quality, reliability and the trustworthiness of the data (White 2012). Just as for small data, the veracity of big data relies on careful data management and processing practices to minimise errors. Through the data management process the data becomes less messy and error strewn, as the unreliability inherent in some data sources, including bias, abnormalities, inconsistencies, duplication, and volatility, is removed (Gandomi and Haider 2015).

Accurate and consistent data offer firms a more robust basis for forecasting, prediction and decision-making and for the formulation of marketing strategies. However, White (2012) notes, given that big data involves the combining of data sources into big data repositories - such as data lakes - the incorporation of poor quality data before the sources are integrated will undermine the veracity of both the big data and the resulting decision-making.

The case study participants described the value of having improved data veracity. The Head of Business Insight at AutoCo (AutoCo01) described how the firm’s aggregation of big data included precise information on customer search patterns drawn from their website, combined with accurate stock control information. The veracity of the collected data enabled the firm to take a more proactive approach to customer service, for example, saying: ‘I noticed you were searching for a so-and-so last week and we’ve just had fifteen of them delivered in’ (*AutoCo01).* The firm used the veracity of their business intelligence to improve their business efficiency, and to enhance their customer communications and responsiveness. A further example is provided in the case study below, where the purpose of EducationCo’s big data initiative was to increase the veracity of the organisation’s data, to improve strategic planning.

Micro-case study: EducationCo and the veracity characteristic of big data

The EducationCo's big data initiative was a Business Intelligence Project, which aimed to deliver a single repository of data; "a single version of the truth" (EducationCo01). The project involved the amalgamation of multiple student databases into a data lake. The data repository could then be queried by administrators with specific, local functional or marketing questions.

> The visualisation is based on dashboards for the most important information. Different roles see different views but the data behind them all is the same…The content is interactive so admin users can draw out the data that's relevant to them. *EducationCo01*

The approach to student information prior to big data, was much more fragmented, which was detrimental to strategic planning, because it prohibited decision-making with an organisation-wide perspective. It required individual searches of multiple databases and spreadsheets, held in different locations by different staff. As the Head of Teaching and Learning explained:

> Everyone …used to go off … and extract data in their own way and present a picture which was an interpretation that they brought to the data, then we'd end up arguing about the data, so I talk about one version of the truth …
> *EducationCo03*

The project outcome helped to achieve more accurate and consistent results from such searches. The Quality and Admissions Manager (EducationCo04) confirmed that increased veracity of data was achieved as a consequence:

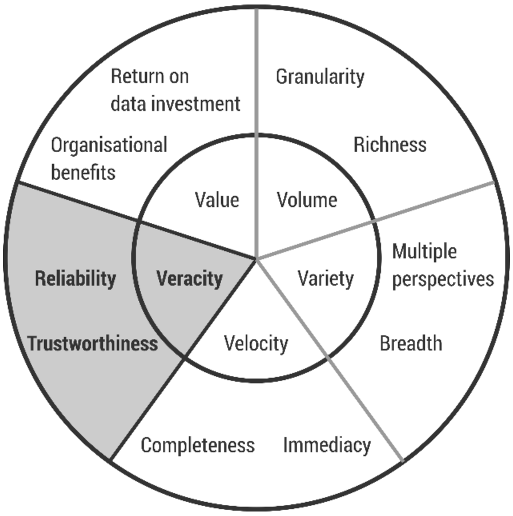
> It's always consistent. It's always a single source of truth, and it always feels like official data. It's not just you going into Universe [the name of their database] and making some judgments that might not necessarily be the right judgments.
> *EducationCo04*

According to the Head of Strategy, the increased veracity resulted in improved information governance and a firmer basis for decision-making and strategic planning:

> It increases our professionalism. Improves the validation of information - having one single answer to the question - 'how many students have we got doing….?' Not multiple answers from multiple sources. *EducationCo01*

In summary, the value of big data veracity is in its capacity to generate **reliable** and **trustworthy** answers to data questions (see Figure 5-4).

Figure 5-4 Outcomes of big data veracity



Veracity of data requires organisation in data management. Digitally capturing data directly from customers or customer/organisation interactions, reduces data fragmentation and can improve data precision. The effect of greater data reliability and trustworthiness is a firmer basis for strategy development and decision-making, but delivering organised data management has implications for firms' reconfiguring and seizing capabilities (see Chapter 6).

5.6 Value

'Value' is defined as 'the extent to which big data generates economically worthy insights and or benefits through extraction and transformation' (Wamba et al. 2015). As value refers to the process of extracting valuable information from large sets of data, to generate useful business information, it might be considered the most important big data characteristic (Bello-Orgaz, Jung and Camacho 2016). It is the perception of this value, that leads to big data being described as digital oil (Yi et al. 2014). Securing value from big data may require a process of transformation. This is because, in its original form, big data may have low value density, while higher value may be obtained when it is analysed in large volumes (Gandomi and Haider 2015).

The case study participants described the value of big data in three ways: the value of having a unique set of big data; the value arising from the fuller picture available from large datasets; and the value arising from the repurposing of data through queries and through pattern-spotting. This section considers how the case study interviewees described these three 'values' and then provides a micro-case study of FMCGCo's approach to securing value from different sources of big data.

The first description of value came from AutoCo's Head of Business Insight (AutoCo01), who saw value as a product of the distinct data held by the firm, positioning big data as an organisational asset. He detailed the variety of data the organisation collected in order to price products and observed: "We have a unique set of data. You can imagine that there's quite a lot of value associated with that" (AutoCo01). EducationCo interviewees, however, presented the value of big data as providing a fuller picture of the customer journey through a mixture of quantitative and qualitative data. EducationCo's Admissions Manager (Education Co08), for example, highlighted the value of big data for market intelligence:

> … a whole load of data which is absolutely revelational in terms of market intelligence on courses…. Is the market declining nationally? Have we got a small percentage of the market or large percentage of the market? *EducationCo08*

The Academic Data Manager (EducationCo09) gained value from a different approach, gathering a fuller picture from capturing customer views from qualitative big data:

> We get a lot out of the qualitative comments, sometimes it can paint a picture that can get lost in quantitative figures. That's the thing, numbers don't always paint the full picture, so you can get quite a lot out of…those comments. *EducationCo09*

The interviewees identified two activities which linked to Marr's (2014) proposition that value can be obtained by repurposing data. FMCGCo presented the more familiar idea that multiple questions may be asked of the large big dataset:

> Our research may be used to address four or five different questions. It can be standardised when the research is answering a similar question, using a similar tool but a different dataset, or the same dataset but ordered differently. *FMCGCo02*

Repurposing data allowed firms to improve the return on their data investment and data-related infrastructure.

In contrast, EducationCo's Director of Teaching and Learning (EducationCo03) described the value of re-purposing of data through pattern-spotting in search of novel outcomes.

> Because by putting all the data together we don't know yet what patterns we'll see that we don't know exist, until we see it together, and allow us to interrogate it differently. *EducationCo03*

In the micro-case study below, FMCGCo participants detailed how they were using big data to secure value for organisational benefit:

Micro-case study: FMCGCo and the value characteristic of big data

FMCGCo's early uses of big data involved aggregating their own data into a data lake. This generated internal operating efficiencies as part of their cost leadership strategies, and enabled faster new product development in support of differential business strategies. As the Project Leader for Digital R&D outlined:

> Aggregating our clinical trial data is one of the ways that we can hold the information more efficiently and improve company wide access to the organisation's knowledge. *FMCGCo01*

The firm drew on the volume, variety and veracity of big data, rather than on the data's velocity, to secure value. The interviewee went on to explain that "drawing on existing data … might not be seen as big data as such, but the scale is huge, and its power is major" (FMCGCo01). It is noteworthy that FMCGCo's big data initiative started when they began organising internal sources of big data:

> Using big data has internally been a big step change. Using it was motivated by the external world moving in this direction in this decade, the last decade or so. The internal driver was initially to optimise production – how to do more with less. Big data is a critical enabler for this. *FMCGCo01*

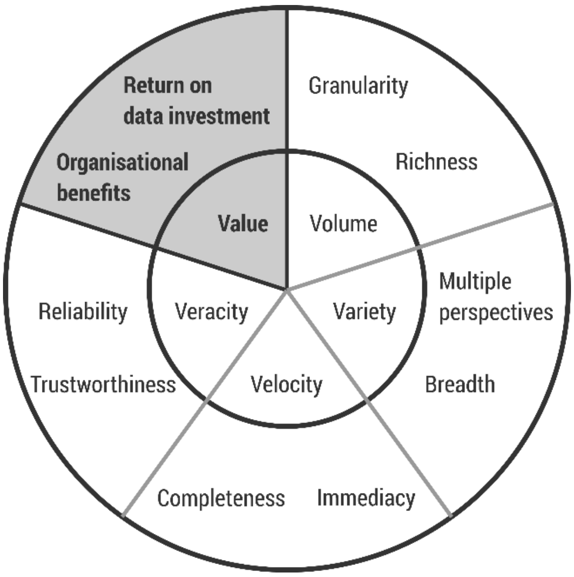
This early emphasis on internal data was common to other case study firms.

The firm was also securing value from the social data insights, in other data-led projects.

> The earliest big data activity was three to four years ago. It took the form of intelligent blog reading using programmed semantic language to identify trends such as youth, anti-corporate views. *FMCGCo01*

As well as identifying "consumer trends and behaviour and anticipat(ing) product opportunities based on consumer behaviour... (it used) behaviour data for targeted advertising" (FMCGCo02). So, as well as using big data in strategic marketing, FMCGCo were also using it within operational marketing intelligence.

Figure 5-5 Outcomes of big data value



In summary, the case study firms describe big data value in terms of uniqueness, completeness and repurposing for **organisational benefit**. These qualities are valuable because they improve firms' customer and market intelligence and lead them to innovate, and secure **return on data investment** (see Figure 5-5). As value is closely aligned to other aspects of big data, securing organisational benefit is likely to require changes to the firms' sensing, seizing and reconfiguring capabilities (see Chapter 6).

5.7 An evolving concept

One of the issues for organisations, in recognising that big data is a fundamentally different resource, is its relative newness. It is early in the big data lifecycle, and extant theory continues to define big data in multiple and evolving ways (Wamba et al. 2015; Kitchin and McArdle 2016). Even though the case study firms are using big data, it is apparent from the study that the firms are also experiencing big data as a complex and evolving concept.

The participants indicated that they had considered whether the data they were using actually constituted big data. EducationCo's Head of Strategy (EducationCo01) stated he thought the term 'big data' to be "pretty ambiguous", as it was used to refer to everything from the student data of a single institution to scientific prediction tools. His organisation's big data initiative involved a high number of data points, from a variety of sources, some in real time, and using data lakes and warehouses for data management, yet he observed:

> What is big data? I think it's pretty ambiguous. I am not sure that what we are using even is big data. Surely the Hadron Collider with data transferring in millions per seconds, that is big data. We have thirty-five thousand students with hundreds of pieces of data… *EducationCo01*

MediaCo's Chief Innovation Officer (MediaCo02) was also dubious as to how big data should be defined. He suggested that the term 'big data' was only relevant at an early point in the data lifecycle. Once big data became embedded in the firm and society, it could be considered “just data”. The implication of his remark is that the ‘big data’ terminology will distil into ‘data’, once it is recognised as a valuable resource, and embraced more comprehensively in industry. Until big data is universally embedded it is useful to retain the distinction between big and small data, because it emphasises the change in characteristics, which may necessitate changes in the firm’s strategic marketing capabilities.

5.8 Chapter summary

In conclusion, the ‘5V’ characteristics identified in extant literature (see Chapter 2) are reflected in this study’s primary research. Analysis of the case study participants’ experiences show that each of the big data capabilities added value to the firm in a different way (see Figure 5-6). In using big data, the firms were able to have a richer, more comprehensive, accurate, and valuable picture of their customers, of marketing phenomena, and of their competitive position. It is evident from the interviews that the choice of datasets was dictated by the organisation’s business strategy and that not every big dataset reflected all five of the characteristics.

Figure 5-6 The big data value wheel data structure

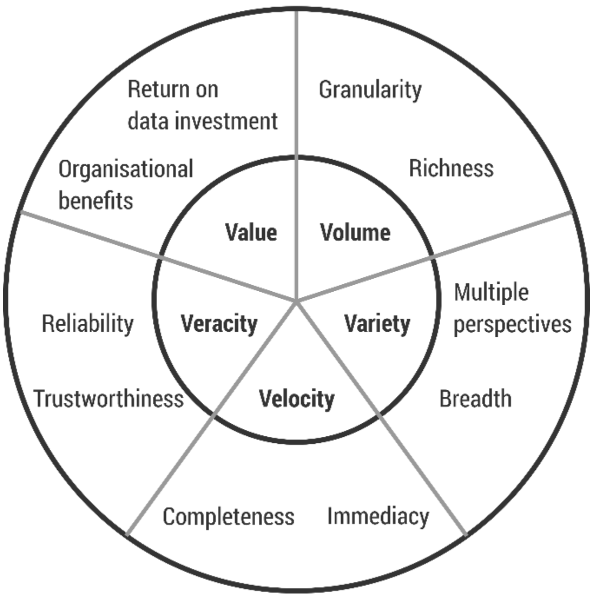


Figure 5-6 is the big data value wheel data structure which encapsulates the case study participants’ experiences. It highlights how each characteristic contributes to making big data a valuable strategic marketing resource for established firms. The data structure aligns to a grounded theory model on securing value from big data, which will be discussed further in Chapter 7.

Chapter 6 presents the dynamic capabilities which the case study firms are using to leverage big data for strategic marketing.

Chapter 6 Findings - Data-driven dynamic capabilities

6.1 Introduction

This chapter presents the findings from the analysis of interviews with senior managers, which address the research question 'How is big data changing firms' strategic marketing capabilities?' To set the context for this Chapter, Chapter 5 identified how the characteristics of big data contribute to making it a valuable strategic marketing resource for established firms. The findings indicated that in order to leverage value from big data, changes in organisational capabilities were required, which is the focus of this chapter.

Firms need to adopt dynamic capabilities to maintain or improve their competitive positioning in technologically turbulent environments. Dynamic capabilities provide a mechanism for firms to alter their resource base, in response to these environmental changes. Chapter 6 addresses the sub-question, 'What dynamic capabilities are established firms using to leverage big data for strategic marketing?'. Analysis of the rich narratives provided by the case study participants, identifies five big data-driven dynamic capabilities used within their strategic marketing. These capabilities will be described in this chapter.

To understand how the dynamic capabilities are formed, this chapter also considers a second sub-question, 'How are established firms constructing the dynamic capabilities that they are using to leverage big data for strategic marketing?'. The findings indicate that the firms constructed big data-driven dynamic capabilities through individual and group level activities such as: employee behaviour and inter-functional coordination. Organisational level constructs were also used, for example, strategic goals and change culture; as well as operational capabilities, including adapting processes to accommodate the new big data resource. These constructs are described in extant theory as microfoundations (see Section 3.5).Understanding how dynamic capabilities are constructed relies on a knowledge of the underlying microfoundations.

The study has adopted a qualitative research methodology, using thirty-five hours of interview material from semi-structured, elite interviews (see Chapter 4). The interviews capture insights from knowledgeable, senior managers on their experiences of using big data for strategic marketing. For the findings to be as rich in detail as possible, participant quotations are incorporated into the analysis, and in supplementary tables, within each chapter. In addition, a number of micro-cases are included, where an in-depth explanation of particular activities described by the interviewees is provided (see Sections 6.4 and 6.5). These micro-cases are important in providing detailed illustrations of how the firms applied big data in their strategic marketing, which improves the understanding of how their firms' capabilities changed.

The interview participants are from the four established firms around which the case studies were created. Their commentaries were analysed using the Gioia Methodology, a seven stage, inductive, data-to-theory process. The findings in Chapter 6 present the first six stages of analysis, originating with thick descriptions of the organisations' engagement with big data, and culminating in two data structures which encapsulate the analysis. Data structures are visual aids that depict the outcomes of the data analysis (see Section 4.3.4). The first structure relates to the dynamic capabilities and the second to the capability microfoundations. The data structures provide the basis for the development of grounded theory models, describing how big data is changing firms' strategic marketing capabilities (see Chapter 7).

The research findings are divided into five big data-driven, dynamic capabilities:

1. Engaging with a new resource (EducationCo03)
2. Straddling legacy and tech (MediaCo02)
3. Constructing an expert team in scarce conditions (MediaCo03)
4. Applied technological thinking (MediaCo02)
5. Data-driven decision-making (EducationCo08).

Each capability will be considered in turn, with reference to the elements the firms used in developing their capabilities. These elements reflect the categories that emerged from the first order analysis and the distillation in the data analysis (see Section 4.6). Distillation involved grouping statements together, which described the same issues relating to the phenomenon. The titles of the categories were determined by the participant descriptions which best described the grouping.

The first capability to be discussed is '*Engaging with a new resource*'(EducationCo03), which represents an important interface between the firms and the technologically turbulent operating environment.

6.2 Engaging with a new resource

One of the five dynamic capabilities that emerged regarding using big data within strategic marketing activity, was '*engaging with a new resource'*. Engaging with the big data resource is an important capability for established firms because it sits at the interface between two elements: the changing operating environment and the potential for improving firm's competitive advantage. The unsettled external environment brings with it changing competition and new business models, as well as fundamentally different types of data that may be of value to the firm. The firm's existing position, process and resource base, and its business strategy provide the microfoundations for new capabilities. These microfoundations may also represent organisational rigidities that prevent the firm from reconfiguring its capabilities. The interaction between the internal and external elements enables the firm to maintain its evolutionary fitness.

Analysis of the case study interviews suggests that there are three elements to the organisations' capability to engage with the new resource.

1. Horizon scanning
2. Looking for and liberating opportunities
3. Leveraging the big data asset,

Each element will be considered in turn, drawing on the interviewees' experiences in relation to their firms' big data initiative.

6.2.1 Horizon scanning

Firms engaging with the new big data resource, use horizon scanning to keep abreast of competitors' data-driven activity and changes in their operating environment. This section presents participants' observations on horizon scanning, including additional, rich interview data, which is presented in Table 6-1.

Environmental turbulence, particularly in relation to the arrival of digital and big data, is transforming the case study firms' operating environment. The interviewees describe their firms as "under siege" (MediaCo01); with "product margins under fire" (FMCGCo01) and "product income being dramatically eroded' (MediaCo01). Horizon scanning has highlighted threats such as ecommerce (FMCGCo01); digital supply of products and digital advertising (MediaCo01); and new competitors (EducationCo08). There is a sense of urgency in their descriptions and, as FMCGCo's Product Leader for Digital R&D notes; "our ability to respond quickly is even more critical" (FMCGCo01).

As well as identifying threats in their operating environment the firms are becoming more alert to the opportunities of big data. The challenges of turbulence and unpredictable competition are leading the firms to investigate how big data is being used in a broader context. EducationCo's Director of Teaching and Learning describes scanning global activity and considering national educational policies and priorities to identify "who is at the forefront" of innovative educational development (EducationCo03). FMCGCo are drawing on other industries' approaches to use big data within their product lifecycle management.

For MediaCo's Head of Digital Product Development, an important outcome of horizon scanning is understanding that the competition has radically changed. Where their customers had historically relied on printed media products for news and entertainment, they are now getting information from digital services, including YouTube and Netflix (MediaCo04). This finding led the firm to take a data-led approach to new product development.

Table 6-1 Big data and horizon scanning - interviewees' perspectives

Subject	The voice of the participant
Margins are under fire	Now our fear is e-commerce – Alibaba. These are unregulated players. Our margins on products are under fire which is why the product lifecycle management and our ability to respond quickly is even more critical. *FMCGCo01*
Income is being eroded	The company is under siege from digital supply of traditionally printed products…. Long-established product income is being dramatically eroded by different product delivery technology and a shift in advertising revenues to digital. *MediaCo01*
Opportunities to capitalise on	Horizon scanning - has an opportunity arisen that we might be able to capitalise on? *EducationCo07*
Monitoring everything	At the moment we monitor everything …. maybe at some stage we decide we want to separate out parts of the business depending on what the results of Brexit are. It's another thing which impacts on prices, like stocks and shares. *AutoCo01*
Who is at the forefront?	We're working with some places in the US who are really at the forefront of this and some places in Australia, they're the two. China of course has just announced a big education strategy change for big data and how they're going to use AI in the classroom and their fifty year strategy. *EducationCo03*
Observing other industries	Like the airline and automotive industries we have been focusing on product lifecycle management (PLM). *FMCG01*
Understanding the competition	We need to understand that our competition is no longer only published and printed media. Our readers are also getting information from Spotify, Netflix, and YouTube. *MediaCo04*

For established firms, horizon scanning in a turbulent environment keeps them abreast of others' approaches to using big data and the threats and pace of competitors' data-driven activity. The insights may be used to inform organisational change and improve the incumbent firms' evolutionary fitness.

6.2.2 Looking for and liberating opportunities

The second aspect of *engaging with a new resource* is looking for and liberating opportunities. Participants emphasised the importance of robust market intelligence to identify market and product development potential. The interviewees' words are included in the text supported by Table 6-2.

Big data is an intangible, intellectual resource (see Chapter 5) and firms *engaging with the new resource* can improve their evolutionary fitness through robust marketing intelligence. As AutoCo's Head of Business Insight commented: "One of the things that sets you aside is your level of knowledge of what is going on in the industry and keeping ahead of others" (Auto01).

The interviewees recognised big data as having the potential to provide new market opportunities for them, as FMCGCo02 commented: "Four fifths of market research is identifying opportunities". The opportunities highlighted by the participants took different forms. The Assistant Dean of Marketing and Recruitment emphasised using big data to improve their market intelligence on growth potential in different market segments (EducationCo07). For MediaCo, using big data prompted a change in service delivery (MediaCo01). Instead of relying solely on their traditional delivery model using retail intermediaries, the capture of end-user data meant that the firm could interact directly with customers. This changed the scope and personalisation of their product delivery. As a result, they anticipated that more growth opportunities would be generated. EducationCo's Admissions Manager (EducationCo08) also observed that granular market information, available in big data, improved their knowledge of their market positioning and drove changes in the business.

In investigating big data's potential, FMCGCo identified that by amalgamating their fragmented data into a big data repository, new development opportunities became available. Examples of these opportunities included "liberating" insights from customers' social media data to inform packaging improvements and making efficiency savings in international product labelling by combining internal, consolidated data and national legislation guidelines from open sources.

Table 6-2 Level of knowledge - interviewees' perspectives

Subject	The voice of the participant
What to offer in the next five years	I was involved in the Portfolio Review which was about, what we offer at the moment, what we could be offering and then the kind of more horizon scanning piece on what should we be offering in the next five years. Big data was one of the key things. AI (artificial intelligence) and big data were the two big things. *EducationCo13*
Market intelligence	People in this part of the world are interested in looking at courses in design because the design industry is growing at x% therefore there is a market for us in that area. So, that is all informed by marketing intelligence. I wouldn't say market research. I would say market intelligence. *EducationCo07*
Looking for opportunities	(Using) big data in Research and Development looking for opportunities and liberating opportunities for R&D product development. This is different from the marketing part of the business who identify market needs for products. *FMCGCo02*
Generating opportunities	Finding these big data sources generates opportunities in 'Grow' part of strategy. *MediaCo01*
Audience potential	Changing portfolio to focus on where audience potential is, rather than legacy footprint. *MediaCo01*
Informing market positioning	We just didn't have this line of information at this level of granularity, whereas we can look at, very easily look at this particular course. Who are our main competitors? Are we low or high end? This has driven massive change … *EducationCo08*
Identifying threats	These are examples of big data questions. The type of industry – banks – they are interested in risk, anomalies in buying patterns,

	access to cash - that sort of thing to look at potential fraud. *AutoCo01*

Big data provides firms with insights into opportunities to improve their market intelligence and to increase their understanding of their customers, competitors and industry. These insights provide a basis for improving customer responsiveness and identifying growth opportunities. This may involve abandoning old routines to incorporate the new resource and new processes.

6.2.3 Exploiting the big data asset

The third element of *engaging with a new resource*, was the comprehensive effect it had on every aspect of the organisation, and the positive effect it had on driving organisational change. Analysis of the participants' observations in this section is supplemented by interview commentary in Table 6-3.

Having made an active decision to engage with the new resource, the case study firms viewed big data as valuable. All the firms acknowledged it as an asset; EducationCo's Head of Strategy confirmed; "big data is absolutely an asset- our project is enabling us to exploit our asset" (EducationCo01). The organisation's Director of Teaching and Learning (EducationCo03) viewed technological changes in the operating environment as both highly disruptive and also as having huge potential to transform the organisation. He thought it was pointless to resist the "tide" of big data and its potential as an asset, and it was in a firm's interest to "embrace the tide" and see what power it could bring. AutoCo01 took a similar viewpoint, noting that once their supply chain experienced the benefits of big data and increased process efficiency, they embraced the data-driven approach and data became recognised as an organisational asset.

MediaCo's Chief Innovation Officer (MediaCo02) also saw a benefit in using the big data asset to generate friction and drive the transformation of incumbent firms. He viewed organisations operating in stable settings as disinclined to change and requiring a catalyst, such as big data, to stimulate different organisational behaviour. The Chief

Innovation Officer (MediaCo02) expressed frustration at entire industries, such as banking and telecommunications, failing to optimise data that would benefit their customers, when they had the wherewithal to do so. An observation of this behaviour is that failing to improve customer responsiveness is likely to encourage new, data-led competitors into the marketplace, worsening the environmental turbulence for incumbent firms.

The impact of this turbulence challenges companies to change (Teece, Pisano and Shuen 1997) in order to survive and thrive. MediaCo's Head of Product Development believes that firms can reduce the business impact and weather the disruption, if they understand the comprehensive nature of big data:

> If you understand that your data informs every angle, opportunity and user and you understand the changes in your marketplace, you can reduce the impact of the paradigm shift on the business. *MediaC04*

"Big data, it disrupts the entire business" (MediaCo04), with the result that incumbent firms may resist the radical changes to established routines and processes needed to engage with the new resource. As the Head of Product Development (MediaCo04) explained; "Organisations are not structured to be evolutionary, they are embedded in 'this organisation works'" (MediaCo04 cited Christensen 2013). This participant was inferring that even before companies engage with big data, there is an internal resistance to assimilating it, making the development of new 'seizing' capabilities even more valuable.

Table 6-3 Exploiting the data asset - interviewees' perspectives

Subject	**The voice of the participant**
What power data can bring	I just have this picture of, you know, the King Canute sitting on the beach trying to push the tide back. It's like actually embrace the tide and let's see what power it can bring to us. *EducationCo03*
Benefit from friction	You benefit from tapping into a small crisis, because otherwise it's frictionless. You need to build in friction which doesn't exist when

	the business is stable. It is difficult to achieve transformation with stability and without friction. *MediaCo02*
Seeing the value of data	… is changing now because they are starting to see the value for having that data and being able to process more vehicles and buying more vehicles using tech than they can with scraps of paper and travelling between six or seven different auction houses. *AutoCo01*
No incentive to use data	A lot of firms can pseudo optimise because of the abundance of information but have no incentive to properly use the data. *MediaCo02*
No idea how to use data	There are a number of industries you would expect to be - but have no idea how to use data – banks, insurance, Telco's (telecommunications) … which are all data, hardware and have the infrastructure have no idea what they should be doing. They should be putting the user in the centre… *MediaCo02*
Not optimised data	…are not building loyalty propositions from shopping basket information. They are not really using it for inventory management. It's not optimised data. *MediaCo02*

Big data can be an asset to the firm and assist in the transformation of the business. However, organisations may not optimise the benefits of big data if they do not have the incentive to use it properly, or leadership that encourages them to discard traditional behaviours. Resistance to engaging with the new data resource may limit the organisation's ability to transform, in response to environmental turbulence.

In summary, big data is changing firms' strategic marketing capabilities by introducing a new resource that can be used to improve market intelligence and highlight possible development opportunities. Market-orientated firms are alert to big data's potential because they scan the environmental horizon, looking for changes that may improve or threaten their ability to be competitive. Those engaging with the new big data resource are acting on the new intelligence by adapting their routines and processes, with a view to achieving differential advantage. Awareness of the resource does not automatically result in engagement with it. Established firms may be reluctant to accommodate the radical organisational changes needed to secure value from big data. Their resistance constrains the firm's evolutionary fitness, making them less able to respond to environmental turbulence and more vulnerable to data-led competitors.

The next section considers how established organisations are adopting new capabilities, to straddle legacy and tech.

6.3 Straddling legacy and tech

The second dynamic capability being discussed is *straddling legacy and tech (MediaCo02)* which addresses the dichotomy of delivering established routines and practices, whilst adopting new ones stimulated by the availability of the new big data resource.

Firms engage with big data because it is an additional resource, with the ability to generate competitive advantage (Reed and DeFillippi 1990). Established firms find it more challenging than new market entrants because it requires them to accommodate a new business approach alongside their existing approach. This dichotomy requires leadership that is responsive to the divergent approaches. Digitally-born companies are much less hindered by the legacy of position, paths and processes defined by these incumbent firms' historical development. In contrast, incumbent firms are balancing traditional operating practices, whilst investigating the new opportunities generated by digital technologies and the big data generated by those technologies.

Navigating this duality is challenging, as MediaCo04 explained; "… transformation is cross-functional but it is difficult when you straddle a mode, between legacy and tech". This dual focus is described in the dynamic capabilities literature as ambidexterity (Duncan 1976). In line with the ambidexterity literature, the case study participants indicated that to improve their competitive position, their firms were both exploiting the processes and resources already in place, while exploring the novel big data-led opportunities.

The interviews identify three essential elements to the firms' capability for *straddling legacy and tech*, which are:

1. Accommodating opposing business and funding models
2. Having strategic clarity to opt for radical change
3. Securing buy-in from stakeholders

The first two elements are pre-requisites to *straddling legacy and tech*. The third element reflects organisational tactics used by incumbent firms to embrace the new technology-initiated resource and to provide traction for future data-led developments.

6.3.1 Accommodating opposing business and funding models

The first pre-requisite for *straddling legacy and tech* is to accommodate the distinct differences between the business and funding models of established and digital businesses. The differences represent a clash of cultures which must be overcome if firms are to 'seize' the new resource. This section identifies three challenges to balancing the legacy business with the new technologies, and the firms' responses. Participants' comments are provided in the analysis and the supporting Table 6-4.

Only MediaCo participants talked about these issues in any detail, maybe because of the radical way in which digital capabilities were organised. MediaCo had established a digital division, in order to cope with the impact of new technologies on its traditional news media business. Their experiences are relevant, because they highlight the challenges in key aspects of resourcing, which are likely to have repercussions for other firms as they increase their data-led activity. The four MediaCo interviewees identified three differences in the business models of established and digital operations. These are the:

- Expectations of profitability
- Types of investment in new product development
- Measurements of value

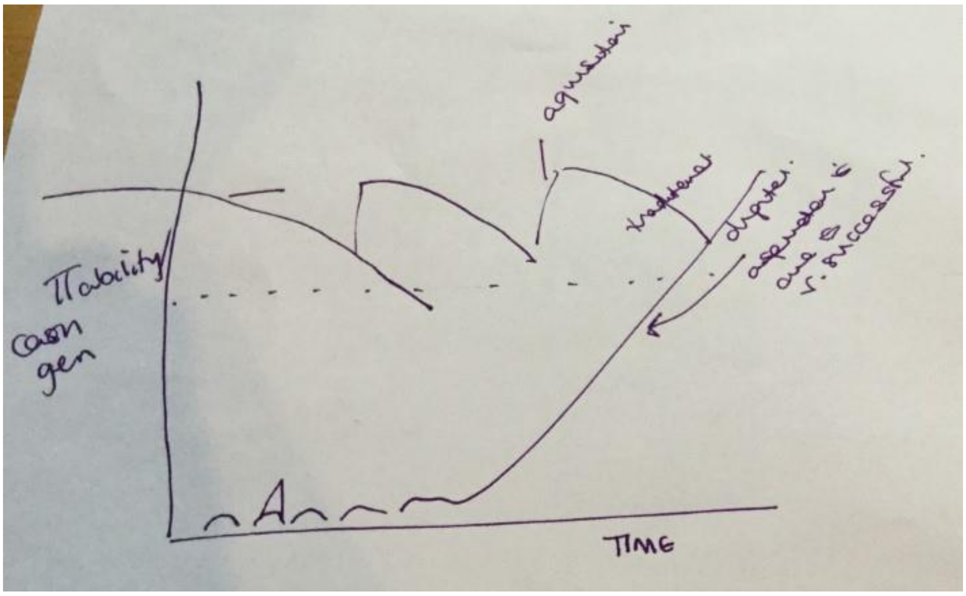
To understand the scale of these challenges to the firm, it is helpful to understand the nature of the three highlighted differences.

6.3.1.1 Expectation of profitability

The Managing Director of MediaCo's traditional print business (MediaCo01) sketched out the differing expectations of the traditional and digital divisions, regarding cash generation over time. As a result of accommodating the data-led approach, the incumbent organisation experienced more than one mode of profitability.

Figure 6-1 MediaCo balancing profitability of legacy and tech

(Source: MediaCo01)



In MediaCo01's sketch (see Figure 6-1), the traditional business generates the majority of the firm's cash, and carries out periodic corporate acquisitions to maintain those levels. In contrast, the new digital division delivers multiple data-led projects, contributing small amounts to profitability but with an aspiration that in time at least one of the projects will be extremely successful.

The Director of Innovation (MediaCo03) explained the challenges stakeholders face in coping with this contrast. An incumbent firm has an expectation of relatively linear profitability, compared with the more erratic data-led model, in which timing and scale of profitability are entirely unpredictable. To accept this uncertainty, the stakeholders need to believe in the future of the data-driven division and the prospects for future returns. The benefit of introducing the data-led and digital activities is that they support the firm's differentiation strategy through entering new markets with the potential for new income streams. This is particularly significant if the firm is operating in a static or declining market.

6.3.1.2 Types of investment in new product development (NPD)

The second difference in business and funding models between established and data-led business is in the available types of investment in new product development (NPD). Where incumbent firms have traditional funding mechanisms such as overdrafts, digital-born firms are able to secure more agile finance sources such as venture capital funding. Furthermore, established firms have historic financial burdens, such as pension commitments. These investment issues raise challenges for established firms which are becoming data-led, because constraints on access to the scale and sources of funding can limit the cost advantages of data-led NPD.

The resource intensity of establishing a data infrastructure means the return on big data-related investments is small and slow, relative to the significant financial investment (MediaCo04). The Head of Digital Project Development commented; "You are innovating but small projects don't give very satisfactory, impactful results" (MediaCo04). This can lead to frustration amongst stakeholders, because of concerns over the ratio of costs to returns, resulting in resistance to seizing the big data opportunities when the digital division asks to scale-up projects (MediaCo02).

6.3.1.3 Measurements of value

The third difference between established and digitally-born business models is in the way the different business types assess value. Established businesses use traditional measures, such as return on investment (ROI) and other metrics relating to cash realisation. In contrast, digital business measures relate to the valuation of the firm in terms of, for example, cost per customer acquired. Internally to the firm, this prevents a direct comparison of the success of different parts of the business, and risks antagonising the different divisions or business functions and impeding internal cohesion. The juxtaposition of valuation methods requires the Board and senior leadership team to change their business model to one which recognises and values both types of indicator. This ensures that the contributions of all internal parties to the firm's competitive position are understood.

Table 6-4 Accommodating opposing business and funding models - interviewees' perspectives

Subject	The voice of the participant
Whole funding structure is different	The whole funding structure is completely different. It's entirely the opposite approach to the legacy business approach… They are used to a linear scale which increases, rather than a model where you have 0% value (in year 1) which increases to 400% by year 3. It's typically a very different financial model *MediaCo03*
Legacy and technology funding models	The legacy business's funding comes from banks, overdrafts, it considers ROI (return on investment), has existing burdens, pensions, overheads. The technology-based enterprises use venture capital firms with a different focus on value. If you look at the venture capital role, you are looking at its future value of the company. *MediaCo03*
Investing in data lakes	Very few are data-driven from the ground up, so the firm has to invest in data lakes and data warehouses. … but the infrastructure … can take a year. *MediaCo04*
Meeting resistance	… small projects when scaled meet resistance. *MediaCo02*
Different terms, and measures	… digital developments are aiming for valuation rather than cash realisation. – different set of measures. Important metric is cost per customer acquired (betting is £30/head plus % revenue shared).

	KPIs include unique views (UVs), PV (page view), newsletter subscriptions, videos streamed, social following. *MediaCo01*

Established firms which are engaging with big data find themselves *straddling legacy and tech*. The challenges of accommodating new data-led, business models, using a new resource and different processes, generates internal frustrations which undermine organisational cohesion and result in resistance to new data-led developments. For the organisation to maintain evolutionary fitness it is imperative that its stakeholders see the value in accommodating the contradictory approaches involved in *straddling legacy and tech*.

6.3.2 Having strategic clarity to opt for radical change

Big data disrupts the entire business (MediaCo04), so the second aspect of *straddling legacy and tech* requires the organisation's Board to communicate clearly the firm's commitment to radical change, through its business strategy. The interviews emphasise the importance of the Board's mandate to engage with big data and how that mandate is conveyed. Table 6-5 provides additional detail from the interviewees' perspectives.

Stakeholders of established firms have experience of the custom-and-practice in their firm's operations. However, technological turbulence disrupts the firm's competition, marketplace and customer behaviour. This disruption generates new business opportunities which can facilitate competitive advantage for the firm. Realising these opportunities requires Board-level understanding of the complex, new resource and commitment to adapt to engage with it.

The characteristic size, speed, variety, precision and value-creation of big data (Wamba et al. 2015) require the Board and the leadership team to step back from their traditional expectations of data and understand the potential and challenges of the new resource. Understanding big data's potential informs the firm's corporate and strategic direction, through market-led decisions on whether to exploit or explore the organisation's data assets. Strategic marketing choices such as market segmentation, targeting and market strategy are also informed. Insight into big data's potential also directs resourcing and investment decisions relating to changes in internal processes and routines. The Chief Innovation Officer of MediaCo commented:

> It's a leadership issue, whether to optimise existing assets or create a future-driving business. How transformative the firm is willing to be, to replace one business with another. It's a challenge to the company… *MediaCo02*

The case study firms highlight two dimensions of Board leadership that are required for big data initiatives to be implemented. Firstly and primarily, a mandate from the Board to reconfigure and transform the firm, stimulated by big data. Secondly, the communication of their commitment to radical change within the corporate strategy and other key strategic documents. These two dimensions are considered in more detail below.

6.3.2.1 Board mandate

Assimilation of complex, big data into the organisation, with a view to improving its competitive advantage, demands infrastructure investment and cross-functional involvement. These activities require the Board's mandate. For some firms, this mandate is initiated through Board-level championing of big data. EducationCo's Director of Strategy (EducationCo01) commented that the vision of a single Board member provided the impetus for the organisation to become data-driven. Similarly, AutoCo's Head of Business Insight observed that a Board-level champion of data usage was a pre-requisite to the data-led transformation process.

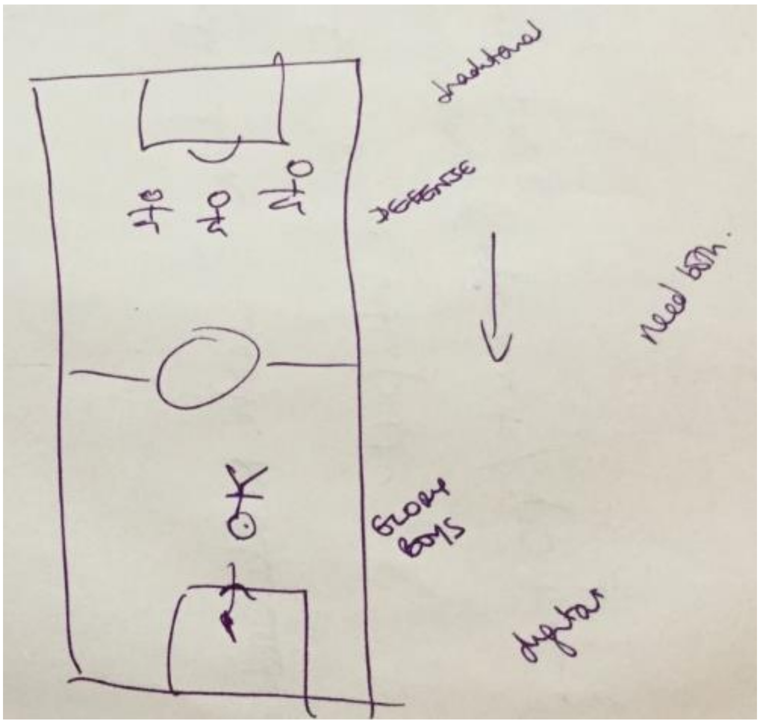
Whilst championing big data engages the firm in its use, embracing big data requires a changed understanding and mind-set from the Board, and a commitment to becoming data-led. As MediaCo's Chief Innovation Officer confirmed "… the decision to adopt a data-led approach forces the need for strategic clarity on decisions to opt for radical change" (MediaCo02).

The firm's Managing Director (MediaCo01) described how this strategic clarity was manifested in their organisation through the establishment of a digital division. The new division was a response to turbulent market conditions and capability gaps in the firm's digital competence. The firms was able to use the two different divisions to handle different market approaches. MediaCo made market exploitation the domain of the established business and market exploration using big data, the domain of the digital business.

The Managing Director of the traditional news business (MediaCo01) used a football analogy to explain their distinct contributions to the organisation's strategy. He presented the data-led digital division as the 'glory boys' 'attacking' new market opportunities and delivering the differential strategy. Meanwhile, the traditional business 'defends' the existing market position and secures the cost leadership strategy (See Figure 6-2). Accommodating both strategic approaches allows the organisation to address the ambidexterity (Duncan 1976) resulting from the combination of legacy and tech business approaches, and to capitalise on the strategic contributions of both positions.

Figure 6-2 MediaCo's strategic clarity to address market opportunities

(Source: MediaCo01)



The need for a Board mandate is not unique to big data initiatives, nor even to IT projects. However, the cross-organisational impact of the different resource investments, including the need for cloud-based technologies and data scientist recruitment, make it distinct from other IT projects. Furthermore, the commercial impetus of engaging the data results in changes to the organisation’s processes and routines, while also requiring transformation to benefit from the data, which has repercussions for the wider organisation.

6.3.2.2 Communicating radical change

The need for the Board mandate is complemented by the need to communicate the increased significance of big data to the wider organisation. The case study interviews indicate that two approaches were followed. The first approach involved communicating through the corporate strategy and corporate plan, as noted by the EducationCo’s Director of Teaching and Learning: “The anchor is the corporate plan, which provides a defined methodology and guide to data developments” (EducationCo01).

The second approach involved Board-level guidance being interpreted through both functional and business unit strategies. The communication of radical changes is reflected in revised functional plans, such as digital revenue strategies, which dictate strategic marketing and operational behaviours (MediaCo01). From a business unit perspective, the commitment to change can be seen in business unit strategies of, for example, research and development or sales and marketing (FMCGCo01).

Table 6-5 Strategic clarity to opt for radical change - interviewees’ perspectives

Subject	**The voice of the participant**
Data-driven philosophy	… the Vice Chancellor’s philosophy is that we should be a data-driven institution. *EducationCo01*
Board mandate	… top down transformation process with access to the Board and therefore more mandate. *EducationCo01*

Top level saying do this	That's why a lot of companies never get to the point where they start to look at what they need to do, because unless there is someone at the top saying we need to do this … *AutoCo01*
Demonstrating to the Board	… and being able to demonstrate that (we've done something) and to say that in a fairly absolute sense to, to the Board who put the investment in is, has been a real boon. *EducationCo03*
Corporate plan is anchor	The anchor is the corporate plan, which provides a defined methodology and guide to data developments. *EducationCo01*
Driven by corporate strategy	The central activity now is driven by the corporate strategy and focused on agile visualisation of our data across the group. *EducationCo01*
Swapping revenue streams	The strategy was swapping one revenue stream (advertising and paper sales) for another (digital). *MediaCo01*
Big data built into strategy	Our product lifecycle management strategy has 3 components – discover, design and deploy. Our big data activities fall into the discover element. *FMCGCo01*

The Board plays a crucial role in driving the firm's use of big data as a value-creating resource, emphasising its importance in delivering strategic goals and facilitating the organisational capabilities to 'straddle legacy and tech'. Initial Board-level championing of the importance of the big data resource is the catalyst for engagement. However, mandating the use of big data through corporate strategies secures organisation-wide buy-in to its importance and value to the firm.

6.3.3 Securing buy-in from stakeholders

The final element to 'straddling legacy and tech' is the need for 'securing buy-in from stakeholders' to the organisation's use of big data. In this section, the case study interviewees describe the tactics they employed to engage stakeholders. Table 6-6 provides additional detail in the words of the participants.

To optimise a firm's competitive position, all business resources and capabilities must be engaged to achieve higher levels of performance than their competitors (Christiansen and Fahey 1984). Incumbent firms need to 'secure buy-in' from a range of internal stakeholders, to embrace the new technology-initiated resource and to provide traction for future data-led developments.

Big data is a complex and novel resource. Consequently, the demands for significant infrastructure investment, with unclear outcomes, can lead to resistance from organisational stakeholders. Securing buy-in from interested strategic and operational partners is an important tactic for leadership teams. It increases stakeholder familiarity with big data, reduces the risk of resistance, and therefore aids traction for the wider use of big data-led developments. The two approaches to securing buy-in from stakeholders highlighted by the case study participants were running old and new systems side-by-side, and using a project-based approach.

6.3.3.1 Running old and new systems side-by-side

For EducationCo, the big data initiative discussed in the interviews involved the replacement of a fragmented data system serving hundreds of users, ranging from Board members to faculty administrators. The old system was replaced with a single big data repository, with 'dashboard' data visualisation and access for administrators, based on their needs and interests. Reassuring the operational stakeholders of the integrity of the new data system led the project team to operate for an initial period with the old and new systems running side-by-side (EducationCo01). The team used parallel data systems and prioritised small, phased but strategically impactful big data projects to increase the familiarity and the understanding of the new resource, and reduce resistance to the new data arrangements. Even so, the transition to organisation-wide engagement with big data took time and was challenging, because as the project's leader, EducationCo01, acknowledged; "We were asking them to move from comfy slippers to running shoes".

6.3.3.2 A project-based approach

Like EducationCo01's early use of impactful projects, the Head of Data at FMCGCo (FMCGCo02) also emphasised a project-based approach to big data to help overcome the "step change" of working with the new resource. FMCGCo started using big data for lower risk, exploitative project activity, increasing users' awareness of the potentially greater returns from using the data, before moving into more exploratory projects. The Head of Strategy (EducationCo01) also indicated that their early big data activities had involved strategically significant projects of specific interest to stakeholders in the Board and senior leadership team. Engaging stakeholders in the big data projects increased their exposure to big data and their knowledge of its value and its potential as a tool for improved business performance. Building on the success of key projects provided the project team with traction to introduce more big data initiatives.

Table 6-6 Securing buy-in from stakeholders- interviewees' perspectives

Subject	The voice of the participant
Stakeholder buy-in	We decided to opt for senior stakeholder buy-in - so from the top down - with small, phased projects, as were going along. We started with the league tables which is central to the Corporate Strategy then went onto to other Corporate Plan information. This gave the project exposure to the Board of Governors and then they knew what it would look like. *EducationCo01*
Board-level interest in data	You need Board-level interest in doing something with the data and systems. That's where strategists come in – What do we need to do? What do we need to know? How do we find out? They just need to start asking those questions. You need organisations to prioritise asking the questions. *AutoCo01*
Engaging the senior team	Engaging the senior team relies on recognising their time constraints. Focusing on what is important to them. Business Intelligence is the front door… *EducationCo01*

Running old and new side-by-side	We pretty much ran the old and new systems side by side. It gave users time to see the benefit of new systems, also allowed validation that the new system wasn't losing information available on the old system. *EducationCo01*
Project-by-project basis	Using big data has internally been a big step change. It tends to be on project by project bases. The internal driver was initially to optimise production – how to do more with less. Big data is a critical enabler for this. *FMCGCo02*
Gaining traction	In the first 12 months we had 60 users which gave us the traction to move forward. It was valuable, giving us support at a senior level. The next step … has given us 400 users. *EducationCo01*

When a firm is 'straddling legacy and tech', there is a need to advocate the benefits of the 'tech' element, in the form of big data, in order to increase understanding and secure the buy-in of stakeholders. Securing buy-in reduces the risks of resistance, by increasing familiarity with the value that is added by the new resource. Stakeholder buy-in acknowledges big data as an asset to the organisation's strategic marketing and provides traction for future big data developments.

In summary, incumbent firms that are using big data find themselves challenged by straddling legacy and tech. On the one hand, this may result in culture clashes, but on the other hand it provides friction that may stimulate organisational transformation. The arrival of big data introduces technological turbulence into the firms operating environment. Unlike digitally-born firms, which may be unencumbered by historic paths and processes, established firms find themselves straddling the legacy practices with those of new technology. Firms are overcoming the inherent challenges of different types of business model through strategic commitment to the data-led approach, which requires them to accommodate contradictory positions regarding opposing business and funding models. The Board plays an important role in overcoming stakeholder and organisational resistance to big data, by advocating its value as an essential resource to delivering business competitiveness. Engaging stakeholders with early big data initiatives, can reduce risk and resistance, which provides traction for wider big data engagement.

The next section considers how firms are *constructing an expert team in scarce conditions*, in order to leverage value from big data in strategic marketing. This is the third dynamic capability arising from the interview analysis.

6.4 Constructing an expert team in scarce conditions

The technological origins of big data require a new skills base to internalise the data and to enable the firm to use it to transform and innovate (see Section 2.7). This is particulary challenging as the technological changes are worldwide and there is a global shortage of data-related skills. The related capability, which emerged from the case study interviews, is '*constructing an expert team in scarce conditions*' (MediaCo03).

The practical handling of big data requires operational IT to capture and process data, and data science expertise in programming and analytical competence. In addition, the application of the data to direct strategic marketing activity requires knowledge of the business and the operating environment (Alvarez 2016). The global demand for this new skills base has resulted in talent shortages (McAfee and Brynjolfsson 2012), requiring companies to develop new capabilities to put together a suitably skilled team.

The case study interviewees highlight three different elements, being used to differing degrees by their companies, to construct their expert teams:

1. Breadth of skills and breadth of vision
2. Contracting with 'untraditional' partners
3. Entrepreneurship and experimentation

The contributions of each of these elements to constructing an expert team, will be considered in turn, supported by the case study participants' comments.

6.4.1 Breadth of skills and breadth of viewpoint

To *construct an expert team in scarce conditions*, the case study participants highlighted the need for breadth of skills and breadth of viewpoint, to make effective use of big data. This section presents the different approaches described by the interviewees as shown in Table 6-7, and provides a micro-case of MediaCo's tactic of 'making strong hires' to secure that breadth of input.

To secure the breadth of skills and viewpoint, all four case study firms emphasised the importance of inter-functional co-ordination. This term describes collaboration between marketing, technology and other functions in the organisation-wide generation of market intelligence (Gresham, Hafer, and Markowski 2006). EducationCo's Head of Strategy (EducationCo01) described the amalgamation of skills and viewpoints via an inter-functional project team. This included representation from Strategy and IT Services teams and consultancy input on the data science elements. The Strategy team had previously used a similar collaborative approach in designing the big data initiative, involving stakeholders as well as operational representatives. Those interviewed from this organisation highlighted the value of bringing together different areas of expert knowledge:

> There are areas of business I understand that others don't. There are areas of business others understand that I haven't got a clue about. And having that conversation … that's a really good conversation to have. *EducationCo10*

The other firms' representatives emphasised the need for expert skills from different business functions. Although big data might be viewed as a purely technological domain, the need to apply it requires high level inputs from at least three perspectives. Firstly, business process and business intelligence perspectives are required to provide the knowledge of the business, market and industry (FMCGCo01 and AutoCo01). Secondly, information technology expertise is required on areas such as the technical infrastructure, data warehousing, and software availability (EducationCo01). Thirdly, big data requires expertise in data science from technical specialists in software design programming, mathematics and statistics (FMCGCo01, EducationCo02, MediaCo03).

Unlike the other three case study firms, MediaCo engaged a recruitment strategy which sought to capture breadth of skills and viewpoint within individual recruits. Their Director of Innovation (MediaCo03) explained that they recruit managers with multi-disciplinary knowledge to work with big data, for example, computer scientists with knowledge of economics or cognitive psychology. This polymathic approach enables a purposeful, commercial output from the big data processing. In this way, they are looking to the comprehensive skills of team members to outperform their competitors.

Table 6-7 Breadth of skills and viewpoint - interviewees' perspectives

Subject	The voice of the participant
Close working team	We stabilised the project board and the contribution from Information Technology Services (ITS) from 6 to 10 people. ITS is led by a different PVC (director), so it needs close working, which has worked successfully. The teams work well together. *EducationCo01*
Group design ***Involving the main stakeholders***	… designing it, I mean obviously we were kind of brought in as a group to kind of go through what we would like from a dashboard which looked at admissions-based data. So there were representatives from Registry, from the international office. There were representatives of ITS (Information Technology Services) as well. The planning office. I think that's probably the main stakeholders that were involved. *EducationCo10*
Internal understand business process	Internal staff understand the analytics and oversee the quality and they understand the process behind the business process. *FMCGCo01*
In-house business intelligence	The Business Intelligence side of things that is in-house… you need to have a certain level of understanding of the market and the industry in order to be able to know where you need to get to and what the benefits are. *AutoCo01*

Working with technicians	We have been working with a group of people from analytics, statistics and maths and more recently have added skills in computer programming and computation. *FMCGCo01*
Combining different specialisms	We have two technical specialists, programmers. Our project leaders understand our business need and they have specialist knowledge. *EducationCo02*
Technicians with wider knowledge base	Product managers … probably have an interest in computer science … but certainly have a business or economics background. Design researchers, probably have a background in computer related design and or … cognitive psychology, or HCI (human computer interaction), so sort of related fields but not necessarily programmers…. You need to have that breadth of skills and that breadth of viewpoint. *MediaCo03*

The findings indicate two dimensions to securing expert skills in scarce conditions, one which concerns the need for inter-functional co-ordination of knowledgeable people; and the other, involving the recruitment of highly skilled, specialist personnel.

Recruitment of skilled and competent experts in an environment which has a global skills shortage may involve competing with digitally-born rivals. The nature of MediaCo's news-based product means they are competing with highly data-driven firms such as Facebook. In order to respond, their digital skills base needs to equal their rivals, so it has an aggressive expert recruitment strategy. A micro-case of their approach is outlined here, taken from comments made by their Chief Innovation Officer.

Micro-case study: MediaCo expert team recruitment strategy

MediaCo's strategy for constructing teams in scarce conditions differed from the other case study firms. They sought to recruit polymaths with knowledge of business and data science, to address their digital capability gap. One of the ways they did this was to "make strong hires" from the big technology brands (MediaCo02).

MediaCo was a traditional news media organisation with a legacy of printed products. In the face of new digital media competition, the firm made the strategic decision in 2016 to establish a digital division. The division was tasked to seek digital and data-led opportunities to consolidate, build, protect and grow the established business (MediaCo01). The new division had no existing staff base, so was unencumbered by established skills or perceptions of market opportunity. The Chief Innovation Officer (MediaCo02) explained that the firm targeted talent from global technology giants, recruiting staff:

> …from cutting edge technological firms such as Twitter, Google, BBCi, EBay, Ocado, Tesla, Spotify and blockchain. We are hiring 'famous people' in the tech domain. *MediaCo02*

Targeting these firms provided a quality assurance for the recruits' technical capabilities for handling big data:

> We are hiring 'google capability' talent – it's an attractive company with a super solid hiring bar. Picking people from Google therefore guarantees specific tech strengths; they are culturally geeky. *MediaCo02*

This strategy secured highly technical staff, from digitally-born firms, with experience of data-led product innovation. However, there was a disadvantage to this approach as these types of firm do not experience product development using the existing resources of a traditional firm, as he observed: "… they have other shortcomings – put them into a legacy business in a transformative situation and you get friction and problems." (MediaCo02).

So, although recruiting from digital-born firms can help bridge the technical capability gap for the firm, it may generate a culture gap which needs to be addressed. To some degree, closing the cultural gap can be assisted by the inter-functional co-ordination of skilled project teams, highlighted earlier.

Despite its technological origins, constructing an expert team requires a matrix of expertise (see Figure 6-3). On one dimension, the firms engage inter-functional co-ordination of teams with a breadth of skills and viewpoints. Within a big data initiative, contributions from data science, information technology and a market-orientated perspective are vital. On another dimension, each business function engaged with big data contributes specific expertise. Inter-functional co-ordination can help overcome the risk of culture clashes between the specialisms, which might detract from the data-led developments required to improve competitiveness.

Figure 6-3 A matrix of big data expertise

		Breadth of skills and viewpoints (e.g.)			
		Data science	**Information technology**	**Market intelligence**	**Corporate strategy**
Business functions with specific expertise (e.g.)	**IT**				
	Strategy				
	Finance				
	Marketing				
	External agencies				

6.4.2 Contracting with 'untraditional' partners

The second element raised by the interviewees regarding *construction of an expert team in scarce conditions*, relates to the contractual relationships established with external organisations. These relationships are needed when the capability gaps cannot be addressed internally, and thus the competitive position cannot be optimised. Table 6-8 provides additional details from the participants' perspectives. The term 'untraditional', referring to the firm's engagement in contractual relationships that would have been thought unusual or untypical in the past, is retained as the expression used by the interviewee, even though 'non-traditional' would be the more commonly used term.

Shortages of skilled staff internally and in the marketplace, as well as unfamiliarity with the new data-orientated technologies, led the case study firms to establish contractual and partnership relationships with non-traditional partners. These relationships enabled the companies to resolve capability gaps, particularly in technical areas, such as data science and programming, analytics and software design. This approach also offered the potential to bring the capabilities of different firms together to address new strategic opportunities.

FMCGCo has adopted an organisation-wide "third-party ecosystem" (FMCGCo01) to use contracts to address skills gaps. The Project Leader for Digital R&D explained that FMCGCo benefits from the more modern and advanced skills of their partners through these agreements. However, they also hinted at the cultural challenge of the large, established firm contracting with non-traditional partners. For example, analytics micro-firms bring technical expertise but, because of their reliance on a few key players, they may not survive for the length of the big data initiative. Previously, traditional partners were selected partly for their cultural similarity to FMCGCo, as being larger and long-established they were perceived as robust and a good partnership fit.

The benefits of project-based, contractual relationships are commended by MediaCo's Managing Director (MediaCo01) as offering short-term agility. If the long-term potential of the developments does not appear sustainable, then short-term contracts represent a more flexible source of skills which may be terminated more readily than employed relationships. Although the case study participants talked about contracts, they also used the word 'partner'. This suggests that rather than a traditional arms-length relationship, the contracts were closer, more collaborative alliances. In the fast-evolving data field, defining clear contractual terms and outcomes may be difficult, and a more flexible partnership or project-based arrangement may provide a solution.

As well as addressing technical skills gaps, strategic partnerships provide the firms with the potential to engage with new market opportunities, which they do not have the capability to pursue alone. EducationCo's Director of Teaching and Learning (EducationCo03) noted the potential of an alliance with two large, technology brands. In this strategic marketing relationship, the firm could contribute digitised content of the institution's materials and could rely on the online delivery systems of the partners to "develop something rather interesting" (EducationCo03).

Table 6-8 Contracting with untraditional partners - interviewees' perspectives

Subject	The voice of the participant
External partners with advanced skills	Our external partners are more modernised and have more advanced skills and data scientist capability. *FMCGCo01*

Contracting with non-traditional partners	We have a third-party ecosystem. FMCG1 has a group of data scientists and statisticians but … we are contracting with untraditional partners. We use both large tech-based firms and the technology on their platform such as IBM and Google and smaller analytics companies. They tend to be technology agnostic and use any existing technology but bring skills-based analytics and computation. *FMCGCo01*
Contracting for agility	We are buying in software design and analytical skills. Our software designer is based in Spain – they have a project-related contract with the company. This type of relationships gives us short-term, agility and it allows for failure. *MediaCo01*
Partners for developments	It's what Amazon do, it's what Apple do. So we are talking to those companies about how we might partner and develop something rather interesting. *EducationCo03*

When there is a shortage of employable skills, establishing an expert team with the technical skills to capitalise on big data can be achieved by contracting. Contracting allows short-term gaps to be filled by specialists and provides an agile solution to a problem where the outcome is not clearly defined. Firms also use more collaborative approaches such as alliances and strategic partnerships to secure expertise. These collaborations are useful in relation to new product and market development, where technical and marketing expertise are both required. New types of contractual relationships require adaptation of the firm's culture, processes and routines.

6.4.3 Entrepreneurship and experimentation

The third element raised by the case study firms, *in constructing an expert team in scarce conditions* is the introduction of more entrepreneurial and experimental processes. Table 6-9 presents the interviewees' perspectives on these innovative processes.

New opportunities identified from big data provide a stimulus for a more entrepreneurial approach within the organisations' strategic marketing activity. The concept of employees within organisations being given freedom and support to create new products and services, systems and processes, without following the organisation's usual routines or protocols may also be described as corporate entrepreneurship (Garcia-Morales, Bolivar-Ramos and Martin-Rojas 2014) or intrepreneurship (Bosma, Stam and Wennekers (2010). Although the other terms would be equally appropriate to this analysis, the term entrepreneurship is chosen because it is the term used by the case study interviewees.

This entrepreneurship is reflected in more experimental and innovative behaviours. MediaCo's Chief Innovation Officer (Media Co02) described the organisation's people-based changes, such as the recruitment of an "entrepreneur in residence", tasked with identifying radical new product development from existing resources and new partnerships. The firm's innovative approach is also evident from establishing an in-house "product experimentation team", challenged to get new products to market in short timescales. The focus of this team is speed-to-market, accepting the need for post-launch revision of products, but increasing the firm's agility and market responsiveness.

While MediaCo02 described tasking individuals and teams to behave more experimentally to optimise the firm's competitive position, FMCGCo01's Project Leader for Digital R&D, noted a shift in FMCGCo's culture to embrace a more innovative approach. For example, using a Dragons' Den[8]-style model to recruit new data-related suppliers; positioning established divisions in research parks with digital start-ups; and a new emphasis on empowering small groups in problem-solving networks. These examples allowed the experienced teams to benefit from innovative approaches and mind-sets.

[8] Dragons' Den is a reality television programme in which entrepreneurs pitch their business ideas to a panel of venture capitalists in the hope of securing investment finance from them.

Table 6-9 Entrepreneurship and experimentation - interviewees' perspectives

Subject	The voice of the participant
Entrepreneur-in-residence	Entrepreneur-in-residence – this involves researching the network. It's more radical in nature. We will have to look to venture capital to launch these products, with Media co having an equity state, because of the cash constraints of the firm. *MediaCo02*
Experimentation	A product experimentation team with autonomy. They chose a leader…they chose ten (people), enough to manage, cross functional. Then they were targeted to launch a product in one month to users. They proved it could be done. Also it didn't have to be perfect – it had to be live…. *MediaCo02*
'Shark tank' for recruitment	The IT marketing team used a 'Shark Tank'[9], a sort of Dragons' Den to find suppliers. They are often start-ups, young companies; sometimes they have developed their own platform. FMCG01
Digital incubation	…shifting geographically to research parks, in conjunction with these digital start-ups. For example, in food innovation we have a 'discover space'. We are designing the space for smart companies to develop marketing plus. *FMCGCo01*
Empowered smaller groups	It has empowered smaller groups – different agendas – global, local and local jewels. It produces a project matrix base which stimulates networking. *FMCGCo01*

Constructing an expert team to work with big data in scarce conditions, requires established firms to take a more entrepreneurial approach to delivering organisational goals. Introducing experimentation and innovation into their business routines increases their agility and market responsiveness. For some firms, this inventive approach is the responsibility of key personnel or relates to specific projects; for others, the

[9] Shark Tank is the American version of Dragons' Den.

entrepreneurial perspective is reflected throughout the firm, and embedded in everyone's remit.

In summary, big data is changing firms' strategic marketing capabilities by necessitating variations in the skills base, to secure value from the new resource. Constructing an expert team in scarce conditions requires the engagement of highly-skilled specialist personnel. The firm may hold the necessary skills within its skills base, or may need to secure them from outside the firm. Recruitment of expertise, such as in data science, may be challenging with a global data skills shortage. Alterative solutions to meeting capability gaps include contracting, alliances and partnering with organisations who have the in-demand skills. Constructing an expert team then requires robust inter-functional co-ordination to bring together disparate skills, combining the new expertise with in-house competence; for example, knowledge of business strategy and IT. The unconventional approach to capturing expertise is reflected in more innovative and agile approaches to market responsiveness.

The next section addresses the fourth dynamic capability needed to use big data in strategic marketing, a capability for *applied technological thinking*.

6.5 Applied technological thinking

Applied technological thinking is not a term used in extant management and computer science literature, but it was used by one of the case study firms' Chief Innovation Officer (MediaCo02) and effectively encapsulates activities described by other interviewees. For the purpose of this section, the term *applied technological thinking* offers a more holistic perspective than the narrowly focused terms of 'big data' and 'big data analytics' (see Chapter 2). It encompasses all aspects of the practical application of the data, such as the firm's objectives for the big data; the identification of relevant customers or users; the preferred sources of big data; the selection of big data analytics software; and extends further still, into skill requirements and the demands for technological investment. *Applied technological thinking* is a concept which has emerged from the primary research in this study, but is not explicitly identified in extant management or big data theory.

To make the firm more competitive, requires the capability to consider how technology and data might practically be used to seize the opportunities identified or generated, from big data. MediaCo's Chief Innovation Officer (MediaCo02) captured the essential nature of this phenomena: "Firms need *applied technological thinking* – if it's missing you can't deliver". Breaking down the components of that statement clarifies that organisations need to carry out processes to consider (thinking) the practical use (applied) of big data (technological). EducationCo's Head of Marketing and Recruitment (EducationCo05) described the combination of those processes as the "holy grail", which establishes the connection between "the data and the data analysis and the business decisions and driving (the business) with great insight."

The Head of Business Insight (AutoCo01) confirmed that this type of thinking starts before the analytics stage: "…you need a view on how to take advantage of the technology but which data? Which tech? Which people?" (AutoCo01). These questions apply beyond the technology function. In section 6.3.2, which discussed the construction of expert teams, the interview participants confirmed that the effective use of big data required a triumvirate of perspectives. Firstly, business intelligence bringing knowledge of the business, the market and the industry; secondly, information technology to establish technical infrastructure; and thirdly, data science from technical specialists in subjects such as programming and software design.

MediaCo's Head of Digital Product Development (MediaCo04) felt that this kind of thinking should be even more integral to the organisation than inter-functional collaboration. He suggested that if "part of the goal of data is to increase transparency" then big data "needs to be part of an organisation's workflow DNA, not only part of its culture" (MediaCo04). This viewpoint suggests that *applied technological thinking* needs to be an organisation-wide activity.

In order to improve understanding and engagement with big data, as part of its *applied technological thinking*, the firm needs to overcome the mystery associated with working with this resource. EducationCo's Dean of Postgraduate Studies (EducationCo06) and AutoCo's Head of Business Insight (AutoCo01) used the terms "black art" and "dark art", respectively, to describe working with big data, which suggests that it is not yet a well-understood process. EducationCo06 indicated that for them the use of visualisation software in their business intelligence project improved the clarity and reduced the mystery of their big data activity:

> And there's far more science now because of Tableau[10] than ever before but it's in part still a bit of a dark art. And the less it can be dark art and the more it can be science the better. *EducationCo06*

The interview participants highlighted five elements of the *applied technological thinking* capability, of which big data analytics is only one. The terminology used for the elements reflects the interview participants' chosen wording:

1. Starting with a question or looking at patterns
2. Profiling users by data
3. Different forms of big data give better insights
4. Analytics and the analysis tools
5. Finding insights to drive business decisions

The next sections will consider each of the five elements and their contribution to *applied technological thinking*.

6.5.1 Starting with a question or looking at patterns

According to those interviewed, big data is changing firms' strategic marketing capability by driving organisational development of *applied technological thinking.* The first element of this new capability relates to the organisation's plans for a data-led strategy and whether to start "with a question or looking at patterns" (AutoCo01). This section identifies how the firms apply these different approaches and provides a micro-case

[10] Tableau is data visualisation software which provides graphical representation of information and data.

study of EducationCo's use of pattern-spotting, as a basis for a strategic marketing intervention. Table 6-10 provides supplementary detail in the words of the interviewees.

Chapter 5 introduced the big data volume characteristic and identified the necessary changes in data storage required to manage data volume. Big data requires firms to move from individual databases to large scale data repositories, such as data warehouses and data lakes. The latter term, particularly, indicates a vast pool of data from which the firm will need to 'fish' for the appropriate data to help improve their business competitiveness. This sentiment is reflected in the Head of Digital Product Development's (MediaCo04) observation that the purpose of data is "discovery".

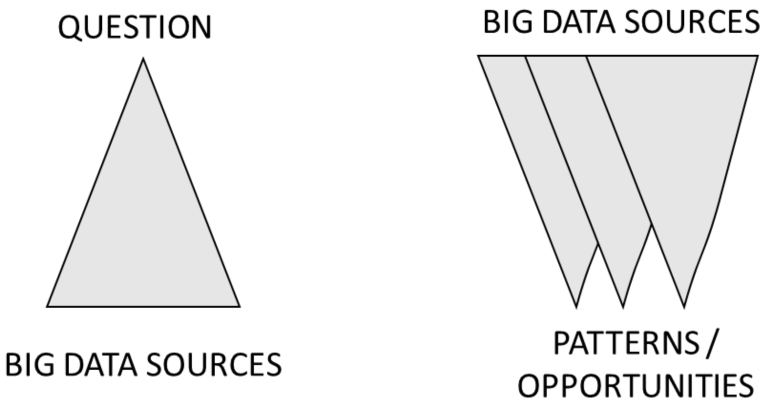
Before choosing which big data are needed and the consequences of that decision, the firm needs to narrow their focus by considering their strategic aims, the purpose of the data and the information they need (MediaCo04). AutoCo's Head of Business Intelligence (AutoCo01) described that process as "chicken and egg":

> …you need some sort of overriding concept of what you are trying to achieve… You also need to understand what's in there…kind of chicken and egg. Giving me a dump of today's data and let me look at it and then, 'ok, now I understand what's out there', and the question I need to ask, or query I need to write, or filters I need to apply to get what I am interested in. *AutoCo01*

This iterative process further clarifies the purpose for which the data were being used. The participating organisations' initial approaches to big data tended to reflect the methods of traditional data use, looking to big data to answer a specific question (AutoCo01), or to investigate an idea for business improvement or development (EducationCo03). These cases would start with the query which, to some extent, dictates the choice of data source.

An alternative approach, which was highlighted by the Head of Business Intelligence (AutoCo01), involved looking for patterns in the data. Through pattern identification, companies can present different queries to the pooled data and look at patterns and "see things that we wouldn't expect to see" (EducationCo03). This "blue sky" approach enables a more versatile use of the big data resource (see Figure 6-4). Using big data inverts the traditional, question-answering, data analysis process. It involves pulling together multiple data sources and detecting patterns, which identify opportunities for strategic change or development. In addition to using multiple sources to address one problem or question, adding data sources within the pattern-seeking approach generates additional and different opportunities.

Figure 6-4 Using big data sources to address a question or pattern-spot



The nature of big data allows organisations to address specific questions or problems, as well as to identify new patterns and opportunities. Organisations which start by using big data to problem solve can evolve to undertake pattern-spotting, once the potential of the data becomes apparent (AutoCo01). The changes in how the organisation views, interacts with, and analyses the data, improve its capacity to transform in response.

Table 6-10 Pattern-spotting or starting with a question - interviewees' perspectives

Subject	**The voice of the participant**
What info do we need?	…about discovery - What do we want to do? What information do we need? *MediaCo 04*
Starting with a question	Some companies start with a fundamental question they want an answer to … which is much easier because you have sort of focus ... sometimes you need to be able to look at other data to clarify what you have found and some will just start looking at patterns. Let's see if there is any type of correlation between this data that what we have got. *AutoCo01*

Looking at patterns in data	Because with a lot of things you can start off with an idea or a question and go away and find the data for it. But one of the things with insights and the predictive analysis is that you start to find things that you weren't expecting to find and you are looking then at patterns. You are looking at blue sky type "Let's see what happens if you change this or how can I link these bits of data – is there anything I can link between these 2 areas? Is there a pattern. If I add information to it does that create a new pattern?" *AutoCo01*
Seeing things we don't expect to see	…by putting all the data together we don't know yet what patterns we'll see that we don't know exist … until we see it together… have the ability to see things that we wouldn't expect to see". *EducationCo03*

Pattern-spotting in data enables firms to connect units of data that are otherwise independent and draw from them different inferences on customer behaviour, trends and feedback to inform strategic marketing activity. EducationCo used pattern-spotting as a basis for new service development to help retain student customers, as outlined in the micro-case study, below.

Micro-case study: EducationCo's use of big data to increase student retention

As part of their focused strategy to improve business competitiveness, EducationCo's first big data initiative was their Business Intelligence Project (BIP). The BIP aimed "to report a single version of student data across the organisation's administration" (EducationCo01). The organisation's student data was recorded in a multiplicity of databases, including personal data in the registry database; course and chosen units in another location and student scores in a further separate store. EducationCo administrators expressed their frustration that this approach meant it was not possible to get a consistent response to the question: 'how many students do we have?' As well as maintaining multiple data sources, the institution relied on a centralised system for handling data inquiries through its strategy team, so data access and analytical competence was constrained.

Under the leadership of the Director for Teaching and Learning, the strategy team were directed to "make the most of their data assets" (EducationCo01). A consultation team, including stakeholders, was established to decide the priorities for the BIP. A project team was formed including members from the Strategy function, IT Services, and a visualisation software firm, Tableau. Within the Project, multiple student-related data sources were aggregated in a data lake and made accessible to administrators via Tableau dashboards, which presented a visualisation of the data. The dashboards allowed more analysis to be accessed at the user level, rather than centrally. This gave administrators greater control over the data they used, and the decentralisation freed the strategy team to quality assure the process. It improved the organisational administrator's involvement in using and analysing data, improving the firm's skills base and directing functional strategies and decisions.

Having successfully addressed their business intelligence problem by capturing "a single version of the truth" (EducationCo01), the strategy team were able to look at the pooled student data for patterns. The team were invited to use big data as the basis of a pilot project to increase student retention. The project team investigated correlations between student attendances over time; grades of coursework; deterioration in attendance; and deterioration in coursework grades. From the data they identified 200 students who were at risk of failing or withdrawing from their courses and, in conjunction with the customer service team, piloted a student retention intervention with this group. The Director of Teaching and Learning (EducationCo03) described the pilot:

> …so we have an algorithm that sits behind student data that brings together and creates an engagement score. For the students who are deemed to be least engaged in a course, compared to their cohort, we'd call them and say, Are you okay? Can we help? Is something going wrong? *EducationCo03*

This data-led intervention resulted in improvement in coursework marks at their next assessment for all but one of the two hundred students. Thus, pattern-spotting in the data led to changes in the strategic marketing capability, through new service development.

Organisations are using *applied technological thinking* to change the ways that they engage with their data and the resulting knowledge. Where previously their data focused on problem-solving, they now have the potential to look for patterns and therefore new opportunities, in their big data resource. Changing their resource base and data-related processes is leading to greater innovation in strategic marketing.

6.5.2 Profiling users by data

The second element of *applied technological thinking* is 'profiling users by data' to improve customer intelligence. The interviewees' views on profiling by data are presented in Table 6-11.

Big data enables firms to understand their customers at a more granular level, as outlined in section 6.2.1. This gives them more precise knowledge of their customers, offering the potential to outperform their competitors. This knowledge is not limited to behaviours and buying habits; it extends to demographics, geography, preferences and qualitative commentary on products and experiences. All of these big data attributes inform the customer profile differently, so the choice of data source whether GPS location data or product reviews on social media, can generate a different user perspective. In the Chief Innovation Officer's (MediaCo02) view, to enhance customer-centric decision-making, firms should be mapping this data to users in the same way that they would map user profiles against products.

To direct the firm to the most valuable data sources requires a process which oscillates between the organisation's strategic and operational aims, which customer or stakeholder opinions are being targeted, which data sources users are engaging with, and which data aspects need more detailed consideration. The Head of Business Insight (AutoCo01) talked about his firm's approach to using social media in user profiling. This involves interacting with the data sources used by the firms' customers, such as Instagram and Snapchat. Although these sources were not the traditional domain of the incumbent firm, social media platforms were considered to represent an important source of data including customer comments concerning their user experience and the firms' products. Using *applied technological thinking* to define user profiles ensures firms are drawing on relevant and targeted data sources as a basis for data-driven decision-making.

User profiles provide a basis for short and long-term product portfolio planning, reflecting the life stage data of the established customer base. For example, eighteen year-old customers with an interest in buying cars or renting accommodation will potentially be car-leasees and house-hunters in five years' time. Using forecasted life stage data to inform product portfolio planning, supports customer retention in the long-term, by reflecting the evolution of these users' likely interests and priorities.

Not all user profiles can be precisely defined with personal data. Where precise data are not available, inferred identities can be used to approximate aspects of the user profile (MediaCo02). Inferred identifies include data such as postcodes, which in conjunction with demographic data, may be sufficient to approximate a user profile as a basis for segmentation or targeting activity. As MediaCo's news products are predominantly purchased by customers through intermediary retailers, the firm's knowledge of users' personal information is limited. Inferred geographic and demographic data from retailer data collection is therefore combined with specific customer data from competitions, reader offers and online footprints, to develop a semi-inferred user profile. This profile informs data-driven decision-making in strategic marketing and new product development, for example, in the form of new, localised, online products.

Table 6-11 Profiling users by data - interviewees' perspectives

Subject	The voice of the participant
Mapping data to users	You would map the portfolio of products to follow users, you should do the same with data. (MediaCo02).
Understand customer to	The first step is understanding where you need to start looking and you need to understand quite a lot about your customer in order to

look in right place	be able to then look in the right places. You can't go into Facebook and say give me your data. You would drown in it very quickly. You need something that is targeted. In order to do that, the first question is what are you trying to do? Whose opinion are you interested in? *AutoCo01*
Whose opinion?	Before you can start doing that you need to know whose opinion you want and what they use to talk on and so with the younger generation Instagram, Snapchat and all those things. *AutoCo01*
Invest in products based on user profiles	Profile users, for example, high frequency and invest in companion products based on comparative life stage data. That might be an inferred user profile but they build products round that, which fuels further products. They consider in five years' time where will that user be? MediaCo02
Inferred identity	…or use a postcode as a semi-identifier… an inferred identity. M*ediaCo02*

Profiling users through big data enables firms to analyse customers in more detail. User data profiles from multiple sources, provide the firm with more comprehensive and granular customer data. This informs long and short-term data-driven decision-making, in areas such as portfolio planning and new product development.

6.5.3 Different forms of big data give better insights

The third element of *applied technological thinking*, is that the use of "different forms of data give(s) better insights" (FMCG02). Rather than being overwhelmed by the scale and scope of big data, the case study firms are selecting data sources that are relevant to their marketing strategy. Chapter 5 highlighted the five big data characteristics and how they can contribute value to the firm in different ways. Part of the contribution of *applied technological thinking* is in the selection of data inputs to support business strategy delivery. This section presents the case study firms' choices; the analysis is supported by interviewee comments in Table 6-12.

The firm's marketing strategy determines the nature and selection of the preferred data source. Depending on the context, the organisation may choose to focus on high volume data, such as social media providers (AutoCo01), or use the veracity of qualitative data to paint a richer picture of a situation (EducationCo09). For example, FMCGCo focused on big data from social media platforms to capture consumer behaviour and anticipate product opportunities to inform different strategies. The Head of Big Data commented that they used:

> …different forms of big data, particularly social data – consumer trends and behaviour … it gives better insights on consumers and why they like the properties of the product, so we can optimise the product and the packaging. *FMCGCo02*

Where immediacy of data is important, a high velocity data source may be selected, as used by EducationCo on enrolment days (EducationCo01). Where value is the central characteristic, internal data sources that are unavailable to competitors may be selected, as highlighted by the Head of Business Insight (AutoCo01). So, the selection of data sources involves simultaneous consideration of a variety of factors. The characteristics are not mutually exclusive; firms' choice of inputs depends on consideration of all the characteristics, and selection of those which will help deliver the firm's competitive strategy.

Alternatively, the choice of data may involve aggregation of a range of sources with variety of scope, size, cost and accessibility. MediaCo's Head of Digital Product Development explained that their data lake relied on pooling a variety of sources:

> It brings together different types of data – imported big data; smaller data; 70% external and 30% internal sources. Some from users and some from content pipelines. *MediaCo04*

Sources of data are not limited to organisation-held information. Where the problem being addressed is well-defined, firms may look outside the organisation for sources and buy-in data that enhance their existing resources and improve their understanding of the wider market. EducationCo's Data Insight Manager explained his team's *applied technological thinking* when selecting an external data source to support the organisation's strategic marketing:

> There are things that can enrich these datasets though. I've talked with planning about purchasing different datasets that can enrich, let's say the recruitment one we've looked at previously. There's a UCAS dataset that we've seen which has schools and colleges information on. And it relates to things like the number of people enrolled in the cohort. So if we could understand the number of applications we've had versus the size of cohort we can understand the proportion of that market in that individual school. We've actually sewn up what we need to pursue and grow, and whether there's growth. It's about getting that context, isn't it? *EducationCo11*

Table 6-12 Using different forms of big data - interviewees' perspectives

Subject	The voice of the participant
Deciding on necessary timing (velocity)	…on things like student numbers and applications, we, we should be as real time as we possibly can afford to be because it's amazing what sort of differences you can make if you can act promptly. *EducationCo01*
Own datasets (value)	Even within a company different areas of the business have their own datasets…. By joining those up you are starting to gain insight and you can affect all the different business processes. *AutoCo01*
All messages containing a word (volume)	Imagine that you are pulling down social media data. So you have said to the Application Programming Interface (API) on Facebook "give me all the messages that contain the word AUTO and have a negative sentiment". *AutoCo01*

Painting a full picture (veracity)	We get a lot out of the qualitative comments, sometimes it can paint a picture that can get lost in quantitative figures, that's the thing, numbers don't always paint the full picture, so you can get quite a lot out of…those comments. *EducationCo09*
Consider whole market	…you can see your own stats and get overly concerned with being introspective when there's a whole big market issue to consider *EducationCo05*

Firms' resource choices depend on their organisational strategy. Firms are applying technological thinking to making their selection from a wealth of internal and external data sources. Big data has a variety of characteristics and the selection of big data source needs to be appropriate to the business need, if it is to deliver insights that can enable improved business competitiveness.

6.5.4 Analytics and the analysis tools

Big data analytics (BDA) is the fourth of the elements of *applied technological thinking*. BDA is often presented in conjunction with big data because it is the activity observably related to generating adding value from big data (Côrte-Real, Oliviera, and Ruido 2016). Unlike the elements described previously, which reflect both marketing and technological perspectives, the 'analytics and the analysis tools' element is described predominantly in technical terminology (see Table 6-13). The case study interviewees talked about analytics in terms of the practical application of algorithms to bodies of data.

The interviewees' comments relating to algorithm use, are purposeful and strategic. The Director of Teaching and Learning (EducationCo3) describes how the institution's course 'health' is measured using key indicators generated from a range of data sources. These sources are "built up, so there's an algorithm behind each one… so there might be a student numbers algorithm which is applications and enrolments and it's built up from a course level, to a school level…". AutoCo use algorithms to capture consumer comments from social media, for example, to assess the impact of pricing decisions (AutoCo01). MediaCo focuses on the application of algorithms on metadata, such as organisation-owned photographic and journalistic data, to create operational efficiencies and contribute to organisational profitability (MediaCo02).

Applying technological thinking to the process of data analytics may reveal a lack of in-house capability to define and generate the algorithms needed for data analysis. Whilst MediaCo and AutoCo indicate in-company competence in this area, FMCGCo contract out their algorithm development to external partners. The organisation's concerns over the potential loss of data control, through third party contracting, is managed through contracts that relate intellectual property to the third party's algorithm, rather than to the firm's data.

The final consideration of 'analysis tools and analytics' is the shifting position of analytics in the organisation. This issue was raised by EducationCo's Head of Strategy (EducationCo01), who noted that the engagement with big data had enabled a shift away from a centralised analytics function in the Strategy team, towards administrators using the data for insight. This was achieved by using Tableau visualisation software, which presented big data in a user-friendly way, giving customer-facing staff access to extensive data, to make well-informed decisions. Users were enabled to "discover insights with data that is relevant to them" (EducationCo01). The changing analytical positioning has ramifications for the extension of skills, experience and big data interaction across the wider organisation, and the ability of more employees to make informed decisions relating to improved business competitiveness.

Table 6-13 Big data analytics - interviewees' perspectives

Subject	The voice of the participant
Algorithms behind indicators	I need to give them a holistic picture about, say undergraduate and postgraduate course health across the campus. What we're trying to do is to have 7 or 8 indicators … and they're built up, so there's

	an algorithm behind each one … so there might be a student numbers algorithm which is applications, enrolments and it's built up from a course level, to a school level, to a faculty level. *EducationCo03*
Analysis tools	Then you have the analysis tools – you have the data, you've processed, cleaned it up, you have it to the point you want to do something with it. Then you have to decide what you want. So you say show me all the services and group them by area that have had a negative comment this month, or within last week. *AutoCo01*
Bulk analytics of metadata	We have produced our own in-house analytics and search platform. We can now bulk analyse content including metadata of articles and pictures to reduce agency fees, support legal arguments. *MediaCo02*
Intellectual Property of algorithms	Traditionally the Intellectual Property (IP) was about recipes and packaging. With data analytics the IP relates to algorithms. We may not have a problem with the supplier retaining the IP for the algorithm as we want to apply the algorithm not hand over the data. *FMCGCo01*
Shifting analytics towards users	…has shifted analytics towards users and away from a central analytics team... It frees the strategic team for extracting, validating and producing data because they have time and towards users analysing, discovering insights with data that is relevant to them. *EducationCo01*

Extant literature tends to treat big data analytics as the sole activity that can leverage value from big data. However, the case study interviewees indicate that big data analytics is only one element within five relating to *applied technological thinking*. This suggests that, for the case study firms, there are wider implications of using big data, such as how to secure analytics to generate new knowledge. Analytics is a technical function but software innovations, such as visualisation tools, develop the analytics skills of those working nearer to the customer, improving the organisation-wide, data-led decision-making capabilities.

6.5.5 Finding insights that drive business decisions

The final element of *applied technological thinking* is "…finding the insight that would direct and drive business decisions" (EducationCo05). In this section, the case study firms describe the pivotal role that big data insights make in the transformation of the firm into data-driven decision-making, to improve their market responsiveness. Table 6-14 provides additional detail in the participants' own words.

The Head of Marketing and Recruitment (EducationCo05) highlights that the tripartite relationship between data, data analytics and insight is essential to driving improved business decision-making. Bringing together these three elements to drive and direct business decisions and secure competitive advantage is the "holy grail" that firms are trying to achieve with big data (EducationCo05).

The case study participants explained the importance of selecting appropriate data to provide insights that address specific business needs. For example, as part of cost leadership strategies, the firms gathered insights from their own data to inform production efficiency (FMCGCo02); from internal and competitor sources to improve operational efficiency (MediaCo04); and from data on consumer behaviour to optimise product and packaging developments (FMCGCo02). The Head of Digital Product Development (MediaCo04) described how insights from their own and their competitors' data, were used to inform editorial teams about consumer reading habits, to ensure the optimum length and preferred topics for article content. In a separate big data initiative, the organisation adopted an in-house, machine-learning approach to improve the accuracy of their financial forecasting. Thus, MediaCo used different forms of data to provide insights to different business functions.

MediaCo participants use highly visual terminology when discussing insights from big data. Expressions such as "primarily writing blind" and "won't be looking through foggy glasses” reinforce the notion that ‘applied technological thinking’ plays an important role in providing transparent and clear data, as a basis for organisational decision-making.

Table 6-14 Finding insight to drive business decisions - interviewees’ perspectives

Subject	The voice of the participant
Driving decisions with insight – the holy grail	There is a disconnect between the data and the data analysis and the business decisions and driving it with great insight and that’s the bit that’s missing at the moment, but that’s no criticism of the planning department, that’s the holy grail and I don’t think many people are doing that. *EducationCo05*
Analytics to make decisions based on data	From an R&D perspective we concentrate on data analytics … to generate productive efficiencies; making decisions based on data. *FMCGCo02*
Better insights on customers	…(data analytics for) better insights on consumers and why they like the properties of the product, so we can optimise product and the packaging. *FMCGCo02*
Insights driving internal efficiencies	One of our products is HA which gives us insights internally, using article word counts on our sites and those of competitors…. from google, from social media and the rest from our own sites. We can see what in articles sells, what competitors are writing about, how much space they are giving. Previous they were writing blind. The old style made sense but couldn’t support operational efficiencies. *MediaCo04*
Forecasting based on machine learning	We are currently developing a future forecast model for sales, based on real computation. Previously…forecasts (were) based on historical data. This year we have built a statistical machine-learned model, to make finance more accurate and make decisions based on that. We won’t be looking through foggy glasses. *MediaCo04*

Finding insights from big data, to direct and drive business decisions, is the firms' aim. An applied technological thinking capability allows the firm to gain insights from the big data resource, that address the organisation's business strategy and are more accurate, detailed and transparent than the resources previously available.

In summary, big data is changing firms' strategic marketing capabilities by requiring a comprehensive approach to data management and analytics, described by one participant as applied technological thinking. Extant theory emphasises the importance of big data analytics in securing value from big data. The study findings show that analytics are only one of a number of elements in applied technological thinking. The firms appear to emphasise the application, rather than the analysis of the data. Part of this application is in the selection of appropriate big data sources to deliver the organisation's business strategy. As with small data, big data may be used to answer specific questions or address particular problems. In addition, big data analysis may show patterns, such as trends, or patterns in customer behaviour, or it may supply details which inform customer or user profiles. These insights may be used as a basis for new market or product development or to drive other business decisions.

The next section addresses the final dynamic capability, revealed by this study, to use big data in strategic marketing, a capability for *data-driven decision-making*. As with *engaging with a new resource*, *data-driven decision-making* provides an interface between the firm and its external environment through its customer and market interactions.

6.6 Data-driven decision-making

For big data to affect an organisation's competitive position, it must influence the decisions the firm is making. The interface between firms' *applied technological thinking* and their *data-driven decision-making* (EducationCo08) is central to making better informed decisions. Through *applied technological thinking*, firms generate insights from a richer, granular, more accurate, immediate and more purposeful dataset than previously. Decisions based on this more comprehensive dataset support the organisations' evolutionary fitness in a turbulent environment.

EducationCo's Admissions Manager (EducationCo08) observed their decision-making was more dynamic in response to big data:

> Loads of the decisions we're making are based on data of some kind … It's allowing us to go in at any time point and get some of that data, that's changing all the time and feed the decision-making process in a far more proactive way than we would have done in the past. *EducationCo08*

The case studies suggest that the outcomes of *data-driven decision-making* improve business competitiveness through greater innovation in customer recruitment, enhanced customer retention, improved customer experience, altering market positioning and enabling more customer-centric operational marketing decision-making.

The case study interviews indicated changes in the organisation's *data-driven decision-making* capabilities in four areas:

1. 'Fail fast' and 'digital scale' product development
2. Personalising customer engagement
3. Commoditising big data
4. Increasing the firm's agility

Participants from all four case study firms spoke about *data-driven decision-making*. More detailed insights were provided by the EducationCo and MediaCo interviewees, reflecting the knowledge base of the participants.

6.6.1 'Fail fast' and 'digital scale' product development

The first element of *data-driven decision-making* identified in the case study interviews is the novelty and change of pace affected in the firms' product development. Two innovations in data-driven new product development (NPD) are being used by the 'digital-born' firms with which incumbent firms are competing. 'Fail fast' and 'digital scale' NPD may offer data-driven firms new tactics to support differential advantage. These innovations were explained by MediaCo interviewees, who had transferred their knowledge from working in digitally-born firms, into the incumbent media firm.

6.6.1.1 Fail fast product development

Incumbent firms follow a product development process which aims to achieve long-term growth through continuous innovation (Durmusoglu, Calantone, and McNally 2013). This type of incremental NPD involves piloting (evidenced by EducationCo03) and trialling product ideas (evidenced by FMCGCo01), with high expectations of incremental revenue expansion. In contrast, digitally-orientated firms are more likely to adopt a fail fast approach to secure faster data-led new product developments, discarding unsuccessful developments promptly (Crawford 1992). Fail fast is closely related to digital products because it is data-driven. Digital products require high financial investment in data storage, hardware, software and expert skills. As these are sunk costs, discarding data-driven NPD may be perceived as relatively low cost compared to manufactured products. As discussed in *straddling legacy and tech* (see Section 6.3), the drawback is that this approach requires high initial investment. It is also premised on the expectation of a limited number of significant successes, acknowledging that much development investment and activity will be wasted.

MediaCo's Head of Digital Product Development explained the fail fast approach:

> The company needs an innovation culture, the challenge for legacy businesses is the difference in speed of decision-making. We (digital divisions) accept that there will be failures - we call it 'fail fast'. We do our learning through failure – making many low value mistakes quickly to get the best understanding of what works. *MediaCo04*

As any firm can choose to use the speed of big data to their advantage, the new phenomenon is relevant to both digital and incumbent, data-led firms. From a digital perspective, a fail fast process enables increased agility and speed of decision-making, and supports the development of an innovative culture. The Director of Innovation outlined the criteria for their product development team's new data-led initiative:

> … they were targeted to launch a product in one month to users. They proved it could be done. Also it didn't have to be perfect – it had to be live…. *MediaCo02*

The fail fast process accommodates product launches of imperfect products, to be tested and adjusted after their launch, and accepts high frequency of failures. Both of these digital benefits are at odds with traditional business approaches, which presents a challenge to established firms.

6.6.1.2 Digital scale new product development

The second innovation in *data-driven decision-making* is 'digital scale' NPD, which involves generating big data-led products that reach as wide an audience as possible, without significantly increasing operating costs. It is reliant on algorithms, which are applied to larger or different datasets, to expand the product scale or make the product available to a different market (Swaminathan and Meffert 1992).

MediaCo's Director of Innovation (MediaCo03) explained that, for digital firms, data-led new product development involved the concept of 'digital scale'. He commented:

> There is almost a light bulb moment that happens in a digital company that doesn't happen in a traditional company. It's to do with scale….it's relevant in any data-led company. 'Is this idea one which has true digital scale?' What that means is 'is that idea bounded by physical limitations in order to scale it?' *MediaCo03*

Digital scale enables a firm that holds vast amounts of data, to use it to generate services without geographic constraints and without increasing costs of delivery:

> If I take Google Search, as one extreme, once you have defined the algorithm you simply switch it on, your growth is unbounded, scale is unbounded… there are a

> number of products we have here, which … also have the potential for that same type of digital scale. *MediaCo03*

For example, an online service available in England, could be replicated in France, by applying the same algorithm to a different set of data. The Chief Innovation Officer gave two examples of such products, one for news and one for health. The first example was news product built on organisation-curated news content, accessed online through localised web portals. The product allowed the whole firm's nationally generated news content to be available digitally, with data presentation tailored to local interests. This new product had been achieved; "…by drawing content from existing sources, based on a new CMS (content management system) for quick access to existing content" (MediaCo02). The second example was the development of a totally data-led, online health service introducing service providers and customers: "A platform which makes connections between clients and health professionals using viral recruitment and viral connection" (MediaCo02).

In the latter example, the big data generation was a product of digital development which could then be commoditised through targeted, advertising revenue or even establishing it as an independent business. In these data-led, digital developments the data resource is viewed as an asset to the firm, reflecting a different mind-set from traditional NPD.

To facilitate *data-driven decision-making*, incumbent firms require knowledgeable individuals to introduce more innovative and experimental data-led processes. Based on the evidence from the case studies, both fail fast and digital scale *data-driven decision-making*, represent innovations in NPD which have the potential to transform the organisation, through increased speed and scale of product launches. They can support the incumbent firm's competitive position by engaging both existing and new customers, and establishing differential advantage over digital competitors.

6.6.2 Personalising customer engagement

The findings, in this section, highlight the use of *data-driven decision-making* in personalising customer engagement, with a view to improving customer experience and retention. Big data provides companies with access to greater insights about customers and their behaviour, and can help firms to provide more innovative solutions to meet customer demands and needs.

The increased customer knowledge allows firms to target products and services more precisely than with small data, and to personalise services in response. EducationCo's Director of Teaching and Learning described how the availability of a single repository of customer data provided the basis for an early-intervention student retention project. Using big data, the project identified students who were at risk of failing or withdrawing from their course, by correlating their registration data, falling attendance and reducing assessment scores. They then telephoned the students:

> …to see whether after the call, they become more engaged or not. The really interesting thing is it shows very clearly … there are several hundred students who are now on course who would historically not have been. *EducationCo03*

The use of a big data 'engagement score', generated from a collated big data source, made it possible to readily identify, contact and track the progress for the 'at risk' group, and then evaluate the intervention's success. This personalised intervention enabled the organisation to improve its customer experience and retention. Furthermore, using the concept of 'digital scale' described by MediaCo's Director of Innovation (MediaCo03), the pilot project may be easily scaled up, because the algorithm can be extended to a larger student data pool. Although the intervention has costs related to the help centre telephone calls, the 'at risk' data allows the organisation to target support activity and pre-empt student withdrawals, so the income is greater than the costs.

Data-driven decision-making is not constrained to new customers and online product development. The more granular customer intelligence available from big data enables firms to target specific individuals and groups, and to adapt their processes to provide a more personalised approach.

6.6.3 Commoditising big data

The third element of *data-driven decision-making* is the commoditisation of big data. This section outlines how firms are commoditising their data or data-related systems to develop differential advantage.

Strategic marketing involves decision-making related to the position of the firm as well as its products. The new big data resource provides an opportunity for firms to generate a new income stream or change its market position. The commoditisation of data is not solely related to selling customers' personal data, whether complete or anonymised, which is constrained by legislation such as the General Data Protection Regulation. It can also involve the commercialisation of proprietary data, such as MediaCo's news content, or EducationCo's learning resources. AutoCo took an alternative approach to commoditisation by choosing a marketing strategy, which established their data management system in a separate division, and subsequently in a dot com firm (AutoCo). This strategic marketing choice enabled the firm to serve and generate income from a retail customer base, as well as their core business-to-business customers.

The Chief Innovation Officer of MediaCo explained that the commoditisation of big data to improve the firm's competitive position, is a common-practice mind-set in technology-led firms, saying "…those following trending technology are using it either to provide focus or in a commoditised form" *(MediaCo02).* He described data-led firms, such as Twitter, Facebook and the digitally-born banks, acting as 'data shops', exploiting what has been built by other companies. He commented that for new start-up banks, such as Monza, commoditised data defines their selling proposition:

> They're data shops rather than data-driven. They present your finances and spending in categories, so customers can see where they spend their money. *MediaCo02*

EducationCo's Director of Teaching and Learning (EducationCo03) explained how the organisation was looking at commoditising their intellectual content, in conjunction with global, digital delivery partners, such as Amazon and Apple. These partners would bring technical and distribution competences unavailable within EducationCo:

> So we are talking to those companies about how we might partner and develop something rather, rather interesting… they've got the AI (artificial intelligence) and … they've got the system, they've got money. *EducationCo03*

Other case study firms were engaged in data-driven commoditisation partnerships, with the aim of achieving business growth by global expansion. MediaCo was invited to commoditise their news content by "… engaging in content partnerships with global partners wanting a UK foothold" (*MediaCo02*). For AutoCo, commoditisation of data provided a step-change in market positioning. The firm commoditised their data management system and big data content by establishing it as a distinct, online business. The new service was aimed at retail customers, rather than the business-to-business service offered by the mainstream business. The new service became market-leading and has subsequently been sold, generating additional revenue for the firm.

Big data provides an opportunity for step-changes in an organisation's competitive position as a result of big *data-driven decision-making*. Innovative activities, such as the commoditisation of a firm's big data or the related systems, may stimulate changes in operating expectations, processes and relationships, providing differential advantage and changing the firm's competitive positioning.

6.6.4 Increasing the firm's agility

The fourth way in which big data is changing incumbent firms' decision-making capabilities is by increasing the firms' agility. The participants' supporting comments are provided in Table 6-15.

Big data characteristics, specifically velocity, mean that firms are able to make decisions more promptly (see Chapter 5.4). As the senior manager for recruitment and marketing (EducationCo07) observed, they can "make a decision fairly quickly" and "in a timely way" because "the sooner we are aware…the better we are able to respond". This timeliness also enables companies to anticipate and predict behaviours, further improving the organisation's responsiveness, which in itself improves customer experience (FMCGCo02). By using big data to anticipate customer needs and respond more promptly, the firm is increasing its agility, as a result of big data.

For EducationCo, this increased agility is reflected in improved student recruitment, customer experience and operating efficiency. Using big data has provided the organisation with improved market intelligence. This has enabled better inter-departmental co-ordination, meaning that more students could be accommodated on courses, with benefits for the overall competitiveness of the organisation. (EducationCo07). The Head of School (EducationCo12) gave another example of data-driven agility, resulting from the regular customer feedback collection: "which generates data and insight to inform decisions…. because we can identify problems and actions ahead of time" (EducationCo02). The organisation benefitted in other ways from this timely decision-making because it ensured its compliance with customer contracts, reduced operating costs associated with contract penalties, and helped maintain the organisation's reputation (EducationCo07).

FMCGCo took a different approach; their Head of Big Data provided examples of agile, *data-driven decision-making* focused on product related activities, drawing on the flow of consumer data from social media platforms (FMCGCo02). Customer commentary on social media increased the firm's anticipation and prediction capabilities on product opportunities, directing them to customer-responsive changes in products and packaging (FMCGCo01).

Table 6-15 Increasing the firm's agility - interviewees' perspectives

Early awareness	I can see the picture of the group, and see that other parts of the group are perhaps not doing as well as we need them to do. In order to tackle strategy targets, I know that we're going to have to take some of that strategy. So, it helps me prepare. I can see that there's going to be a call for the need for us to take more students. The sooner we are aware of that, the better we are able to respond. *EducationCo07*

Identify actions ahead of time	For example, our MEQ (Module Evaluation Questionnaire) is themed as per the NSS (National Student Survey), which generates data and insight to inform decisions…. It has a significant impact on the outcome of NSS - because we can identify problems and actions ahead of time. *EducationCo12*
Timely decision-making	And if we have to make a decision fairly quickly about something not running, because we are legally liable now through things like CAN. If we have made a commitment to students… so we have to make decisions in a timely way, so we don't disadvantage what might have been a candidate for us. *EducationCo07*
Anticipate product opportunities	Using different forms of Big Data, particularly social data – consumer trends and behaviour and anticipating product opportunities based on consumer behaviour. *FMCGCo02*
Optimise product and packaging	Better insights on consumers and why they like the properties of the product, so we can optimise product and the packaging. *FMCGCo01*

Big *data-driven decision-making* is shown to be changing the agility of the case study organisations. Improved customer intelligence and the prompt availability of data is improving customer responsiveness and experience. It is also encouraging inter-functional co-ordination, to deliver data-led solutions, to meet the organisations' goals.

In summary, big data is changing firms' strategic marketing capabilities by encouraging greater organisational agility and flexibility, to respond to big data-led opportunities and by adjusting processes to accommodate data-led decision-making. Amongst the changes effected by big data, are increased experimentation and innovation in product development processes. The velocity of big data can affect the speed of products to market, whilst the granularity resulting from volume and variety of data can lead to increased personalisation of products and services. In addition, the value and rarity of data can lead to its commoditisation and a change in market positioning, or a new revenue stream. In short, firms which adopt data-led decision-making are able to use big data to respond to the technological turbulence in their operating environment and improve their evolutionary fitness.

6.7 The data structures

This chapter has identified that organisations which are leveraging value from big data in their strategic marketing are drawing on five new dynamic capabilities. These can be encapsulated in a data structure, which is an important outcome of the Gioia Methodology data-to-theory process. In this study, two data structures resulted from the investigation into strategic marketing capabilities:

1. Big data-driven capabilities data structure (Figure 6-5)
2. Big data-driven capabilities microfoundations data structure (Figure 6-6)

In Chapter 7, the data structures will be reviewed in conjunction with extant literature, to identify precedents and novel concepts to inform the resulting grounded theory. The data structures are presented here to summarise Chapter 6.

6.7.1 The big data-driven capabilities data structure

A data structure of the dynamic capabilities that firms are employing, in order to use big data in their strategic marketing, is presented in Figure 6-4. The data structure is the product of applying a seven-step data-to-theory process to analysing the 'voices' of knowledgeable agents in this domain (see Chapter 4). The structure has seven interacting elements; elements 1 and 7 relate to the operating environment, whilst elements 2-6 are the five big data-driven dynamic capabilities.

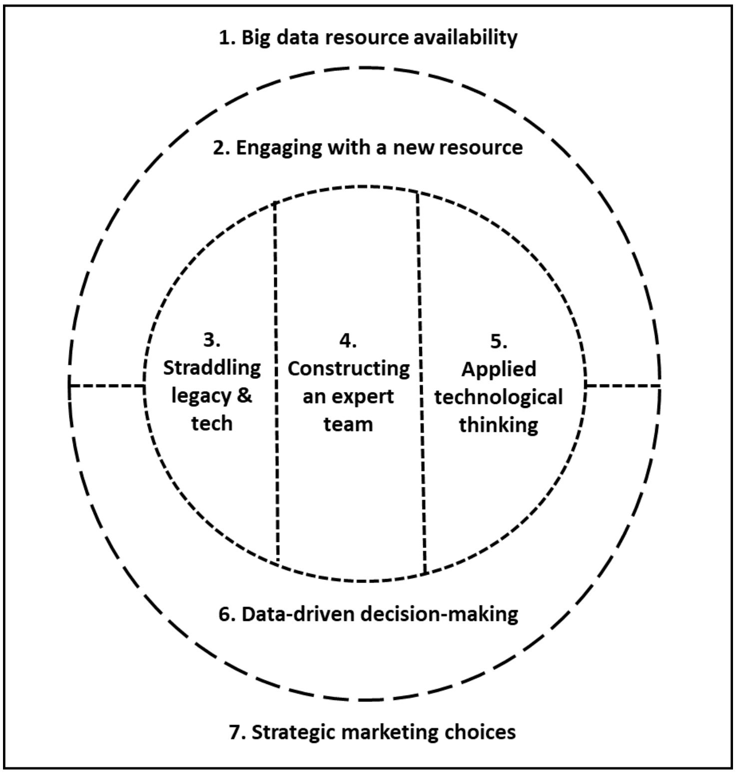
1. Big data resource availability

The technological turbulence in the firms' operating environment has resulted in the availability of a new intellectual resource, big data. As described in the new data value wheel data structure (see Figure 5-5), big data has five characteristics that can be leveraged to improve firms' evolutionary fitness.

2. Engaging with a new resource

Market-orientated firms are alert to big data's potential because they scan the environmental horizon looking for changes that may improve or threaten their ability to be competitive. Those engaging with the new big data resource, are acting on new market intelligence and identification of development opportunities, by adapting their routines and processes, with a view to achieving differential advantage.

Figure 6-5 The big data-driven capabilities data structure



Awareness of the big data resource does not automatically result in engagement with it, but resistance constrains the firms' evolutionary fitness, making them less able to respond to environmental turbulence and more vulnerable to data-led competitors.

The interface between organisation and data is shown in a broad dotted line, to indicate that data can travel between the organisation and its environment

Firms which choose to engage with big data, require dynamic capabilities that enable them to take on board and make use of the new resource. These internally-orientated capabilities (numbered 3, 4 and 5) are positioned in the middle of the structure, as they are central to the organisation's response to the available data. A short, dotted line is used here to show the interaction between the capabilities within the organisation.

3. Straddling legacy and tech

Established firms find themselves *straddling legacy and tech* as they manage their existing business and simultaneously accommodate new business models. This may result in internal culture clashes but it also provides the friction that may act as a catalyst for organisational transformation. The Board plays an important role in overcoming stakeholder and organisational resistance to big data, by advocating its value as an essential resource to delivering business competitiveness.

4. Constructing an expert team in scarce conditions

Big data has characteristics which are fundamentally different from those of small data. The firm may hold the necessary skills within its skills base, or may need to secure them from outside the firm. Recruitment of expertise, such as data science, may be challenging with a global data skills shortage and may require alterative solutions to meet capability gaps, such as partnering with organisations who have the in-demand skills. Constructing an expert team then requires robust inter-functional co-ordination to bring together the disparate skills. Unconventional approaches to capturing expertise may be reflected in more innovative and agile approaches to market responsiveness and maintaining evolutionary fitness.

5. Applied technological thinking

Big data changes the way organisation engage with data. The findings of this study are that analytics are only one, of a number of elements, in applied technological thinking. The firm's emphasis is on the application, rather than the analysis of the data. Part of this application is in the selection of appropriate big data sources to deliver the organisation's business strategy. Another consideration is how to use data to generate insights, which may be used as a basis for new market or product development, or to drive other business decisions.

6. Data-driven decision-making

Where firms are using big data to become data-led, they are adopting innovative behaviours. Using digital NPD, personalised customer engagement and commoditising their data systems, improves their operating capability and increases their agility.

7. **Strategic marketing choices**

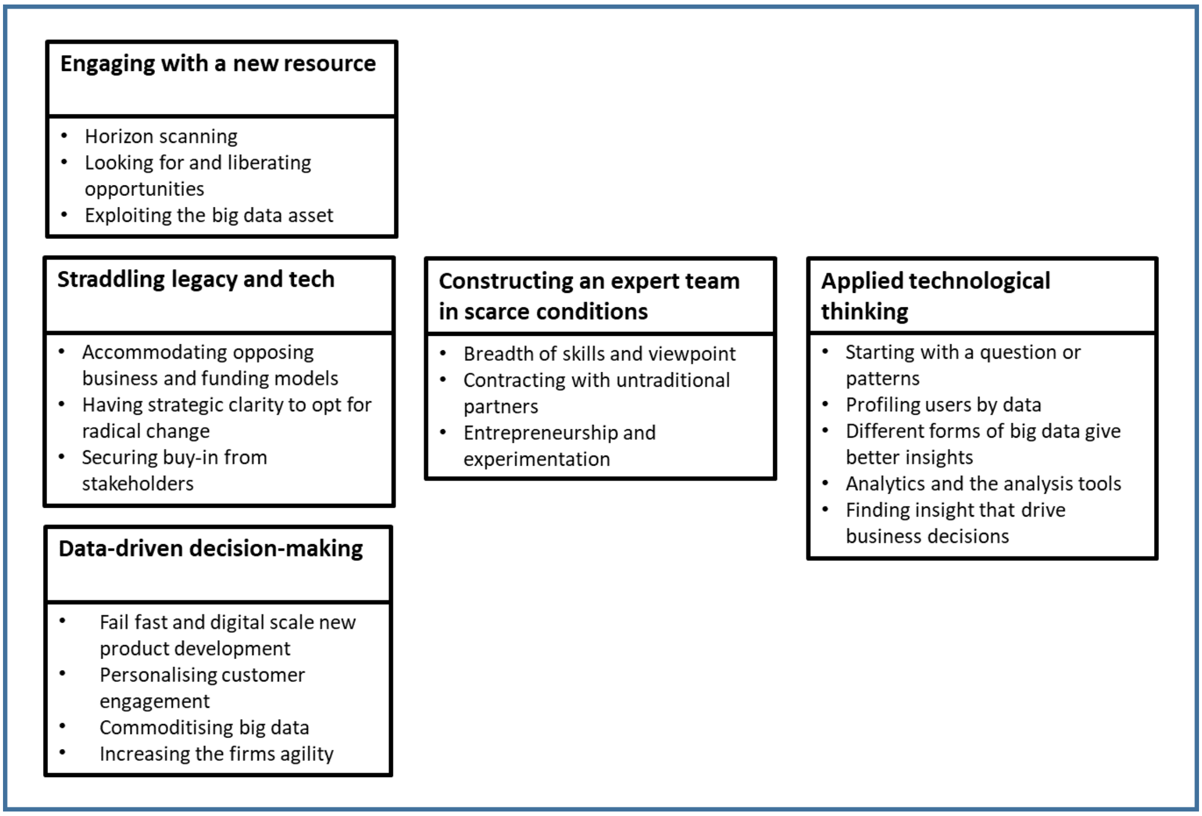
Firms which adopt data-led decision-making are able to use big data in their strategic marketing, to respond to the technological turbulence in their operating environment. They may use the data to develop differential advantage and improve their evolutionary fitness.

The next section identifies how the case study firms are constructing these capabilities.

6.7.2 The big data-driven capabilities microfoundations data structure

As well as identifying the big data-driven dynamic capabilities, analysis of the rich interview materials also explained how the firms were constructing these capabilities.

Figure 6-6 The big data-driven capabilities microfoundations data structure



The case study firms' approaches to constructing each dynamic capability have been described within the sections and subsections of this chapter. The capabilities are underpinned by microfoundations, described by Teece (2007) as being; “composed of distinct skills, processes, and organizational activities”.

Using Teece’s definition, the microfoundations are summarised in a third data structure. The big data-driven capabilities microfoundations data structure (Figure 6-6) deconstructs the five data-driven dynamic capabilities into their under-pinning elements (see Figure 6-5). As can be seen in the data structure, the findings show a greater density of microfoundations relating to changing internal capabilities. This suggests that in order to use big data for their strategic marketing, firms need to change the capabilities that enable them to assimilate the new resource.

In Chapter 7, the elements of both data structures will be discussed, in relation to extant management and information systems theory, with a view to developing new theoretical concepts.

6.8 Chapter summary

This chapter drew on the insights of the case study firms to identify which dynamic capabilities the firms used to leverage big data in their strategic marketing. The analysis of the findings indicated that the firms used big five data-driven dynamic capabilities, which were: e***ngaging with a new resource; straddling legacy and tech; constructing an expert team in scarce conditions; applied technological thinking****;* and ***data-driven decision-making****.*

In *engaging with a new resource*, the interviewees described scanning the horizon to understand how their competitors and others in industry were using big data. Their market orientation led to improved marketing intelligence, awareness of development opportunities, and improved their ability to respond to the changing market.

Assimilating big data was challenging as the firms were managing their legacy business and accommodating new data-led business models at the same time. *Straddling legacy and tech* was disruptive for the organisations but provided the stimulus for data-led business transformation. The interviewees highlighted the importance of delivering, small, strategically significant, big data projects. The success of the projects engaged stakeholders, and increased traction for future big data investment and development.

The characteristics of big data demanded a different skills base to secure value from the new resource. The organisations identified that the global uptake of new technologies had led to a worldwide shortage of data- related skills. The case study firms *constructed an expert team in scarce conditions* by taking innovative approaches to address skills gaps, through international recruitment, unusual alliances and partnerships. Cross-functional co-ordination was vital in combining this disparate expertise.

When talking about the technical aspects of leveraging value from big data, the case study firms described the importance of *applying technological thinking* to the data. Their focus was not limited to big data analytics but included data management, and alignment of data selection and use to their business strategy. As an example, spotting patterns in trends and customer behaviour in big data informed strategic marketing choices, which supported the firms' objectives.

The fifth dynamic capability identified from the empirical data analysis was *data-driven decision-making*. The case study firms were using data to direct strategic decisions, such as changes in market position and new revenue stream as well as innovative product development. They described drawing on the characteristics of big data (see Chapter 5) to respond to changes in the market with greater agility and flexibility.

The data analysis resulted in two data structure outcomes. Firstly, the *big data–driven capabilities data structure,* which identifies the dynamic capabilities that the case study firms used to leverage big data in their strategic marketing. This structure is supported by the *big data-driven capabilities microfoundations data structure*, which identifies how the firms constructed the five dynamic capabilities.

In line with the Gioia Methodology, the next stage of the data analysis is to consider the data structures in the light of extant theory. In this case, the data structures are studied with reference to management, marketing and IS literature, with a view to developing new grounded theory models. The resulting discussion will take place in Chapter 7.

Chapter 7 Discussion

7.1 Introduction

In this chapter, new theoretical models are developed by bringing together the findings from the case study interviews with extant information systems and management theories. Bringing the two elements together allows the confirmation of existing theory and highlights the divergence between the theory and the case study experiences.

This research addresses the question, 'How is big data changing organisations' strategic marketing capabilities?' by answering three sub-questions:

1. What are the characteristics of big data that make it a valuable strategic marketing resource for established firms?
2. What dynamic capabilities are established firms using to leverage big data for strategic marketing?
3. How are established firms constructing the dynamic capabilities that they are using to leverage big data for strategic marketing?

The study used the Gioia Methodology to collect and analyse interview data and draw the findings together into data structures. Chapters 5 and 6 described three data structures, which were produced from analysis of the 'voices of experience'. These structures respond to the research sub-questions and provide the focal points for this discussion. In this chapter, the data structures are considered with reference to the literature presented in Chapters 2 and 3. This process provides the basis for two new theoretical models.

This discussion chapter is divided into nine sections. Section 7.2 introduces the novel big data phenomenon and explains how the case study firms approached their engagement with the new resource. Section 7.3 addresses the first research sub-question by identifying the value emerging from big data, and presents a new theoretical model, the **New Data Value Wheel (NDV Wheel)**. Section 7.4 addresses the second research sub-question and presents the **Big Data-Driven Capabilities Model (BD-DC Model)**, which identifies the five dynamic capabilities that the case study firms are using to leverage big data for strategic marketing. This is followed by three sections which discuss the five capabilities from the BD-DC Model, in relation to Teece's (2007) sensing, reconfiguring and seizing classifications. Section 7.5 considers the sensing capability, *Engaging with a new resource*. Section 7.6 discusses the reconfiguring capabilities of *Straddling legacy and tech*, *Constructing an expert team in scarce conditions* and *Applied technological thinking*. Section 7.7 explains how the case study firms are seizing new strategic marketing opportunities, using their *Data-driven decision-making* capability. Section 7.8 addresses the third research sub-question and presents a supporting framework to the BD-DC Model, which describes construction of dynamic capabilities through the microfoundations and mesofoundations of big data-driven capabilities. Section 7.9 provides a chapter summary. The research conclusions are presented in Chapter 8.

The next section considers the novelty of the big data phenomenon and how the firms approached their engagement with the new resource.

7.2 The novel big data phenomenon

In terms of established management theory, big data is a relatively novel phenomenon. Whilst a common definition between management and information systems literature has been elusive (Chen, Chiang, and Storey 2012), both literatures have adopted a single descriptive framework. The predominant framework identifies big data as having '5V' characteristics: volume, variety, velocity, veracity and value (Wamba et al. 2015).

All five of the characteristics were incorporated in the case study firms' big data initiatives, as is evident in the big data value wheel data structure, presented in Chapter 5 (see Figure 5.6). In practice, the case study firms confirmed that not all '5V' characteristics were applied in each big data initiative, which reflects Kitchin and McArdle's findings (2016). Nor were the data characteristics applied equally in each instance. As an example, MediaCo's big data initiative, which underpinned the development of online local news products, emphasised high volumes of multi-media content; a wide variety of sources; and veracity, through the use of quality assured news content. The firm also repurposed their own content data to gain value from the data. However, there was a low requirement for data velocity, as the nature of the products meant that material was not critically time sensitive. Similarly, EducationCo's Business Intelligence Project (BIP) relied on four of the characteristics. Real-time data was only required for a short period each year as part of new student recruitment, so velocity was not a consistent requirement of the BIP.

This finding raises a question regarding the definition of big data and whether it is a requirement that all '5V's are applied in any data-led initiative. The literature definitions of big data imply that all five Vs are always in use. However, the approach commonly used by the four case study firms was to select the 'V's of big data which would deliver their strategic aim. While a firm might on occasions use all five of the 'V's, on others they might use fewer. In this study, EducationCo used big data to deliver a strategic aim of having a 'single version of the truth' from their student-related information. The case study firm prioritised the veracity of data in their data-led initiative to deliver that strategy, without reference to data velocity. This example suggests that existing academic definitions of big data, indicating that all five 'V's are always in play, may be too restrictive. Inpractice, the findings suggest that firms are able to gain benefits from big data in instances where not all five 'V's are present.

The new resource may be viewed as disruptive to every aspect of the business (MediaCo02), with firms needing to understand the scale and scope of change to weather the disruption. The firms took different approaches to this disruption, on the one hand "embracing the tide" (EducationCo03) and seeing what it brought; and on the other hand, viewing it as a cause of friction and internal resistance to change. Firms such as MediaCo, which experienced organisational friction as a result of applying big data, were positive about exploiting that friction as a catalyst for business transformation. Those interviewed suggested that engaging with the new resource forced the firm to overcome organisational rigidities. This finding mirrored Vial's (2018) observation that adopting digital transformation provides firms with a strategic response to digital disruption, facilitating transformation in their value creation processes.

The case study firms began their engagement with big data by using internal sources of data, which helped them manage the challenges of the new resource. An advantage of selecting internally-curated data on customers, customer interactions and buying behaviours, is that the firms are using valuable and rare resources (Peteraf and Barney 2003). For several of the firms (FMCGCo, MediaCo and EducationCo), the use of big data originated with plans to improve operational efficiencies; this was then followed by extending its use in strategic marketing. Examples of this approach included EducationCo's repository of student data informing their subsequent customer retention project, and MediaCo's comprehensive photographic image repository being commoditised. In this way, the initial use of internal big data led to innovative and novel strategic marketing solutions. The stepped approach favoured by the case study firms, also led to the addition of external and more diverse data sources, which added to the firm's innovation. FMCGCo combined their repository of product data with open source, international legislation and machine learning, to improve the effectiveness of their global product labelling. The firms' decisions to start with internal data may relate to their stage of digital maturity (Kane 2017), where internal data is a more accessible and familiar resource, than external data, for firms early in their digital transformation.

Another benefit from taking an incremental approach to implementing big data initiatives was that the success of individual projects built the confidence of the users and the stakeholders. Starting with internal big data sources, allowed firms to achieve 'quick wins', by building on data with which their teams were familiar. This approach had further benefits because familiarity allowed data to be repurposed and reduced the risks associated with financial investment in the big data infrastructure. This made it more acceptable to the Board of Directors and investment-related stakeholders, which led to further big data-led product / service innovation. An example is EducationCo's investment in the Business Intelligence Project, which led to the customer retention pilot project (see Section 6.5.1).

Having experienced success using internal data, the case study firms used external data sources. Literature suggests that an external focus on data, leads to more radical solutions than when relying on proprietary, internal sources (Chui et al. 2016). External sources encourage interaction with the opportunities and sources being generated within the turbulent operating environment (Baum and Wally 2003). Utilisation of a wider range of data therefore enlarged the potential opportunities for the firms and encouraged more innovative behaviours, such as pattern-spotting in data (EducationCo), and investigating new digital product development (MediaCo). Awareness of the commercial potential of their ‘app’, led to AutoCo’s identification of new market segments and the development of a new business model.

The novelty of the big data phenomenon means that it continues to evolve. Table 2-1 shows how the development between Web 1.0 to 4.0 has introduced new forms of data at each step. Continued development is likely to affect how big data characteristics evolve. In the same way that Laney’s 3V big data description (2001) developed into Wamba et al.’s (2015) ‘5V’ framework, there are theories in extant literature that suggest that the ‘5V’ framework is already incomplete. Literature highlights other characteristics, such as scalability (Marz and Warren 2012), indexicality (Dodge and Kitchin 2005), and exhaustivity (Mayer-Schonberger and Cukier 2013). In this study, the firms’ evidenced some of these other characteristics; for example, MediaCo03 commented about 'digital scale’ and big data’s potential to allow products to be scaled up, without investment in additional resources. FMCG sought to improve the organisational knowledge base by constructing an exhaustive big data repository of all of the global firms ‘recipes’ for products. Although this study does not seek to draw conclusions about whether the ‘5V’ framework is accurate, it is important to note that the big data phenomenon continues to evolve (Cheah and Wang 2017), and that the framework is likely to alter over time.

The next section considers the emergence of the New Data Value Wheel model, drawing on the value of the big data characteristics identified in the case study interviews.

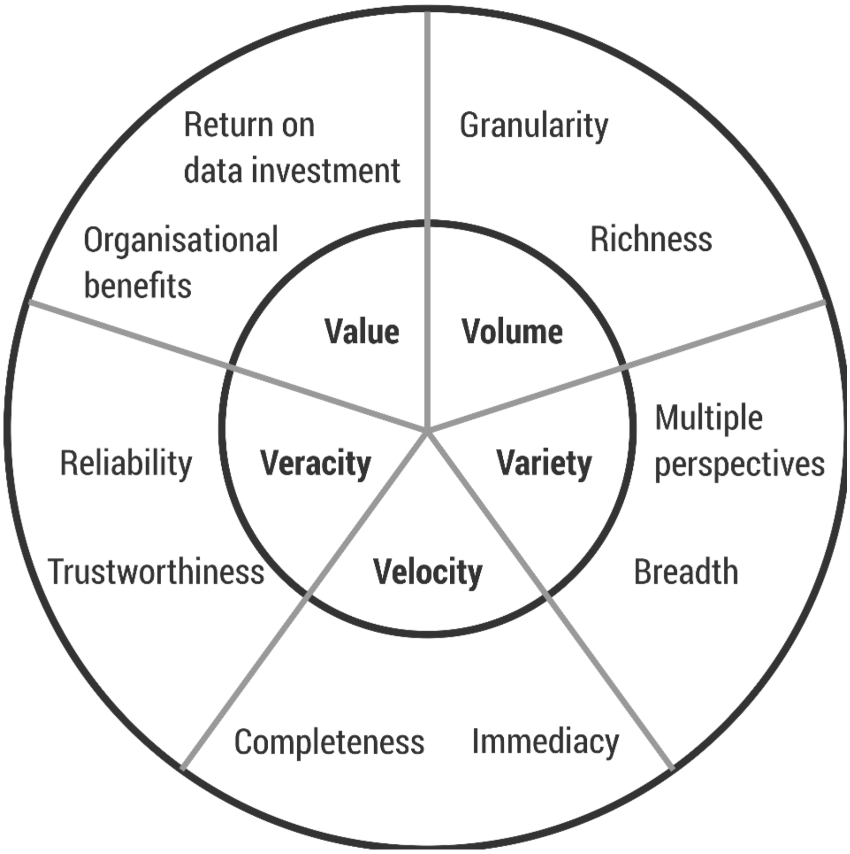
7.3 The New Data Value Wheel

This section of the discussion chapter addresses the first sub-question, 'What are the characteristics of big data that make it a valuable strategic marketing resource for established firms?' It introduces the **New Data Value Wheel (NDV Wheel)** as a tool to explain how big data adds value in strategic marketing.

The New Data Value Wheel (NDV Wheel) (see Figure 7-1) is the first theoretical model to emerge from this research. It mirrors the data structure provided in Figure 5-6, because the case study findings aligned closely to Wamba et al.'s (2015) '5V' framework. Although Wamba et al. (2015) identify the characteristics of big data, they do not identify how these characteristics add value. The NDV Wheel (Figure 7-1) draws on the interviewees' narratives to identify how the big data characteristics contribute to the firms' strategic marketing.

Figure 7-1 The New Data Value Wheel (NDV Wheel)

(Source: Author)



Through the interviews, the firms expounded on their application of the big data characteristics and the valuable contribution that they offered. Knowledge of how the case study firms benefit from using big data is an important, previously missing step, in understanding the sorts of criteria that firms might apply in selecting big data. As an example, understanding that data velocity adds value through its immediacy, might influence firms to improve speeds of customer responsiveness. Using this approach, led AutoCo to offer a real-time pricing service to customers, which relied on high velocity data sources.

The rest of this section describes the implications and potential of each of the '5V' characteristics.

In the extant literature, the definition of *volume* focuses on data storage requirements (Russom 2011). However, the interviewees placed a different emphasis on volume, explaining that big data increased the granularity and richness of the information they had on a single customer, product or market. This increased granularity improved their market intelligence, and awareness of market and customer development opportunities. In addition, it provided a better understanding of the firms' own strategic positioning, which allowed them to develop better-informed strategies. MediaCo was able to use big data volume to improve the granularity of their organisation-wide product knowledge, which informed their digital product development. For AutoCo, the finer insights gained into customers' buying preferences captured in high volume, social media commentary, led to new routes to market.

Variety is defined in the extant literature as the application of multiple data sources (Laney 2001). Variety in small data involves firms in individually accessing multiple data sources. In big data, a variety of sources are aggregated into a single data repository, producing a complex and multi-dimensional dataset (Russom 2011). The implications of this aggregation are that a broader picture is achieved of customers, products, and markets, with multiple perspectives on the problem under investigation (see Figure 5-2). In the example of the EducationCo's BIP internal and external data were combined. The organisation used big data on their own course and faculty performance, in conjunction with data on competitors, to identify market segments which offered them growth potential. The revised segmentation then informed their operational marketing plans for student recruitment. MediaCo used a variety of data from Google, social media platforms, and their own media content, to develop digital distribution channels for their news products.

The theoretical definition of *velocity* concentrates on the speed of data generation, processing, and availability (Laney 2001). The implication of big data velocity, is that firms can capture an immediate snapshot of their position, or that of a customer; at any one moment, whether for stock availability, transaction records, or customer opinion. This provides the firm with real-time intelligence (Gandomi and Haider 2015) and the potential to respond more swiftly or even in real time, improving customer experience. An example was AutoCo's service-to-sales intermediaries, which used data velocity to capture up-to-date information at the time of a customer enquiry, to enable immediate vehicle pricing.

The theory on big data *veracity* highlights the importance of trustworthy data as a basis for sound decision-making (White 2012). The case study firms emphasised the value of data veracity, evident in increased data reliability and trustworthiness. Better-quality data, provided a stronger basis for strategic decision-making, which resulted in increased confidence in strategic marketing choices. MediaCo gathered an exhaustive dataset of their digitised photographic archive into a single data repository. The comprehensive and trustworthy nature of the stored data led to operating efficiencies, for example, by avoiding duplication of image purchases. In addition, it provided the firm with new opportunities for product and partnership development, and the potential to commoditise the photographic data to generate income.

Extant theory defines the *value* of big data in two different ways; value from the reuse of the data, and value from big data's contribution to the corporate strategy (Gandomi and Haider 2015). The case study firms described activities which reflected both elements. With reference to the first definition, the value of reusing data was to improve the data investment returns, which are likely to be met favourably by financial stakeholders and increase their enthusiasm for further investment in this value-creating resource. The potential of reused data, highlighted by Kitchin and McArdle (2016), was evidenced by

EducationCo, which used their repository of aggregated student data records, to improve the firm's administrative effectiveness in pattern-spotting issues that might affect student retention.

The second definition from extant theory, proposes that value is garnered from big data through its contribution to the organisations' strategy (Akter et al. 2016). Each of the case study big data initiatives were designed in line with the firms' strategies. FMCGCo described the "power" (FMCGCo01) of company-wide access to the firm's knowledge, through having a single repository of big data. The firm secured value from the data by improved operating efficiencies, which had the effect of improving product-to-market timeframes.

In summary, the NDV Wheel makes the case that each of the five characteristics contributes to big data being recognised as an intangible, value-creating resource. This view is consistent with the experiences of the case study firms and is in line with recent management literature (Cheah and Wang 2017). Therefore, big data's five characteristics provide a more granular, accurate, reliable, and valuable view of customer products and markets, to inform the firms' strategic marketing choices. Furthermore, understanding the benefits of big data may assist firms in deciding which data sources to use to inform their strategic marketing. The NDV Wheel therefore contributes to theory and practice, as will be further discussed in Chapter 8 (see Section 8.3).

The next section investigates the dynamic capabilities that firms are using to leverage big data in their strategic marketing.

7.4 The Big Data-Driven Capabilities Model

This section of the chapter addresses the second research sub-question, 'What dynamic capabilities are established firms using to leverage big data for strategic marketing?'. It presents the **Big Data-Driven Capabilities Model** (**BD-DC Model**) (see Figure 7-2), which identifies five dynamic capabilities firms have developed into order to use big data within their strategic marketing. The model also identifies the relationships between the capabilities and the firms' operating environment. The section starts by recapping the methodology used to build the BD-DC data structure (See Section 6.7.1). The data structure is then considered in the context of extant theory, which culminates in the generation of a new grounded theory model. To provide a more detailed understanding of the model, the capabilities and the elements that the case study firms used to construct them, are discussed in the subsequent Sections 7.5 to 7.7.

Big data is becoming recognised as an intellectual resource which sits alongside other intangible resources such as brand awareness, intellectual property and knowledge (Cheah and Wang 2017). The combination of big data proliferation and data analytics developments bring firms "huge opportunities in relation to market insights and the identification of target markets as well as providing broader insights which can inform marketing strategy" (Quinn et al. 2016: 2122). However, this valuable new resource also provides a challenge to firms. They can find themselves overwhelmed by new forms of information which are beyond their capability to comprehend and use (Day 2011). To leverage value for strategic marketing from the new resource, involves overcoming organisational rigidities and inertia, diverging from existing operational methods, and addressing any emerging capability gaps.

The study shows that the case study firms developed five new dynamic capabilities to leverage big data for strategic marketing. The five capabilities were: *Engaging with a new resource; Straddling legacy and tech; Constructing an expert team in scarce conditions; Applied technological thinking;* and *Data-driven decision-making*. Before looking at each dynamic capability, the next section will briefly outline the context of the BD-DC Model's development.

7.4.1 Setting the big data-driven capabilities model in context

In line with the Gioia Methodology, the next stage in the development of the **BD-DC Model** (see Figure 7-2) was to consider the data structure in the light of extant dynamic capabilities theory. The initial literature review, identified two seminal works in dynamic capabilities theory, which underpin much of the subsequent literature (Peteraf, Di Stefano, and Verona 2013). Teece, Pisano, and Shuen's (1997) theory introduced the notion that firms seeking to achieve competitive advantage in turbulent operating conditions need dynamic capabilities, in order to change their resource base and respond to the changing external environment. The other seminal work by Eisenhardt and Martin (2000) also views dynamic capabilities as tools to achieve resource synthesis and reconfiguration. However, whereas Teece, Pisano, and Shuen emphasised the changing operating environment and competitive advantage, Eisenhardt and Martin highlighted the importance of the microfoundations and individual actions which underpin dynamic capabilities. Microfoundations are described later in this chapter (see Section 7.8).

Later, Teece (2007) classified dynamic capabilities into three functions: sensing, reconfiguring, and seizing; to explain the contributions that capabilities were making to achieving competitive advantage. In reviewing the BD-DC data structure alongside the theory, it became apparent that the five dynamic capabilities identified from the firms' narratives could be aligned to Teece's three classifications. Furthermore, the case study firms identified an inter-connection and a flow between the capabilities, which then highlighted the central role of the reconfiguring capabilities.

- Sensing capabilities: *Engaging with a new resource*,
- Reconfiguring capabilities: *Straddling legacy and tech, Constructing an expert team in scarce conditions,* and *Applied technological thinking,*
- Seizing capabilities: *Data-driven decision-making.*

Embedding the data structure with Teece's (2007) dynamic capabilities classification, and identifying the inter-connections and flow between the capabilities, were important in the development of this grounded theory model.

7.4.2 Describing the Big Data-Driven Capabilities model

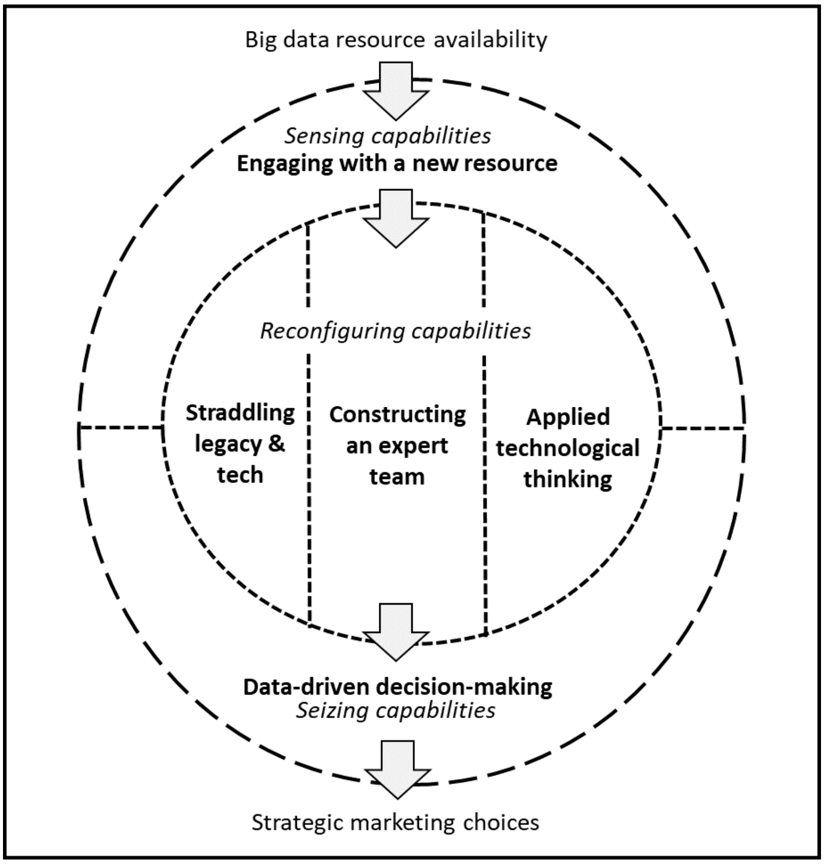
The **Big Data-Driven Capabilities Model (BD-DC Model)** (Figure 7-2) develops the data structure (Figure 6-7.1) by placing it in the context of Teece's classification framework. The resulting model includes: the operating environment; the firm and the sensing, reconfiguring, and seizing capabilities These will be discussed in turn, with reference to Figure 7-2.

1. The BD-DC Model's frame represents the firm's operating environment. The firm is positioned within the operating environment, where big data is available. As explained in the NDV Wheel, big data represents a valuable potential resource to firms which choose to engage with it.
   After the data is assimilated, the firms have a second interaction with the environment. This interaction is when the firm makes data-driven strategic marketing choices, with the aim of achieving differential advantage or evolutionary fitness.
2. The firm is shown within the operating environment as an oval form. The boundary between the firm and the external environment is represented by wide, dashed lines which suggest that data can pass between the two.
   Within the firm, the separations between the capabilities are represented by fine, dotted lines, suggesting that there may be interaction between the capabilities, such as the sharing of resources.
3. The firm has five dynamic capabilities, which are clustered together within one body, using Teece's (2007) sensing, reconfiguring, and seizing classification (see points 4, 5 and 6 in the data structure, Figure 6-5).
4. The sensing capability, *Engaging with a new resource,* operates at the interface between the firm and the availability of big data in the firms' operating environment. As well as the boundary with the external environment, the

capability has relationships with the three reconfiguration capabilities, which are assimilating the sensed data. There is also a boundary with the seizing capability, which reflects a connection between opportunity-spotting and opportunity-seizing.

Figure 7-2 Big Data-Driven Capabilities Model (BD-DC Model)

(Source: Author)



5. The reconfiguration capabilities*, Straddling legacy and tech, Constructing an expert team,* and *Applied technological thinking,* are positioned in the middle of the model because they represent the internal processes and activities, which are central to leveraging value from big data. Without the reconfiguration capabilities, it is not possible for the organisation to translate big data into new strategic or commercial opportunities. The three reconfiguration capabilities interface with both sensing and seizing capabilities; these are shown with a

dotted line to indicate that information can flow between all three classifications of capability.

6. The seizing capability, *Data-driven decision-making*, is an internal organisational process. Seizing capabilities also operate at the interface between the firm's internal processes and its capacity to make strategic marketing choices, in response to changes in the external environment. The boundary between the firm and the external environment is represented by wide dashed lines, which indicate the interdependence between the two.

Arrows are included in the model to show the interconnectivity of the elements, starting with big data and ending in changes in strategic marketing choices.

The BD-DC Model shows that the reconfiguration capabilities played an important role in the case study firms' application of big data to their strategic marketing. The firms identified three reconfiguration capabilities, with one involving sensing and another involving seizing. In the context of using big data in strategic marketing, the firms emphasised the importance of their reconfiguring capabilities to assimilate the new resource. This finding contrasts with other studies that identify the capabilities which are the most significant in contributing to firms' competitiveness. Examples of these are:

- the importance of sensing and reconfiguring capabilities, because the outcomes are difficult for competitors to imitate (Helfat and Winter 2011);
- sensing and seizing capabilities (Droge, Calantone, and Harmancioglu 2008; Makadok 2001), because of their external focus and their ability to respond to opportunities and threats;
- sensing and reconfiguring capabilities because they were embedded in the firm, and increased organisational adaptability to the external environment (Braganza et al. 2017; Chui et al 2016).

The empirical evidence that informed the BD-DC Model also showed that each firm took a very different approach in the construction and delivery of their capabilities. The diversity of approach reflects Eisenhardt and Martin's (2000) theory of equifinality, in which each firm has different outcomes based on firm-specific decisions. This diversity can be seen in the BD-DC microfoundations data structure (see Figure 6.7.2) and will be discussed further in Section 7.8.

In summary, the big data-driven capabilities data structure identified five new dynamic capabilities that the firms were using to leverage value from big data to inform their strategic marketing. Reviewed in the context of dynamic capabilities theory, the data structure aligns closely with Teece's sensing, reconfiguring, and seizing classification framework. The outcome of this contextualisation is the **Big Data-Driven Capabilities Model** (BD-DC Model).

Each of the five dynamic capabilities will now be considered in relation to extant theory. The aim is to identify points of interest, including commonalities, anomalies, new concepts, or areas for future research. The next section addresses the role that sensing capabilities played in enabling firms to respond to turbulence in their external environment, and addresses the sensing capability identified in this study, *Engaging with a new resource*.

7.5 Sensing capabilities

This section responds to the second research sub-question, by identifying the sensing capability that firms are using to engage with the new big data resource. Sensing "involves gathering and filtering technological, market and competitive information from both inside and outside the enterprise, making sense of it, and figuring out implications for action" (Teece 2007: 1326). Although the shorthand term 'sensing' suggests simply scanning the external environment, it also includes other activities, which indicate a degree of data processing. These activities include shaping, filtering and calibrating the sensed information (Teece 2007: 1326).

In the BD-DC Model (Figure 7-2), this capability operates at the interface between the firm and the availability of big data within its operating environment. The case study firms operate in highly volatile environments, describing themselves as "under siege" (MediaCo01); "under fire" (FMCGCo01) and in "fear" (FMCGCo01). As described in

Chapter 2, they were subject to the widespread effects of technological innovation, global and increasingly entrepreneurial, competition. The diversity and intensity of the turbulence was destabilising; increasing the significance of the firms sensing what had changed, identifying the resulting opportunities, and reconfiguring their resource base, if they were to respond to the changing nature of competition in order to maintain their competitive advantage.

The case study firms were alert to the potential of big data to add value to the organisation. Section 7.3, and the NDV Wheel in Figure 7-1, explain the ways in which big data added this value and was positioned as a new intellectual, intangible resource. The availability of big data does not inevitably result in firms utilising it. This may be because of the overwhelming nature of disruptive change that big data brings (Baesens et al. 2014), or because of organisational rigidities that operate as “strategic straitjackets” (Teece 2007: 1322). The case study firms opted to increase their resource bases to encompass big data, in order to improve their market intelligence and identify new development opportunities. As well as reconfiguring their resource base, the firms were also configuring their sensing capabilities, by actively engaging with big data.

The next section describes how big data is changing firms’ strategic marketing capabilities through a new ‘sensing’ capability; *Engaging with a new resource*.

7.5.1 Engaging with a new resource

This section describes the sensing capability *Engaging with a new resource*, highlighted in the BD-DC Model (Figure 7-2). Chapter 6 described how the case study firms engaged with the new resource through three activities; *horizon scanning*, *looking for and liberating opportunities*, and *exploiting the big data asset*.

Extant theory suggests that horizon scanning is used to improve intelligence on markets and potential target segments (Slater and Narver 2000); the customer base (Morgan, Anderson, and Mittal 2005) and competitors (Teece 2018). The firms used horizon scanning to ascertain changes in market stability, emergent development opportunities, alternative business methods, and new innovations (see Section 6.2.1).

The firms scanned the horizon for customer intelligence. FMCGCo described using machine learning based on social media to identify trends, and to gather negative feedback on the firm or its products. MediaCo's awareness of customers' increased engagement with digital devices and communications, led to digital product development and online distribution channels. As well as benefitting from more detailed market intelligence, the firms used big data to establish a more accurate perspective on their own market position, on which to base their strategic marketing decisions. This was evident in all of the case study firms' big data initiatives.

Evidence shows that the firms also used their horizon scanning to improve their competitor intelligence, including of other industries and digitally-born organisations. Prioritising competitor activity is a logical response in a volatile environment because competitive turbulence directly affects firms' survival (Greve 2008). For the case study firms, the turbulent operating environment introduced new digitally-born competitors with new business models. Observing competitor activity alerted the firms to new opportunities and ways of working, such as the potential of digital distribution channels (MediaCo).

For all of the firms, sensing activity involved more than simply scanning (Teece 2007: 1326) to improve their market intelligence. The firms also engaged with the new resource to look for, and liberate development opportunities, to maintain their evolutionary fitness. The firms described how engagement with big data alerted them to new market opportunities (MediaCo) and the growth potential of market segments (EducationCo), captured direct customer/firm interactions (MediaCo), and highlighted product development opportunities (EducationCo). Identifying these opportunities provided the basis for future strategic marketing choices.

Research suggests that firms that are not yet engaged with the new resource may experience institutional roadblocks, which obstruct their engagement. Despite big data's potential as an intellectual, intangible asset, due to a lag between information technology and accounting practices, it is not yet recognised as such within corporate accounting (Gartner 2017). This lack of recognition is likely to affect its perceived strategic value at Board level and may stifle investment commitments, when compared with universally recognised and valued strategic assets. A lack of stakeholder commitment, in conjunction with the continuing changes in the form of big data, may be a factor in its under use by UK firms (Whishworks 2019).

In summary, *Engaging with the new resource* involved the case study firms in scanning the horizon for market intelligence. This intelligence included competitor and industry responses to big data and alerted the firms as to how they might approach big data, based on the experience of others. Scanning for new intelligence also improved the firms' own understanding of their market position, and therefore the basis of future strategic marketing choices. These insights provided a catalyst for business transformation and assisted the firms in overcoming organisational rigidities, such as inertia and past path choices.

The next section considers the three reconfiguration capabilities (Teece 2007) that the case study firms applied to assimilate big data for their strategic marketing. The section goes on to describe the ways in which they constructed those capabilities.

7.6 Reconfiguring capabilities

Teece's (2007) second type of dynamic capabilities are reconfiguration capabilities, which "recombine and … reconfigure assets and organisation structures…as markets and technology change" (Teece 2007: 1334). In the BD-DC Model (Figure 7-2), the reconfiguration capabilities are positioned at the core, because they represent the internal processes and activities which are central to leveraging value from big data. They interface with both the sensing and seizing capabilities, as without the reconfiguration capabilities, it is not possible for the organisation to translate big data into strategic marketing choices.

This section identifies the three reconfiguring capabilities that the case study firms used to transform their internal processes and structures to assimilate big data. The capabilities are: *Straddling legacy and tech,* which is specific to established firms; *Constructing an expert team in scarce conditions,* which includes the firms' responses to capability gaps; and *Applied technological thinking,* which comprises the generation of insights from big data and are distinct from big data analytics.

When established firms start their engagement with big data, they have a recognised market position, historic and planned paths of direction, and embedded processes (Teece 1997). Their stakeholders are familiar with the firm's assets, processes and custom and practice in their decision-making, and accordingly have an expectation of the organisation's strategic development journey. This differs from digitally-born firms, which are able to establish themselves with a data-driven business model because they lack these historic encumbrances. Digitally-born firms may therefore take a more radical, innovative approach in their responses to the turbulent operating environment. Table 2-2 described these changes in business models following the arrival of digitally-born firms such as AirbBnb, Uber and Amazon. The case study firms described their market-following rather than market-leading approaches to data, which built on the experiences of these digitally-born market leaders.

Reconfiguration capabilities are needed to maintain organisations' evolutionary fitness and to escape from unfavourable path dependencies. As such, they play an important role when firms' growth or market responsiveness are inhibited because of organisational rigidities. Reconfiguration may involve constant asset realignment, updating of routines, or more radical business model redesign (Capron, Dussauge, and Mitchell 1998). MediaCo adopted a radical solution to addressing capability gaps in their strategy to become a data-driven organisation. They established a separate digital division, making market exploitation the domain of the established business; and market exploration using big data, the domain of the digital division.

The next section describes how the availability of big data is changing firms' strategic marketing capabilities through, *Straddling legacy and tech*.

7.6.1 Straddling legacy and tech

This section describes how the case study firms managed to assimilate the new resource by *straddling legacy and tech* (see **BD-DC Model**, Figure 7-2). MediaCo's Head of Digital Product Development commented that; "… transformation is cross-functional but it is difficult when you straddle a mode, between legacy and tech". *Straddling legacy and tech* was identified as a vital capability for incumbent firms which were simultaneously managing their existing business and investigating big data-led opportunities for differential advantage and growth. The findings identified that the firms were using three approaches to deliver the capability; by *accommodating opposing business and funding models,* they had *the strategic clarity to opt for radical change,* and they had *secured buy-in from stakeholders* to use big data.

The complexities arising for incumbent firms which are *straddling legacy and tech* are best understood with reference to the organisational ambidexterity literature (see Tushman and O'Reilly 1996). As March (1991) observes, the challenge is how firms exploit their own resources enough to maintain current viability, whilst exploring enough to secure future viability. To do so, firms have to prioritise and allocate resources between exploration and exploitation (Gupta, Smith, and Shelley 2006), determining how to manage the tension between the two (He and Wong 2004). Applying ambidexterity requires the accommodation of different business models, stakeholder buy-in, and clear strategic decision-making, which were all themes identified by the case study firms as elements of *straddling legacy and tech*.

The firms used different modes of ambidexterity to combine the exploitation of their existing position with exploration of new business opportunities. In line with the extant literature, four modes of ambidexterity were evidenced: structural (O'Reilly and Tushman 2004); temporal (Tushman and O'Reilly 1996); and contextual (Birkinshaw and Gibson 2004). The fourth mode, expert project ambidexterity, was evident in the case study practices but was not specified within existing ambidexterity theory. Figure 7-3 is an adaptation of a model proposed by Prange and Schlegelmilch (2009: 219), which has been adapted to accommodate the fourth mode identified in this study.

Figure 7-3 Four modes of ambidexterity

		Timing of activity	
		SIMULTANEOUS	*SEQUENTIAL*
Level of activity	*ORGANISATIONAL*	**STRUCTURAL AMBIDEXTERITY**	**TEMPORAL AMBIDEXTERITY**
	INDIVIDUAL	**CONTEXTUAL AMBIDEXTERITY**	**EXPERT PROJECT AMBIDEXTERITY**

Source: adapted from Prange and Schlegelmilch (2009: 219)

The ambidexterity modes are complementary, with the firms applying different combinations depending on the timing and level of their big data initiatives (Jansen 2015).

Each mode will be considered in turn. Three of the case study firms described *structural* ambidexterity in their firm's response to big data. The firms were *straddling legacy and tech*, at an organisational level, through simultaneous exploitation and exploration activities. FMCGCo, MediaCo and AutoCo described their management of the conflicting demands of exploitation and exploration, by allocating different activities to different business functions. FMCGCo made big data exploitation the responsibility of the research and development team, while exploration was carried out by the sales and marketing functions. MediaCo facilitated the potential of new exploratory, data-led activity by establishing a new digital division, to run in parallel with the exploitation activities of the traditional print-based business. The new division also had an entirely new skills base to those of the core business. Finally, AutoCo's predominant target market was business-to-business. By exploiting the potential of their big data systems developed for the mainstream business, they produced a business model which could explore a separate business–to-consumer market.

The organisational ambidexterity literature suggests that where firms are experiencing technological shocks, an ideal approach to take is *temporal* ambidexterity, where exploration and exploitation are separated by sequential timing (Tushman and O'Reilly 1996). Using temporal ambidexterity, long periods of incremental data exploitation might be punctuated with significant strategic, big data, exploration projects. AutoCo's structural ambidexterity example reflected this exploit-then-explore temporal approach, as did EducationCo's exploitative, big data initiative (BDI) which was followed by an exploratory customer retention project.

The case study firms explained how *straddling legacy and tech* resulted in tensions in the demands for resources. These were addressed using delegation of decision-making through the organisations' structures and routines; referred to in theory as *contextual* ambidexterity (Birkinshaw and Gibson 2004). This delegation gave individual employees the autonomy to make their own judgements on how to divide time between conflicting demands. For MediaCo and FMCGCo, the intuiting of opportunities for exploration and exploitation remained with senior level individuals, with clear alignment to the corporate strategy. In EducationCo, contextual ambidexterity involved senior managers making strategic decisions on exploration or exploitation of data, whilst delegating tactical and operational decisions to departmental staff, using the same repository of data.

An anomaly arose in the experience of the case study firms compared to ambidexterity theory, and specifically to Prange and Schlegelmilch's (2009) fourth 'peripatetic' mode. In their definition, peripatetic ambidexterity required a change of the top management team, which was not reflected in the case study findings. Instead, the case study firms carried out sequentially-timed and individually-led big data projects. Interview participants, notably EducationCo, described the contributions of individual experts from different business functions operating in cross-functional, time-bound project teams. Based on this study, 'expert project' could replace 'peripatetic' as the fourth mode in Prange and Schlegelmilch's (2009) framework. The expert project approach allowed the teams to focus on either exploration or exploitation activities, depending on the strategic priorities of the firm. It also reduced risk and the resistance of stakeholders, providing traction for wider big data engagement. Examples of the expert project mode were identified in MediaCo's multiple project digital new product development; and AutoCo's delivery of their business-to-business app, while at the same time, developing a business-to-customer app.

All of the ambidexterity modes require the prioritisation and allocation of resource, strategic clarity for change, and the buy-in of stakeholders. In competitive environments, firms have to support and invest in the resources and capabilities that are critical to delivering the strategy (Amit and Schoemaker 1993; Dietrickx and Cool 1989). MediaCo's Chief Innovation Officer noted:

> It's a leadership issue, whether to optimise existing assets or create a future-driving business. How transformative the firm is willing to be, to replace one business with another. It's a challenge to the company… *MediaCo02*

The demands of ambidexterity require the Board and stakeholders to find innovative solutions in order to adjust their established position, paths and processes, and improve their evolutionary fitness (Braganza et al. 2017).

In summary, the case study firms differ from their digitally-born competitors because they had to develop capabilities allowing them to 'straddle legacy and tech'. The firms' approaches are best understood with reference to the organisational ambidexterity literature. The case study firms applied structural, temporal, and contextual ambidexterity to maintain their evolutionary fitness, by balancing their exploration and exploitation activities. However, they also exhibited a further mode of expert project ambidexterity. The new category involved individual experts contributing to cross-functional, time-bound project teams, focused on exploiting the legacy or exploring the tech, as required by the firm's strategy. *Straddling legacy and tech* required Board and stakeholder engagement because of the strategic and structural organisational changes that were required.

The next section describes how big data is changing firms' strategic marketing capabilities through the development of a second 'reconfiguring' capability, C*onstructing an expert team in scarce conditions*.

7.6.2 Constructing an expert team in scarce conditions

This section describes the firms' reconfiguring capability of C*onstructing an expert team in scarce conditions*, highlighted in the **BD-DC Model** (Figure 7-2). The section describes how the case study firms used innovative approaches to address the capability gaps that might have prevented them from becoming data-driven. The firms secured expert teams with *breadth of vision and viewpoint, contracted with 'untraditional' partners,* and *showed entrepreneurship and experimentation,*

The assimilation of big data is critical to organisations' capabilities to adapt to the changing technological environment. The growth in global technological developments means that data-related skills are in short supply, particularly those of data scientists (McAfee and Brynjolfsson 2012), who play a central role in big data analytics. However, the case study firms spoke more broadly about the need for a triumvirate of skills to provide a broad viewpoint. The skills they highlighted were a knowledge of the business, computer science and Information Technology (IT). In the first instance, the firms addressed the need for new capabilities, by forming cross-functional teams of appropriate experts, including contracted partners. The teams were formed and disbanded for each project. As an example, EducationCo described successfully operating a project board comprising between 6 and 10 stakeholders, who brought complementary expertise.

Where capability gaps arise, firms seek alternative, innovative, and experimental processes to address those gaps (Rice et al. 2001). For example, MediaCo hired "Google-capability talent" (MediaCo04) from amongst the technology giants. The talent took the form of expert polymaths, who combined data, IT and business expertise. They found that these relationships were relatively unstable because these personnel were in high demand and likely to be offered financial incentives to move to other firms. As a result, the commercial experiences of these individuals were short-term and they often lacked operational insight into the core business. Pisano, Di Stefano, and Verona (2013) observed that innovative recruitment solutions could have unpredictable outcomes, which was MediaCo's experience.

The case study firms also constructed expert teams in scarce conditions by contracting with new suppliers to address their capability gaps. FMCGCo01's Project Leader of Digital Research and Development described their relationships with non-traditional technology suppliers. These were often microbusinesses, which was in contrast to their historical contracts with large, experienced technology firms, such as IBM. Contracting with microbusinesses was also a relatively unstable solution. FMCGCo experienced their new suppliers failing to survive within the timespan of a project, because of their reliance on relatively small numbers of personnel with specialised skills (FMCGCo01). To improve the stability of their supply of expertise, the firm sought to establish a more collaborative approach. Their approaches included buying technology micro-businesses to share knowledge, and setting up business incubation parks to improve their access to specialist technological expertise (FMCGCo01). To address capability gaps in securing new market opportunities, the case study firms also established partnerships with suppliers, and even competitors. For example, EducationCo03 was planning partnerships with organisations such as Amazon, to combine the partner's online distribution capability with EducationCo's academic content. Establishing these new types of partnerships is viewed as important in helping firms to increase access to a wider skills base and, as a result, to overcome organisational rigidities (Jagadish et al. 2014).

The case study interviewees described their firms' increasingly experimental and entrepreneurial behaviours. MediaCo had adopted innovative behaviours in changing their new product development dynamics, enabling them to improve product-to-market times and market responsiveness. FMCGCo, meanwhile, used more entrepreneurial approaches to supplier recruitment processes; working with start-ups, and in inter-firm networking to address the threat of resource gaps.

In summary, the firms reconfigured their skills base to engage with big data by introducing innovative approaches to constructing an expert team. All the firms combined expertise in business functions within short-term, cross-functional teams. This helped to provide a stable skills base and optimised in-house expertise. Skills shortages in the wider business environment, specifically of data scientists, forced some firms to seek more novel, and less predictable solutions. This put even greater emphasis on the importance of inter-functional co-ordination, to bring together the disparate skills. Taking a more entrepreneurial mind-set towards *constructing an expert team in scarce conditions* had the effect of increasing firms' agility, flexibility, and experimentation.

The next section describes how the availability of big data is changing firms' strategic marketing capabilities through the development of another 'reconfiguring' capability; *Applied technological thinking*.

7.6.3 Applied technological thinking

This section introduces the reconfiguration capability, described by the Chief Innovation Officer of MediaCo as *Applied technological thinking* (see **BD-DC Model**, Figure 7-2). Applied technological thinking encompasses big data analytics (BDA), and is the capability used to manage the technological aspects of assimilating big data to improve business competitiveness. The case study firms identified five aspects to applied technological thinking: *starting with a question or looking at patterns; profiling users by data; different forms of big data giving better insight; analytics and the analysis tools;* and *finding insights that drive business decisions.* The term *Applied technological thinking*, and the related activities, emerged from the case study interviews and is not explicitly referred to in the existing information systems or management literature.

Information systems literature focuses on big data analytics (BDA) as the core activity in gaining value from big data (Ferraris et al. 2018), although other broader perspectives are emerging. Rialti et al (2018) identify that the assimilation of big data involves establishing routines and processes that allow it to be converted to an asset that adds value to the firm. Applied technological thinking reflects this more holistic perspective. MediaCo's Chief Innovation Officer observed that "firms need applied technological thinking – if it's missing you can't deliver". Applied technological thinking includes defining the firm's data objectives (EducationCo05); identifying customers or users by their data records (MediaCo02); selecting data sources and data forms (FMCGCo02); data preparation and management (AutoCo01); and identifying the requirements of big data analytics, such as processes and software (EducationCo02). More extensive observations on these elements were provided in Section 6.5. Taking this range of activity into consideration, BDA should be viewed as a sub-process of the overall process of insight extraction from big data (Sivarajah et al. 2016). The narrow BDA-focused viewpoint taken in the literature, may have arisen because big data has largely been discussed in the information systems literature, which is especially interested in the data analytics issues (Wamba et al. 2015). In contrast, the significance of big data's business application has received less attention.

Big data analytics has an important role in securing value from big data (Corte-Real, Oliviera, and Ruivo 2014). To affect the firms' marketing strategy, the new data needs to be viewed as more than a technical competence, within the domain of data scientists. By aligning big data analytics with the business strategy, the firms secured the insight that could drive better and more focused strategic decision-making. This generation of insight provided the distinction between the organisation having useful data-based material and being able to make data–driven decisions. In their innovative, big data initiative EducationCo, analysed their single repository of student data to identify correlations and patterns that would support their firm's customer retention objectives. The combination of big data, analytics and IT was considered to be the "Holy Grail" (EducationCo05) for informed strategic marketing decisions.

In summary, big data is changing firms' strategic marketing abilities to seize new opportunities by offering more detailed insight into customers, products, and markets. This insight is a product of *applied technological thinking,* which aligns the application of the new data sources, to delivering the firms' strategic objectives. The information systems literature infers that big data analytics is the key to value creation from big data. This study proposes that BDA is a sub-process of the *applied technological thinking*, and that the wider view is needed to transform data, and to secure the necessary insight to drive strategic decision-making.

The next section considers the seizing capabilities (Teece 2007) that firms adopted in order to translate big data into strategic marketing choices.

7.7 Seizing capabilities

This section explores the role that seizing capabilities play in the application of big data to strategic marketing. Seizing capabilities are used by firms to leverage value from big data by responding to; “sensed opportunities through new products, processes and services” (Teece 2007: 1326). In the **BD-DC Model** (Figure 7-2), the seizing capability operates at the interface between the organisation’s reconfiguration capabilities, which enables them to assimilate big data, and the strategic marketing choices they make to respond to the external environment.

Addressing new opportunities involves investment in the technology, product, or service designs most likely to get market acceptance (Teece 2007). Section 7.2, supported by the NDV Wheel, evidences how the case study firms used big data to enhance their market intelligence, their knowledge of customer needs and behaviours. At the same time, the case study firms were experiencing data-driven changes in their operating market, including the creation of new business models, such as sharing communities and online customer engagement, which challenged the status quo.

Big data provided the firms with new opportunities for competitiveness, innovation, and efficiency (Braganza et al. 2017; Jagadish et al.2014; Manyika et al. 2011). Teece (2007: 1327) observes that “incumbent enterprises tend to eschew radical competency-destroying innovation in favour of new incremental competency-enhancing improvements”. In contrast to Teece’s observation on resistance to radical solutions, the case study firms made far-reaching, data-driven strategic choices to improve their evolutionary fitness.

The next section describes how big data is changing firms’ strategic marketing capabilities through the seizing capability of *Data-driven decision-making*.

7.7.1 Data-driven decision-making

This section describes the firms' seizing capability, *data-driven decision-making*, highlighted in the **BD-DC Model** (Figure 7-2). It describes how the case study firms adapted their decision-making capabilities using *fail fast and digital scale product development, personalised customer engagement* and *commoditisation of big data,* to *increase the firms' agility* and leverage value from big data in their strategic marketing choices.

Data-driven decision-making is operationally, and culturally distinct, from decisions based on small data and intuition (Ferraris et al. 2018). As described in the literature (Cheah and Wang 2017) and the NDV Wheel, the characteristics of big data are associated with value-creating potential. The case study firms used this potential, to identify new innovative solutions, to respond to market turbulence. These solutions ranged from those which were product-based, such as the adoption of digitally-born new product development processes (MediaCo); to changing the revenue structure of the business (MediaCo); altering the firm's organisational boundaries, as EducationCo planned with new partnerships; and identifying and targeting new market segments (AutoCo).

Digitally-born firms may establish data-driven business models from the outset. Established firms tend to follow a new product development process based on continuous improvement to secure long-term growth (Durmusoglu, Calantone, and McNally 2013). However, the case study firms had become data-driven by adopting innovative practices (Cheah and Wang 2017) that originated with digitally-born firms, an described by. With regard to product development, MediaCo03 described a fail fast approach, which involved high volumes of product development, launched quickly and discarded swiftly if found to be unsuccessful. This approach to product development involved high expectations of product failure, in conjunction with a strong belief that the products that were successful would be highly lucrative (see Figure 6.1). In addition, MediaCo devised products with a view to digital scale, and fast expansion with minimal additional resources (MediaCo03). MediaCo's Head of Innovation commented; "there is almost a light bulb moment that happens in a digital company that doesn't happen in a traditional company. It's to do with scale…It's that idea bounded by physical limitations in order to scale it?". He went on to say that digital scale was relevant to any data-led company. MediaCo seemed to be open to these data-oriented techniques because they could draw on a skills base recruited from amongst the global tech giants. Firms which lack awareness of these types of digitally-born, *data-driven decision-making*, are therefore at risk of losing out to their competitors (MediaCo02).

In contrast to the extensive digital scale approach, the firms also used the value-creating potential of big data to determine differentiated strategies, which were hard for competitors to emulate (Peteraf and Barney 2003). Two such data-driven options were personalised customer engagement, and the commoditisation of the data or systems. The fuller and improved customer intelligence provided by big data, allowed precise targeting of customers, which improved the firms' potential to address their individual needs. EducationCo's retention project provided an example of how data-led personalisation improved their customer experience and retention. Changes in strategy, were often reflected in radical changes in organisational processes and structures to deliver them; for example, where customer demand shifted hard copy news products online (MediaCo). This restructuring activity (Girod and Whittington 2017) was usually delivered in conjunction with reconfiguration of other business practices, to optimise responsiveness to changes in the external marketplace.

Radical data-driven approaches were also reflected in firms adopting entirely new business models. AutoCo adopted a data-driven growth strategy, which included commoditising their big data system into an 'app', aimed at a different market segment. The firm sold the resulting spin-off company to generate income for the core business. Another example of data-driven changes in business model, involved alliances with partners, with different digital competencies to extend product ranges (EducationCo).

In summary, the case study firms used *data-driven decision-making* to leverage value from big data, using data insights to direct their strategic marketing choices. Their unfamiliarity with the data resource and the new processes and systems required to gain insight from it, led to greater innovation and risk-taking. The firms emulated digitally-born firms in adopting novel approaches to product development, with significantly different expectations of return to their traditional approaches. They selected differentiated business strategies, which capitalised on big data's VRIO characteristics (Barney 2007), making it difficult for their competitors to emulate.

The next section considers how the five big data-driven dynamic capabilities were constructed, drawing on the dynamic capabilities literature, highlighted in Chapter 3.

7.8 Dynamic capability microfoundations

This section of the Discussion chapter addresses the final research sub-question, 'How are established firms constructing the dynamic capabilities that they are using to leverage big data for strategic marketing?'. The big data-driven capabilities (BD-DC) microfoundations data structure emerged from the analysis (Figure 6.6) and identified how the firms' five data-related dynamic capabilities were constructed. In this section, the structure is considered in the light of extant microfoundations theory.

Microfoundations literature identifies a more comprehensive range of foundational constructs underpinning dynamic capabilities, than the routines and capabilities most often referred to (Abell, Felin, and Foss 2008). Reviewing the data structure in the context of this literature, showed that rather than depicting microfoundations, the data structure describes meso-level activities. These activities occurred between the microfoundations and the macro level dynamic capabilities. The Big Data-Driven Capabilities Mesofoundations Framework (see Figure7-3) is the result of contextualising the BD-DC Microfoundations data structure.

The dynamic capabilities view of the firm (DCV) literature, considers how organisations respond to changes in their operating environment, by altering their resource base. The literature focuses on activity at the macro corporate or organisational levels, rather than at the level of individual actions (Abell, Felin, and Foss 2008). Although dynamic capabilities literature is starting to consider the contributions made by individual and organisational actions (Yeow, Soh and Hansen 2018). DCV theory has been criticised for its poor understanding of the detail and construction of the dynamic capabilities (Bowman and Ambrosini 2003; Teece, Pisano, and Shuen 1997). The literature suggests that an improved understanding may come from taking a micro-level view of how firms keep renewing and reconfiguring their resource base and creating new capabilities (Al-Aali and Teece 2014). This insight may also help to explain how dynamic capabilities contribute to competitive advantage (Abell, Felin, and Foss 2008).

This section discusses the insights gained from the findings into the microfoundations of dynamic capabilities. It then introduces the concept of mesofoundations and considers the third data structure in the light of the literature review.

7.8.1 Microfoundational components

Teece (2007: 1319) describes the microfoundations of dynamic capabilities as; "the distinct skills, processes, procedures, organizational structures, decision rules, and disciplines - which undergird enterprise-level sensing, seizing, and reconfiguring capacities". Eisenhardt and Martin (2000) were early protagonists of the view that microfoundations involved understanding the "underlying individual level and group actions that shape strategy, organisations and more broadly dynamic capabilities" (Eisenhardt, Furr, and Bingham 2010: 1263), which stimulated microfoundations theory.

Extant theory has tended to refer to routines and capabilities, as the fundamental units of analysis, for how resources are reconfigured to form dynamic capabilities (Abell, Felin, and Foss 2008). However, this underestimates the scope of constructs and capabilities that have emerged in the study of microfoundations. The microfoundations movement, underpinned by the works of Felin and Foss, seeks to deconstruct macro level capabilities into contributions made at an individual level (Abell, Felin, and Foss 2008; Felin, Foss, and Ployhart 2015). Literature review identified three broad groupings of microfoundational theory: individual-level constructs; organisational level constructs; and operational constructs. All three types of construct were evidenced in this study.

As the microfoundations were not part of the initial literature review, they are outlined here to support the subsequent discussion of the case study firms' experiences. *Individual level constructs* identified in the literature include: employees (Wang and Ahmed 2007); employee behaviour (Strauss, Lepoutre, and Wood 2016); co-working and knowledge sharing (Takeuchi et al. 2009); and cross-functional teams and the engagement of individual contributions (Majchrzak, More, and Faraj 2012; McDonough 2000). *Organisational level constructs* include: culture, leadership and organisation structures (Strauss, Lepoutre, and Wood 2016); path dependencies (Barney and Felin 2013; Barreto 2010); processes (Felin et al. 2012); organisational position (Strauss, Lepoutre, and Wood 2016); goals, obligations and expectations (Eisenhardt, Furr, and Bingham 2010); and rules (Eisenhardt and Martin 2000). *Operational constructs* include: resources, routines and competences (Teece, Pisano, and Shuen 1997); knowledge resources (Jansen, Vera, and Crossan 2009); and organisational relationships for knowledge exchange (Eisenhardt and Martin 2000).

In addition to individual, organisational and operational constructs, recent dynamic capabilities theory is emphasising the role that individual and organisational actions play in changing and realigning the resource base to fit the firm's strategy (Yeow, Soh and Hansen 2018). The emphasis on this aligning actions theory is on the actions taken to modify the microfoundations, rather than on the microfoundational constructs.

Before looking at these constructs and actions in more detail, it is useful to consider the big data-driven capabilities microfoundations data structure, presented in Chapter 6 (see Figure 6-5). The data structure was deconstructed into the dynamic capabilities' constituent parts. The capabilities and their component were reviewed against the three microfoundational constructs identified above. The outcomes are presented in Figure 7-4. The analysis did not aim to ascertain the frequency of each construct but to understand the construction of the capabilities.

To explain the review process, it may be useful to consider two examples. With regard to the sensing capability of *Engaging with a new resource*, the case study firms identified organisational constructs such as the position of the firm, its goals, culture and processes, and operational constructs, including routines and knowledge development.

It also highlighted organisational and individual actions, such as horizon scanning and learning about new opportunities.

In *Straddling legacy and tech,* there continued to be strong emphasis on the organisational constructs, including leadership, organisational goals and expectations; as well as the operational constructs of resources, routines and knowledge, and the individual constructs of employee behaviour, and group/team interactions. The capabilities also involved individual actions in leveraging existing resources, and in creating and accessing new resources and processes.

What became clear early in the analysis, was that the macro-level dynamic capabilities data structure could be broken down into smaller units than those described in the data structure. As an example, *Engaging with a new resource* could be deconstructed into *horizon scanning*, which then could be further broken down into the microfoundations of goals, position and knowledge, that are identified in the literature. As such, it can be concluded that this data structure represents a middle level – a meso level - between the macro dynamic capabilities and the microfoundations.

This led to further consideration of whether there was mesofoundational research in dynamic capabilities literature, which is discussed in the next section.

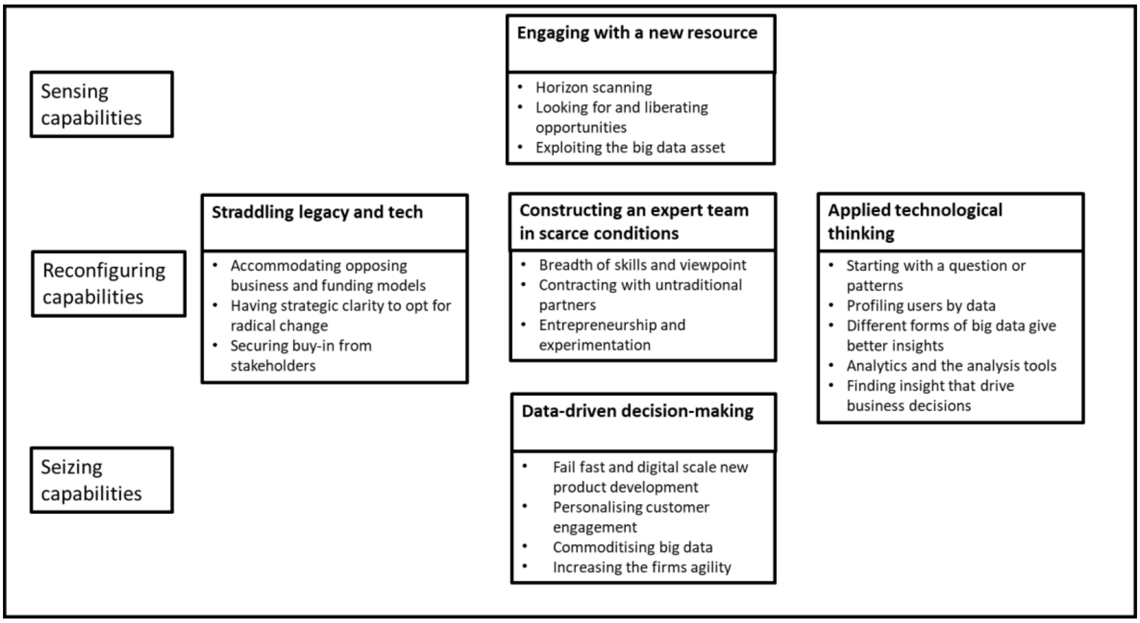
7.8.2 Mesofoundations of dynamic capabilities

The disaggregation of dynamic capabilities into more specific activities, presented in the data structure as microfoundations, does not conform with the existing microfoundation parameters provided in the literature. Since decisions on the actions taken to select and combine microfoundations are not taking place at the macro or micro dynamic capabilities level, it is reasonable to assume that they are occurring at the meso level, as indicated in the BD-DC Mesofoundations Framework. Like the dynamic capabilities, the mesofoundations can be shown in relation to Teece's (2007) sensing, reconfiguring, and seizing classifications (see Figure 7-4).

The interaction between the micro and macro levels of dynamic capabilities is poorly described and has been under-researched (Fallon-Byrne and Harvey 2017). Returning to Coleman's Bathtub (1990) (see Figure 3.2), the mesofoundations level could be viewed as filling the bathtub-shaped void in Coleman's model. Nonaka, Hirose, and Takeda (2016) proposed a theory of the mesofoundations level analysis of dynamic capabilities, although this proposal is not a widely observed or adopted phenomenon.

Figure 7-4 The Big Data-Driven Capabilities Mesofoundations Framework

(Source: Author)



However, their paper stimulated the researcher to view the construction of dynamic capabilities differently and to consider whether the microfoundations described in the third data structure, combined with the aligning actions of individuals, highlighted by Yeow, Soh and Hansen (2018), were mesofoundations. Further research to investigate the mesofoundations of dynamic capabilities could be invaluable in improving understanding of dynamic capability construction (see Section 8.3.4 Future Research).

In summary, understanding how dynamic capabilities can contribute to competitive advantage requires an improved understanding of how they are constructed. Extant theory has tended to use resources and capabilities as a shorthand for the components of dynamic capabilities, although the literature identifies an extensive range of microfoundations. These include individual level, organisational level, and operational level constructs, and the aligning actions associated with sensing, reconfiguring and seizing. The study suggests that an additional level of activity exists between the macro dynamic capabilities level and the micro foundations. This mesofoundational level, reflects how microfoundations are aggregated in the construction of dynamic capabilities and the actions of individuals and groups, such as cross-functional teams and departments. Mesofoundation theory is not well understood or adopted but is central to an improved understanding of the formation of dynamic capabilities, and therefore provides a worthwhile topic for future research (see Section 8.3.4).

7.9 Chapter summary

The case study firms found engaging with the novel big data phenomenon to be disruptive. The disruption was viewed as a valuable catalyst for overcoming organisational inertia and transforming the business. The firms initially used internally–curated data sources and as their experience and confidence grew, they added external sources, which led to more innovative and experimental outcomes. The firms applied all of the '5V' big data characteristics, but to varying degrees, depending on whether the characteristics would contribute to enabling the firms' strategy.

The New Data Value Wheel (NDV Wheel) was generated from the interview data, and in relation to Wamba et al.'s (2015) '5V' characteristics of big data. The narratives described the value attributed to each characteristic in delivering the firms' strategic marketing activity. For firms which are not fully engaged with big data, these insights can improve their understanding of the value of the resource and inform their selection of big data sources.

The Big Data-Driven Capabilities Model (BD-DC Model) identifies five dynamic capabilities, which the case study firms used to leverage big data in their strategic marketing. The capabilities emerged from using the systematic Gioia Methodology (Gioia, Corley, and Hamilton 2012). With reference to extant literature, it was apparent that the five capabilities were closely aligned to Teece's (2007), sensing, reconfiguring and seizing classifications. However, in line with the empirical works of Wang and Ahmed (2007) and Yeow et al. (2018), the model re-orders the classifications as sensing, reconfiguring and seizing, because the case study firms identified that seizing activities rely on the reconfiguration of resources having taken place beforehand. Using Teece's theory, the firms were using one sensing, three reconfiguring, and one seizing capability to apply big data in their strategic marketing activities.

The case study firms used one sensing capability, *engaging with a new resource*, to scan for market intelligence and to identify development opportunities. Initial engagement with big data relied on internal sources, which enabled the firms to build confidence and to engage stakeholders. Subsequently, external data sources were applied that encouraged novelty and innovation. *Engaging with a new resource* was viewed by the case study firms as a catalyst to business transformation, stimulating them to overcome inertia and organisational rigidities, to improve their evolutionary fitness.

Of the five dynamic capabilities used by the case study firms, three were reconfiguring capabilities. Despite their role in big data initiatives focused on strategic marketing, the reconfiguring capabilities are internally-focused, transfunctional processes and routines, and are not specifically marketing capabilities.The first reconfiguring capability, *straddling legacy and tech*, applies to established but not to digitally-born firms. This capability required commitment from the firm's Board and stakeholders, to accommodate new types of business and funding models. *Straddling legacy and tech* is best understood with reference to ambidexterity literature, which emphasises the distinctions between firms exploiting their existing market position and exploring new business opportunities. The findings suggest that, in addition to the known structural, contextual, and temporal ambidexterity modes identified in the management literature, the case study firms implemented expert project ambidexterity. This mode of ambidexterity has not previously been observed in the literature.

The second reconfiguration capability relates to the *construction of an expert team in scarce conditions*. The case study firms developed innovative solutions to the data-based, global skills shortage. They addressed capability gaps through novel engagement in non-traditional, high risk partnerships and by recruiting expert polymaths from the technology giants, such as Facebook. In addition, they developed new capabilities through inter-functional co-ordination of disparate skills and expertise, often with unconventional, new partners.

The third reconfiguration capability is *applied technological thinking*, an expression coined by MediaCo's Chief Innovation Officer. Extant IS literature highlights big data analytics (BDA) as the central activity in securing value from big data. This research suggests that BDA is only a sub-process of insight extraction and that a vital part of value creation from big data is alignment of the data with the organisation's strategic goals.

The fifth dynamic capability is a seizing capability, *data-driven decision-making*. Having reconfigured their capabilities to engage and assimilate the new resource, the firms responded to the sensed opportunities by making data-driven strategic marketing decisions. These decisions included changes to internal processes and structures, novel product development processes, differential marketing strategies, and changes in strategic direction. Using *data-driven decision-making* led to the case study firms being increasingly agile, flexible, and innovative.

The BD-DC Model shows the interconnection between the five capabilities. Commencing from being sensed in the firm's external environment, and from the decision to engage with the new resource, big data flows through the organisation. The data is assimilated into the firm through reconfiguration of its resources and capabilities, and the resulting data insights are used to seize new opportunities.

Understanding how dynamic capabilities are constructed improves the firm's ability to build capabilities that can contribute to its competitiveness. The literature review described microfoundations that are found at the individual, organisational and operational levels and the modification of these microfoundations through individual and organisational actions. However, the case study firms did not describe their actions in this way. The interviewees described how their activities combined the microfoundations to deliver the dynamic capabilities. Their descriptions were neither at the macro or the micro level, but occurred between the two, at the mesofoundations level. The *Big Data-Driven Mesofoundations Framework* presents the firms' activities at the meso level, helping to bridge this gap in the literature. Activities at this level are an important consideration for firms seeking to construct their capabilities to improve competitiveness.

The research conclusions are presented in Chapter 8.

Chapter 8 Conclusion, contributions and reflections

8.1 Introduction

This chapter brings together the research conclusions with a number of reflections on the study. Section 8.2 presents the research conclusions, with reference to the research questions, sub-questions and aims. Section 8.3 identifies the contributions to theory, methodology and practice that are made, based on the New Data Value Wheel and the Big Data-Driven Capabilities Model. Limitations of the study and areas for future research are also discussed. Section 8.4 presents the researcher's autobiographical reflections on the positioning of the research, the research process, and the doctoral experience.

8.2 Research Conclusion

The research concludes by reviewing the main research question and the three sub-questions, and considers how the research addresses each of them. The achievement of the research aims is also described, with reference to the research methodology and the findings.

8.2.1 Addressing the research question

In response to the paucity of research regarding big data and strategic marketing in the management and the information systems (IS) literature (see Section 1.2), the researcher defined the research question: 'How is big data changing organisations' strategic marketing capabilities?'.

The study shows that big data is providing case study firms with a new, valuable, intangible resource. The characteristics of the resource have the potential to improve customer and market intelligence, providing a robust basis for strategic marketing decision-making. The distinct nature of the big data characteristics requires firms to adopt new dynamic capabilities. In response, the case study firms developed five new dynamic capabilities. The majority of the firms' capability development is in reconfiguring to assimilate the new big data resource. Developing new dynamic capabilities enabled the case study firms to create value from big data that improved their evolutionary fitness.

8.2.2 Addressing the research sub-questions

Further detailed evidence on how big data is changing organisations' strategic marketing capabilities is provided in response to the three research sub-questions.

8.2.2.1 Big data: a valuable strategic marketing resource

The first research sub-question asked: 'What are the characteristics of big data that make it a valuable strategic marketing resource for established firms?'. The research shows that in varying degrees the firms are applying all of the '5V' characteristics of big data (Wamba et al. 2015); volume, variety, velocity, veracity and value. Each of the characteristics can contribute to making big data a valuable resource for strategic marketing. The **New Data Value Wheel** (NDV Wheel) (Figure 7-1) presents the big data characteristics, identified by the case study firms, and explains the value that the firms were able to extract from the different characteristics. The study positions big data as an intangible, intellectual, value-creating resource that can improve a firm's understanding of customers, threats and opportunities, inform value-enhancing propositions and enable firms to satisfy customer needs (Dibb et al. 2019). This suggests that firms that engage with big data have an additional resource with which to address the challenges of a volatile, highly competitive operating environment, and maintain their evolutionary fitness.

8.2.2.2 Dynamic capabilities to leverage big data

In response to the second research sub-question: ‘What dynamic capabilities are established firms using to leverage big data for strategic marketing?’, the research shows that the case study firms developed five dynamic capabilities. These capabilities are: *Engaging with a new resource; Straddling legacy and tech; Constructing an expert team in scarce conditions; Applied technological thinking;* and *Data-driven decision-making*. These capabilities were identified through the analysis of the case study interviews, using the rigorous, Gioia Methodology, with reference to extant management and IS literature. The research process culminated with the development of the **Big Data-Driven Capabilities Model** (BD-DC Model) (Figure 7-2). The BD-DC Model presents the empirical findings in the context of Teece’s (2007) classifications of sensing, reconfiguring, and seizing capabilities. The firms had developed five capabilities; one sensing, three reconfiguring and one seizing capability. The contributions that each of the dynamic capabilities make to leveraging big data for strategic marketing are described below.

The case study firms used one sensing capability, *engaging with a new resource*, to develop their market orientation. Their enhanced knowledge of markets, customers and competitors improved the knowledge base for their planning, decision-making and capacity to align with target markets.

The new resource was viewed as a catalyst to business transformation, helping firms to overcome inertia and organisational rigidities, to improve their evolutionary fitness.

Of the five dynamic capabilities used by the case study firms, three were reconfiguring capabilities. The first, *straddling legacy and tech*, emphasised the distinctions between firms exploiting their existing market position and exploring new business opportunities. The case study firms used four different modes of ambidexterity: structural; contextual;

temporal; and expert project ambidexterity to explore and exploit their market opportunities.

The second reconfiguration capability relates to the *construction of an expert team in scarce conditions*. The case study firms addressed capability gaps through novel engagement in unusual alliances and partnerships, and by recruiting expert polymaths from the technology giants. The need for inter-functional co-ordination was made more important by bringing together disparate skills and expertise.

The third reconfiguration capability, *applied technological thinking*, highlights that big data analytics (BDA) is a central activity in securing value from big data. However, it is not the only value creating capability, and the findings indicated that firms' viewed alignment of the data with the organisation's strategic goals as a vital part of value creation from big data.

The fifth dynamic capability, *data-driven decision-making,* is a seizing capability, which uses big data to drive the firms' strategic marketing choices, and respond to emergent market opportunities. These choices may involve changes to internal structures, product development processes or differential marketing strategies and changes in strategic direction. Moving to *data-driven decision-making* led to the firms being increasingly agile, and innovative.

There are two additional, key insights provided by the BD-DC Model; the importance of reconfiguring capabilities, and the relationship between the five dynamic capabilities.

Extant literature identifies different classes of capabilities, or combinations of classes, as making greater contributions to firms' competitiveness (see Section 7.4.2). For example, Droge et al. (2008) view sensing and seizing capabilities as the most important combination. In the context of using big data within strategic marketing, the BD-DC Model shows that the case study participants placed greater emphasis on the reconfiguring capabilities. These capabilities allowed them to assimilate big data (see Figure 7-2).

With regard to the relationships between capabilities, the BD-DC Model presents the five dynamic capabilities in the context of three classifications; sensing, reconfiguring and seizing. The capabilities interconnect with one another, allowing resources and capabilities to be shared. In addition, the BD-DC Model presents big data as flowing through each of the classifications of capabilities, originating as available data and ending in data-driven strategic marketing choices to improve competitiveness. The inter-relationships between the component parts are significant for practitioners who wish to better understand how to generate benefits from big data. The BD-DC Model records that the five capabilities are dependent on each other and interrelated. For example, a firm making data-driven decisions can only do so if the firm has first engaged with the new resource, and then reconfigured its capabilities to assimilate the data.

8.2.2.3 The construction of dynamic capabilities

The third research sub-question asked: ‘How are established firms constructing the dynamic capabilities that they are using to leverage big data for strategic marketing?’. The research identifies two levels of activity in constructing dynamic capabilities; microfoundations level and mesofoundations level activities.

Microfoundations theory is an established strand in dynamic capabilities literature. The literature identifies microfoundations as the individual, organisational and operational constructs that enable firms to reconfigure their resource base (Abell, Felin, and Foss 2008). The literature suggests that dynamic capabilities are constructed at the micro level of individuals, resources and processes and through individual actions (Yeow, Soh and Hansen 2018) . However, the case study firms described the construction of dynamic capabilities at a mesofoundation level, where the microfoundations were being selected and aggregated. The BD-DC Mesofoundations Framework (Figure 7-4) highlights the activities the case study firms carried out in constructing the five big data-driven dynamic capabilities. The mesofoundational level of dynamic capabilities is not well understood in the extant literature and provides an opportunity for future research (see Section 8.3.4).

The next section addresses the research aims.

8.2.3 Addressing the research aims

This research has five aims, which are addressed in this thesis. Each aim is considered below with reference to the research methodology.

The first aim was to *address the lack of empirically-based, academic research on big data within the marketing discipline*. The aim is addressed in this thesis, which presents a piece of academic research investigating 'How is big data changing organisations' strategic marketing capabilities?' The empirical basis for the study is provided by case study research, using interviewing as the means of data collection. Twenty-two interviews were carried out, generating thirty-five hours of interview data. The findings have been contextualised and positioned within management and IS literature.

The second aim was to *investigate big data initiatives in a number of different organisational cases, to make the emergent theory more credible and trustworthy*. This aim is addressed through the four case studies of established firms from different industry sectors (see Table 4-3). Interviews were carried out with knowledgeable agents on the firms' use of big data in strategic marketing and a thematic analysis of the findings was conducted. To ensure the emergent theory was credible and trustworthy, the study adhered closely to the Gioia Methodology, a systematic approach to data collection and reporting (see Section 4.6).

The third aim was to *collect rich, qualitative data from knowledgeable agents on their experiences of using big data within a strategic marketing initiative*. This aim was addressed through the use of elite interviews with senior managers, capturing their voices of experience on their firms' big data initiatives in strategic marketing.

The fourth aim was to *generate an inductive, conceptual framework, which addresses the research questions and is grounded in empirical data, and presents the informants' experiences in theoretical terms.* This aim was addressed through the generation of three data structures, (see Figures 5-6, 6-5 amd 6-6) that were grounded in the empirical evidence of the experienced managers. The data structures were then contextualised within the IS and management literature, resulting in two grounded theory models: The

New Data Value Wheel (NDV Wheel); and the **Big Data-Driven Capabilities Model** (BD-DC Model).

The fifth aim was to *develop a model which is valuable to academia, as well as practitioners, by identifying the capabilities required to engage with and leverage big data for their strategic marketing activity*. This aim is addressed through the contributions made by the NDV Wheel and the BD-DC Model to academia and practice, as outlined in the Contributions section (see Section 8.3). The models clearly show how big data can add value to strategic marketing (NDV Wheel), and the dynamic capabilities needed to use big data in strategic marketing (BD-DC Model).

In summary, the research has addressed the research questions and aims. Using the Gioia Methodology, two grounded theory models have been developed: the **New Data Value Wheel;** and the **Big Data-Driven Capabilities Model**; supported by the Big Data-Driven Capabilities Mesofoundations Framework. The framework identifies the activities the case study firms carried out to assemble the necessary individual, organisational and operational microfoundations (see Figure 7-4). Both models have the potential to contribute to theory and practice. The research contributions will be discussed in the next section.

8.3 Contributions

This section of the chapter presents the NDV Wheel and BD-DC Model and explains how the research contributes to management, information systems (IS), and dynamic capabilities theory. The two models also provide new frameworks for marketing practice. This section also identifies limitations of the study and proposals for future research.

8.3.1 Theoretical contributions

The study contributes to two theoretical domains. Firstly, it bridges the IS and management literatures, and secondly, it enhances dynamic capabilities theory. The study repositions big data in management theory, by investigating how the IS big data concept translates into value and by highlighting the role of big data in strategic marketing. It also contributes to dynamic capabilities literature, by highlighting the importance of reconfiguring capabilities.

8.3.1.1 Theoretical contribution to bridging IS and management literature

Three features of the study that address challenges stimulated by previous literature will be discussed here. Firstly, the majority of big data theory is documented in the IS literature, which undermines its importance in management practice. Secondly, there is a lack of understanding of how big data translates into economic value (Gunther et al. 2017). Thirdly, there is a dearth of existing theory regarding big data's role in marketing (Rialti et al. 2018). This study addresses each of these challenges and, in so doing, makes a theoretical contribution that bridges the management and IS literatures.

Big data originates in technology which may explain why the majority of big data research is found in the IS literature. Most of the recent papers can be found in the growing body of IS literature on big data analytics (Wang, Kung, and Byrd 2018). This is evidenced by recent systematic literature reviews, including Wamba et al. (2015) and Rialti et al. (2018). However, given the application of big data has the potential to be significant in improving the competitiveness of firms, a better understanding of its strategic implications is urgently needed (McAfee and Brynjolfsson 2012; Wang, Kung, and Byrd 2018).

The first theoretical contribution made by this research is in bridging the IS and management literatures. This bridging is achieved by using a management theory, dynamic capabilities lens to investigate the technologically-orientated, big data phenomenon. The outcomes are two empirically-based models, which combine IS and management perspectives, and therefore contribute to both bodies of theory. The **New**

Data Value Wheel (NDV Wheel) extends the '5V' characteristics of big data from the IS literature (Wamba et al. 2015) and highlights the value-creating potential of each characteristic. The **Big Data-Driven Capabilities Model** (BD-DC Model) identifies the capabilities that firms are using to apply the big data resource. The research therefore provides a better understanding of the strategic implications of big data. For readers of the IS literature theoretical insights are offered into the importance of business strategy in the application of big data. A contribution is also made to management theory, through insights into the benefits of big data in business practice, and the need for specific strategic marketing capabilities.

A second theoretical contribution is that the study helps explain how big data adds value to firms. Extant studies (George, Haas and Pentland 2014; Markus and Topi 2017) highlight that academe has "a limited understanding of how organisations translate big data's potential into social and economic value" (Gunther et al. 2017: 191). The two models produced in this research address different aspects of Gunther et al.'s observation. The NDV Wheel identifies *what* value the characteristics of big data can offer firms, whilst the BD-DC Model identifies *how* firms are translating big data into value through changes in capabilities, resources, and routines.

This study makes a third theoretical contribution to the management literature by examining the impact of big data on strategic marketing. Marketing is under-represented in literature related to big data. Two recent big data-related, systematic literature reviews have emphasised the dearth of marketing papers (Wamba et al. 2015; Rialti et al. 2019). These reviews cite Erevelles, Fukawa, and Swayne (2016) and Martin (2017) as the only significant contributors in this domain, both of which concern operational marketing, such as pricing, promotion and product positioning. This study is distinct from those two papers, in that it emphasises the use of big data in strategic marketing, focusing on market intelligence and opportunity spotting to secure business competitiveness, rather than on operational decision-making.

8.3.1.2 Theoretical contribution to dynamic capabilities literature

The research contributes to a second theoretical domain; that of dynamic capabilities theory. This contribution is made by highlighting and evidencing the importance of the reconfiguring capabilities in contributing to firms' competitiveness. Studies have placed varying emphases on which of Teece's (2007) classifications, or which combinations of these, contribute the most to a firm's competitiveness (see Section 7.4.2). The BD-DC Model illustrates that, in the context of applying big data in strategic marketing, the firms placed greater emphasis on the development of reconfiguring capabilities. Three of the five capabilities identified in the BD-DC Model were reconfiguring capabilities, which are shown to be central to the transformation of data into data-driven strategic marketing decisions.

In summary, the research and the research outcomes, in the forms of the NDV Wheel and the BD-DC Model, have contributions to make to management, IS and marketing theory. The BD-DC Model has a further contribution to make to knowledge in dynamic capabilities theory, by highlighting the importance of reconfiguration capabilities for firms using big data in strategic marketing. The next section considers the practical contributions of the study.

8.3.2 Methodological contribution

The research also offers a methodological contribution. The Gioia Methodology (Gioia, Corley and Hamilton 2012) proposes a five-step approach (See Section 4.3.4). From the outset, the Gioia methodology indicates that the five steps are a guideline and should be adapted to suit the research. In this study, two additional steps of data analysis were added to assist with data reduction, and the categorisation and theming of the analysis (see Section 4.5 and Figure 4-1).

The 'First order analysis' proposed by Gioia et al. (2012), represents an informant-centric analysis of the data and involves categorising the informants' contributions. In this research, some interview material was discarded at this step because it was not relevant to the research question, or was thought too sensitive (see Section 4.5, Ethical Considerations). This process was therefore identified as a separate step, entitled: 'First order distillation' (see Section 4.6.3). In Gioia at al.'s (2012) five-step model, the 'Second order analysis' was a researcher-led activity to sort the data categories into themes and dimensions. In this study, the 'Second order analysis' required two steps. Firstly, the participant contributions were grouped into themes, such as horizon scanning or contracting with non-traditional partners. This was then followed by distillation of these themes into aggregate dimensions, such as *Engaging with a new resource,* which condensed the eighteen themes into five dynamic capabilities and simplified the view of the phenomenon. This additional step was called 'Second order aggregation' (See Section 4.6.5).

Adding the two steps clarifies the data-to-theory process, to accurately reflect the researcher's actions in the analytical process. This approach adds rigour to the qualitative research process, to support the view that the conclusions are plausible and defensible. In addition, the supplementary steps improve the communication of the process, improving the capacity for others to replicate the methodology.

8.3.3 Practical contributions

Despite the recognised value to firms of engaging with big data (Davenport and Harris 2007), 53% of UK firms are disengaged, which represents approximately three million firms (Whishworks 2018). The research, therefore, has a substantial audience and considerable potential to make a timely contribution to the practice of marketing.

The research offers a practical contribution to firms which are considering engaging with big data to improve their competitive position. The NDV Wheel and the BD-DC Model, together with the supporting mesofoundations framework, offer tools for practitioners who want to engage more fully with big data. The models can help practitioners to understand the value of big data and the capabilities that experienced firms have developed to apply big data in their strategic marketing. The practical contribution of each model will now be considered.

8.3.3.1 The New Data Value Wheel

The New Data Value Wheel (NDV Wheel) (Figure 7-1) provides organisations with a framework for understanding how big data can add value to the business.

Previous literature shows that all of big data's '5V' characteristics (Wamba et al. 2015) have implications for firms' resource bases, routines and processes. For example, firms seeking to benefit from the volume of big data, require different data storage arrangements than previously, while those wanting to make marketing decisions in real-time need data velocity.

However, the existing literature reveals little about how firms benefit from each characteristic, and this could influence whether firms choose to engage with big data. A lack of understanding of these benefits may be a factor in the low uptake of big data by UK firms (Whishworks 2018). The NDV Wheel builds on the participants' insights to identify the value to firms of each big data characteristic. For example, firms engaging with the volume of customer-related big data, benefit from a more granular view of their customer on which to base segmentation, targeting and positioning activities. This is evidenced by EducationCo, which established a single repository of all their student helping to identify different customer segments, which would not have been visible otherwise.

The practical contribution of the NDV Wheel is that it provides a simple visual model to improve understanding of the motivation for engaging with big data. It reveals how the new resource might add value to a firm not fully engaged with big data. The NDV Wheel provides a valuable tool to inform the Board, stakeholders, senior marketers, and information systems personnel, as to the value of engaging with big data. It is particularly useful in relation to sensing new opportunities and also as a basis for strategic decisions on resource reallocation, such as funding new data storage arrangements or recruiting a data-oriented skills base.

8.3.3.2 The Big Data-Driven Capabilities Model (BD-DC Model)

A further practical contribution from the research emerges from the BD-DC Model's (Figure 7-2) a visual representation of firms' capabilities in relation to their external operating environment. It relates the capabilities which emerged from the interviews to the existing dynamic capabilities theory by aligning them to Teece's (2007) sensing, seizing and reconfiguring capabilities.

The BD-DC Model may be used as a tool by firms which are not fully engaged with big data. The model explains the capabilities needed to apply big data, and the process of transforming big data from a resource, into better informed marketing choices. The BD-DC Model presents the five dynamic capabilities in the context of a firm's operating environment. The data is sensed through *engaging with a new resource*. The firm reconfigures its internal processes to assimilate the new resources by *straddling legacy and tech, constructing an expert team in scarce conditions* and *applied technological thinking.* The firm is then able to make *data-driven decisions* regarding its strategic marketing choices. For practitioners, understanding that experienced firms view the application of the dynamic capabilities as a process, is a valuable insight.

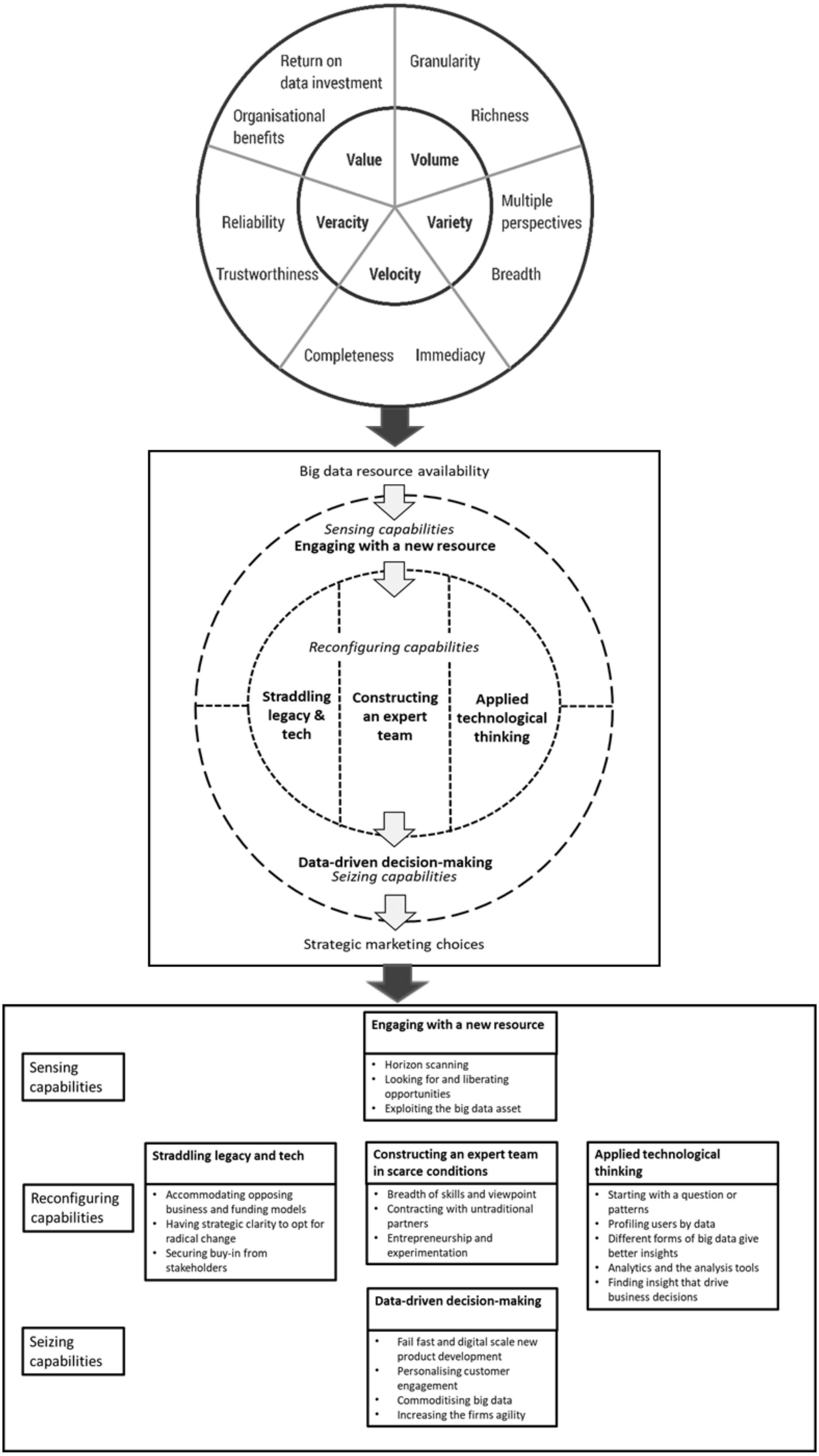
The BD-DC Model is supported by the **BD-DC Mesofoundations Framework.** The framework identifies the activities the case study firms carried out to assemble the necessary individual, organisational, and operational microfoundations (see Figure 7-3).

In summary, the research offers three tools for firms to learn about the capabilities needed to leverage value from big data. These three linked tools are the **New Data Value Wheel**, the **Big Data-Driven Capabilities Model,** and the **Big Data-Driven Capabilities Mesofoundations Framework**.

Figure 8-1 provides an illustration of the relationship between each of the tools, which might be used to support practitioners wishing to use big data to improve their competitive position. Although this research provides a starting point for practitioners, future work is needed to explore how the models might be further developed and applied.

The next section identifies three limitations of the research.

Fig 8-1 Linkages between the big data for strategic marketing models



8.3.4 Limitations of the research

The thesis has presented research to determine how big data is changing organisations' strategic marketing capabilities. A robust research design has adopted the systematic Gioia Methodology, which "is designed to bring 'qualitative rigor' to the conduct and presentation of inductive research" (Gioia, Corley and Hamilton 2012: 15). The research outcomes are two grounded theory models, the New Data Value Wheel and the Big Data-Driven Capabilities Model, which make contributions to theory and practice.

The research has been designed and delivered to ensure it is credible and trustworthy (Lincoln and Guba 1985) and the robustness of this process is reported in detail within this thesis. However, there are limitations to the study. Three limitations have been identified and will be discussed here; sample saturation, the contextualisation of the research, and the inhibited lines of enquiry.

8.3.4.1 Sample saturation

There is a viewpoint in research methodology literature that in qualitative research sample saturation point should be achieved. Sample saturation is the point at which no additional insights are being found, and the data properties can be developed into categories (Glaser and Strauss 1967). This is not a universally held opinion. O'Reilly and Parker (2013) note that, in novel research areas, it is not always possible to achieve saturation point, whilst Dubois and Gadde (2002) suggest that applying numerical measurement is in appropriate in qualitative research.

Despite the volume of interview material, the researcher did not feel that saturation point was entirely reached, as each interview continued to introduce new material. Even so, the analysis generated robust aggregate dimensions, in the form of five, distinct big data-driven dynamic capabilities (see Section 4.6). Further interviews might only have added additional 'examples' or microfoundations to these capabilities. To test this assumption would require continuation of this study, which was not possible within the parameters of the doctoral research or this thesis. Current literature on qualitative methodology suggests that this study has achieved satisfactory saturation, given the novelty of the big data phenomenon (O'Reilly and Parker 2013).

8.3.4.2 The labels of the dynamic capabilities

The second limitation relates to the nomenclature of the dynamic capabilities. The study adhered closely to the Gioia Methodology, which directs the researcher to "make extraordinary efforts to give voice to the informants in the early stages of data gathering and analysis and also to represent their voices prominently in the reporting of the research" (Gioia, Corley, and Hamilton 2012: 17). The researcher took pains to retain the participants' words verbatim from the initial interviews, through the categorisation and theming carried out during analysis. As a result, the labels of the five dynamic capabilities are terms used by case study participants. However, some of these terms are not widely used in literature or practice, for example, *straddling legacy and tech* (MediaCo02), and *applied technological thinking*.

Klein & Myers (1999) note that, to ensure that research is transferable, the research context should be closely considered so that the intended audience can comprehend how the specific situation under investigation emerges and how it might apply to them. In the context of the thesis, the capabilities' labels do not present a limitation. However, in communicating the research beyond the thesis, for example in research papers or to practitioners, the dynamic capabilities labels should be carefully defined for these audiences.

8.3.4.3 Incomplete lines of enquiry

The third limitation relates to incomplete lines of enquiry within the interviews, which partly arose as a result of the chosen methodology and data collection method.

The first steps of the Gioia Methodology involve the collection of data from "knowledgeable agents", which are people within an organisation, with insight into the phenomenon under investigation. In this study, the knowledgeable agents were interviewed using a semi-structured format (see Appendix 5). The Gioia Methodology guides the researcher to be semi-ignorant or to apply self-enforced ignorance of the relevant literature before the interviews, to avoid confirmation bias. As a result, the line of questioning can move in many directions, which generates rich descriptions of the phenomenon.

A limitation of this approach is that not all avenues of discussion may be followed. Consequently, the significance of an unfollowed discussion may not be identified until the data analysis, which can be unsatisfactory when reporting the research. An example in this study, was that late in the data analysis it appeared that the *velocity* characteristic of big data was applied less frequently by the case study firms than the other characteristics. With hindsight, it would have been useful to further explore this observation, to ascertain whether there were specific obstacles to using velocity, or in the capabilities needed to apply it.

This oversight might have been remedied if the interviewer could have returned to the interviewees with additional questions. However, it was not possible within the constraints of the study, and in some cases key informants had left their jobs or changed role.

In summary, this research has been carried out in a way that is credible, dependable, confirmable and transferable (Lincoln and Guba 1985). The limitations of sample saturation and inhibited lines of enquiry could be addressed by carrying out further research. The study's transferability may be increased by improving the nomenclature of the dynamic capabilities to suit a wider audience.

8.3.5 Future research

The exploratory nature of this research provides a variety of opportunities and directions for future research. In this section, four proposals for further research are presented. The first two proposals relate to the limitations of this study; addressing sample saturation, and pursuing research on topics raised in this study. The other two proposals are for applying the same research approach to digitally-born firms, and investigating the mesofoundations of dynamic capabilities.

8.3.5.1 Addressing sample saturation

The first proposition for future research is to replicate the Gioia-based, research process in this study, with other established firms which have run big data initiatives. These additional case studies could come from different industrial sectors or include different sized firms, for examples SMEs, which would provide different perspectives. This would ascertain whether the same capabilities are described, and would add to the literature by indicating different tactics used by the additional participant firms. It would also increase the robustness of the models presented in this research, by addressing the issues of sample saturation highlighted earlier (see Section 8.3.4.1).

8.3.5.2 Pursuing research on topics raised in this study

Within the empirical research process, a number of emerging topics were not pursued, either because they were not pertinent to the research question, or because their significance only became apparent in the analysis. These offer possible directions for future research in the big data-strategic marketing capability domain. The topics included: the potential of artificial intelligence (AI); judging the performance success of big data initiatives; and the significance of data velocity in strategic marketing. Investigating these ideas would have the potential to add to the existing literature on the impact of big data in strategic marketing.

8.3.5.3 Comparison with digitally-born firms

A further approach for future research would be to replicate the same Gioia-based research process with digitally-born firms that are delivering big data initiatives. The current research assumes that these new firms' capability requirements are less significant than those of established firms. This study identifies that big data is an evolving concept and the changes in the business environment remain turbulent. One approach to further research would be to test the hypothesis that digitally-born firms are subject to the same impacts of turbulence on their strategic marketing capabilities. Comparative research could help to confirm or extend the models, and consider the extent of their applicability within IS, dynamic capabilities, management and marketing theory.

8.3.5.4 Investigating the mesofoundations of dynamic capabilities

The empirical research highlighted an anomaly in existing management theory, which could be investigated. Extant dynamic capabilities literature describes the components of dynamic capabilities as microfoundations, particularly at an individual level (Abell, Felin, and Foss 2008). Within this study, the participants almost always talked about the implementation of the big data initiative in terms of the project team, the group, or the firm. The research indicates that the case study firms were directing their use of microfoundations at a mesofoundation level through group, team, and department level activities. Yet, the literature is unclear about how group and team activities are viewed in relation to microfoundations. Given the mesofoundations of dynamic capabilities are considered an under researched area of dynamic capabilities literature (Nonaka, Hirose, and Takeda 2016), further research into this subject could provide a useful addition to theory.

8.3.6 Contributions Summary

Extant literature indicates that big data has the potential to improve the competitiveness of firms, and identifies that a better understanding of its strategic implications is urgently needed (McAfee and Brynjolfsson 2012; Wang, Kung, and Byrd 2018). This study contributes to addressing the gap in understanding by presenting two empirically based models, which combine IS and management perspectives and therefore contribute to both bodies of theory. The **New Data Value Wheel** extends the '5V' characteristics of big data from the IS literature (Wamba et al. 2015) and highlights the value-creating potential of each characteristic. The **Big Data-Driven Capabilities Model** identifies the capabilities that firms are using to apply the big data resource.

In addition to bridging IS and management literature, the models indicate how big data translates into economic value. The NDV Wheel identifies *what* value the characteristics of big data can offer firms, whilst the BD-DC Model identifies *how* firms are translating big data into value. Furthermore, the research adds to marketing theory by explaining how big data is used in strategic marketing to secure business competitiveness. Through the BD-DC Model the research also contributes to dynamic capabilities knowledge, by highlighting and evidencing the importance of the reconfiguring capabilities in contributing to firms' competitiveness.

Despite the recognised value to firms of engaging with big data, more than half of UK firms are not using big data fully. The research, therefore, has a substantial audience and considerable potential to make a timely contribution to the practice of marketing. The NDV Wheel and the BD-DC Model, together with the supporting mesofoundations framework, offer tools for practitioners who want to engage more fully with big data. The New Data Value Wheel provides organisations with a simple visual model to explain how big data can add value to the business. The BD-DC Model provides a visual representation of the capabilities needed to apply big data, and the process which transforms big data from a resource into better informed strategic marketing choices. The BD-DC Model is supported by the BD-DC Mesofoundations Framework, which identifies the activities the case study firms carried out to build their dynamic capabilities.

In addition to highlighting the contributions that the research makes to theory and practice, this section also identifies three limitations to the research. Two of the limitations, sample saturation and incomplete lines of enquiry are proposed as areas of future research. The third limitation, the labels of the dynamic capabilities, will be addressed when the research is communicated to wider audiences. Two further areas for future research are suggested. The first involves using this study's method with digitally-born firms, to ascertain any differences or similarities with the findings from this research. The final suggestion for future research is an investigation into the construction of dynamic capabilities at a group or team level, known as the mesofoundations level.

The next section provides the researcher's autobiographical reflections on the research process and the doctoral experience.

8.4 Autobiographical reflections

This section of the chapter provides autobiographical reflections on the PhD candidate's experience of the research process and the doctoral experience. Thomson (2014: 1) comments that reflecting on learning is "the final act in the thesis".

The section is divided into four parts. The first introduces the background of the PhD candidate which provides context for subsequent sections. The following parts consider the positioning of the research, the research process, and the doctoral experience. Each provides a narrative describing the research experience and culminates with the lessons learnt by the candidate, which will inform their future academic career. As the narrative is autobiographical, it uses the first person.

8.4.1 The researcher's background

I came to the PhD as an experienced marketing and project manager with twenty-five years' practical experience in industry within private, public sector and not-for-profit firms. I was conscious that the firms I had been working for were not using big data and did not have plans to do so. From an academic perspective, I had completed a Master's degree in Business Administration twelve years previously. As a precursor to the PhD, I had completed a Master's degree in Research (MRes). My business experience and academic research interests were brought together within my MRes dissertation on 'Big data and marketing strategy' (Brewis, 2015). The opportunity to undertake a PhD represented a career change and an opportunity to research an area that I had practical experience of, which was still relatively new and poorly understood by practitioners, and which appeared to be under represented in academic research.

8.4.2 Positioning of the research

This part of the 'Autobiographical reflections' section addresses the positioning of the research, with commentary on the research question, the research domain and the positioning of the research within existing theory.

The choice of research question emerged as a future research topic, from my MRes dissertation research in 2015. At that time, there was very limited management literature on the organisational application of 'big data', and even less from an empirical perspective. Because of the novelty of the topic, a qualitative research approach was selected. Interviews with senior managers in small and medium-sized firms highlighted that the firms were not using big data for marketing, and for a number it was not in their five-year planning horizon. This led me to wonder if there were specific differences between firms which were and were not using big data and whether I could identify common themes in firms which were, that could be passed on to non-users. This led me to my choice of PhD question and my chosen methodology. *The lesson from this experience was that the initial 'pilot' research confirmed a need and parameters for a future larger piece of research on the use of big data in strategic marketing.*

The research domain was identified in response to various calls for research (Rialti et al. 2018; Wamba et al. 2015). The choice of research topic involved a review of the literature in three fields – strategic marketing, big data, and dynamic capabilities, which were in varying stages of maturity. Strategic marketing theory was mature, but big data was novel, which required extensive study of 'grey' practitioner journals, such as information from McKinsey. The extensive body of dynamic capabilities literature had relatively little theory in the mesofoundations area, a topic that became important within this study. *The lessons from this experience were that investigating a research subject that bridges different research domains is possible. However, doing justice to the subject while adhering to a thesis word count is challenging.*

Assessment of the research context was an important factor in the positioning of the new research in extant theory. During the research period (2015-2019), big data was an emerging and changing field of research; the capitalised term 'Big Data' had changed to 'big data', as the concept had become more widely adopted within academic literature. The theory highlighted a distinction between the engagement of the new resource by 'digitally-born' firms such as Amazon, Facebook, AirBnB and Uber, and the incumbent firms in the same industries. The incumbent firms were managing their existing business and at the same time embracing new technologies and new ways of working. This required executive-level decisions to direct changes in strategy, and investments in physical, human and organisational resources to engage with it. This insight resulted in a research focus on strategic marketing. *The lesson from this experience was that the assessment of research context was an important factor in the positioning of new research within existing theory.*

8.4.3 Research process

Implementing the research methodology generated two research process lessons: the importance of abstraction in codifying research data; and the value of visualising the findings.

One lesson from the research process related to my skills in abstracting and codifying data. The chosen Gioia Methodology (Gioia et al. 2012) involved collecting the voices of those with experience of the big data phenomenon. The methodology proposed that these voices were then coded and analysed, in a number of iterations, to highlight key themes. The codification of the participant voices was the most challenging part of using the Gioia Methodology. The first order analysis had to be carried out twice (see Section 4.7). Once the interviews were transcribed, I moved straight into NVivo coding. However, after the first primary coding I was frustrated that the dynamic messages that came from interviews like 'Canute holding back the tide'(EducationCo03) or 'surrounding yourself with Special Forces' skilled staff (MediaCo02), had been replaced with summary themes that sounded very flat and unengaging. When I reviewed the coding, I found that I had subconsciously drawn out terms which followed the semi-structured interview format. In the second round of coding, I was able to abstract the content in order to identify different themes and to retain the energy of the interviews rather than simply reporting them. Some of the resulting themes were in line with extant theory such as the importance of 'expert teams', others were entirely novel such as 'applied technological thinking'. *The lesson from this experience was the importance of the researcher's role in abstracting the research findings to develop new connections and develop new theory. This requires a balance to be achieved between communicating the participant voices and conceptualising the broader themes and connections.*

Another lesson from the research process was the value of visualising the findings. The Gioia Methodology indicated that the researcher would generate a data structure from the analysed primary research. I did not have a sense of how this might come about until I started to explain the findings to other people at conferences and events. I found myself sketching out the headline information for the firms' capabilities in the form of a diagram, and I realised that I was generating the big data-driven dynamic capability data structure. I found that, by producing a visualisation of the findings, I was able to explain the research more easily and to construct a conceptual framework by aligning the findings to extant theory. I subsequently used visual representations to describe the findings on big data value and on the mesofoundations of dynamic capabilities for using big data for strategic marketing. *The lesson from this experience is that a visual representation has the potential to simplify the research explanation and therefore improve its impact for practitioner and academic audiences.*

8.4.4 The doctoral experience

This section of the autobiographical reflections addresses my doctoral experience through the development of academic writing skills and joining the research community.

The doctoral experience involved the development of academic writing skills. I came to the PhD from industry, with a long track record in producing business reports. It was challenging to transition to writing in an academic style and to using different formats, referencing systems, sentence structures, drafting and editing processes. In order to build a better understanding of academic writing, I drew on training from Coventry University's RECAP and Centre for Academic Writing and the British Academy of Management (BAM). I wrote copious drafts of the literature review chapters and findings; I responded to and applied supervisor feedback; and reviewed academic conference papers written by others, to learn from their experience. I practiced presenting research to non-specialist audiences through the Three-Minute Thesis Competition, poster competitions and research centre events. In September 2019, I was awarded BAM's award for the best strategy development paper, which boosted my confidence in the progression of my academic writing. *The lesson from this experience is that I have been able to continuously improve the quality of my academic writing by taking advantage of a range of learning environments throughout my PhD. This will continue with writing journal articles, based on the doctoral research.*

As a final observation of the doctoral experience, I have benefitted from being an active member of the research community. Early in PhD life I decided to become an active member of research-related University life. I engaged with other academics through the Centre for Business in Society's 'Data, Organisations and Society' research cluster. This drew me into working with other academics, ranging from Professors to other PhD students, researching in similar fields. As a result, I co-ordinated the planning and organisation of an international conference: "Tension in the data environment: can organisations meet the challenge?", bringing in international speakers who were writing in my domain. I am also actively involved in BAM special interest groups, which facilitates potential co-authoring connections. Within the University, I have been invited to deliver sessions on social media for academics, to both the research centre and to the University's postgraduate community. I have also written a number of University research blogs on qualitative research with businesses, which have connected me with other faculty colleagues. *The lesson from this experience is that being an active member of the research community has helped to build my credibility and connections, which will be valuable in my future career.*

In summary, whilst the culmination of doctoral research is the thesis and viva voce, the research process has taught me skills that will last beyond the PhD award. These skills include research design and execution, and methodological competences, but also proficient academic writing skills and an enthusiasm to join the academic research community.

References

Aaker, D. (2009) ‘Branding and Contemporary Art’. *Marketing News,* 43 (19), 14.

Abell, D. (1978) ‘Strategic Windows’. *Journal of Marketing (pre-1986)*, 42, 21.

Abell, P., Felin, T. and Foss, N. (2008) ‘Building microfoundations for routines, capabilities and performance links’. *Managerial and Decision Economics,* 29 (6), 489-502.

Aberbach, J. and Rockman, B. (2002) ‘Conducting and Coding Elite Interviews’. *Political Science and Politics,* 35 (4), 673-676.

Adler, P. and Shenhar, A. (1990) ‘Adapting Your Technological Base: The Organizational Challenge’. *Sloan Management Review,* 32 (1), 25-37.

Adner, R. and Helfat, C. (2003) ‘Corporate effects and dynamic managerial capabilities’. *Strategic Management Journal*, 24, 1011-1025.

Akpobi, T. C. (2017) *Dynamic capabilities and strategic management: explicating the multi-level nature of dynamic capabilities - insights from the information technology security consulting industry.* Unpublished PhD thesis. Stirling: University of Stirling.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R. and Childe, S. J. (2016) ‘How to improve firm performance using big data analytics capability and business strategy alignment?’ *International Journal of Production Economics,* 182, 113-131.

Al-Aali, A. and Teece, D. (2014) ‘International entrepreneurship and the theory of the (longlived) international firm: A capabilities perspective’. *Entrepreneurship Theory and Practice,* 38 (1), 95-116.

Alvarez, A. (2016) *First mover or fast follower? Santander UK’s big data journey.* ‘Strata and Hadoop World Conference’ held 5-6 December 2016 at Suntec Singapore Convention and Exhibition Centre, Singapore.

Ambrosini, V. and Bowman, C. (2009) ‘What are dynamic capabilities and are they a useful construct in strategic management?’ *International Journal of Management Reviews,* 11 (1), 29–49.

Ambrosini, V., Bowman, C. and Collier, N. (2009) ‘Dynamic capabilities: An exploration of how firms renew their resource base’. *British Journal of Management,* 20 (s1), S9–S24.

Amit, R. and Schoemaker, P. J. H. (1993) ‘Strategic assets and organizational rent’. *Strategic Management Journal,* 14 (1), 33–46.

Aram, J. and Salipante, P. (2003) ‘Bridging scholarship in management: Epistemological reflections’. *British Journal of Management,* 14 (3), 189-205.

Arndt, F. and Jucevicius, G. (2013) ‘Antecedents and outcomes of dynamic capabilities: The effect of structure’. *Social Sciences*, *81* (3), 35-42.

Augier, M. and Teece, D. J. (2007) ‘Dynamic capabilities and multinational enterprise: Penrosean insights and omissions’. *Management International Review,* 47, 175-192.

Avenier, M. and Thomas, C. (2015) ‘Finding one's way around various methodological guidelines for doing rigorous case studies: A comparison of four epistemological frameworks’. *Systèmes D'Information Et Management*, 20 (1), 61-98.

Baesens, B., Bapna, R., Marsden, J., Vanthienen, J. and Zhao, J. (2014) ‘Transformational Issues of Big Data and Analytics in Networked Business’. *MIS Quarterly: Management Information Systems*, 38, 629-631.

Barney, J. (1991) ‘Firm resources and sustained competitive advantage’. *Journal of Management*, 17, 99–120.

Barney, J. B. (2001) ‘Is the resource-based view a useful perspective for strategic management research? Yes’. *Academy of Management Review*, 26 (1), 41-56.

Barney, J. B. (2007) *Gaining and sustaining competitive advantage.* 3rd edn. Upper Saddle River, NJ.: Pearson /Prentice Hall International.

Barney, J. and Felin, T. (2013) ‘What are microfoundations?’ *The Academy of Management Perspectives*, 27 (2), 138–155.

Barrales-Molina, V., Bustinza, O. F., and Gutierrez-Gutierrez, L. J. (2013) ‘Explaining the causes and effects of dynamic capabilities generation: A multiple-indicator multiple-cause modelling approach’. *British Journal of Management*, 24 (4), 571– 591.

Barreto, I. D. (2010) ‘Dynamic capabilities: A review of past research and an agenda for the future’. *Journal of Management*, 36, 256–280.

Baskarada, S. and Koronios, A. (2014) ‘A Critical Success Factor Framework for Information Quality Management’. *Information Systems Management*, 31 (4), 276–295.

Baum, J. R. and Wally, S. (2003) ‘Strategic decision speed and firm performance’. *Strategic Management Journal*, 24, 1107–1129.

Bean, R. and Davenport T. H. (2019) ‘Companies are falling behind in their efforts to become data driven’. *Harvard Business Review*. Feb. [online] available from https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven. [03.03.2018]

Becker, S., Bryman, A. and Ferguson, H. (2012) *Understanding Research for Social Policy and Social Work: Themes, Methods and Approaches.* Bristol: Policy Press.

Bello-Orgaz, G., Jung, J. J., and Camacho, D. (2016) 'Social Big Data: Recent Achievements and New Challenges'*. Information Fusion* 28, 45-59.

Benbasat, I., Goldstein, D. and Mead, M. (1987) ‘The case research strategy in studies of information systems’. *MIS Quarterly*, 11 (3) 369–386.

Berger, P.L. and Luckmann, T. (1967) *The Social Construction of Reality.* New York: Anchor Books.

Berners-Lee, T. and Shadbolt, N. (2011) ‘There’s gold to be mined from all our data’. *The Times*, London. [online] Available from https://www.thetimes.co.uk/article/theres-gold-to-be-mined-from-all-our-data-s3qffdkz7kq [20.07.2019]

Bessant, J., Birley, S., Cooper, C., Dawnson, S., Gennard, J., Gardiner, M., Gray, A., Jones, P., Mayer, C., McGee, J., Pidd, M., Rowley, G., Saunders, J. and Stark, A. (2003) ‘The State of the Field in UK Management Research: Reflections of the Research Assessment Exercise (RAE) Panel’, *British Journal of Management*, 14: 51–68.

Birkinshaw, J. and Ansari, S. (2015) *Understanding Management Models. Going Beyond" What" and" Why" to" How" Work Gets Done in Organizations. Foss, JN, & Saebi*, 85-103.

Birkinshaw, J. and Gibson, C. (2004) ‘Building Ambidexterity Into an Organization’. *MIT Sloan Management Review*, 45 (4), 47-55.

Blackwell, G. W. (1953) ‘Behavioral science and health’. *Social Forces*, 32 (2), 211-215.

Blazquez, D. and Domenech, J. (2018) ‘Big Data sources and methods for social and economic analyses’. *Technological Forecasting and Social Change*, 130, 99-113.

Borodo, S.M., Shamsuddin, S.M. and Hasan, S. (2016) ‘Big data platforms and techniques’. *Indonesian Journal of Electrical Engineering and Computer Science*, *1* (1), 191-200.

Bosma, N. S., Stam, F. C., and Wennekers, A. (2010) 'No Title'. *Intrapreneurship: An International Study.*

Bowman, C. and Ambrosini, V. (2003) ‘How the resource-based and the dynamic capability views of the firm inform corporate-level strategy’. *British Journal of Management*, 14 (4), 289–303.

Braganza, A., Brooks, L., Nepelski, D., Ali, M., and Moro, R. (2017) ‘Resource management in big data initiatives: Processes and dynamic capabilities’. *Journal of Business Research*, 70, 328–337.

Brannen, J. and Moss, G. (2012) ‘Critical issues in designing mixed methods policy research’. *American Behavioral Scientist*, 56 (6), 789-801.

Braun, V. and Clarke, V. (2006) ‘Using thematic analysis in psychology’. *Qualitative Research in Psychology*, 3 (2), 77-101.

Brewis, C. (2015) *Big Data and Marketing Strategy*. Unpublished dissertation. Milton Keynes: The Open University.

Brown, S. and Eisenhardt, K. (1997) ‘The Art of Continuous Change: Linking Complexity Theory and Time-Paced Evolution in Relentlessly Shifting Organizations’. *Administrative Science Quarterly*, 42 (1), 1-34.

Bruni, D. S. and Verona, G. (2009) ‘Dynamic marketing capabilities in science-based firms: An exploratory investigation of the pharmaceutical industry’. *British Journal of Management*, 20 (s1), S101–S117.

Bryman, A. (2008). *Social Research Methods.* 3rd edn. Oxford: Oxford University Press.

Bryman, A. (2016) *Social Research Methods*. 5th edn. Oxford: Oxford University Press.

Brynjolfsson, E., Hitt, L. M. and Kim, H. (2011) 'Strength in Numbers: How Does Data-Driven Decision Making Affect Firm Performance? (April 22, 2011). Available at SSRN: https://ssrn.com/abstract=1819486

Bughin, J. (2016) 'Big Data, Big Bang?'. *Journal of Big Data* 3 (1), 1-14.

Calantone, R., Garcia, R. and Dröge, C. (2003) 'The effects of environmental turbulence on new product development strategy planning'. *Journal of Product Innovation Management*, 20, 90-103.

Capron, L., Dussauge, P. and Mitchell, W. (1998) 'Resource deployment following horizontal acquisitions in Europe and North America, 1988-1992'. *Strategic Management Journal*, 19 (7), 631–661.

Carrillat, F. A., Jaramillo, F., and Locander, W. B. (2004) 'Response to Comment: Starting to Solve the Method Puzzle in Salesperson Self-Report Evaluations'. *Journal of Personal Selling & Sales Management*, 24 (2), 141–145.

Cavagnou, D. (2011) 'A conceptual framework for innovation: An application to human resource management policies in Australia'. *Innovation: Management, Policy and Practice*, 13 (1), 111-125.

Cayla, J. and Arnould, E. J. (2008) 'A cultural approach to branding in the global marketplace'. *Journal of International Marketing*, *16* (4), 86-112.

Chakravarthy, B. (1986). 'Measuring strategic performance'. *Strategic Management Journal*, 7, 437–458.

Cheah, S. and Wang, S. (2017) 'Big data-driven business model innovation by traditional industries in the Chinese economy'. *Journal of Chinese Economic and Foreign Trade Studies*, 10 (3), 229–251.

Chen, T., Drennan, J and Andrews, L. (2012) 'Experience sharing', *Journal of Marketing Management*, 13/14 (28), 1535-1552.

Chen, C. P. and Zhang, C. Y. (2014) 'Data-intensive applications, challenges, techniques and technologies: A survey on Big Data'. *Information Sciences*, 275, 314–347.

Chen, H., Chiang, R. H. and Storey, V. C. (2012) 'Business intelligence and analytics: from big data to big impact'. *MIS Quarterly*, 36 (4), 1165-1188.

Christensen, C.M. (1997) *The Innovator's Dilemma*. Harvard Business School Press. *Boston MA*.

Chiu, W., Chi, H., Chang, Y., and Chen, M. (2016) 'Dynamic Capabilities and Radical Innovation Performance in Established Firms: A Structural Model'. *Technology Analysis & Strategic Management* 28 (8), 965-978.

Chiu, C. M., Hsu, M. H., and Wang, E. T. (2006) 'Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories'. *Decision Support Systems*, 42 (3), 1872–1888.

Ciani, A., Hyland, M.C., Karalashvili, N., Keller, J., Ragoussis, A. Tran, T.T. (2020). *Making It Big : Why Developing Countries Need More Large Firms.* Washington, DC: World Bank. © World Bank. https://openknowledge.worldbank.org/handle/10986/34430 online access September 20th 2020]

Cohen, W. and Levinthal, D. (1990) 'Absorptive capacity: a new perspective on learning and innovation'. *Administrative Science Quarterly*, 35, 128–152.

Coleman, J. S. (1990) *Foundations of Social Theory*. Cambridge, MA/London: Belknap Press of Harvard University Press.

Collis, D. J. (1994) 'Research note: how valuable are organizational capabilities?' *Strategic Management Journal*, 15, 143–152.

Conner, K. (1991) 'Historical comparison of resource-based theory and five schools of thought within industrial economics: do we have a new theory of the firm'. *Journal of Management*, 17, 121-154.

Constantiou, I.D. and Kallinikos, J. (2015) 'New games, new rules: big data and the changing context of strategy'. *Journal of Information Technology*, 30 (1), 44-57.

Cope, J. (2005) 'Researching entrepreneurship through phenomenological inquiry: philosophical and methodological issues'. *International Small Business Journal*, 23 (2), 163-189.

Corbin, J. M. and Strauss, A. L. (2014) *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory.* 4th edn. Los Angeles: Sage Publications.

Corley, K. G. and Gioia, D. A. (2004) 'Identity Ambiguity and Change in the Wake of a Corporate Spin-Off'. *Administrative Science Quarterly*, 49 (2), 173-208.

Corley, K. G. and Gioia, D. A. (2011) 'Building theory about theory building: What constitutes a theoretical contribution?' *Academy of Management Review*, 36 (1), 12-32.

Côrte-Real, N., Oliveira, T. and Ruivo, P. (2014) *Understanding the hidden value of business intelligence and analytics (BIandA).*Twentieth American Conference of Information Systems. Savannah, Georgia: Association of Information Systems.

Côrte-Real, N., Oliveira, T. and Ruivo, P. (2017) 'Assessing business value of big data analytics in European firms'. *Journal of Business Research*, 70, 379–390.

Crawford, M. (1992). The world in a shopping mall. *The City Cultures Reader*, 125-140.

Creswell, J. W. (2014) *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. 3rd edn. Los Angeles: Sage Publications

Crotty, M. (2006) *The Foundations of Social Research: Meaning and Perspective in the Research Process*. London: Sage.

Crowe, S., Cresswell, K., Robertson, A., Huby, G., Avery, A., and Sheikh, A. (2011) 'The Case Study Approach'*. BMC Medical Research Methodology; BMC Med Res Methodol* 11 (1), 100.

Cukier, K. (2010) ‘Data, data everywhere’. *The Economist.* 394 (8671), 3-5.

D’Aveni, R. A. (1994) *Hypercompetition*. New York: The Free Press.

D'Aveni, R.A., (2007) ‘Mapping your competitive position’. *Harvard Business Review*, *85* (11), 110-20.

Daft, R. L., Sormunen, J. and Parks, D. (1988) ‘Chief executive scanning, environmental characteristics, and company performance: an empirical study’. *Strategic Management Journal*, 9, 123–139.

Danneels, E. (2002) ‘The dynamics of product innovation and firm competences’, *Strategic Management Journal*, 23, 1095-1121.

Daniels, J. D. and Cannice, M. V. (2004) 'Interview Studies in International Business Research'. *Handbook of Qualitative Research Methods for International Business*, 185-206

Davenport, T. H. and Harris, J. G. (2007) ‘The dark side of customer analytics’. *Journal of Direct, Data and Digital Marketing Practice*, 9 (2), 219.

Day, G. S. (1994) ‘The capabilities of market-driven organizations’. *Journal of Marketing*, 58, 37–52.

Day, G. S. (2011) ‘Closing the marketing capabilities gap’. *Journal of Marketing*, 75, 183–195.

Day, G.S., Weitz, B.A. and Wensley, R. (eds.) (1990) *The interface of marketing and strategy* (Vol. 4). Jai Press.

De Massis, A. and Kotlar, J. (2014) 'The Case Study Method in Family Business Research'. *Journal of Family Business Strategy,* 5 (1), 15-29.

Denzin, N. K. and Lincoln, Y. S. (2011) *The Sage Handbook of Qualitative Research*. 3rd edn. Thousand Oaks: Sage Publications.

Devinney, T. M. (2013) ‘Is microfoundational thinking critical to management thought and practice?’ *The Academy of Management Perspectives*, 27 (2), 81–84.

Dewan, M. (2018) 'Understanding Ethnography: An ‘exotic’ ethnographer’s Perspective'. in *Asian Qualitative Research in Tourism*. ed. by Anon: Springer, 185-203.

Dibb, S., Simkin, L., Pride, W. M., and Ferrell, O. C. (2019) *Marketing Concepts and Strategies.* 8th edn. Australia: Cengage.

Diebold, F. X. (2012). *Empirical modelling of exchange rate dynamics,* Vol. 303. Springer Science & Business Media.

Dierickx, I. and Cool, K. (1989) ‘Asset stock accumulation and sustainability of competitive advantage’, *Management Science*, 35 (12), 1504-1511.

Dobre, C. and Xhafa, F. (2014) ‘Intelligent Services for Big Data Science’. *Future Generation Computer Systems*, 37, 267–281.

Dodge, M. and Kitchin, R. (2005) ‘Codes of life: Identification codes and the machine-readable world’. *Environment and Planning D: Society and Space,* 23 (6), 851–881.

Downes, L. and Nunes, P. F. (2013) 'Big-Bang Disruption'*. Harvard Business Review* 91 (3), 44.

Doyle, C. S. (1994) *Information literacy in an information society: A concept for the information age*. Diane Publishing.

Drnevich, P. L. and Kriauciunas, A. P. (2011) ‘Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm performance’. *Strategic Management Journal*, 32, 254–279.

Droge, C., Calantone, R. and Harmancioglu, N. (2008) ‘New product success: is it really controllable by managers in highly turbulent environments?*’ Journal of Product Innovation Management*, 25, 272–286.

Dubois, A. and Gadde, L. (2002) 'Systematic Combining: An Abductive Approach to Case Research'. *Journal of Business Research,* 55 (7), 553-560,

Duncan, R. B. (1972) ’Characteristics of organizational environments and perceived environmental uncertainty’. *Administrative Science Quarterly*, 17, 313–327.

Duncan, R. B. (1976) ‘The ambidextrous organization: designing dual structures for innovation’. *The Management of Organization*, 1 (1), 167-188.

Durmusoglu, S., Calantone, R. and McNally, R. (2013) ‘Ordered to Innovate: A Longitudinal Examination of the Early Periods of a New Product Development Process Implementation in a Manufacturing Firm’. *Journal of Product Innovation Management*, 30 (4), 712-731.

Easterby-Smith, M., Lyles, M. A., and Peteraf, M. A. (2009) ‘Dynamic capabilities: current debates and future directions’. *British Journal of Management*, 20, S1–S8.

Edwards, J. and Bagozzi, R. (2000) ‘On the Nature and Direction of Relationships Between Constructs and Measures’. *Psychological Methods*, 5 (2), 155-174.

Eisenhardt, K. M. (1989) ‘Building theories from case study research’. *The Academy of Management Review*, 14 (4), 532–550.

Eisenhardt, K. M. and Graebner, M. E. (2007) 'Theory Building from Cases: Opportunities and Challenges'. *Academy of Management Journal*, 50 (1), 25-32.

Eisenhardt, K. and Martin, J. (2000) ‘Dynamic capabilities: what are they?’ *Strategic Management Journal*, 21, 1105–1121.

Eisenhardt, K. M., Furr, N. R. and Bingham, C. B. (2010) 'Microfoundations of performance: Balancing efficiency and flexibility in dynamic environments'. *Organization Science*, 21 (6), 1263–1273.

Elgendy, N. and Elragal, A. (2014) 'Big Data Analytics: A Literature Review Paper'. *Advances in Data Mining. Applications and Theoretical Aspects*. ICDM 2014. Cham: Springer.

Elliott, A. (2014) *Contemporary Social Theory: An Introduction*. London: Abingdon

Erevelles, S., Fukawa, N. and Swayne, L. (2016) 'Big Data consumer analytics and the transformation of marketing'. *Journal of Business Research*, 69 (2), 897–904.

Eriksson, P. and Kovalainen, A. (2008) *Qualitative Methods in Business Research*. Los Angeles: Sage Publications.

Fahey, L. and Christiansen, H.K. (1986) 'Evaluating the Research of Strategy Content'. *Journal of Management*, 12, 167–183.

Fahy, J. (2002) 'A resource-based analysis of sustainable competitive advantage in a global environment'. *International Business Review*, 11 (1), 57–77.

Fahy, J. and Smithee, A. (1999) 'Strategic Marketing and the Resource Based View of the Firm'. *Academy of Marketing Science Review*, (10), 1-20.

Fainshmidt, S., Pezeshkan, A., Lance Frazier, M., Nair, A. and Markowski, E. (2016) 'Dynamic capabilities and organizational performance: a meta-analytic evaluation and extension'. *Journal of Management Studies*, *53* (8), 1348-1380.

Fallon-Byrne, L. and Harney, B. (2017) 'Microfoundations of dynamic capabilities for innovation: A review and research agenda'. *Irish Journal of Management*, 36 (1), 21-31.

Farquhar, J. D. (2012) *Case Study Research for Business*. London: Sage Publications.

Felin, T. and Foss, N. J. (2009) 'Organizational routines and capabilities: historical drift and a course-correction towards microfoundations', *Scandinavian Journal of Management*, 25, 157-167.

Felin, T., Foss, N. J. and Ployhart, R. E. (2015) 'The microfoundations movement in strategy and organization theory'. *The Academy of Management Annals*, 9 (1), 575–632.

Felin, T., Foss, N. J., Heimeriks, K. H. and Madsen, T. L. (2012) 'Microfoundations of routines and capabilities: Individuals, processes, and structure. *Journal of Management Studies*, 49 (8), 1351–1374.

Ferraris, A., Mazzoleni, A., Devalle, A. and Couturier, J. (2018) 'Big data analytics capabilities and knowledge management: impact on firm performance', *Management Decision* 57 (8), 1923-1936.

Ferrier, W. J., Smith, K. G. and Grimm, C. (1999) 'The role of competitive action in market share erosion and industry dethronement: a study of industry leaders and challengers'. *Academy of Management Journal*, 42, 372–388.

Filippini, R., Güttel, W.H., Nosella, A. (2012) 'Ambidexterity and the evolution of knowledge management initiatives'. *Journal of Business Research*, 65 (3), 317-324.

Fiorini, de Camargo, P., Seles, B.M.R.P., Jabbour, C.J.C., Mariano, E.B. and de Sousa Jabbour, A.B.L. (2018) 'Management theory and big data literature: From a review to a research agenda'. *International Journal of Information Management*, *43*, 112-129.

Flyvbjerg, B. (2011) 'Case Study'. In *The Sage Handbook of Qualitative Research.* 4th edn. ed. by Denzin, K. and Lincoln, Y.S. London: Sage, 301-316.

Fogarty, D. and Bell, P. (2014) 'Should You Outsource Analytics?' *MIT Sloan Management Review,* 55 (2), 41–45.

Fontana, A. and Frey, J. (1994) 'The Art of Science'. In *The Handbook of Qualitative Research*. ed. by Denzin, K. N. and Lincoln, Y.S. Thousand Oaks: Sage Publications.

Gandomi, A. and Haider, M. (2015) 'Beyond the hype: big data concepts, methods', *International Journal of Information Management*, 35 (2), 137-144.

García-Morales, V. J., Bolívar-Ramos, M. T., and Martín-Rojas, R. (2014) 'Technological Variables and Absorptive Capacity's Influence on Performance through Corporate Entrepreneurship'. *Journal of Business Research* 67 (7), 1468-1477.

Gassmann, O., and Enkel, E. (2004) 'Towards a Theory of Open Innovation: Three Core Process Archetypes*. Proceedings of the R&D Management Conference*, held on July 6–9 2004, Lisbon, Portugal.

Geertz, C. (1973*) The interpretation of cultures*. New York: Basic Books.

George, G. (2005) 'Learning to be capable: patenting and licensing at the Wisconsin Alumni Research Foundation 1925–2002'. *Industrial and Corporate Change*, 14, 119–151.

George, G., Haas, M.R. and Pentland, A. (2014) 'Big data and management', *Academy of Management Journal*, 57 (2), 321-326.

Gephart, R. P. J. (2004) 'Qualitative Research and the Academy of Management Journal'. *Academy of Management Journal*, 47 (4), 454-462.

Ghauri, P. N. and Grønhaug, K. (2005) *Research Methods in Business Studies: A Practical Guide*. 3rd edn. Harlow: Pearson Education.

Gibson, C.B. and Birkinshaw, J. (2004) 'The antecedents, consequences, and mediating role of organizational ambidexterity', *Academy of Management Journal,* 47 (2), 209-226.

Giddens, A. (1984) *The Constitution of Society: Outline of the Theory of Structuration* [online] . Cambridge: Cambridge: Polity Press.

Gillham, B. (2000) *Case Study Research Methods*. London: Continuum.

Gioia, D. A. and Pitre, E. (1990) 'Multiparadigm Perspectives on Theory Building'. *The Academy of Management Review*, 15 (4), 584–602.

Gioia, D. A., Corley, K. G. and Hamilton, A. L. (2012) ‘Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology’. *Organizational Research Methods*, 16 (1), 15–31.

Girod, S. J. G. and Whittington, R. (2017) 'Reconfiguration, Restructuring and Firm Performance: Dynamic Capabilities and Environmental Dynamism'*. Strategic Management Journal* 38 (5), 1121-1133.

Glaser, B. G. and Strauss, A. L. (1967) *The Discovery of Grounded Theory*. Chicago: Aldine

Goulding, C. (1999) ‘Consumer research, interpretive paradigms and methodological ambiguities’. *European Journal of Marketing*, 33 (9/10), 859-873.

Gresham, G., Hafer, J. and Markowski, E. (2006) ‘Inter-functional Market Orientation Between Marketing Departments and Technical Departments in the Management of the New Product Development Process’. *Journal of Behavioral and Applied Management*, 8 (1), 43–65.

Greve, H. R. (2008) ‘A behavioral theory of firm growth: sequential attention to size and performance goals’. *Academy of Management Journal*, 51, 476–494.

Gunther, W. A., Rezazade Mehrizi, M. H., Huysman, M. and Feldberg, F. (2017) ‘Debating big data: A literature review on realizing value from big data’. *The Journal of Strategic Information Systems*, 26 (3), 191-209.

Gupta, M. and George, J.F. (2016) ‘Toward the development of a big data analytics capability’. *Information and Management*, 53 (8), 1049-1064.

Han, J., Kamber, M. and Pei, J. (2012) *Data Mining: Concepts and Strategies*. 3rd edn. Morgann Kaufman Publishers: Waltham, MA.

Harvey, W. S. (2011) 'Strategies for Conducting Elite Interviews'. *Qualitative Research*, 11 (4), 431-441.

Hay, C. (2002) *Political Analysis: A Critical Introduction.* Basingstoke: Palgrave Macmillan

Helfat, C. E. (2007a) *Dynamic capabilities: understanding strategic change in organizations.* Malden, MA.: Blackwell Publishing.

Helfat, C. E. (2007b) ‘Stylized facts, empirical research and theory development in management’. *Strategic Organization*, 5 (2), 185–192.

Helfat, C. E. and Peteraf, M. A. (2009) ‘Understanding dynamic capabilities: Progress along a developmental path’. *Strategic Organization*, 7 (1), 91–102.

Helfat, C. E. and Raubitschek, R. S. (2018) 'Dynamic and Integrative Capabilities for Profiting from Innovation in Digital Platform-Based Ecosystems'*. Research Policy* 47 (8), 1391-1399.

Helfat, C. E. and Winter, S. G. (2011) ‘Untangling dynamic and operational capabilities: strategy for the (N)ever-changing world’. *Strategic Management Journal*, 32 (11), 1243-1250.

Hennink, M., Hutter, I., and Bailey, A. (2011) Qualitative Research Methods. London: Sage Publications

Herriott, R. E. and Firestone, W. A. (1983) 'Multisite Qualitative Policy Research: Optimizing Description and Generalizability'. *Educational Researcher*, 12 (2), 1419.

Hofer, C. and Schendel, D. (1978) *Strategy formulation: Analytical concepts*. St. Paul, MN: West.

Holloway, I. and Todres, L. (2003) ‘The Status of Method: Flexibility, Consistency and Coherence’. *Qualitative Research*, 3 (3), 345–357.

Hudson, L.A., and Ozanne, J.L. (1988) ‘Alternative Ways of Seeking Knowledge in Consumer Research’. *Journal of Consumer Research*, 14 (4), 508-521.

Hunt, S.D. (2018) ‘Advanced marketing strategy in the marketing disciple and beyond’. Journal of Marketing Management, 34 (1), 16-51.

Hunt, S.D. and Derozier, C. (2004). ‘The normative imperatives of business and marketing strategy: grounding strategy in resource-advantage theory’. *Journal of Business and Industrial Marketing*, 19 (1), 5–22.

Hunt, S.D. and Morgan, R.M. (1995) The Comparative Advantage Theory of Competition. *Journal of Marketing*, 59 (2), 1–15.

Inan, G. G. and Bititci, U. S. (2015) ‘Understanding Organizational Capabilities and Dynamic Capabilities in the Context of Micro Enterprises: A Research Agenda’. *Procedia - Social and Behavioral Sciences*, 210, 310-319.

Jagadish, H., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J., Ramakrishnan, R., and Shahabi, C. (2014). ‘Big data and its technical challenges’. *Communications of the Association for Computing Machinery, 57* (7), 86-94.

Jansen, J. J. P., Vera, D., & Crossan, M. (2009) ‘Strategic leadership for exploration and exploitation: The moderating role of environmental dynamism’. *The Leadership Quarterly,* 20 (1), 5 – 18.

Jaworski, B. J. and A. K. Kohli (1993) ‘Market Orientation: Antecedents and Consequences’. *Journal of Marketing*, 57 (July), 53-70.

Johnson, P. and Harris, D. (2003) 'Qualitative and Quantitative Issues in Research Design'. in *Essential Skills for Management Research*. ed. by Partington, D. London: Sage Publications, 99-116.

Kaisler, S., Armour, F. Espinosa J.A. and Money, W. (2013) ‘Big Data: Issues and challenges moving forward. In system sciences’ (HICSS). At the *46th Hawaii International Conference on System Sciences*, USA: IEEE.

Kane, G.C. (2017) ''Digital maturity, not digital transformation'. http://sloanreview.mit.edu/article/digital-maturity-not-digitaltransformation/ [online access: September 1st 2017].

Katkalo, V., Pitelis, C. and Teece, D. (2010) 'Introduction: on the nature and scope of dynamic capabilities'. *Industrial and Corporate Change*, 19 (4), 1175-1186.

Kitchin, R. and McArdle, G. (2016) 'What makes Big Data, Big Data? Exploring the ontological characteristics of 26 datasets', *Big Data and Society*. doi: 10.1177/2053951716631130.

Kleinbaum, A. M., Stuart, T. E. (2014) 'Inside the black box of the corporate staff: Social networks and the implementation of corporate strategy'. *Strategic Management Journal*, 35 (1), 24.

Kogut, B. and Zander, U. (1992) 'Knowledge of the firm, combinative capabilities, and the replication of technology', *Organization Science*, 3, 383-397.

Kohli, A. K. and Jaworski, B .J. (1990) 'Market Orientation: The Construct, Research Propositions, and Managerial Implications'. *Journal of Marketing*, 54 (2), 1–18.

Komorowski, J. (2014)' Looking For The Fundamentals Of Post-Crisis Economics'. *The International Business and Economics Research Journal*, 13 (3), 671.

Labrinidis, A. and Jagadish, H. V. (2012) 'Challenges and opportunities with big data'. *Proceedings of the VLDB Endowment*, 5 (12), 2032–2033.

Lam, J and Tan, G (2019) 'Should data be recognised as an asset on the balance sheet? [online] available from https://www.acutus-ca.com/2019/07/31/should-data-be-recognised-as-an-asset-on-the-balance-sheet/ [04/01/2020]

Laney, D. (2001) '3D data management: Controlling data volume, velocity and variety'. Available from http://blogs.gartner.com/doug-laney/files/2012/01/ ad949-3D-Data-Management-Controlling-Data-VolumeVelocity-and-Variety.pdf.

Laney, D., LeHong, H and Lapkin, A. (2013) 'Gartner says worldwide Business Intelligence and Analytics Market to reach $18.3bn in 2017'. *The Financial Times.* [online: accessed 17th February 2017].

Laney, D. (2016) 'Data and Analytics Strategy Predictions Through 2021' Gartner Report [online] Available from https://blogs.gartner.com/doug-laney/data-analytics-strategy-predictions-through-2021/ [03.03.2017]

Lavie, D. (2006) 'Capability reconfiguration: an analysis of incumbent responses to technological change'. *Academy of Management Review,* 31, 153–174.

Leonard-Barton, D. (1992). 'Core capabilities and core rigidities: a paradox in managing new product development'. *Strategic Management Journal,* 13 (Special Issue), 111-125.

Leonardi, P. M., Nardi, B. A., and Kallinikos, J. (2012) *Materiality and Organizing: Social Interaction in a Technological World* [online]: Oxford university press on demand.

Levinthal, D. (1991) ‘Organizational adaptation and environmental selection-interrelated processes of change’. *Organization Science*, 2, 140–145.

Li, T. and Calantone, R. J. (1998) ‘The impact of market knowledge competence on new product advantage: conceptualization and empirical examination’. *Journal of Marketing*, 13–29.

Liebowitz, S. J. and Margolis, S. E.(1994) ‘Network Externality: An Uncommon Tragedy’. *Journal of Economic Perspectives*, 8 (2), 133–150.

Lincoln, Y.S. and Guba, E.G. (1985). *Naturalistic Inquiry*. London: Sage.

Locke, K (2001) *Grounded Theory in Management Research.* Thousand Oaks: CA: Sage.

Maclean, M., Harvey, C., and Chia, R. (2012) 'Reflexive Practice and the Making of Elite Business Careers'. *Management Learning,* 43 (4), 385-40.

Mahoney, J. T. and Pandian, J. R. (1992) ‘The resource-based view within the conversation of strategic management’. *Strategic Management Journal*, 13 (5), 363-380.

Majchrzak, A., More, P. H. B. and Faraj, S. (2012). ‘Transcending Knowledge Differences in Cross-Functional Teams’. *Organization Science*, 23(4), 951–970.

Makadok, R. (2001) ‘Toward a synthesis of the resource-based and dynamic-capability views of rent creation’. *Strategic Management Journal,* 22, 387–401.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., and Roxburgh, C. (2011) ‘Big data: The next frontier for innovation, competition, and productivity’. *McKinsey Global Institute*, 1–156.

March, J.G. (1991) ‘Exploration and exploitation in organizational learning’. *Organization Science*, 2, 71–87.

Markus, M. L. and Topi, H. (2015) ‘Big data, big decisions for science, society, and business: report on a research agenda setting workshop’. *ACM Technical Report*. [online] Available from <http://dl.acm.org/citation.cfm?id=2849516> [09/05/2017].

Marr, B. (2014) *Big data: The 5Vs everyone must know*. [online] Available from https://www.linkedin.com/pulse/ 20140306073407-64875646-big-data-the-5-vs-everyone-must-know [06/03/2017].

Marz, N. and Warren, J. (2012) *Big Data: Principles and Best Practices of Scalable Realtime Data Systems*. MEAP edition. Westhampton, NJ: Manning.

Mayer-Schonberger, V. and Cukier, K. (2013) *Big Data: A Revolution that will Change How We Live, Work and Think*. London: John Murray.

McAfee, A. and Brynjolfsson, E. (2012) ‘Big data: the management revolution’. *Harvard Business Review,* 90 (10), 60-68.

McDonough, E. F. (2000) ‘Investigation of factors contributing to the success of cross-functional teams’. Journal of Product Innovation Management, 17 (3), 221 – 235.

Miles, M. B. and Huberman, A.M. (1994) *Qualitative Data Analysis: An Expanded Sourcebook* [online] 2nd edn. Thousand Oaks, Calif.; London: Thousand Oaks, Calif; London: SAGE Publications.

Miller, D. and Friesen, P. H. (1983) 'Strategy-Making and Environment'. *Strategic Management Journal,* 4, 221-235.

Mithas, S., Tafti, A. and Mitchell, W. (2013) 'How Firms Competitive Environment and Digital Strategy Posture Influence Digital Business Strategy'. *MIS Quarterly*, 37 (2), 511–536.

Moisander, J.K., Hirsto, H. and Fahy, K.M. (2016) 'Emotions in Institutional Work: A Discursive Perspective'. *Organization Studies*, 37 (7), 963–990.

Moorthy, J., Lahiri, R., Biswas, N., Sanyal, D., Ranjan, J., Nanath, K., and Ghosh, P. (2015) 'Big Data: Prospects and Challenges'. *Vikalpa* 40 (1), 74-96.

Moran, D. (2000) *Introduction to Phenomenology*. London: Routledge.

Morgan, N. A. (2012) 'Marketing and business performance'. *Journal of the Academy of Marketing Science*, 40, 102–119.

Morgan, N. A., Anderson, E. W., and Mittal, V. (2005) 'Understanding firms' customer satisfaction information usage'. *Journal of Marketing*, 69, 131–151.

Morse, J.M., (2016*) Developing grounded theory : the second generation*. New York: Routledge.

Myers, M. (2009) *Qualitative research in business and management*. London: Sage.

Nag, R., Corley, K. and Gioia, D. (2007) 'The intersection of organizational identity, knowledge and practice: attempting strategic change via knowledge grafting'. *Academy of Management Journal*, 50 (4), 821–847.

Nelson, R. and S. Winter (1982) *An Evolutionary Theory of Economic Change*. Harvard University Press, Cambridge, MA.

Newey, L.R.R. and Zahra, S.A.A. (2009) 'The evolving firm: How dynamic and operating capabilities interact to enable entrepreneurship'. *British Journal of Management*, 20 (1), S81–S100.

Nonaka, I., Hirose, A. and Takeda, Y. (2016) 'Meso'-Foundations of Dynamic Capabilities: Team-Level Synthesis and Distributed Leadership as the Source of Dynamic Creativity. Global Strategy Journal, 6 (3), 168–182.

O'Regan, N., Ghobadian, A. and Jaseem Ahmad, S. (2008) *Drivers of Strategic Direction in High Technology Small Firms In New Technology-Based Firms in the New Millennium*. Emerald Group Publishing Limited, 219–237.

O'Reilly, M. and Parker, N. (2013) 'Unsatisfactory Saturation: A critical exploration of the notion of saturated sample sizes in qualitative research'. *Qualitative Research*, 13(2), 190–197.

O'Reilly, C. and Tushman, M. (2004) ‘The Ambidextrous Organization’. *Harvard Business Review*, 82(4), 74–81.

O’Reilly, K., Paper, D. and Marx, S. (2012) ‘Demystifying Grounded Theory for Business Research’. *Organizational Research Methods*, 15 (2), 247–262.

Orlikowski, W.J. and Baroudi, J.J. (1991) ‘Studying information technology in organizations: Research approaches and assumptions’. *Information Systems Research*, 2 (1), 1–28.

Orlikowski, W.J. and Gash, D.C. (1994) ‘Technological frames: making sense of information technology in organizations.’ *ACM Transactions on Information Systems (TOIS)*, 12 (2), 174–207.

Orlikowski, W. J. (2000) 'Using Technology and Constituting Structures: A Practice Lens for Studying Technology in Organizations'. *Organization Science (Providence, R.I.)* 11 (4), 404-428.

Parkin, F. (2002). *Max Weber*. 2nd edn. Milton Park: Routledge.

Patton, M. (2002) Qualitative Research and Evaluation Methods. 3rd edn. London: Sage Publications

Pauwels, P. and Matthyssens, P. (2004) 'The Architecture of Multiple Case Study Research in International Business'. *Handbook of Qualitative Research Methods for International Business*, 125-143.

Penrose, E. (1959). The Theory of the Growth of the Firm. Basil Blackwell, London.

Perrons, R.K. and Jensen, J.W. (2015) ‘Data as an asset: What the oil and gas sector can learn from other industries about Big Data’. *Energy Policy*, 81(C), 117–121.

Peteraf, M.A., and Barney, J.B. (2003) ‘Unraveling the Resource-Based Tangle’. *Managerial and Decision Economics*, 24 (4), 309-323.

Phillips-Wren, G. and Hoskisson, A.(2015) ‘An analytical journey towards big data’. *Journal of Decision Systems: Decision Support and Analytics*, 24(1), 87–102.

Pidgeon, N. (1996) Grounded theory: theoretical background. In Richardson, J. T. E. (ed.), *Handbook of Qualitative Research Methods*. Leicester: BPS: 75-86.

Piekkari, R., Welch, C., and Paavilainen, E. (2009) 'The Case Study as Disciplinary Convention: Evidence from International Business Journals'. *Organizational Research Methods,* 12 (3), 567-589.

Pisano, M., Di Stefano, G., and Verona, G. (2013) The elephant in the room of dynamic capabilities: Bringing two diverging conversations together. *Strategic Management Journal*, *34* (12), 1389–1410.

Ployhart, R. and Hale, D. (2014) ‘The fascinating psychological microfoundations of strategy and competitive advantage’. *Annual Review of Organisational Psychology and Organisational Behavior,* 1, 145-172.

Ployhart, R. and Hale, D. (2014).'The fascinating psychological microfoundations of strategy and competitive advantage'. *Annual Review of Organisational Psychology and Organisational Behavior*, 1, 145-172.

Porter, M. (1985). *Competitive advantage: Creating and sustaining superior performance.* New York, NY: The Free Press.

Porter, M. (1996) 'What is strategy?' *Harvard Business Review*, 74 (6), 61–78.

Porter, M. E. (2008) 'The Five Competitive Forces That Shape Strategy', *Harvard Business Review*, 86 (1), 78–93.

Prange, C. and Schlegelmilch, B. (2009) 'The Role of Ambidexterity in Marketing Strategy Implementation: Resolving the Exploration-Exploitation Dilemma'. *Business Research*, 2 (2), 215–240.

Pratt, M.G. (2009). From the editors: 'For the lack of a boilerplate: Tips on writing up (and reviewing) qualitative research'. *Academy of Management Journal*, 52 (5), 856-862.

Protogerou, A., Caloghirou, Y., and Lioukas, S. (2012) 'Dynamic capabilities and their indirect impact on firm performance'. *Industrial and Corporate Change*, 21, 615–647.

Provost, F. and Fawcett, T. (2013) 'Data science and its relationship to big data and data-driven decision making'. *Big Data*, 1 (1), 51-59.

Quinn, L., Dibb, S., Simkin, L., Canhoto, A. and Analogbei, M. (2016) 'Troubled waters: the transformation of marketing in a digital world', *European Journal of Marketing,* 50 (12), 2103-2133.

Raghupathi, W., Raghupathi, V. (2014) 'Big data analytics in healthcare: promise and potential'. *Health Information Scientific Systems*. 2 (3), 1–10. http://dx.doi.org/10.1186/2047-2501.

Ragin, C. C. (1992) 'Introduction: Cases of "What is a Case?"'. in *What is a Case? Exploring the Foundations of Social Inquiry*. ed. by Ragin, C. and Becker, H. Cambridge: Cambridge University Press, 1-17.

Ramesh, S., Dursun, D. and Efraim, T. (2010) *Decision Support and Business Intelligence Systems.* 9th edn. Prentice-Hall, Englewood Cliffs, NJ.

Rahmandad, H. (2012) 'Impact of growth opportunities and competition on firm-level capability development trade-offs'. *Organization Science*, *23* (1), 138-154.

Rajendra Prasad, M., Manjula, B. and Bapuji (2013) 'A Novel Overview and Evolution of World Wide Web: Comparison from Web 1.0 to Web 3.0', *International Journal of Computer Science and Technology.* 4 (1) Jan- March. 349-354.

Ready, D. and Conger, J. (2007) 'Make Your Company a Talent Factory'. Harvard Business Review, 85(6), 68–77.

Reed, R. and DeFillippi, R.J. (1990) 'Causal ambiguity, barriers to imitation, and sustainable competitive advantage'. *Academy of Management Review*, *15* (1), 88-102.

Rezazade Mehrizi, M.H. and Lashkarbolouki, M. (2016) Unlearning Troubled Business Models: From Realization to Marginalization. *Long Range Planning*, 49 (3), 298–323.

Rialti, R., Marzi, G., Ciappei, C., and Busso, D. (2019) 'Big data and dynamic capabilities: A bibliometric analysis and systematic literature review'. *Management Decision, 57* (8), 2052-2068.

Rialti, R., Marzi, G., Silic, M., and Ciappei, C. (2018). Ambidextrous organization and agility in big data era. *Business Process Management Journal, 24* (5), 1091-1109.

Rice, G. (2006) 'Individual values, organisational context, and self-perceptions of employee creativity: Evidence from Egyptian organizations'. Journal of Business Research, 59 (2), 233-241.

Ridder, H.-G., Bruns, H.-J. and Spier, F. (2006) 'Managing Implementation Processes: The Role of Public Managers in the Implementation of Accrual Accounting – Evidence from Six Case Studies in Germany'. *Public Management Review*, 8 (1), 87–118.

Ritchie, J., Lewis, J., Elam, G., Ritchie, J. and Lewis, J. (2003) Chapter 4 in *Qualitative Research Practice: A Guide for Social Science Students and Researchers.* Los Angeles: SAGE.

Rumelt, R. P. (1974). *Strategy, Structure, and Economic Performance.* Harvard University Press, Cambridge. MA.

Rumelt, R. (2011) 'The perils of bad strategy'. *McKinsey Quarterly*, 1 (3), 1-10.

Runfola, A., Perna, A., Baraldi, E., and Gregori, G. L. (2017) *The use of Qualitative Case Studies in Top Business and Management Journals: A Quantitative Analysis of Recent Patterns* [online].

Russom, P. (2011) *The Three Vs of Big Data Analytics*: TDWI.

Sanchez, R. (1995) 'Strategic flexibility in product competition'. *Strategic Management Journal*, *16* (S1), 135-159.

Santiago-Delefosse, M., Gavin, A., Bruchez, C., Roux, P. and Stephen, S.L. (2016) 'Quality of qualitative research in the health sciences: Analysis of the common criteria present in 58 assessment guidelines by expert users'. *Social Science & Medicine*, *148*, 142-151.

SAS (2012) 'Big data meets big data analytics: Three key technologies for extracting real time business value from the Big Data that threatens to overwhelm traditional computing architectures', *SAS Institute,* Marlow.

Saunders, M., Lewis, P., and Thornhill, A. (2016) *Research Methods for Business Students*. 7th edn. Harlow: Pearson.

Schilke, O., Hu, S., and Helfat, C. E. (2018) 'Quo Vadis, Dynamic Capabilities? A Content-Analytic Review of the Current State of Knowledge and Recommendations for Future Research'. *Academy of Management Annals* 12 (1), 390-439.

Schreyögg, G. and Sydow, J. (2010) 'Crossroads—organizing for fluidity? Dilemmas of new organizational forms'. *Organization Science*, *21* (6), 1251-1262.

Schwandt, T.A. (2003) ‘Three epistemological stances for qualitative inquiry’. in Denzin. N.K. and Lincoln, Y.S. (2013) *The landscape of qualitative research* (4th ed). Thousand Oaks, Calif. ; London: SAGE.

Sebastian, I., Ross, J., Beath, C., Mocker, M., Moloney, K., and Fonstad, N. (2017) 'How Big Old Companies Navigate Digital Transformation'.

Simons, H. (2009) *Case Study Research in Practice*. London: Sage Publications.

Sirmon, D. G., Hitt, M. A., Arregle, J.-L., and Campbell, J.T. (2010) ‘The dynamic interplay of capability strengths and weaknesses: investigating the bases of temporary competitive advantage’. *Strategic Management Journal*, 31, 1386–1409.

Sivarajah, U., Kamal, M.M., Irani, Z. and Weerakkody, V. (2017) ‘Critical analysis of big data challenges and analytical methods’. *Journal of Business Research*, 70 (1), 263-286.

Slater, S.F. and Narver, J.C. (1994) ‘Does Competitive Environment Moderate the Market Orientation-Performance Relationship?’ *Journal of Marketing*, 58 (1), 46–55.

Slater, S.F. and Narver, J.C. (2000) ‘Intelligence generation and superior customer value’. *Journal of the Academy of Marketing Science*, *28* (1), 120.

Smith, M. J. (1999) *The Core Executive in Britain*. Basingstoke: Macmilla

Sokolowski, R. (2000) Introduction to phenomenology. Cambridge, Cambridge University Press.

Srinivasan, R., Rangaswamy, A. and Lilien, G. (2005) “Turning adversity into advantage: does proactive marketing during a recession pay off?”, International Journal of Research in Marketing, 22 (2), 109-125.

Staber, U. and Sydow, J. (2002) ‘Organizational adaptive capacity: A structuration perspective’. *Journal of management inquiry*, *11* (4), 408-424.

Stewart, J. (2012) ‘Multiple-case Study Methods in Governance-related research’. *Public Management Review.* 14: (1), 67-82.

Stake, R. E. (1995) *The Art of Case Study Research* [online]. Thousand Oaks, Calif.; London: Thousand Oaks, Calif; London: Sage.

Stake, R. (2005) 'Case Studies'. in *Handbook of Qualitative Research*. ed. by Denzin, N. and Lincoln, Y. Thousand Oaks: Sage Publications, 435-455.

Stone, M. and Woodcock, N. (2014), ‘Interactive, direct and digital marketing: a future that depends on better use of business intelligence’, *Journal of Research in Interactive Marketing*, 8 (1), 4-17.

Strauss, A. L. and Corbin, J. M. (1990) *Basics of Qualitative Research: Grounded Theory Procedures and Techniques*. Newbury Park: Sage Publications.

Strauss, A. and Corbin, J. (1998), *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*. Sage, Thousand Oaks, CA.

Strauss, K., Lepoutre, J., and Wood, G. (2017) ‘Fifty Shades of Green: How Microfoundations of Sustainability Dynamic Capabilities Vary across Organizational Contexts’. *Journal of Organizational Behavior,* 38 (9), 1338-1355.

Swaminathan, A. and Meffert, J. (2017) *Digital@Scale.* Hoboken, New Jersey: Wiley.

Takeuchi, R., Chen, G. and Lepak, D. (2009) ‘Through the looking glass of a social system; cross-level effects of high-performance work systems on employees’ attitudes’. *Personnel Psychology*, 62: 1, 1-29.

Teddlie, C. and Tashakkori, A. (2009) *Foundations of Mixed Methods Research: Integrating Quantitative and Qualitative Approaches in the Social and Behavioral Sciences*. Thousand Oaks: Sage Publications.

Teece, D. J. (2007) ‘Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance’. *Strategic Management Journal*, 28, 1319–1350.

Teece, D. J. (2009) *Dynamic Capabilities and Strategic Management: Organizing for Innovation and Growth.* Oxford University Press, Oxford.

Teece, D. J., (2010) Business models, business strategy and innovation. *Long Range Planning*. 43 (2–3), 172–194.

Teece, D. J., (2014) ‘The foundations of enterprise performance:dynamic and ordinary capabilities in an (economic) theory of firms’. *Academy of Management Perspectives*. 24 (4), 328-352.

Teece, D. J. (2018) ‘Business models and dynamic capabilities’. *Long Range Planning*, 51 (1), 40–49.

Teece, D.J., Pisano, G. and Shuen, A. (1997) ‘Dynamic capabilities and strategic management’. *Strategic Management Journal*, 18 (7), 509-533.

Thompson, C. J. (1991) ‘May the Circle Be Unbroken: A Hermeneutic Consideration of How Interpretive Approaches to Consumer Research Are Understood by Consumer Researcher’. *Advances in Consumer Research*, 18, 63-69.

Thompson, M. (2007). ‘Innovation in work practices: A practice perspective’. *The International Journal of Human Resource Management*, 18: 7, 1298-1317.

Thompson, C. J., Locander, W. B. and Pollio, H. R. (1989) ‘Putting consumer experience back into consumer research: The philosophy and method of existential-phenomenology’. *Journal of Consumer Research*, 16 (2), 133-146.

Thompson, C.J., Locander, W.B. and Pollio, H.R., (1990) ‘The lived meaning of free choice: An existential-phenomenological description of everyday consumer experiences of contemporary married women’. *Journal of Consumer Research,* 17 (3), 346-361.

Thompson, C.J., Pollio, H.R. and Locander, W.B. (1994) ‘The spoken and the unspoken: a hermeneutic approach to understanding the cultural viewpoints that underlie consumers' expressed meanings’. *Journal of Consumer Research*, 21 (3), 432-452.

Thompson, N., Kiefer, K. and York, J.G. (2011). 'Distinctions not dichotomies: exploring social, sustainable, and environmental entrepreneurship.' *Advances in Entrepreneurship, Firm Emergence and Growth*, 13, 201-229.

Thorpe, E. and Morgan, R. (2007) 'In pursuit of the 'ideal approach' to successful marketing strategy implementation'. *European Journal of Marketing*, 41 (5/6), 659-677.

Tracy, S. J. (2010) 'Qualitative Quality: Eight "big-Tent" Criteria for Excellent Qualitative Research'. *Qualitative Inquiry* 16 (10), 837-851.

Trost, J.E. (1986). 'Statistically non-representative stratified sampling: a sampling technique for qualitative studies.' *Qualitative Sociology*, 9 (1), 54-57.

Trunfio, M. and Della Lucia, M (2016) 'Toward Web 5.0 in Italian Regional Destination Marketing'. *SYMPHONIA Merging issues in Management* (2) 60-75.

Tsoukas, H. (1994). 'Refining common sense: types of knowledge in management studies.' *Journal of Management Studies*, 31(6), 761-780.

Tushman, M.L. and O'Reilly, C.A. (1996) 'The ambidextrous organizations: managing evolutionary and revolutionary change'. *California Management Review*, 38 (4), 8-30.

Twining, P. (2010) Educational information technology research methodology: looking back and moving forward. In *Researching IT in Education* (169-184). Routledge.

Twining, P., Heller, R.S., Nussbaum, M. and Tsai, C.C. (2017) 'Some guidance on conducting and reporting qualitative studies'. *Computers and Education.*106, A1-A9.

Van Maanen, J., (1983) *Reclaiming qualitative methods for organisational research*, in Van Maanen, J. (ed.), Qualitative Methodology, London: Sage Publications.

Varadarajan, P.R. (2010), 'Strategic marketing and marketing strategy: domain, definition, fundamental issues and foundational premises'. *Journal of the Academy of Marketing Science*, 38 (2), 119-140.

Varadarajan, R. (2015) 'Strategic marketing, marketing strategy and market strategy'. *AMS Review* (5) 78-90.

Verona, G., and Ravasi, D. (2003) 'Unbundling dynamic capabilities: an exploratory study of continuous product innovation'. *Industrial and Corporate Change*, 12, 577–606.

Vial, G. (2019) 'Understanding Digital Transformation: A Review and a Research Agenda'. *The Journal of Strategic Information Systems* 28 (2), 118-144.

Wamba, S.F., Akter, S., Edwards, A., Chopin, G., and Gnanzou, D. (2015) 'How 'big data 'can make big impact: Findings from a systematic review and a longitudinal case study'. *International Journal of Production Economics*, 165, 234–246.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R. and Childe, S.J. (2017) 'Big data analytics and firm performance: effects of dynamic capabilities', *Journal of Business Research*, 70, January, 356-365.

Wang, C. L., and Ahmed, P. K. (2007). Dynamic capabilities: A review and research agenda. *International Journal of Management Reviews*, 9 (1), 31–51.

Wang, Y., and Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research*, 70, 287–299.

Wang, Y., Kung, L. and Byrd, T.A. (2018) 'Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations'. *Technological Forecasting and Social Change*, 126, 3–13.

Warren, C. (2001). Qualitative interviewing. In Gubrium, J. F., and Holstein, J. A. *Handbook of interview research* (83-102). : SAGE Publications.

Weber, R. (2004) 'The rhetoric of positivism versus interpretivism: A personal view'. *MIS Quarterly*, 28, III–XII.

Weber, Y., Shenkar, O., Raveh, A. (1996) 'National and corporate cultural fit in mergers/acquisitions: an exploratory study'. *Management Science*. 42 (8), 1215–1227.

Wei, L.Q. and Lau, C.M. (2010). 'High performance work systems and performance: The role of adaptive capability'. *Human Relations*, 63: 10, 1487-1511.

Weick, K.E. (1984) 'Small wins: Redefining the scale of social problems'. *American Psychologist*, *39* (1), 40.

Wernerfelt, B. (1984) 'A resource-based view of the firm, *Strategic Management Journal*, Vol. 5 No. 2, 171-180.

West, D., Ford, J and Ibrahim, E. (2015) *Strategic marketing: Creating competitive advantage*. 3rd edn.*Oxford:* Oxford University Press.

Whishworks (2018) 'The state of big data in the UK 2016/2017'. [online] available from https://www.whishworks.com/big-data-report-2016/2017 [15.06/2017]

White, M. (2012), 'Digital workplace: vision and reality'. *Business Information Review*, 29 (4), 205-214.

Whitfield, K. and Strauss, G. (1998) *Researching the World of Work: Strategies and Methods in Studying Industrial Relations*. Ithaca: Cornell University Press

Whittington, R. (2014) 'Information Systems Strategy and Strategy-as-Practice: A Joint Agenda'. *The Journal of Strategic Information Systems* 23 (1), 87-91.

Whittington, R., Regner, P. Angwin, Johnson, G., and D. Scholes, K. (2019) *Exploring strategy: text and cases.* 12th edn. Harlow, England: Pearson.

Wilden, R. and Gudergan, S.P. (2015) 'The impact of dynamic capabilities on operational marketing and technological capabilities: investigating the role of environmental turbulence'. ‚*Journal of the Academy of Marketing Science*, 43 (2), 181-199.

Wilden, R., Devinney, T.M. and Dowling, G.R. (2016) 'The architecture of dynamic capability research', *The Academy of Management Annals*, 10 (1), 997-1076.

Wilden, R., Gudergan, S., Nielsen, B. B., and Lings, I. (2013). Dynamic capabilities and performance: strategy, structure and environment. Long Range Planning, 46, 72–96.

Winter, S. (2003). 'Understanding dynamic capabilities'. *Strategic Management Journal*, 24, 991–995.

Winter, S. G. (2011) *'Problems at the foundation?* Comments on Felin and Foss'. Journal of Institutional Economics, 7 (2), 257 – 277.

Wixom, B., Ariyachandra, T., Goul, M., Gray, P., Kulkarni, U. and Phillips-Wren, G. (2011) 'The current state of business intelligence in academia'. *Communications of the Association for Information Systems*, 29, October, 299-312.

World Federation of Advertisers (2013) *Survey results on Big Data.* https://wfanet.org/knowledge/item/2013/11/01/Survey-results-on-Big-Data [online: accessed on 3rd July 2016].

Xu, Z., Frankwick, G. L., and Ramirez, E. (2016) 'Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective'. *Journal of Business Research*, 69 (5), 1562–1566.

Yeow, A., Soh, C., and Hansen, R. (2018) 'Aligning with New Digital Strategy: A Dynamic Capabilities Approach'*. The Journal of Strategic Information Systems* 27 (1), 43-58.

Yi, X., Liu, F., Liu, J. and Jin, H. (2014) *Building a Network Highway for Big Data: Architecture and Challenges*. IEEE Network, 28, 5-13. https://doi.org/10.1109/MNET.2014.6863125

Yin, R. K. (1981) *The case study as a serious research strategy*. Knowledge, 3 (1), 97–114.

Yin, R. K. (1984) *Case Study Research: Design and Methods*. Beverley Hills, CA: Sage.

Yin, R. K. (2009) *Case Study Research Design and Methods*. London: Sage.

Yin, R. K. (2012). *Case study methods.* In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf, & K. J. Sher (Eds.), *APA handbooks in psychology®. APA handbook of research methods in psychology, Vol. 2. Research designs: Quantitative, qualitative, neuropsychological, and biological* (p. 141–155). American Psychological Association.

Yin, R. K. (2013) *Case Study Research: Design and Methods*. London: Sage.

Yin, R. K. (2014) *Case Study Research: Design and Methods*. 5th edn. Thousand Oaks: Sage Publications.

Yin, R. K. (2018) *Case Study Research and Applications: Design and Methods.* Sixth edition. edn. Thousand Oaks: Sage Publications.

Yiu, C. (2012) *The big data opportunity: making government faster, smarter and more personal.* Policy Exchange, London.

Zahra, S., Sapienza, H., and Davidsson, P. (2006) ‘Entrepreneurship and dynamic capabilities: a review, model and research agenda’. .*Journal of Management Studies*, 43, 917–955.

Zaltman, G. and Moorman, C. (1988) ‘The Importance Of Personal Trust In The Use Of Research’. *Journal of Advertising Research*, 28 (5), p.16.

Zhou, K. Z., and Li, C. B. (2010(‘How strategic orientations influence the building of dynamic capability in emerging economies’. *Journal of Business Research*, 63, 224–231.

Zollo, M., and Winter, S. (2002) ‘Deliberate learning and the evolution of dynamic capabilities’. *Organization Science*, 13, 339–351.

Zott, C. (2003) ‘Dynamic capabilities and the emergence of intra-industry differential firm performance: insights from a simulation study’. *Strategic Management Journal*, 24, 97-125.

Appendix 1

A synopsis of alternative theoretical lenses

To select an appropriate lens through which to investigate how big data is changing firms' strategic marketing capabilities, a number of alternative theories to dynamic capabilities were considered. These included: dynamic management capabilities (DMC) and dynamic marketing capabilities (DMktgC) theories. This appendix offers a brief synopsis of these alternative lenses and the reasons they were not adopted by this study.

Dynamic managerial capabilities (DMC)

Dynamic managerial capabilities (DMC) and dynamic capabilities theory are closely aligned. DMC emphasises the role of managers in sensing and seizing new opportunities, and refreshing and transforming the resource base to maintain competitive advantage. DMC argues that superior organisational performance is not possible solely through possession of dynamic capabilities, but requires management of the capabilities to gain performance related benefits (Zahra et al. 2006).

In choosing elite interviews as the method of data collection for the study, the potential to utilise a DMC lens was feasible, as the narratives took a managerial perspective. Adner and Helfat (2003) identified three antecedents to DMC: human capital relating to managers' skills and knowledge shaped by their backgrounds; social capital resulting from managers' relationships and connections, which confer influence and control; and managerial cognition realting to managers' individual belief systems, mental models and the basis of their decision-making. The interviews addressed issues of human and social capital which are captured in the Findings (see Chapter 6) and discussed in relation to the microfoundations of dynamic capabilities (see Section 7.8). By starting the research taking a firm's perspective on big data, the interview structure and therefore the interviewee contributions were not focused on the individual. As a result, a study using a

DMC lens would have lacked sufficient data on individual managerial cognition and would have been incomplete.

Dynamic marketing capabilities

Dynamic marketing capabilities (DMktgC) are a subset of dynamic capabilities theory. The purpose of DMktgC is the creation, use and integration of market knowledge with marketing resources, to match and create marketing and technological change (Bruni and Verona 2009). Their emphasis is on market orientation, the dissemination of market knowledge within the firm and creating customer value with a view to enhancing organisational performance. Extant literature emphasises the contributions of DMktgC to operational marketing and the development of marketable products and services (Kachouie, Mavondo, and Sands 2018). As the focus of the interviews was a big data initiative being used in strategic marketing, there was a lot of content which was relevant to DMktgC.

There were two factors in the primary research which led to a decision to opt for the wider dynamic capabilities lens. Firstly, the interviewees talked extensively about organisational capabilities outside marketing including those related to technology and finance. A focus on DMktgC would have rendered much of the valuable empirical data irrelevant to the choice of lens. Secondly, the emphasis of the case study firms was on strategic marketing decisions, including changes in organisational infrastructure and business models, rather than an operational focus on delivering marketable products and services. The dynamic capabilities lens was chosen, in order for the research to benefit from the breadth of information provided by the case study firms.

Appendix 2 Introductory email for EducationCo evaluation

Business Intelligence Project – Introductory Email

Dear....

I am carrying out an evaluation of the dashboards introduced in 2017, as part of the University's Business Intelligence Project, implemented by the Strategy Planning and Analytics Office.

As part of the evaluation I would like to interview you, to get your views on your experiences of using the dashboards.

The interview will ask you about:

- your dashboard usage and what you find helpful and unhelpful,
- how easy to use you find the dashboards ,
- what other data you would find helpful,
- how you learnt to use the dashboards and your thoughts on the system guides and training.

It would be very valuable to the evaluation to have your feedback. The interview would take approximately 45 minutes.

To give you more information on the nature of the research an Information and Consent Sheet for Participants is attached to this email. You will see from the information that the evaluation aligns with and will feed into, my PhD research which is looking at how organisations adapt to engage with Big Data.

If you have any concerns regarding the use of your feedback, I can assure you that your responses will be anonymised from the time that we meet. None of the evaluation findings will be attributed to individuals, departments or job roles. I will also adhere fully to the stringent rules of Coventry University Research Ethics policy and process.

Content removed on data protection grounds

With best wishes

Claire

Claire Brewis MBA, MRes

PhD research student

Appendix 3 Research Information Sheet

DO FIRMS REQUIRE NEW DYNAMIC CAPABILITIES TO BENEFIT FROM BIG DATA?

Coventry University

INFORMATION SHEET FOR PARTICIPANTS – KEY INFORMANT

Purpose of the project

The project's purpose is to address the broad research question: **Do firms require new dynamic capabilities to benefit from Big Data?**

And to answer the sub questions:

- What resources and capabilities does the organisation need to use Big Data for customer engagement?
- Are specific dynamic managerial capabilities required?
- How is the organisation providing or enabling these capabilities?

By *Big Data* the researcher means large scale data sets, generated through advanced technologies, which require IT architectures and analytics to produce insight. By *dynamic capabilities* the researcher means the attributes that enable the firm to alter its resources in response to changes in its external environment.

Purpose of the interview

The purpose of the interview is to gather insights from those with experience of using data in customer relationship initiatives, such as customer retention and customer loyalty projects. The researcher will be interviewing participants in different industries in order to develop a deeper understanding of the capabilities required to use Big Data in strategic customer relationship projects. This understanding will inform a theoretical model which will be relevant to academia. The research will also have implications which will be relevant to practitioners.

Why have I been chosen to take part?

We have identified you as having experience of using large scale data within a customer-related project and we would like to interview you for this study.

Do I have to take part?

You may choose not to participate in this research, omit or refuse to respond to any question, retract any comment or the whole of your interview up to the end of July 2019.

1

What do I have to do?

You are being asked to take part in an interview for approximately 1 hour. The interview will explore your experience of using Big Data and the capabilities needed to use it within a customer-related initiative. You may ask the researcher questions to clarify any further points about the study.

If you are willing to introduce the researcher to colleagues involved in the same project, your support would be appreciated.

What are the risks associated with this project?

The interview will cover topics related to customer relationships, which may be commercially sensitive. Care will also be taken to anonymise the firm and the participants details, to minimise any commercial risk.

What are the benefits of taking part?

By taking part you will be sharing your knowledge of this new area, and contributing to the development of new theories which will inform academics and practitioners. In addition, participation connects you with world-renowned researchers at The Times 'University of the Year'.

Data collection and your confidentiality

The interview may be conducted either at your workplace, at Coventry University or in a public place at an agreed time. The interview will be digitally audio-recorded, but if you are not comfortable with this, only manual notes will be taken. To maintain anonymity the interview will be coded so that your identity will be kept separate from the data unless you give additional consent for disclosure.

The data collected will be anonymised and securely stored on password-protected computers for a period of 5 years, only transferred using encrypted USB Flash Drivers and after that period securely destroyed. Electronic data will be only accessible to the researchers and if required to the personnel for an authorized academic audit. The researcher will ensure the data handling and storage comply with data protection legislation.

What will happen with the results of the study?

The data from the interview and any documentary evidence you provide will only be used for academic purposes, including journal publications, conference presentations and a Doctor of Philosophy dissertation.

Who has reviewed this study?

The project has been reviewed and approved by the Research Ethics and Governance Leader, Faculty of Business and Law, Coventry University.

Withdrawal options

You may retract any comment or the whole of your interview up to the end of July 2019.

What if things go wrong?

If you have any concerns regarding the project, please contact the researcher, in the first instance. If your concerns are not resolved to your satisfaction, please contact the research supervisors. Contact information is provided below.

Content removed on data protection grounds

Appendix 4 Participant Consent Form

DO FIRMS REQUIRE NEW DYNAMIC CAPABILITIES TO BENEFIT FROM BIG DATA?

Coventry University

STATEMENT OF CONSENT

The purpose of this consent form is to clearly state the conditions of your participation in the research. It is designed to protect your rights as described in the information sheet. Please complete and sign below if you are happy with these conditions.

I consent to participate in this research project concerning the impact of Big Data. I have been given a written description of the project which has been explained to me.

1. I confirm that I have read and understood the participant information sheet for the study and have had the opportunity to ask questions. ☐
2. I understand that my participation is voluntary and that I am free to withdraw at anytime, without giving a reason. ☐
3. I understand that all the information I provide will be treated in confidence. ☐
4. I understand that I have the right to change my mind about participating in the study for a short time after the study has been concluded (July 2019). ☐
5. I agree to be audio-recorded as part of the research project. ☐
6. I agree to take part in the research project. ☐

Name of participant: ....

Signature of participant: .... Date: ....

Name of researcher: CLAIRE BREWIS

Signature of researcher: .... Date: ....

4

Appendix 5 Interview Structure

DO FIRMS REQUIRE NEW DYNAMIC CAPABILITIES TO BENEFIT FROM BIG DATA?

This document will be used, by the researcher, to provide a semi-structure to the interviews

Interview Aims

The aim of the interview is to capture the views of those with experience of the use of Big Data in a strategic customer relationship initiative within their organisations. It will uncover which Big Data organisations are using, how it is processed and the capabilities required to transform it into customer insight. A subsidiary aim is to identify other research participants involved in the same project, from the same organisation or its partners.

The interviews have been designed to be semi-structured allowing the interviewer to gather data in a comparable format across the case study interviews.

All interviews will be carried out by a single researcher and will take up to 1 ½ hours.

Interview Structure

1. **Project background** *(rough timing 10 minutes)*
    - Participants will be given a verbal explanation of the project, its background and aims.
    - Interview timing of up to 1½ hours will be identified.
    - Permission to record will be requested, as per email brief; participant consent may be withdrawn at any time.
    - Confirmation of the anonymisation of the data will be provided.
    - Confirmation will be given that the interviewee will be given a copy of the research findings.
    - Consent form will be signed.

2. **Interviewee background** *(rough timing 10 minutes)*
    - Interviewee role in the organisation; time with the firm; background / experience in data / Big Data.
    - Interviewee involvement with data / Big Data and customer relationship projects.
    - What does Big Data mean to you? (to generate a description of what Big Data is, from the participants perspective)
    - Identify an example of a significant strategic customer relationship project using Big Data or discussion in more detail on a project outlined within their Marketing Conference paper.

3. **Forms of Big Data being used** *(rough timing 15 minutes)*

    In relation to the customer relationship project identified:

    - What data does the firm collect? External/ traditional / Big Data / internal?
    - How are the data / insight used?
    - *Questions relating to the chosen project*

How is Big Data used? *(rough timing 15 minutes)*

- Who specifies the purpose and the data to be used?
- What is the process for transforming the data into marketing action?
- What and how are the data analytics carried out?
- What actions result from the analytics?

4. **Who is involved in the Big Data initiative?** *(rough timing 15 minutes)*
   - CEO involvement?
   - Representation of business functions?
   - In house or contracted? Role of partners?

5. **Capabilities for using Big Data in customer relationship initiatives?** *(rough timing 15 minutes)*

   How do you adapt, bring together and reconfigure the firm's resources (skills, investment) to use the data to deliver the project?

   Minimal prompting. Where necessary prompting could include:

   - Integrating resources *e.g. combining skills / functions or pooling expertise*
   - Reconfiguring resources *e.g. copying/transferring resources in the firm or distributing scarce resources or collaborating for new resource*
   - Gaining new resources *e.g. knowledge creation or alliance and acquisition routines*
   - Releasing resources *e.g. jettisoning resource combinations*

6. **Thank you for your time** *(rough timing 10 minutes)*
   - Confirmation of the timescales for the research & completion of the report.
   - Confirmation regarding consent and withdrawal from the research.
   - Any questions from the interviewee?
   - Identify other research participants within the organisation.

Ends..

Appendix 6 Certificate of Ethical Approval – PhD research

Certificate of Ethical Approval

Applicant:

Claire Brewis

Project Title:

How is Big Data impacting on the way in which organisations manage their customer relationships?

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Medium Risk

Date of approval:

28 May 2020

Project Reference Number:

P46387

Appendix 7

Certificate of Ethical Approval – EducationCo Business Intelligence Project

Coventry University

Certificate of Ethical Approval

Applicant:

Claire Brewis

Project Title:

Evaluation of Coventry University Business Intelligence Project (student data dashboards)

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Medium Risk

Date of approval:

14 May 2018

Project Reference Number:

P69294

Appendix 8

Business Intelligence Project (BIP) Information Sheet

EVALUATION OF COVENTRY UNIVERSITY BUSINESS INTELLIGENCE PROJECT (DASHBOARDS)

PARTICIPANT INFORMATION SHEET

You are being invited to take part in research to evaluate Coventry University's Business Intelligence Project (dashboards). Claire Brewis, PhD research student at Coventry University is leading this research. Before you decide to take part it is important you understand why the research is being conducted and what it will involve. Please take time to read the following information carefully.

What is the purpose of the study?
The purpose of the study is to evaluate Coventry University's Business Intelligence Project, specifically in relation to dashboards.

The evaluation will capture the experiences of view of a range of users from amongst Coventry University academic and professional services staff. The interviews will be semi-structured to allow the interviewees to express their views on the dashboards and, if preferred, to demonstrate them on the computer. The data collected will be anonymised - no feedback will be attributable to individual evaluation participants.

The research findings will inform:

- Improvements to the dashboards
- The range of data collected and available
- Improvements in communications and training
- Future developments in the University's business intelligence.

The researcher will collect and assimilate the findings into a report to guide the Strategic Planning and Analytics Office team. The findings will also inform the researcher's PhD which investigates how organisations adapt to engage with Big Data.

What is the purpose of the interview?
The purpose of the interview is to capture feedback from dashboard users to inform improvement, expansion, communication and training in the future development of the Business Intelligence Project (dashboards).

Why have I been chosen to take part?
You are invited to participate in this study because your role involves using the Business Intelligence dashboards. The researcher will be interviewing a cross-section of dashboard users from academic and professional services. Some participants will use the dashboards a great deal, some will use them infrequently – all experiences will be invaluable in informing the evaluation. As your role involves you in using this system I would like to interview you for this study.

What are the benefits of taking part?

By taking part you will be sharing your knowledge of the University's Business Intelligence Project (dashboards) and helping the University to improve the system for current and new users as well as directing future developments.

Are there any risks associated with taking part?
This study has been reviewed and approved through Coventry University's formal research ethics procedure. There are no significant risks associated with participation. You may have concerns over the anonymity of

your responses. Your data will be anonymised as soon as the researcher collects it from you. All documents will be stored and referred to by a code number. Neither individual participants nor departments will be identifiable in the report. The research has no relevance to your line manager and will not be communicated to them by the researcher.

Do I have to take part?
No – it is entirely up to you. If you do decide to take part, please keep this Information Sheet and complete the Informed Consent Form to show that you understand your rights in relation to the research, and that you are happy to participate. Please note down your participant number (which is on the Consent Form) and provide this to the lead researcher if you seek to withdraw from the study at a later date. You are free to withdraw your information from the project data set at any time until the data are destroyed on July 2020. You should note that your data may be used in the production of formal research outputs (e.g. journal articles, conference papers, theses and reports) prior to this date and so you are advised to contact the university at the earliest opportunity should you wish to withdraw from the study. To withdraw, please contact the lead researcher (contact details are provided below). Please also contact the Faculty Research Support Office (email researchproservices.fbl@coventry.ac.uk; telephone +44(0)2477658461) so that your request can be dealt with promptly in the event of the lead researcher's absence. You do not need to give a reason. A decision to withdraw, or not to take part, will not affect you in any way.

What will happen if I decide to take part?
You are being asked to take part in an interview which will explore:

- Which dashboards are useful to you
- Which elements of the dashboards work well for you and why
- Whether using dashboards have changed how you do your job
- Areas you think need improvement (including communications and training)
- Areas you would like to see developed in the future.

The interview will take place in a safe environment at a time that is convenient to you. Ideally, we would like to audio record your responses (and will require your consent for this), so the location should be in a fairly quiet area. The interview should take around 45 minutes to complete.

Data Protection and Confidentiality
Your data will be processed in accordance with the Data Protection Act 1998 (up until 24th May 2018) and the General Data Protection Regulation 2016 (GDPR) thereafter. All information collected about you will be kept strictly confidential. Unless they are anonymised in our records, your data will be referred to by a unique participant number rather than by name. If you consent to being audio recorded, all recordings will be destroyed once they have been transcribed. Your data will only be viewed by the researcher/research team. All electronic data will be stored on a password-protected computer file held by the researcher. All paper records will be stored in a locked filing cabinet at the researcher's home. Your consent information will be kept separately from your responses in order to minimise risk in the event of a data breach. The lead researcher will take responsibility for data destruction and all collected data will be destroyed on or before July 2020.

Data Protection Rights
Coventry University is a Data Controller for the information you provide. You have the right to access information held about you. Your right of access can be exercised in accordance with the Data Protection Act 1998 (up until 24th May 2018) and the General Data Protection Regulation thereafter. You also have other rights including rights of correction, erasure, objection, and data portability. For more details, including the right to lodge a complaint with the Information Commissioner's Office, please visit www.ico.org.uk. Questions, comments and requests about your personal data can also be sent to the University Data Protection Officer - enquiry.ipu@coventry.ac.uk

What will happen with the results of this study?

The results of this study may be summarised in the researcher's thesis, published articles, reports and presentations. Quotes or key findings will always be made anonymous in any formal outputs unless we have your prior and explicit written permission to attribute them to you by name.

Making a Complaint

Content removed on data protection grounds

Appendix 9

Business Intelligence Project (BIP) Participant Consent Form

Participant No.

INFORMED CONSENT FORM:
BUSINESS INTELLIGENCE PROJECT (DASHBOARDS)

You are invited to take part in this research study for the purpose of collecting data to evaluate Coventry University's Business Intelligence Project (dashboards).

Before you decide to take part, you must **read the accompanying Participant Information Sheet.**

Please do not hesitate to ask questions if anything is unclear or if you would like more information about any aspect of this research. It is important that you feel able to take the necessary time to decide whether or not you wish to take part.

If you are happy to participate, please confirm your consent by circling YES against each of the below statements and then signing and dating the form as participant.

1	**I confirm that I have read and understood the Participant Information Sheet for the above study and have had the opportunity to ask questions**	**YES**	**NO**
2	**I understand my participation is voluntary and that I am free to withdraw my data, without giving a reason, by contacting the lead researcher and the Faculty Research Support Office at any time until the date specified in the Participant Information Sheet**	**YES**	**NO**
3	**I have noted down my participant number (top left of this Consent Form) which may be required by the lead researcher if I wish to withdraw from the study**	**YES**	**NO**
4	**I understand that all the information I provide will be held securely and treated confidentially**	**YES**	**NO**
5	**I am happy for the information I provide to be used (anonymously) in the researcher's PhD thesis**	**YES**	**NO**
6	**I am happy for the information I provide to be used (anonymously) in academic papers and other formal research outputs**	**YES**	**NO**
7	**I am happy for the interview to be audio recorded**	**YES**	**NO**
8	**I agree to take part in the above study**	**YES**	**NO**

Thank you for your participation in this study. Your help is very much appreciated.

Participant's Name	Date	Signature
Researcher	**Date**	**Signature**

Consent form

Coventry University

Appendix 10

Business Intelligence Project (BIP) Interview Structure

EVALUATION OF COVENTRY UNIVERSITY
BUSINESS INTELLIGENCE PROJECT (STUDENT DATA DASHBOARDS)

Coventry University

Key Informant Interview Structure

This document will be used, by the researcher, to provide a semi-structure to interviews used to evaluate the Business Intelligence Project (student data dashboards).

Interview Aims

The aim of the interview is to evaluate Coventry University's Business Intelligence Project (student data dashboards). The evaluation will use interviews to capture the experiences of those familiar with the student data dashboards. The purpose is to inform improvements and developments of the University's Business Intelligence system.

The interviews have been designed to be semi-structured allowing the interviewer to gather data in a comparable format across the participant interviews. All interviews will be carried out by a single researcher and will take approximately 45 mins.

The interview venue will include a computer to enable the interviewee to demonstrate which data / dashboard pages they use.

Interview Structure

1. **Project background** *(rough timing 5 minutes)*
    - Participants will be given a verbal explanation of the project, its background and aims.
    - Interview timing of approximately 45 mins will be identified.
    - Permission to record will be requested, as per email brief; participant consent may be withdrawn at any time.
    - Confirmation of the anonymisation of the data will be provided.
    - Confirmation will be given that the interviewee will be given a copy of the research findings.
    - Consent form will be signed.

2. **Interviewee background** *(rough timing 5 minutes)*
    - Interviewee role in the organisation; background / experience in data systems;
    - Frequency of use of the student data dashboard;
    - Dashboards used most frequently & relevance to job role.

3. **Dashboard usage** *(rough timing 10 minutes)*
    - Which dashboards they use and why;
    - Areas of the dashboards they find helpful;
    - Areas that are unhelpful;
    - Whether there are dashboards that they anticipate using but don't use currently?

Claire Brewis
Home/CV/ Primary/ Key informant interview structure 2018 v2

4. **Ease of dashboard use** *(rough timing 10 minutes)*
    - Ease of using the student data dashboards;
    - Any areas where they still maintain a duplicate system;
    - Views on efficiencies as a result of the new system;
    - Views on additional demands as a result of the system.

5. **Future requirements and developments** *(rough timing 5 minutes)*
    - Data they would like to see available on dashboard;
    - Other data requirements participants would like to access.

6. **Training and Communication** *(rough timing 5 minutes)*
    - How were the advised of availability of student data dashboards?
    - How did they learn to use systems? Ease of use at start?
    - Use system guides?
    - Like additional training?

7. **Thank you for your time** *(rough timing 5 minutes)*
    - Confirmation of the timescales for the research & completion of the report.
    - Confirmation regarding consent and withdrawal from the research.
    - Any questions from the interviewee?

Ends..