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A Framework for Accelerated Product Innovation in a Big Data Environment

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A FRAMEWORK FOR ACCELERATED PRODUCT INNOVATION IN A BIG DATA ENVIRONMENT

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Abstract

This dissertation is concerned with the best approaches for accelerated product innovation in a big data environment. It describes the development and examining of a framework consisting of three sets of different phases to support managers to attain accelerated product innovation in high-tech industries. This research also investigates the roles of big data in facilitating new product development, and the factors for successful implementation of big data.

Accelerated product innovation has become increasingly important for both theory and practice in today's rapidly changing business environment. The phenomenon is reinforced by the increasing amounts of data available to business and the associated big data efforts in innovation by new information and communication technologies, as well as by new business models and organisational forms. There are two important issues associated with accelerated product innovation. Firstly, there is an underlying question as to which specific approaches for accelerated product innovation will be successful for a particular company. That is, even as more and more firms begin to acknowledge the significance of accelerated product innovation, they still suffer from a lack of knowledge about how to attain it. Secondly, how do companies apply big data to support accelerated product innovation in new product development? The specific benefits of accelerated product innovation may be summarised as: greater opportunity to incorporate the latest technology; increased market share; higher value; and more accurate forecasts of customer needs. Although previous studies have pointed out that firms can facilitate their product innovation by leveraging the huge potential value of big data, no studies have systematically investigated how firms can apply big data to facilitate accelerated product innovation.

The research was carried out in two stages. Stage one proposed a set of approaches for accelerated product innovation based on the literature studies. The approaches identified were categorised into four innovation phases. Then, the phases were refined from empirical research. The refined phases were further examined in three cases to develop a framework. During the second stage, a set of propositions were established according to the best approaches identified from the framework. The propositions were examined in five in-company case studies, in which qualitative

data collection was applied. As well as this, the qualitative investigation through multiple case studies of diverse companies were executed to explore and compare key elements of big data in the context of product innovation, and more specifically in different phases of new product development.

The primary outcome of this research has been the development and examination of a framework for accelerated product innovation in a big data environment. The approaches identified from the framework demonstrated a high utility in practice. The traditional role of innovation in competitive success has been redefined to reflect a time-based requirement. Accordingly, accelerated innovation is associated with maximisation of the product success rates, higher profitability and competitive advantage. All five companies in the present case study were applying approaches in product development for accelerating NPD, better understanding of customers' needs, higher revenue growth, and faster launch of new products to market. The empirical findings also show that the role of big data in product innovation is highly dependent on the ability to understand a specific objective or problem, and to examine whether using big data is the right approach for solving that problem. There is a prerequisite for securing distinct resources and organisational capabilities to succeed with implementing big data into new product development. Other important factors that need to be well considered by organisations when forming an implementation strategy are organisations' data maturity and effective change management, especially if the organisation is utilising more traditional innovation processes. However, novel methods rely heavily on extensive and varied data which translates in an adoption urgency to sustain competitive advantage and secure responsive innovation.

The main contributions of this research is that it usefully extends the accelerated product innovation literature by clearly defining the concept of accelerated product innovation, and by developing a conceptual framework with six propositions about how, specifically, big data and ICTs can contribute to accelerated product innovation. Then, it offers qualitative evidence from five case studies involving world-leading firms, and explaining how product innovation can most appropriately be accelerated in a big data environment.

Keywords

Primary:	Accelerated Product Innovation; Big Data; New Product Development; Data Analytics; Framework Development; Innovation Phases
Secondary:	Case Study; Chinese Companies; Incremental Innovation; Ecosystem of Innovation; Big Data Implementation

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Preface

This dissertation is submitted to the University of Nottingham in accordance with the requirements for the degree of Doctor of Philosophy. This thesis represents my own original work done while I was registered as a student of this University. None of the material presented has been previously submitted for a degree or diploma at this University or any other institution. However, parts of this dissertation have already been published in the form of conference papers, or they have been submitted to journals for publication.

The dissertation contains 297 pages, 33 tables, 22 figures and fewer than 86,000 words.

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CHAPTER 1.0 INTRODUCTION

This chapter outlines the research background, states the objectives and the research scope. Next, the ways in which this research was planned, approached and conducted are briefly explained. Finally, the structure of this thesis is described.

1.1 Background

According to Cooper (1986) product innovation - the development of new and improved products - is crucial to the survival and prosperity of the modern business. New product is usually defined as one that has been on the market three years or less and that is visibly different to the customer from previous offerings with new features, functionality or performance characteristics (Cooper and Kleinschmidt, 2011). Today, to keep up with the increasingly rapid pace of change in the marketplace, a growing number of companies around the world have begun to reengineer their innovation and R&D processes to make new product development (NPD) dramatically faster and less costly (Hagel and Brown, 2011; Williamson and Yin, 2014; McKinsey, 2015). The literature has accordingly called for "accelerated product innovation" – which we define here as novel tactics and processes which can lead to higher speed to market and lower new product costs in NPD[1] – as a key strategic capability (Millson et al., 1992; Bers et al., 2009; Langerak et al., 1999; Williamson and Yin, 2014), and a growing body of evidence (e.g., Day and Wensley, 1988; Stanko et al., 2012; McKinsey, 2015) suggests that significant competitive advantage will be increasingly conferred on "first mover" firms that play a leading role in their market segment. In this kind of highly competitive environment, an abbreviated NPD cycle time plays a vital role in a firm's ability to be first to the market with a new product or offering (Stanko et al., 2012). The case for accelerating the rate of innovation is bolstered further still by evidence showing that faster NPD capabilities are also required for firms just to be successful as "fast followers" and later entrants (Ernst, 2002; Ahmad et al., 2015). Also, important benefits can be achieved by firms that learn to manage accelerated NPD (Barczak,

[1] This definition is essentially a synthesis of others in the literature. "Speed to market" indicates the pace of activities between idea conception and product implementation (Menon et al., 2002), and "new product costs" include all costs associated with the development effort, from the idea stage through to launch (Langerak et al., 2010).

2012) as resources are utilised more creatively and efficiently, costs are reduced, and work-in-process bottlenecks are minimised (Millson et al., 1992; Bers et al., 2009; Cooper, 2014; Adner and Kapoor, 2010).

Traditionally, NPD has been viewed as a firm-driven activity in which individual companies are responsible for coming up with ideas for new products and, onward from that, deciding which ones should be commercialised and developed (Van Kleef, 2005; Cooper, 2011; Barczak, 2012). But advances in information and communication technologies (ICTs) are enabling new initiatives to be explored, and are materially transforming the NPD domain (Bharadwaj et al., 2009; Noble et al., 2013). Specifically, data from different sources can be captured and used to improve several aspects of NPD processes and workflows. IBM (2013) reports that 90% of the data that exists in the world today was created in the last two years, and some projections estimate that the total amount of data in the world will reach 35 zettabytes by 2020 (Wong, 2012). This is therefore the era of “Big Data” (Chan et al., 2015).

And just as important as the amount of data available is the diversity of the conduits from which it can be collected. Firms can now access potentially valuable digital information from a diverse range of sources that includes click streams, videos, tweets, and other unstructured sources to extract new ideas, or to improve their understanding about their products, customers, and markets (Tan et al., 2015; Noble et al., 2012). A recent survey revealed that 59% of respondents who described their organisation as “data-driven” said that their company is more profitable than competitors (Economist, 2015). Among the characteristics that these organisations had was that their NPD and strategic decisions are guided by data rather than by intuition or personal experience (Chen et al., 2012). In such an environment, data analytics – that is, capturing useful information from data to inform decision making – has given rise to a novel approach to product innovation that is enhancing NPD processes in several important ways (Sanders, 2014). Data analytics can involve qualitative and quantitative techniques that leverage a suite of technologies to enhance productivity and business gains (Chen et al., 2012).

Exactly how the data is extracted and categorised to identify and analyse patterns can vary significantly according to a firm's specific organisational requirements (Lavalle et al., 2011) or market environment factors (Millson et al., 1992; Freve, 2011), but companies applying data analytics in this area agree that it is yielding benefits in spite of these differences. For example, healthcare companies have credited predictive data analytical techniques with cutting three to five years off the approximately 13 years these companies typically need to bring a new drug to market (McKinsey, 2011). Capgemini (2012) estimates that the process improvements enabled by data analytics may lead to an average 26% performance improvement over a three-year period. And these new tools have also been found to deliver substantial operational and strategic impacts on business process innovation both at the firm level and at the supply-chain level (Trkman et al., 2012), thereby helping the adopting firms to achieve additional competitive advantage over industry rivals.

The literature in this area points to several important ingredients that seem to be helpful in bringing about various aspects of accelerated product innovation (Millson et al., 1992; Henard and Szymanski, 2001; Griffin, 1993; 2002; Zirger and Hartley, 1994; Ali et al., 1995; Eisenhardt and Tabrizi, 1995; Kessler and Chakrabarti, 1996; Langerak et al., 2008; Cankurtaran et al., 2013). There is still disagreement on their relative importance, and an integrated perspective and prescriptive framework have remained elusive as a result. For instance, while several studies have found that process formalisation and process concurrency are important determinants for accelerating NPD (Tatikonda and Montoya-Weiss, 2001), others have found no significant effects (Zirger and Hartley, 1996; Barczak et al., 2008). Similarly, while some findings emphasise the importance of a probe and learning approach in accelerating product development (Eisenhardt and Tabrizi, 1995), others have reported that iteration does not significantly affect NPD acceleration (Callahan and Moretton, 2001).

Other important contributions in this area focus on specific aspects of speed. Prior studies on accelerated product innovation were mainly focused on NPD speed (Zirger and Hartley, 1994; Eisenhardt and Tabrizi, 1995; Kessler and Chakrabarti, 1996; Callahan and Moretton, 2001; Griffin, 2002; Langerak et al., 2008), generally focusing on how quickly an idea moves from conception to a product in the marketplace and measuring the ability of firms to move quickly through the NPD process (Chen et al., 2005). While these particular benefits are unlikely to generate radical technological breakthroughs, they can potentially help companies to reduce the time and costs required to conduct incremental innovation in a quickly changing market environment (Stanko et al., 2012; Williamson and Yin, 2014; BCG, 2015; McKinsey, 2015).

There has also been a surprising amount of convergence in the literature with regards to how this area is being developed. The overwhelming majority of these earlier contributions in the area of accelerated product innovation have sought to identify potential success factors by analysing relatively large samples and quantitative methodological approaches (Callahan and Moretoon, 2001; Stanko et al., 2012; Eling et al., 2013). By stark contrast, there has been a relative paucity of investigations in this area that have used case research, and that have explicitly explored approaches for accelerated product innovation in a big data environment. Therefore, a systematic study of the implications of data-supported accelerated product innovation approaches on NPD could greatly extend knowledge in this respect (Bharadwaj and Noble, 2015).

1.2 Research Questions

These problems and considerations lead to the following research questions concerning NPD:

1. *What are the best approaches for accelerated product innovation in a big data environment?*

As noted by Kessler and Bierly (2002), and Chen et al. (2005), most studies on accelerated product innovation focus on its antecedents. Although different terms such as time-to-market (Chen et al., 2005), cycle time (Ittner and Larcker, 1997), innovation speed (Kessler and Chakrabarti, 1996), and speed to market (Meyer and Utterback, 1995) have been used to portray accelerated product innovation, the larger number of prior studies focused on the impact of speed on performance outcomes (i.e., profit and quality). These studies have not been consistent in their findings, with studies finding positive (Ali et al., 1995; Chen et al., 2005; Cooper and Kleinschmidt, 1994; Kessler and Bierly, 2002; Langerak and Hultink, 2005), negative (Crawford, 1992; Karau and Kelly, 1992; Sethi, 2000), nonsignificant (Meyer and Utterback, 1995; Ittner and Larcker, 1997; Davis et al., 2002; Griffin, 2002), and U-shaped relationships (Lukas and Menon, 2004; Langerak and Hultink, 2006). What is more, the overwhelming majority of these earlier contributions in the area of accelerated product innovation have sought to identify potential success factors by analysing relatively large samples and quantitative methodological approaches (Kessler and Chakrabarti, 1999; Callahan and Moretoon, 2001; Swink et al., 2006; Stanko et al., 2012; Eling et al., 2013). In contrast, there has been a relative paucity of investigations in this area that have used case research, and that have explicitly explored approaches for accelerated product innovation in a big data environment.

2. *How can big data be applied to support accelerated product innovation?*

In today's "big data" era, tones of data constitutes an infrastructural resource that could be used in several ways to produce different products and services (Wong, 2012; McKinsey, 2011, Sanders, 2014). However, we are unaware of other research that attempt to bring together big data initiatives on these increasingly important accelerated product innovation approaches. A recent survey revealed that 59% of respondents who described their organisation as "data-driven" said that their company is more profitable than competitors (Economist, 2015). However, the literature remains divided with regards to the specific ways in which companies should apply big data to support accelerated product innovation in new product development processes (Dahan and Hauser, 2002; Wong, 2012; Aloysius et al., 2016). Emerging evidence indicates that accelerated product innovation has already delivered a broad range of benefits in the marketplace, including greater opportunities to incorporate the latest technology, increased market share, the ability to generate higher returns, and more accurate forecasts of customer needs (Hagel and Brown, 2011; Williamson and Yin, 2014; McKinsey, 2015; Ellwood et al., 2016; Calder et al., 2016). While providing high-level evidence of these benefits, however, these contributions have failed to systematically investigate the specific mechanics of how firms can apply big data to realize these benefits. Therefore, a systematic study of the implications of data-supported accelerated product innovation approaches on NPD could greatly extend knowledge in this respect (Bharadwaj and Noble, 2015).

1.3 Research Objectives

In order to answer the research questions as stated above, as well as to satisfy the needs for approaches in attaining accelerated product innovation in a big data environment, this study outlines and addresses the following research objectives that are vital when carrying out the research. In particular, the first research question can be answered by research objectives 1-3, while the research objectives 4 and 5 pay particular attention to answer the second research question.

1) *To identify the best approaches for accelerated product innovation in a big data environment.* Ortt and Duin (2008) point out that current innovation approaches are lacking in market focus and some are becoming too complex to manage efficiently and effectively. Some researchers also argue that current innovation approaches are too time-consuming; as well as having too many time wasters and too little cost effectiveness, some of them are bureaucratic and have no provision for focus (Cooper, 1994). Researchers believe that a good product innovation approach should be adaptable, provide companies with a much more efficient roadmap, bring products to market faster and improve the use of scarce resources (Sheu and Lee, 2011; Wooder and Baker, 2012). Clearly, there is a lack of an effective way to support organisations to utilise big data and drive new product innovation from idea through to launch. With big data, firms can extract new ideas or understanding about their products, customers and markets, which are crucial to innovation. However, how could organisations use big data to better facilitate their accelerated product innovation? Accelerated product innovation is a process, and like other processes, innovation can be managed (Cooper 1990; Ortt and Duin, 2008). The first and most important step is to first understand the best approaches – those approaches that make the difference between winning and losing at accelerated product innovation in a big data environment.

2) *To determine the role and benefits of using big data in product innovation.* Big data is becoming more important to product innovation efforts of global firms. For companies, taking advantage of valuable knowledge that can be drawn from big data is becoming the basis of competition in today's rapidly changing business environment (Barton and Court, 2012; Salehan and Kim, 2015). Consequently, companies are increasingly looking at harvesting big data: a) to better understand their customers; b) to design better products; and c) to provide customers with more customised services. Davenport (2012) argues that one of the greatest potential advantages of collecting big data is its use in NPD for product innovation. However, very few studies have been conducted to investigate how firms can harvest big data to enhance their product innovation process. This research aims to show how firms can use big data to support product innovation, by shortening the time to market, improving customers' product adoption and reducing costs.

3) *To develop a framework to assist managers in achieving accelerated product innovation in a big data environment.* Many sophisticated approaches have been described in the literature, and indeed successfully applied, all over the world (Cooper; 1994; Hartung and MacPherson, 2000; Brandenburg, 2002; Chesbrough, 2003; Hansen and Birkinshaw, 2007; Sheu and Lee, 2011; Williamson and Yin, 2014). Nonetheless, what is required today is a framework to guide the accelerated product innovation process in a big data environment, one which can accelerate the problem-solving element, and shorten the overall process, in part through effective connection to customers, as well as ensuring low cost especially when limited resources are available. According to Argote et al (2003) a framework refers to a coherent set of concepts and relationships that are posited about some phenomena. It is used in research to give an overall picture of the possible courses of action or to bring a preferred approach to a thought or idea. Also, it focuses on presenting the connectivity amongst all aspects of research. Therefore, this research aims to address this objective by developing and examining a framework for assisting managers in achieving accelerated product innovation in a big data environment. The proposed conceptual framework enables managers to better

understand how big data and ICTs can contribute to accelerated product innovation. Also, the approaches identified in the framework can be applied throughout all the phases of NPD.

4) *To examine the framework using in-company case studies.* The overwhelming majority of these earlier contributions in the area of accelerated product innovation have sought to identify potential success factors by analysing relatively large samples and quantitative methodological approaches (Callahan and Moretoon, 2001; Stanko et al., 2012; Eling et al., 2013). By stark contrast, there has been a relative paucity of investigations in this area that have used case research, and that have explicitly explored approaches for accelerated product innovation in a big data environment. Therefore, a systematic case study of the implications of data-supported accelerated product innovation approaches on NPD could greatly extend knowledge in this respect (Bharadwaj and Noble, 2015). The main reason for the comparative case study is due to the novelty of the research topic on accelerated product innovation approaches and how big data is managed and organised to support accelerated product innovation. According to Bryman (2012), the comparative design incorporates the logic of comparison, which implies that we can understand the utilisation, benefits and challenges of each approach for accelerated product innovation in a big data environment better when comparing the cases. This approach is akin to Popper's (1968) approach – using a proposition under consideration to predict outcomes for specific cases and subsequently investigate these cases to see whether the theory holds true for them (Hillebrand et al., 2001). This pattern-matching technique (Campbell, 1966; Yin, 1994) allows for outcome evaluation on multiple dimensions, where as little as one actual observation for a given dimension is available (Bitektine, 2008).

5) *To identify how can big data be applied to support accelerated product innovation.* The traditional role of innovation in competitive success has been redefined to reflect a time-based requirement (Karagozoglu and Brown, 1993). Accordingly, accelerated product innovation is associated with maximisation of the product success rates, higher profitability and

competitive advantage (Menon et al., 2002; Greve, 2011; Williamson and Yin, 2014; Gawer and Cusumano, 2014). However, identifying suitable approaches for accelerated innovation throughout the whole innovation phase has been more difficult, as many approaches have focused on the early innovation stages in terms of collaboration (Shu-Chuan and Kim, 2011; Blazevic and Lievens, 2008; Fuchs and Schreier, 2011). Moreover, in a big data environment, firms can make use of different technology-based or online data analytics to enhance their innovation approaches. So far, there has been a relative paucity of investigations that have explicitly explored how big data can be applied to support each approach of accelerated product innovation. Thus, a systematic study of the implications of big data supported accelerated product innovation on NPD could greatly extend knowledge in this respect.

1.4 Scope of Research

This research does not aim to develop a generic accelerated product innovation framework, but has the following scope:

- *This research is mainly focused on incremental product innovation.* We do not suggest that firms never successfully develop new products. On the contrary, there are many examples of firms that do succeed in developing new products. Often, such projects are managed as 'mindful deviations', exciting enough to gain support, but they do not deviate from current practices to create illegitimacy (Garud and Karnfe 2001). We suggest that accelerated product innovation has a strong impact on organisations, and it favours incremental product innovation more than others (Stanko et al., 2012; Williamson and Yin, 2014; BCG, 2015; McKinsey, 2015). According to McKinsey (2015), accelerated product innovation can redefine the traditional concept of innovation and potentially disrupt a range of industries. However, to the best of our knowledge it has not yet been widely studied. Therefore, getting more detailed information about accelerated product innovation based on incremental product innovation is a valuable addition to the current literature.

- *The framework examination is conducted at the programme level by studying specific innovation projects within the selected five leading companies.* Since all the companies investigated are very large corporations operating globally or nationally, we have only examined the framework by studying specific innovation projects within the five case companies. According to Tidd et al. (1997) conducting innovation research at project level allows you to reflect on your own experience as a researcher during the whole innovation process and become as a part of the project. In particular, all the projects selected were focusing on accelerated product innovation and using a variety of data sources in support. Therefore, future empirical studies can be conducted at the organisational level to identify the implications of the framework. According to Frambach and Schillewaert (2002), studies of organisational adoption of the framework in different disciplines can provide a better identification of factors to influence the acceptance of new products by organisations.
- *The approaches identified for accelerated product innovation were based on the key findings summarised from prior studies.* Since this research does not aim to develop a generic accelerated product innovation framework, the key approaches identified were based on the key findings summarized from prior studies. In particular, I conducted a comprehensive literature review to differentiate the concept of accelerated product innovation and attributed the conflicting results of accelerated product innovation to several integrated approaches that most prior studies have identified and supported. The developed framework is based on the approaches identified and investigates how the approaches can be further facilitated in a big data environment to achieve accelerated product innovation.
- *The case companies investigated were from high-tech industries.* Today, time to market is widely recognised as an important attribute of strong innovators to gain competitive advantages, particularly in high-tech industries in which product life cycles are often three years or less (Datar, 1997; Brexendorf et al., 2015). Many studies have determined that the faster a company completes the product development process, the greater is its likelihood of surpassing its competitors in the marketplace (Day and Wensley, 1988; Ahmad et al., 2013;

McKinsey, 2015). Additionally, important cost benefits can be achieved by companies that learn to develop their products quickly (Barczak, 2012). Significant advantages accrue because resources are utilised more creatively and efficiently, costs are reduced, and work-in-process bottlenecks are minimised (Millson et al., 1992; Cooper, 2014; Adner and Kapoor, 2010).

- *The case companies investigated were leading Chinese companies.* This study investigates these questions through case-based research. Chinese companies were chosen as the research population for this investigation for three reasons. Firstly, several Chinese companies – for example, Xiaomi, the second largest smartphone manufacturer in the country, or Tencent, a leading internet company – have been observed to be aggressively experimenting with data-intensive, novel innovation models that have demonstrably accelerated and achieved cost benefits in their product innovation activities (Williamson and Yin, 2014). In fact, the country's activities on this front have been so impressive that McKinsey (2015), the global consulting firm, has specifically called for other countries to take note of and learn from the Chinese accelerated product innovation model. Secondly, the Chinese economy has grown rapidly over the past several decades. The confluences of the world's largest population and the dramatic growth in per capita consumption have propelled China to become the second-largest economy by Gross Domestic Product in a relatively short period of time (BCG, 2015; McKinsey, 2015). As a result, Chinese organisations are operating in an increasingly demanding consumer market environment that is catalysing these types of innovation (McKinsey, 2015) as the country tries to meet its "innovation imperative". Thirdly, most research into new product development has focused on Western economies and companies (Stanko et al., 2012; Eling et al., 2013; Roberts and Candi, 2014). Because of the size and rapid growth rate of its economy, however, China has emerged as an important new context for new product development. The specific nuances of how accelerated product innovation occurs within the Chinese context are therefore extremely relevant on both a practical and theoretical level, but have been largely overlooked in the literature. In this way, this paper shines a useful amount of light on a knowledge gap that needs to be addressed (Wei and Morgan, 2004; Yang et al., 2012).

1.5 Research Approach

The research design is divided into two main stages: the identification and the refinement of the approaches for accelerated product innovation in a big data environment. Accordingly, four innovation phases were identified based on the approaches and further refined by conducting interviews with academics and industrialists. The refined of three sets of phases were, namely, agile structure, customer involvement, and ecosystem of innovation. Three company case studies were implemented to demonstrate how the three sets of innovation phases can be applied in real companies for accelerated product innovation in a big data environment. Then, a preliminary framework was developed based on the results of the three cases.

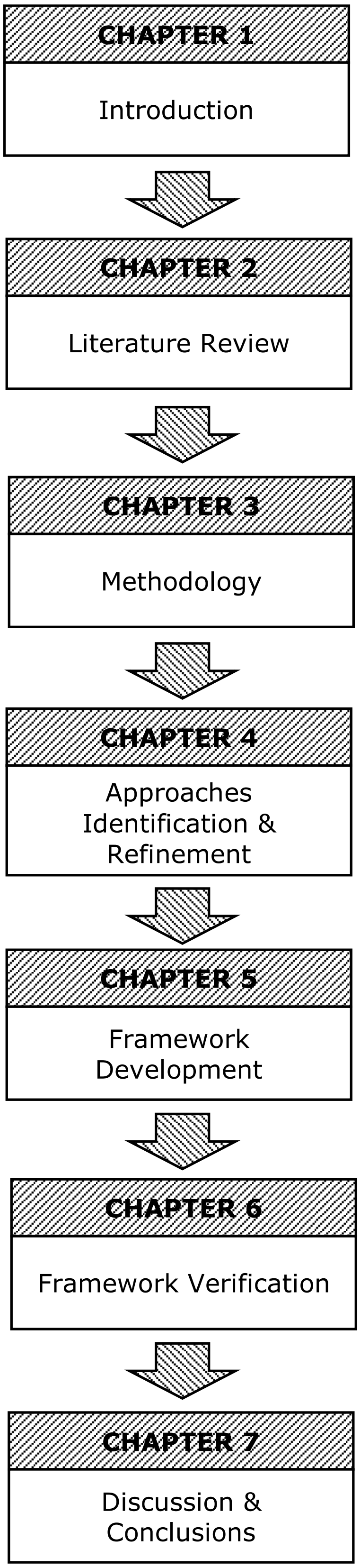
In the second stage, based on the framework and literature supports, a set of propositions concerning the best approaches to innovation and big data in supporting accelerated product innovation are identified. Then, we conducted a comparative case study of five world-leading companies, in which qualitative data collection was applied. The propositions of the framework were verified and enhanced after the case studies for accelerated product innovation in a big data environment that integrates data analytics and different types of information.

1.6 Outline of the Thesis

The remainder of this thesis has been divided into seven chapters. Figure 1.1 shows the outline of this thesis.

a. In Chapter 1, the research background, research questions, research objective, and scopes have been defined.
b. In Chapter 2, the literature on product innovation and big data is reviewed. It describes and explains the existing different methods for innovation management, the antecedents associated with various aspects of accelerated product innovation, and the role big data holds in supporting product innovation.
c. In Chapter 3, the research methodology is discussed. It describes the research design, and also explains and justifies the chosen research approach.

d. In Chapter 4, the identification and refinement of the approaches for accelerated product innovation are explained. It describes the learning from literature studies and feedback obtained from empirical research.
e. In Chapter 5, the development of the framework for accelerated product innovation in a big data environment is described. It explains in detail the activities involved in each phase of the framework.
f. In Chapter 6, the establishment of the propositions followed by verification of the framework in five leading in-company cases is presented.
g. In Chapter 7, the conclusions drawn from the research are summarised and its impact on the practice for accelerated product innovation in a big data environment is discussed. The limitations of the research are indicated and some suggestions for further work are given.



- Product innovation
- Big data

- Interviews with 7 academics
- Interviews with 6 industrialists

- Empirical studies of three company cases

- Establishment of propositions
- Empirical studies of five in-company cases

Figure 1.1: Dissertation Structure

CHAPTER 2.0 LITERATURE REVIEW

Chapter 1.0 explained briefly the research background and described the research objectives. This chapter introduces the relevant literature which underpins this research and describes how this research positions into existing product innovation and big data knowledge. This chapter will cover the following:

- the definition of innovation
- the existing approaches for managing product innovation
- the evolution in product innovation
- the definition and characteristics of accelerated product innovation
- big data and its potential values
- the changes of product innovation in today's big data era
- the approaches for accelerated product innovation in a big data environment
- the position of this research and how it fits into existing product innovation and big data literature.

2.1 Definition of Innovation

Research, over the last 50 years, has consistently linked innovation with business success. Innovation is shown as a major contributory factor in the growth of firms (Mansfield, 1968, 1971); new products and processes, the fastest growing product groups or 'clusters' (Freeman, 1974); the rise and dominance of large corporations ascribed to the use of new technology (Temin, 1979); better business performance related to the higher measures of innovation (Cavanagh and Clifford, 1983); levels of competitiveness linked with the levels of innovativeness (Dosi, 1988); firms using innovation to differentiate their products from competitors being twice as profitable (Pavitt, 1991); innovation as a key element of business success (Nonaka and Takeuchi, 1995); high growth companies getting a higher percentage of sales from new products relative to competitors (O'Gorman, 1997); new product development leading to greater sales volume and enhanced profitability (Kotler, 1999); innovating firms having lower probability of stagnant or declining employment in comparison to non-innovating firms (Frenz et al., 2003) and innovative businesses growing more than non-innovative businesses (Griffith et al, 2006).

Dictionary definitions of innovation usually focus on the development and successive refinement of inventions into usable products or techniques that are deemed worthy of being launched in a market or used internally within an enterprise (Frenz and Oughton, 2005). Amongst scholars, however, there is a noticeable level of disagreement on the definition of innovation. This is attributed to the heterogeneity of sources and outcomes of innovation, which makes it difficult to identify and analyse (Dosi, 1988) and is partly responsible for often conflicting outcomes of research on innovation (Le Bars et al., 1998; Grunert et al., 1997).

As inventions and innovations are associated phenomena, innovation scholars make it a point to clarify the distinction between the two. It is explained that though invention is a prerequisite for many innovations, it is only when an invention is exploited commercially that it results in innovation (Brenner, 1990). Another approach, though less popular, to distinguish innovation from inventions has been to claim that inventions relate to new ideas in general whereas innovations are new ideas within a specific context (Van de Ven et al., 1989; Damanpour and Evan, 1984; Damanpour, 1987).

From yet another perspective, a distinction is made between innovation and R&D, where R&D is shown to be concerned with the commitment of resources to research and the refinement of ideas aimed at the development of commercially viable products and processes whereas innovation is concerned with the subsequent product (or service) development process. From this perspective, the following linear model of the process of innovation is visualised (see Figure 2.1).

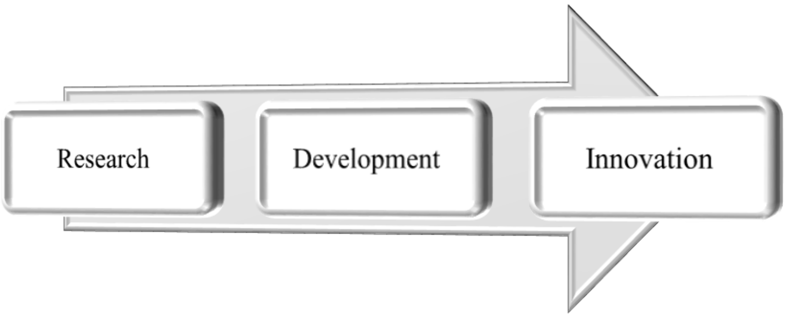


Figure 2.1: Linear Model of Innovation Process

Innovation, however, is considered a nebulous concept. Godin (2002) believes that the ambiguity in meaning is caused by the following factors:

1. Depending on the analyst's research focus and convenience of data availability, it is defined as an outcome or as an action.
2. There is no settled opinion on whether an innovation should be new to the world, to the nation, to the industry or to the firm.
3. With reference to process innovation, a firm can be innovative both by inventing new production processes, and by using new technologies invented by others.
4. Conducting R&D as well as acquiring advanced technologies and employing a highly skilled workforce are both perceived as being innovative.

Factors 2 and 3 in the above do not appear to be valid as the taxonomy of innovation described later in this chapter clarifies these issues. The precarious link between R&D and innovation, however, is indeed not understood adequately and its consequences in product innovation management are discussed in this thesis in some detail. The more important point, however, is that the seeming ambiguity in meaning of innovation is superficial and, as will be explained later in this chapter, it is possible to accommodate all notions of innovation within a unifying concept of innovation-span.

The earliest definitions of innovation are credited to Joseph Schumpeter (1934), who arguably is the most influential early writer on entrepreneurship and innovation and the pivotal role of innovation in the process of economic change. He includes five manifestations of innovation in his definition:

1. Creation of new products or qualitative improvements in existing products
2. Use of a new industrial processes
3. New market openings
4. Developing of new raw material sources or other new inputs
5. New forms of industrial organisation

The influence of the Schumpeterian vision of innovation persists to this day and can be seen in the European Commission's Green Paper (1995) on innovation that defines it as *"…renewal and enlargement of a range of products and services and the associated markets, the establishment of new methods of production, supply and distribution, the introduction of changes in management, work organisation and the working conditions and skills of the workforce"* and in Edquist's (2001) summary description of innovations as new creations of economic significance normally carried out by firms (or sometimes by individuals).

The OECD (1981), however, takes a more restricted view of innovation and limits it only to new product and/or process development effort, though it has a more comprehensive vision of *product*, in which it also includes *social services*. It defines innovation as *"the transformation of an idea into a new or improved saleable product or operational process in industry and commerce or into a new approach to a social service"*. This view of innovation thus consists of:

1. the whole gamut of technical, scientific, financial and commercial activities that are needed to create and market new or improved products,

2. the commercial utilization of new or improved production methods and equipment and
3. new ways to deliver a social service.

The Oslo Manual (OECD, 1997), on which Europe-wide Community Innovation Surveys are based, limits its view of innovation to technological products and processes (TPP) which are defined as *"all those scientific, technological, organisational, financial and commercial steps, including investment in new knowledge, which actually, or are intended to, lead to the implementation of technologically new or improved products or processes"*. For the purpose of measurement, it considers a firm innovative *"if it produces one or more technologically new or significantly improved products or processes in a three-year period"*.

Some analysts also emphasise the beneficial effects of innovation. In one such view, innovation is described as the *"intentional introduction and application within a role, group or organisation of ideas, processes, products or procedures new to the relevant unit of adoption designed significantly to benefit the individual, the group, the organisation or wider society"* (West and Farr, 1990).

The UK government's Department of Trade and Industry has probably the broadest and most comprehensive definition of innovation. It describes it as *"the successful exploitation of new ideas"* and explains that it *"involves new technologies or technological applications, which can deliver better products and services, new, cleaner and more efficient production processes and improved business models. For consumers, it means higher quality and better value goods, more efficient services and higher standards of living. For businesses, it means sustained or improved growth. For a company or organisation, innovation delivers higher profits for its owners and investors. For employees, innovation means new and more interesting work, better skills and higher wages"* (Department of Trade and Industry, 2003).

2.2 Taxonomy of Innovation

A parallel and overlapping effort to define innovation is to construct a taxonomy of innovations. The creation of such a taxonomy is considered necessary and important, as disaggregation is crucial for progress with regard to identifying the determinants of innovation (Edquist, 2001). The following types of innovation emerge from this effort:

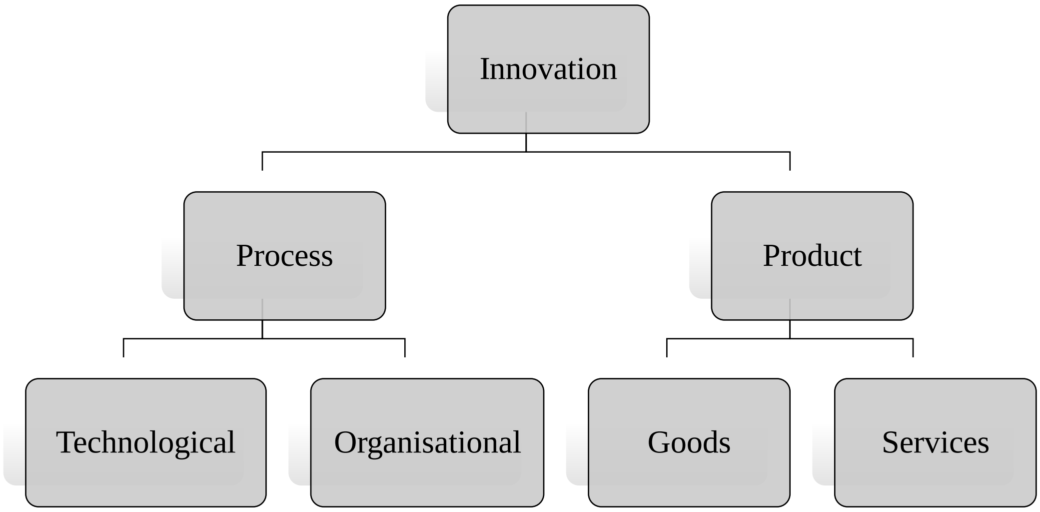


Figure 2.2: Taxonomy of Innovation (Source: Edquist, 2001)

2.2.1 Product versus Process Innovation

Following Hauschildt and Salomo (2011), the objects of development and innovation activities are primarily products and processes. On the one hand, product innovation refers to the new or improved product, equipment or service that is successful on the market (Copper, 2003). It deals with the production of new products and services to create new markets or to satisfy current customers. On the other hand, process innovation is reflected in the improvements or introduction of new production technology (Knight, 1967; Utterback, 1971). It deals with the production of new products and services to create new markets or to satisfy current customers.

According to Hauschildt and Salomo, (2011), products and processes are mutually dependent and partly complement each other. The main aim of a product innovation is to implement its function in a more effective way than before. A new combination of factors to make the manufacturing of a product more competitive, increase the quality and safety levels, reduce time to market etc. is characteristic for process innovations, the increase of efficiency being the main intention (Hauschildt and Salomo, 2011). Therefore, due to the ambiguous meaning of innovation, which can denote both a process and its results, it is difficult to distinguish strictly between product and process innovations.

2.2.2 Technical versus Organisational Innovation

A very common taxonomical effort has been to differentiate between technical and organisational innovation (Daft, 1978). Technical innovation refers to development of new products, services and production processes (Daft, 1978; Damanpour and Evan, 1990; Knight, 1967). Organisational innovation refers to innovations that are related to alteration in an organisation's structural and administrative procedures (Daft, 1978; Damanpour and Evan, 1990; Kimberly and Evanisko, 1981; Knight, 1967). Adam Smith's (1776) analysis of the division of labour is an early example of organisational innovation and the study of its impact on productivity. For example, in the food industry context, the most relevant organisational innovations are those that relate to logistics and supply chain management.

2.2.3 New to the Firm versus New to the Market Innovations

This refers to the diffusion of the innovation from innovator to imitators. It is understood that most of the benefits from innovation arise from the diffusion of the innovation rather than its introduction (Vyas, 2005) and as the notion of innovation-span articulated earlier in this chapter explains, the full economic benefits from research are only realised after the processes of invention, innovation and diffusion are complete (Hollander, 1965). The economic effects of innovation are strongly influenced by the speed of its adoption by follower firms and/or consumers (Frenz and Oughton, 2005) which, in turn, is determined by network effects, the costs of adopting the new technology, the availability of finance, investment in fixed capital, proximity, cooperation between firms, market size and structure as well as institutional, social and cultural factors (Hall, 2005).

2.2.4 Radical versus Incremental Innovation

One of the theoretical typologies that have emerged in the literature on organisational innovation is the dichotomy of radical versus incremental innovation introduction and adoption. One aspect of this dimension appears to be whether or not the innovation incorporates technology that is a clear, risky departure from existing practice (Ettlie et al., 1984; Hage, 1980). If a technology is new to the adopting unit and new to the referent group of organisations (Daft and Becker, 1978), or if it requires both throughput (process) as well as output (production or service) change (Hage, 1980), perhaps the magnitude or cost of change required by the organisation is sufficient to warrant the designation of a rare and radical, as opposed to incremental, innovation. In other words, radical innovation represents a completely new product or process while incremental innovation indicates a significant improvement in an existing product or process. Radical innovations have the power to result in significant and rapid transformation of production whereas the effects of incremental innovation are felt more slowly, though their cumulative impact may be just as significant (Ettlie, et al., 1984). In addition, radical innovation brings about a non-routine change to the very core on how activities are carried out while incremental innovation is usually part of routine changes that do not deviate much from present organisational activities (Dewar and Dutton, 1986 and Ettlie et al., 1984).

Radical Innovation

The definition of radical product innovation can be reviewed from two perspectives. The first perspective originates from disruptive innovation. According to other researchers (Tushman and Anderson, 1986; Christensen, 1997; Danneels, 2004), disruptive innovation can bring a remarkably different value proposition to the market and can significantly challenge the market positions of established products. Based on this definition, Markides (2006) classified disruptive innovation into two types: business model innovation and radical product innovation. Compared to the business model innovation which redefines "*what an existing product or service is and how it is provided to the customer*" (Markides, 2006, p.20), radical product innovation is defined as the disruptive innovation that "*creates new-to-the-world products*" (Markides, 2006, p.22).

The second way of defining radical product innovation is from the perspective of radical innovation. Leifer and McDermott et al. (2000) defined radical innovation as a product, process, or service with any features which can offer potential for significant improvements in performance or cost. Similarly, Markides and Geroski's definition (2005) is that a radical innovation could give rise to new-to-the-world markets and can have a disruptive effect on both customers and producers. According to Schumpeter's theory (Schumpeter, 1982) on categorising innovation, radical product innovation could be defined as radical innovation which focuses on products, and is either non-existent or requires dramatic behaviour changes in existing markets (O'Connor & McDermott, 2004).

Incremental Innovation

Incremental product innovation refers to a process by which an organisation transforms labour, capital, material, and information into products and services of greater value. A distinction is sometimes made between innovations that require very different technological capabilities, so-called radical change, and those that build upon well-practised technological capabilities, often called incremental innovations (Christensen, 2002).

This distinction between incremental and radical change can be traced all the way back to Schumpeter (1942). He stated that "*the function of entrepreneurs is to reform or revolutionize the pattern of production by exploiting an invention or an untried technological possibility…down to such things as making a success of a particular kind of sausage or toothbrush* (Schumpeter, 1942, p.132)". Incremental innovations are changes in products that score low on both level of newness to the firm and level of newness to the market (Booz-Allen, 1982). Modifications to existing products, redesigned products to achieve cost reductions, and product repositioning are three examples of incremental innovation (Kleinschmidt and Cooper, 1991). Incremental innovations are small step-wise changes.

Although not as novel as radical innovations, incremental innovations can contribute positively to firm performance. The well-known Professor at Harvard Business School, Theodore Levitt, stated that imitation (which is one kind of incremental innovation) is not only more abundant than innovation, but actually a much more prevalent road to business growth and profits (Levitt, 1966)". The returns expected from incremental innovations are not as high as from radical innovations, but since the risk associated with their development and commercialization is lower than from radical innovations, incremental innovations are important for the firm's overall profitability (Kleinschmidt and Cooper, 1991). While radical innovations offer opportunities for product advantage and differentiation, incremental innovations are close enough to the base business to gain profit from the effects of resource synergies. Contrary to radical innovation where firms explore new possibilities and often need to invest in new facilities, existing resources are more widely utilized when incremental innovations are developed.

2.2.5 Incremental Product Innovation

In a rapidly developing market environment, incremental product innovation plays a significant role, since it can make continuous improvements to processes, products, or services in an existing or a new market, and has a close connection with technologies. The scope of this research is focused on incremental product innovation which is not radically different from the current product portfolio, but which often comprises refinements and extensions of the existing products of a company and seems to involve, primarily, exploitation-oriented activities (McKee, 1992). Incremental product innovation is, therefore, a critically important competitive factor in established industries (Banbury and Mitchell, 1995) and focuses on leveraging a firm's existing resources and capabilities (Henderson and Clark, 1990; Leonard and Sensiper, 1998).

Incremental product innovation is typically implemented within the organisation, using existing organisational arrangements. Nonetheless, empirical evidence suggests that many firms seem to struggle with this type of innovation, which often results in diminished company performance and lengthened development times (Banbury and Mitchell, 1995; Song and Montoya-Weiss, 1998). Past research on product innovation in both manufacturing and service industries has focused on key determinants that lead to successful product innovation. This large body of literature has examined the development process, what models could support the development process and what key factors separate winners from losers (Cooper, 1990; 1994;

2014; Cooper and Kleinschmidt, 1996). Additionally, important organisational issues such as: working with and listening to lead users (Von Hippel, 1986; Leonard and Sensiper, 1998); involvement and cooperation of multiple functions during the development process (Moenaert and Souder, 1990; Dougherty, 1992); use of flexible organisational structures and cross-functional teams (Souder,1987; Thwaites, 1992; Volberda, 1998) and a close fit between the firms' strategy and resources (Crawford, 1992) have all been cited as contributing to the success of incremental product innovation.

Despite the value of these studies, the problems that firms are confronted with when engaging in this type of innovation seem persistent (Tidd and Bodley, 2002). We do not suggest that firms never successfully develop new products. On the contrary, there are many examples of firms that do succeed in developing new products. Often, such projects are managed as 'mindful deviations', exciting enough to gain support, but they do not deviate from current practices to create illegitimacy (Baker and Sinkula, 2002). We suggest that accelerated product innovation in this research has a strong impact on organisations, and it favours incremental product innovation more than others (Stanko et al., 2012; Williamson and Yin, 2014; BCG, 2015; McKinsey, 2015). According to McKinsey (2015), the accelerated product innovation can redefine the traditional concept of innovation and potentially disrupt a range of industries. However, to the best of our knowledge it has not yet been widely studied. Therefore, getting more detailed information about accelerated product innovation based on incremental product innovation is a valuable addition to the current literature.

2.3 Product Innovation Management

Today, the global market is in a product 'war' and the management of product innovation is the strategic weapon. According to Cooper (2003), product innovation – the development of new and improved products – is crucial to the survival and prosperity of the modern business. A new product is usually defined as one that has been on the market for three years or less and that is visibly different to the customer from previous offerings (with new features, functionality or performance characteristics) (Cooper, 2011). Development of new products can help a company much more quickly and efficiently with a bit of planning before development starts (Cooper, 1990). Facing increased competition from home and abroad, maturing markets, and the heightened pace of technological change, corporations look to new products and new business for sustained growth and competitive advantage. Reports and surveys identify that most companies are counting heavily on product innovation for growth and profitability (Hopkins, 1980; Nieto and Santamaria, 2007). However, research has shown that product innovation has a remarkably high commercial failure rate, at around 40-50%, and this performance has not changed much over the past 20 years (Chiesa and Frattini, 2011). Therefore, the needs for effective product innovation in organisations demand immediate attention.

Product innovation is a process and, like other processes, it can be managed (Cooper 1990; Ortt and Duin, 2008). This translates into the fact that isolated ideas and inventions need to be further implemented through a process of commercialization to be regarded as innovations. According to Damanpour and Schneider (2006), a generic innovation process has a three-stage progression: 1) initiation, 2) adoption decision, and 3) implementation.

The three stages of the generic innovation process can enable organisations to successfully identify, organise, and analyse the key success factors which decisively affect and drive innovation. In the initiation stage, the organisation identifies an opportunity or a problem that needs to be solved. Tidd and Bessant (2009) explain that the initiation stage should be focused on detecting indicators of innovation potential in the corporate environment. Furthermore, the investigation and evaluation of prospective solutions and the proposal for adoption are mentioned to be key organisational activities under the initiation stage (Rogers, 2003). Following the initiation stage is the adoption decision stage which is directed towards the decision-making of either accepting or rejecting the innovation proposal (Wolfe, 1994). Damanpour and Schneider (2006) state that the adoption decision stage requires senior management's involvement for evaluation of the proposed concept and where an approval from senior management would directly lead to resource allocation. Subsequently, the final step in the process is the implementation stage. Rajagopal (2002) explains that the implementation stage incorporates implementation activities, such as acquiring key resources, establishing procedures and policies, in addition to assessing an analysis of the utilization of the innovation.

This study mainly focuses on the first two stages of the new product development process, and what role big data has within those stages. Beside the generic innovation process, four types of innovation process were identified from literature: a flash of genius (Drucker, 2002; Sheu and Lee, 2011), trial-and-error (Takeuchi and Nonaka, 1986), a structured approach to new product development (Yazdani, 1999; Ettlie and Elsenbach, 2007), and systematic innovation through analysis of situation and resources (Sheu and Lee, 2011).

2.3.1 Flash of Genius

Accidental pursuit of new ideas, according to Drucker (1985), cannot be ignored as one of the sources of innovation, albeit not the primary method. It remains one of the ways innovation opportunities are found. However, it is argued that most successful innovations are a result of a focused search for ideas, and this has influenced many other authors to expand on the ideas to find conscious ways of innovation search (Sheu and Lee, 2011).

2.3.2 Trial and Error

The trial and error approach or the empirical approach solves problems through experimenting with ideas generated from brainstorming sessions. As it is hard to cover all possible situations, luck is required to find an optimal solution to the problem (Sheu and Lee, 2011). The trial and error approach is encouraged to challenge the status quo in developing new products, as suggested by Takeuchi and Nonaka (1986), compared to the traditional linear approach of new product development, where the development process is sequential without overlapping (Yazdani, 1999). The new integrated product development process proposed by Takeuchi and Nonaka (1986) inspires new kinds of learning and thinking through trial-and-error, speeding up the innovation process.

2.3.3 Systematic Innovation

Different from other approaches, systematic innovation provides a methodical path to find optimal solutions in the innovation process (Sheu and Lee, 2011). Systematic innovation research started as early as 1946 in the USSR. Known as TRIZ research, it recognized that problems and solutions are recurrent and patterns of technical evolution as well as methods of using scientific effects can be identified; thus innovations require cross-disciplinary efforts (Sullivan et al., 2007).

TRIZ solutions have been developed over the course of 60 years of research, and have been organised in many different ways; some are more analytical, others prescriptive. The 40 Principles of generating ideas are the most accessible “tool” of TRIZ and they are found to repeat across many fields, as solutions at the heart of many problems (The TRIZ Journal). Figure 2.3 below shows the basic framework of TRIZ.

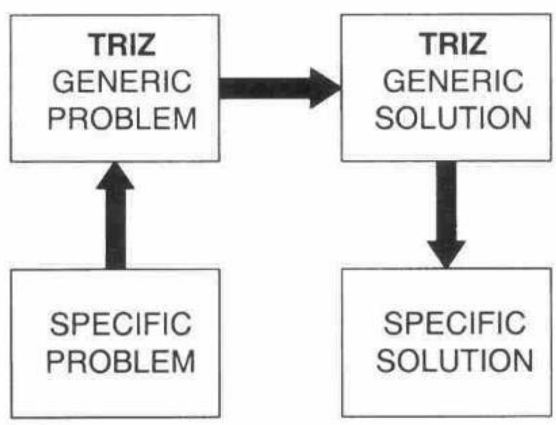


Figure 2.3: Basic Framework of TRIZ (Source: Mann, 2001)

Building on this, Mann and Jones (2002) propose frameworks of systematic innovation process in phases and stages, which follow a similar flow of first defining the problem, then selecting a solution, and finally implementing it. The framework proposed includes four basic steps: define, select, solve and evaluate, involving divergent and convergent thinking with different tools to identify opportunities to exploit existing solutions (Sullivan et al., 2007; Mann and Jones, 2002). It is argued that the gap between the current states of affairs versus the ideal final result creates the drive for innovation. As most problems on hand are recurrent problems that have been resolved before, so defining the problem and selecting the right tool allow the problem to be solved. Analyses of the problem are performed with divergent thinking to identify all the possibilities, and then convergent thinking sets in with the use of the right tool to generate the right solutions. Out of all the possible solutions the best solution is selected and implemented, again changing the mode of thinking from divergent to convergent. After that the solution chosen is evaluated.

In addition, Sheu and Lee (2011) incorporated heterogeneous resources and classified them into TRIZ tools and non-TRIZ tools, which are then integrated into a systematic innovation process in five linked phases and eight stages. The five linked phases are opportunity definition, problem definition, solution definition, project execution, and application exploration. Similar to Mann (2001), Sheu and Lee (2011) suggest that opportunities are first explored in a divergent stage, and then are selected in the convergent stage; this divergence then convergence pattern occurs in the first three definition phases.

Undoubtedly, TRIZ, Mann's (2001) or Sheu and Lee's (2011) frameworks all provide a systematic way of integrating knowledge across disciplines to generate solutions. Indeed, these frameworks have wide applications and are suitable for solving all types of problems. Through providing a shortcut to previously successful solutions of the same situation, a high success rate of using systematic innovation processes in problem solving is ensured. However, systematic innovation processes do have their drawbacks. For instance, the lack of focus in tools deployment lengthens the problem solving process. Besides, the processes are complicated and require much knowledge and skills to deploy all TRIZ and non-TRIZ tools. Furthermore, much expertise and experience are required to select the right tools to generate the optimal solution. Hence, an effective yet simpler innovation framework is desirable.

2.3.4 Structured Innovation Approach

Structured innovation is a term to describe the combination of two simple and common approaches to thinking about the elements of a particular problem or issue, which together form the basis for systematically innovating and generating new ideas (Kumar, 2012). Yazdani (1999) introduces four models of new product development, which include: the sequential model, the design centred model, the concurrent model, and the dynamic model. The first model is the traditional sequential model, which involves adding inputs to activities that are arranged in sequence, processing information at one stage and passed on the next only when it is ready. The second model, the design centred model, requires extensive analysis of the design in the front end of the new product development process to minimize changes made to the prototyping and testing processes downstream. The third model, the concurrent model, overlaps the design and planning of the process development, requiring the use of cross-functional teams with an informal information flow. As a result, downstream activities such as prototyping and production preparation are allowed to start earlier to shorten the whole development cycle. The concurrent model is also characterized by the presence of review-gates in each phase, which brings control for the iterations and design changes involved. The fourth model, the dynamic model, is a modified variation from the concurrent model. Compared to the concurrent model, it is even more integrated with almost all the activities starting at the same time. Although there will be more iterations of downstream activities, especially with prototypes, it is argued that the higher level of communication exchange in the overall process leads to further reduction in lead-time and costs.

Overall, the four models proposed by Yazdani (1999) serves as a generalization of some of the industrial practices; the actual new product development process may contain a mix of characteristics from the above. Nowadays, the trend is more towards the use of Phased Program Planning (PPP) (Takeuchi and Nonaka, 1986), which is also called Phased Review Process (Cooper, 1994), and the Stage-Gate Process, which was developed in the 1980s and has been widely applied since then (Cooper, 1990; Cooper, 1994; Cooper, 2011).

Phased program planning

Endorsed by NASA, PPP was exemplified in the 1960s as a sequential development approach for new products (Takeuchi and Nonaka, 1986; Cooper, 1994). Under PPP, the NPD process was designed like a relay race (Takeuchi and Nonaka, 1986; Cooper, 1994). Project activities were run not in parallel but in sequence, with hand-off points between each phase. The general flow of PPP is illustrated in Figure 2.4 below:

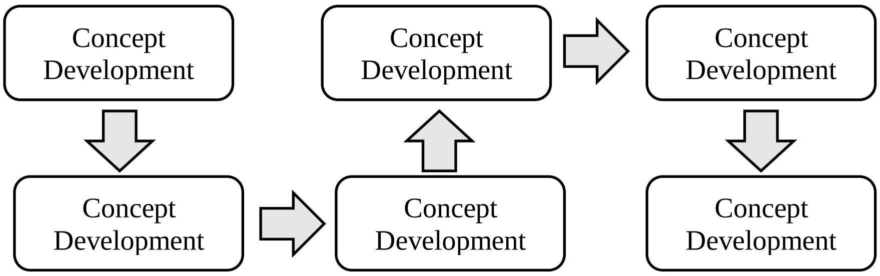


Figure 2.4: A General Flow of Phased Program Planning (Source: Takeuchi and Nonaka, 1986)

As the precursor of stage-gate process, PPP has specialized functions which allow division of labour (Takeuchi and Nonako, 1986). However, it is noted that the time taken to develop new product under PPP is almost twice as much when compared to stage-gate process as all activities are arranged in sequence without overlapping between stages (Cooper, 2008). Nevertheless, there is a lack of commitment for the project as it is passed from one phase to another with hand-off points (Cooper, 2008). Because of all the drawbacks, fewer firms are using PPP nowadays. Instead, stage-gate process is becoming the norm.

Stage-gate process

Stage-gate process (Cooper, 1990) has been modified into different versions, which include: Third-Generation Stage-Gate Process (Cooper, 1994), Next-Generation Stage-Gate Process (Cooper, 2008), and Portfolio Life Cycle Process (Hughes and Chafin, 1996).

Cooper (1990) proposes a stage-gate system which recognizes that innovation is a process which can be managed. The conceptual framework proposed acts as a roadmap to help ensure the effectiveness and efficiency in new product development projects, from idea generation to product launch and beyond. A typical stage-gate process has five stages and five gates, with activities running in parallel for time compression. Each stage requires cross-functional team efforts, with clear governance process and accountability installed while each gate acts as a go/kill decision point by management (Cooper, 1990). An illustration of stage-gate process is shown in Figure 2.5 below:

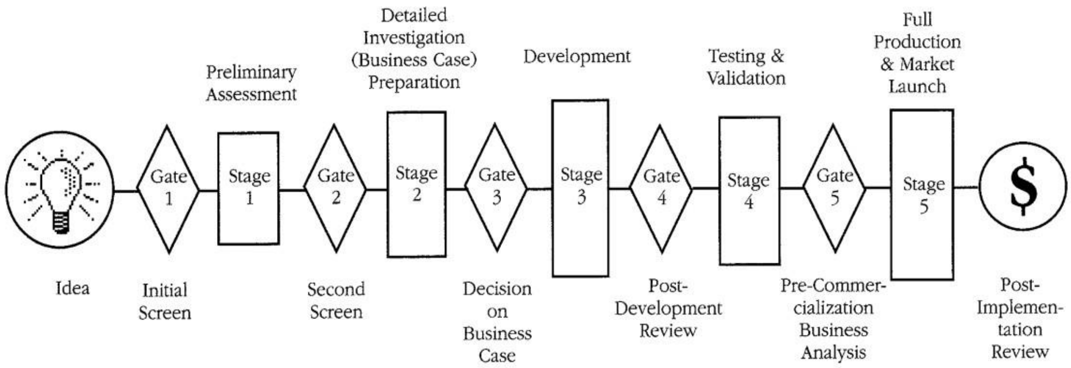


Figure 2.5: Illustration of a typical stage-gate model (Source: Cooper, 1990)

Having evolved over time, the third-generation stage-gate model (see Figure 2.6) is more flexible and adaptable with overlapping stages. It has conditional decision gates to build in project prioritization function and to focus on resources allocation (Cooper, 1994).

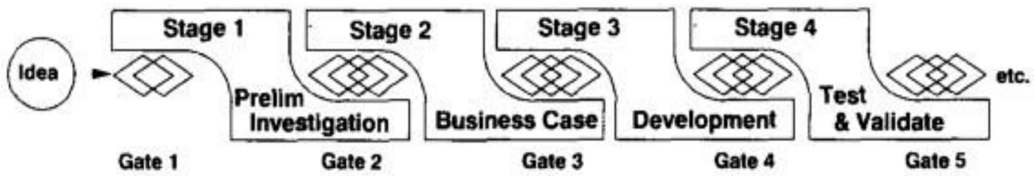


Figure 2.6: Illustration of third-generation stage-gate model (Source: Cooper, 1994)

Next-generation stage-gate process (Figure 2.7) merges different stages together in different ways to scale down the system for smaller projects (Cooper, 2008).

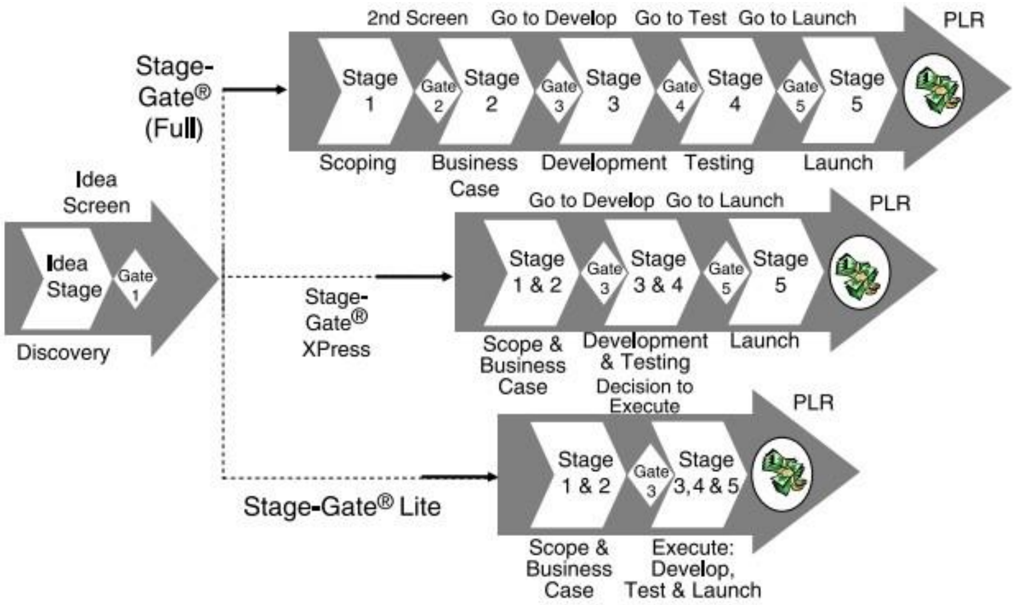


Figure 2.7: Illustration of next generation stage-gate process (Source: Cooper, 2008)

Widely accepted and commonly practised by many firms, stage-gate process shows various features that are superior to the traditional PPP approach in new product development. Firstly, the use of go/kill decision gates allows firms to focus on the quality of the decision process and hence the quality of the output. Secondly, the gating feature of the stage-gate processes helps to ensure complete process with all critical activities. Thirdly, as stage-gate process enables the input of marketing, project evaluation, as well as other functions to be integrated in the new product development process, the new product developed will be more likely to have a strong market orientation and hence better sales performance. Fourthly, there is a strong emphasis on pre-development activities in the stage-gate process; together with parallel processing of activities running, less re-work is required in the overall process, thereby compressing new product development time and also ensuring higher success rate. Through acting as a clear road map to the team with clearly defined tasks and objectives, stage-gate process gives user control over the innovation process with visibility (Cooper, 2011), ensuring high success rate in new product development.

However, as stage-gate process places heavy emphasis on pre-development activities, with much looping, iterations, and back-and-forth play at each stage (Cooper, 2008), so the new product development process is undeniably lengthy. Besides, the stage-gate model is argued to favour only incremental innovation and product development (Verworn et al., 2008). Radical innovation is shown to be effective with more dynamic models than the stage-gate model (Bessant, 2005). Therefore, it is difficult to predict the success of commercialization for radical innovations and using the stage-gate model for that purpose can lead to 'false negatives', where propitious innovations are prematurely eliminated. Also, another limitation is connected to the model's structure, and reluctance to 'kill' projects in succeeding phases due to substantial investment (capital expenditure) escalations (van den Bosch and Duysters, 2014). Innovation development needs strong support from the top management. Nasierowski (2008) indicates that a positive outcome generated from the stage-gate system is dependent on significant commitment and therefore requires resources, which top management can see as problematic. Further, van den Bosch and Duysters (2014) argue that the closed system constrains corporate creativity, and entrepreneurship. In other words, there is a trade-off between strict process organisation and internal creativity.

Portfolio life cycle process

Built on top of Cooper's (1990) stage-gate system, Hughes and Chafin (1996) suggest a continuous learning approach to new product development, making it a dynamic customer-focused process. The framework consists of continuous planning cycles, and an integrated screening methodology – Value Proposition Readiness Assessment (VPRA). On the one hand, the planning cycles consist of essential activities in iterative loops to determine if the activities add value to the new product development opportunity. On the other hand, VPRA assesses the different factors of the essential activities with a structured set of generalized evaluation questions and the results are plotted as a scaling record with three dimensions – evaluation, certainty, and weighting – thereby facilitating team members to use the result graph for discussion to reach common consensus.

The Portfolio Life Cycle Process starts with the idea generation stage, which filters ideas through the Value Sensing Cycle to the planning and specification stage through the Value Proposition Cycle; during the process, the proposition is translated into actual output. Performances of products and services produced then go through the Value Management Cycle which provides feedback as input to the Value Sensing Cycle. It is argued that through a continuous feedback loop the project team will have an increased ability to determine if the proposition is feasible (Hughes and Chafin, 1996).

In addition to facilitating continuous learning in future innovation, the Portfolio Life Cycle Process provides a structured way to collect ideas and analyse decisions, yet being flexible at the same time. For instance, customer values are integrated into the process through the Value Proposition Cycle, thereby ensuring a market focus in the new product developed. Also, by refining questions used in the screens, early knockout factors are reviewed and can be rectified quickly. Furthermore, by adapting to the needs of the firm, VPRA facilitates consensus among team members. It is argued that improved communication helps to improve the new product development process (Hughes and Chafin, 1996).

However, there are a few obvious drawbacks associated with the Portfolio Life Cycle Process. Firstly, the iterations and looping of the cycles mean that the process is lengthy. Next, consensus on value proposition assessment results may not result in the best solution. Besides, the process is too complicated and this requires specific skills and techniques to make its deployment effective. For all these reasons, the Portfolio Life Cycle Process is not very common among industries.

In summary, current approaches are limited for managing product innovation. Ortt and Duin (2008) point out that current innovation management processes are lacking in market focus and some are becoming too complex to manage efficiently and effectively. Researchers also argue that current innovation processes are too time-consuming; as well as having too many time wasters and too much cost ineffectiveness, some of them are bureaucratic and have no provision for focus (Sheu and Lee, 2011; Wooder and Baker, 2012; Cooper, 2008). Therefore, a good product innovation process should be adaptable, provide companies with a much more efficient roadmap, bring products to market faster and improve the use of scarce resources (Cooper, 1994; Sheu and Lee, 2011; Wooder and Baker, 2012). Clearly, there is a lack of an effective way to support organisations to manage and drive new product innovation from idea through to launch.

2.4 Evolution in Product Innovation

By studying the literature, Table 2.1 below summarises the progress made to date in product innovation, historically categorised into four generations (Rothwell, 1994; Niosi, 1999; Liyanage et al., 1999; Miller, 2001; Ortt and Duin, 2008).

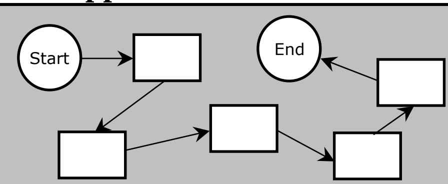
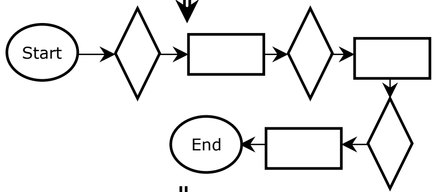
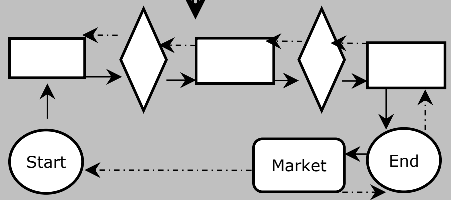
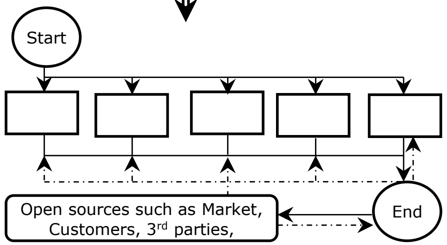
Period	Approach to innovation	Characteristics	Features	Examples
First Generation: the post-war period to the mid-1960s		The innovation process is perceived as a linear progression from scientific discovery to marketplace.	• High degree of uncertainty and serendipity • Focus on R&D • Linear progression	Flash of genius or brainstorming (Knight, 1967)
Second Generation: the mid-1960s to the late 1970s		The innovation process is generally organised in multi-disciplinary projects, with a linear sequential process in a project, starting with market needs.	• Linear progression • Starts with market needs • Well organised to reduce uncertainty	Multi-divisional and sequential process (Utterback and Abernathy, 1975)
Third Generation: the late 1970s to the early 1990s		Models are essentially linear, with sequential progress; innovation is driven by market feedback and requirements.	• Logically sequential but not necessarily a continuous process • Functional departments work interactively • Gathers feedback from each department to improve	Stage-gate innovation process (Cooper, 1990; 1994)
Fourth Generation: the early 1990s to the present		Models are simultaneously processing through a wide range of networks and partners in order to facilitate innovation and increase speed.	• Simultaneous processing • Cross-functional departments work independently • Fast development • Gathers feedback from customers and market quickly	Open innovation (Chesbrough, 2006)

Table 2.1: Evolution of Product Innovation Process

As shown in Table 2.1, the first generation starts from the post-war period to the mid-1960s. During this period, innovation emerged as an activity characterized by a high degree of uncertainty and serendipity. Within the corporation, scientists and engineers in the research lab studied materials, products, and processes and sometimes produced a novel idea that companies could introduce into production (Niosi, 1999). Therefore, the industrial innovation process was generally perceived as a linear progression from scientific discovery, through technological development in firms, to the marketplace, called technology push innovation (Rothwell, 1994). Limitations are obvious in this period such as it only relies on R&D not the transformation process or market (Carter and Williams, 1957); the innovation approach depends on luck and sometimes accidental discoveries; and is not a primary source of an innovative problem solving approach (Sheu and Lee, 2011).

Towards the second half of the 1960s, general levels of prosperity became high and manufacturing productivity increased considerably (Rothwell and Soete, 1983). Organisations put more emphasis on marketing and corporate diversification in order to survive in the intensifying competition. During this period, new products were being introduced based mainly on existing technologies and the arrival of the second generation did not change the linearity innovation process. However, it introduced some order, reduced uncertainty, and increased cost and time controls and accountability into the corporate R&D lab (Niosi, 1999). As one of the most significant limitations, the innovation approaches during this period were neglect long-term prospects and positioned at a high risk level. This could lead companies to become locked into a regime of technological instrumentalism as they adapted existing product groups to meet changing user requirements along maturing performance trajectories (Hayes and Abernathy, 1980).

In the late 1970s and 1990s, third-generation innovation introduced in-house feedback and the integration of R&D within corporate strategy. During this period, it became increasingly necessary to understand the basis of successful innovation in order to reduce the incidence of wasteful failures and, indeed, it was approximately during this period that the results of a number of detailed empirical studies of the innovation process were published (Rothwell et al., 1994; Utterback, 1971; Rubenstein et al., 1976; Cooper, 1980). Most of the innovation models identified are logically sequential, though not necessarily a continuous process that can be divided into a series of functionally distinct but interacting and interdependent stages. The innovation process can be thought of as a complex net of communication paths; it represents the confluence of technological capabilities and market needs within the framework of the innovating firm (Rothwell and Zegveld, 1985). However, since it is still essentially a sequential process, it is time consuming and inefficient. Thus, the development of new product is risky. Rothwell (1994) also points out that the process is focused on product and process innovations rather than market and organisational innovation.

In the early 1990s and 2000s, the fourth generation introduced two of the salient features of innovation in leading Japanese companies: integration and parallel development. During this period, companies integrated suppliers into the new product development process at an early stage while at the same time integrating the activities of the different in-house departments involved, who worked on projects in parallel rather than in series (Maidique and Zirger, 1985). These two factors have largely contributed to innovation approaches by shortening product development life cycles and making the innovation process more effective. Many sophisticated innovation approaches were created and published which describe the theories and provide numerous successful applications all over the world (Alshuler, 1984; Cooper, 1990; 1994; Johnston and Kaplan 1996; Savransky, 2000; Mann, 2002; Hansen and Birkinshaw, 2007). However, since the innovation approaches divided groups to work simultaneously, the communication between groups could be difficult and involve misunderstanding; although innovation could be systematised and scaled up to involve thousands of scientists and engineers worked in parallel, the core R&D activities nonetheless typically revolved around a set of relatively small teams which could slow down the project (Williamson and Yin, 2014); the processes sometimes were too complex to manage, while large varieties of information could also result in inflexibility.

By summarising the progress made to date in NPD (Rothwell, 1994; Niosi, 1999; Miller, 2001; Ortt and Duin, 2008; Cooper, 2016), it has been underpinned by some trends of increasing importance. First of all, the ability to innovate quickly has become an increasingly significant factor in recent years in determining competitiveness in today's rapidly changing business environment, especially in industries where product cycles are short and technological change rates are high (Rothwell, 1994; Niosi, 1999; Adner, 2006; Goktan and Miles, 2011; Greve, 2011). Secondly, companies are tending to conduct simultaneous processing, with cross-functional teams working independently; this improves the speed, efficiency and flexibility of the innovation process (Williamson and Yin, 2014). By conducting simultaneous processing through cross-functional teams, all the elements of the innovation process overlap, which keeps the innovation process moving forward without waiting for perfect information (Williamson and Yin, 2014). This reduces lead times (products are launched as quickly as possible). Besides, the current process of innovation pay more attention to good connections with customers so as to understand customers better and gather feedback quickly for continuous improvement (Bohlmann et al., 2012; Mahr et al., 2014). Cooper (2008) points out that, since 1990, the customer connection has tended to be the weakest process in product development, but is strongly linked to the success of product innovation. Inadequate understanding of customers and a lack of customer connection are the two major reasons for failures in product innovation, especially in high-tech industries (Cooper and Kleinschmidt, 2011; Copper, 2014). Additionally, unlike early generations of innovation processes, which mainly relied on information from internal research, with very little use of external sources (e.g. market ideas, customer complaints), current innovation processes (e.g. open innovation) are more likely to look outside the company, for example to customers, suppliers and competitors, in order to find new partners and build comprehensive networks to create more value and for competitive advantage (Christensen and Overforf, 2000; Chesbrough 2006; Tan et al., 2015).

In short, the evolution in innovation processes has been characterised by a shortening of product lifecycles, increased understanding of customers, and a higher degree of collaboration with partners. Many sophisticated innovation approaches have been described, and indeed successfully applied, all over the world (Cooper, 1994; 2008; Christensen and Overdorf, 2000; Mann, 2002; Brandenburg, 2002; Chesbrough, 2003; Hansen and Birkinshaw, 2007; Sheu and Lee, 2009; Williamson and Yin, 2014).

2.5 Accelerated Product Innovation

While there is broad agreement within the innovaiton literature about the need for accelerated innovation, there is muvch less convergene with regards how it should be realised. As shown in Figure 2.8, our analysis of the product innovation literature revealed many challenges by reviewing different approaches of product innovaiton (in section 2.3). Also, by studying the literature regarding evolution in product innovation (in section 2.4), several main trends were identified with inreasing importance. Therefore, in order to overcome the challenges as well as to address the main trends in produc tinnovation, what is require today is an "accelerated product innovation", one which can accelerate the problem-solving element, and shorten the overall process, in part through effective connection to customers, as well as ensuring low cost (especially when limited resources are available).

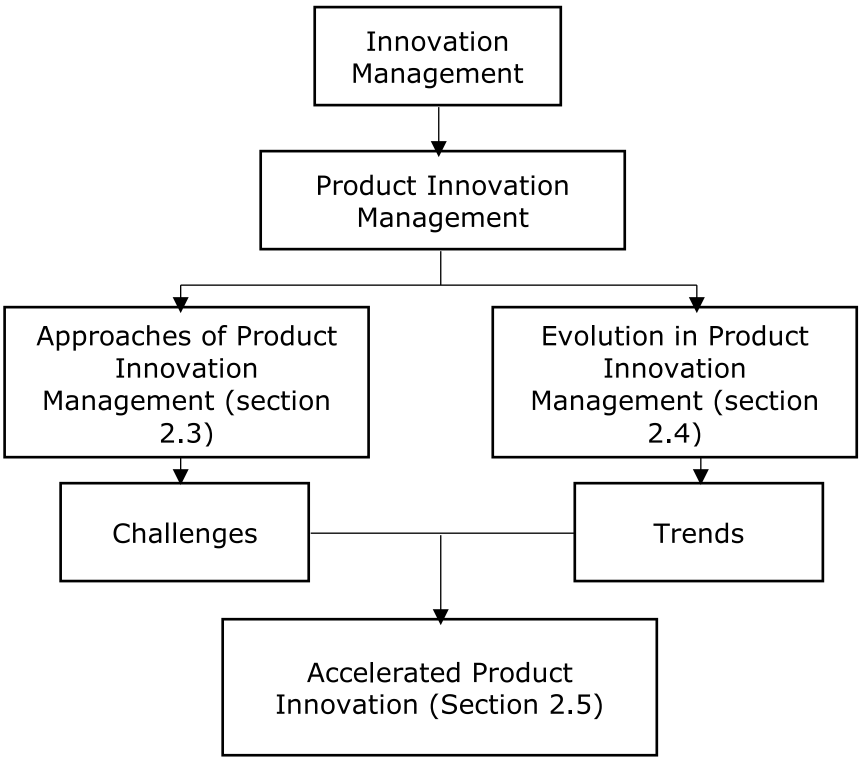


Figure 2.8: Requirements for Accelerated Product Innovation

The current state of business in the world is one of rapid change. Product life-cycles, markets, competitors, suppliers, customers, technologies, and products themselves are just a few of the important variables that affect organisations. The fact that these variables change is not as much of a surprise as is the rate of change. According to Gupta and Wilemon (1990) tomorrow's products will have life-cycles that are much shorter than those experienced by products of the past. For example, that the model life for audio components is about 6 months and for the early facsimile machines it was a mere 4 months. Although these products typically undergo multiple incremental development phases, Crawford (1992) notes that repeated rapid developments cumulate in major product changes that leave competitors behind if they lack a quick-response capability.

Therefore, today, time to market is widely recognised as an important attribute of strong innovators to gain competitive advantage, particularly in high-tech industries (Datar, 1997; Brexendorf et al., 2015). In addition, the life cycle of high-tech industries is short lived and constantly needs to conduct innovation actives in response to changes in the market environment (Liu et al., 2014). Many studies have determined that the faster a company completes the product development process, the greater is its likelihood of surpassing its competitors in the marketplace (Day and Wensley, 1988; Ahmad et al., 2013; McKinsey, 2015). Additionally, important cost benefits can be achieved by companies that learn to develop their products quickly (Barczak, 2012). Significant advantages accrue because resources are utilised more creatively and efficiently, costs are reduced, and work-in-process bottlenecks are minimised (Millson et al., 1992; Cooper, 2014; Adner and Kapoor, 2010).

In this context, lean thinking concepts – aims to provide a new way to think about how to organise human activities to deliver more benefits to society and value to individuals while eliminating waste - have gained a lot of attention in the past decade in terms of identifying and removing wastes from manufacturing and many high-tech industries (Kennedy, 2003; Morgan and Liker, 2006; Tyagi et al., 2015). Besides, the term lean thinking is compatible with a range of what can be called agile manufacturing development methods (Thomke and Reinertsen, 1998) such as Feature-Driven Development, Scrum, Dynamic Systems Development, eXtreme Programming, and Adaptive Software Development Methods (Abrahamsson et al., 2003; Kettunen, 2009). These methods are powerful enablers for shortening time-to-market as well as improving performance. However, it is evident in literature that current product innovation approaches are still too time-consuming; too many are either simply a waste of time or are cost ineffective; others are too bureaucratic and provide no focus (Ortt and Duin, 2008; Sheu and Lee, 2011; Copper, 2014).

2.5.1 Review of the Millson, Raj and Wilemon (MRW) Hierarchy of NPD Acceleration Approaches

Millson et al.'s (1992) review of new product development literature suggests that firms can adopt and implement a large number of methods and techniques to accelerate the NPD process to remain competitive. To reduce NPD cycle time effectively, Millson et al. (1992) have formed five generic NPD acceleration approaches by clustering similar methods and techniques and have proposed an order of implementation. This so-called MRW hierarchy consists of five generic NPD acceleration approaches. Each generic approach is composed of similar methods and techniques aimed sequentially at: (1) simplifying NPD operations, (2) eliminating unnecessary NPD activities, (3) paralleling NPD activities, (4) eliminating delays in the NPD process, and (5) speeding up NPD operations. This implementation sequence stems from an effort to define the order that would provide the greatest ease of implementation and the least amount of wasted effort. Although this is a compelling argument, the conceptual basis of the MRW hierarchy may be challenged for four reasons (Langerak et al., 1999). These reasons will be discussed.

First, the definition of accelerated product innovation has not been addressed clearly. From Millson et al.'s (1992) description, accelerated product innovation seems to be simply a combination of methods and techniques for reducing NPD cycle time. Therefore, it is not clear that accelerated product innovation is a new concept, rather than just a buzzword. Second, Millson et al. (1992) have not provided a systematic overview of the methods and techniques that focus on reducing the time required to complete the overall NPD cycle. As a result, it is not evident which methods and techniques were used as input for the clustering procedure. Furthermore, it is impossible to determine which methods and techniques belong to the different generic NPD acceleration approaches. Third, Millson et al. (1992) fail to unambiguously describe the clustering method, as well as the procedure used to determine the appropriate number of clusters. This causes doubts about the validity of the five generic NPD acceleration approaches. Fourth, Millson et al. (1992) suggest that all five generic NPD acceleration approaches should be adopted and implemented in the order of the hierarchy. Although the hierarchy reflects logical principles for accelerating NPD, cycle time reduction is not the only critical variable that is of concern to product development groups (Langerak et al., 1999). Another critical variable that may affect the implementation decision is development costs. Although Crawford (1992) has questioned whether it is always appropriate to shorten NPD cycle time because of the hidden costs of accelerated NPD, Rosenau (1990) reports that faster NPD can lower development costs in specific product areas. Therefore, when considered jointly, new product costs and speed to market are important with regard to the implementation decision.

Despite the fact that the conceptual basis of the MRW hierarchy is subject to discussion, Millson et al. (1992) have developed the earliest extant knowledge of generic NPD acceleration approaches. To provide a more complete understanding with regard to generic NPD acceleration approaches, this research clearly defines the concept of accelerated product innovation. It also identifies three key characteristics of accelerated product innovation based on prior studies.

2.5.2 Definition of Accelerated Product Innovation

So far, numerous research studies have examined different antecedents associated with various aspects of the accelerated product innovation (e.g., NPD speed, time to market, cycle time, and lead time) (Clark, 1989; Millson et al., 1992; Henard and Szymanski, 2001; Griffin, 1993; 2002; Zirger and Hartley, 1994; Ali et al., 1995; Eisenhardt and Tabrizi, 1995; Kessler and Chakrabarti, 1996; 1999; Langerak and Hultink, 2006; Langerak et al., 2008; Cankurtaran et al., 2013). However, the approaches to accelerated product innovation are still not fully understood. For instance, while several studies have found that process formalisation and process concurrency are important determinants for accelerating NPD (Li and Atuahene-Gima, 1999; Tatikonda and Montoya-Weiss, 2001; Bstieler, 2005), others have found no significant effects (Barczak et al., 2008; Harter et al., 2000; Zirger and Hartley, 1996). Similarly, while some studies emphasise the importance of a probe and learning approach in accelerating product development (Eisenhardt and Tabrizi, 1995), others have reported that iteration does not significantly affect NPD acceleration (Callahan and Moretton, 2001). Moreover, prior studies of accelerated product innovation were mainly focused on NPD speed (Stalk and Hout, 1990;

Zirger and Hartley, 1994; Eisenhardt and Tabrizi, 1995; Kessler and Chakrabarti, 1996; 1999; Callahan and Moretton, 2001; Griffin, 2002; Langerak and Hultink, 2006; Langerak et al., 2008); it generally measures how quickly an idea moves from conception to a product in the marketplace, measuring firms' capabilities to move quickly through the NPD process (Chen et al., 2005). However, the NPD speed is not the only critical variable that is of concern to product development groups. Increasingly, cost management research has focused largely on the accelerated product innovation context (Crawford, 1992; Drucker, 2002; Swink et al., 2006; Cooper and Kleinschmidt, 2011; Hagel and Brown, 2011; Stanko et al., 2012; Davenport, 2013; Williamson and Yin, 2014; McKinsey, 2015). For instance, according to Drucker (2002), those who grasp the new calculus, who appreciate the unprecedented advantages of getting new products to market sooner and cheaper, may well hold the principal tool for achieving competitive pre-eminence in the coming years. Davenport (2013) indicates that the role of accelerated product innovation has become central to many firms' strategies because of its focuses on developing new products, speeding products to market, and reducing product and process costs. Williamson and Yin (2014) referred to accelerated product innovation as new ways to innovate that speed up problem solving and reduce costs. Based on the review of a wide range of studies, we have suggested a definition of accelerated product innovation as:

> *Novel innovative tactics and process which can lead to higher speed to market and lower new product costs in new product development.*

This definition is essentially a synthesis of other literature. In particularly, speed to market indicates the pace of activities between idea conception and product implementation (Menon et al., 2002), while new product costs include all costs associated with the development effort, from the idea stage through launch (Langerak et al., 2010). While these particular benefits are unlikely to generate radical technological breakthroughs, they can potentially help companies to reduce the time and costs required to conduct incremental innovation in a quickly changing market environment (Stanko et al., 2012; Williamson and Yin, 2014; BCG, 2015; McKinsey, 2015).

2.5.3 Characteristics of Accelerated Product Innovation

Our analysis of the new product literature revealed many approaches for accelerated innovation in NPD. Although there is a lack of a clear definition of accelerated product innovation (because each firm seems to be creating its own methods of accelerating the new product process), there are three threads in summary.

The first thread relates to the different processes in NPD. This thread aims to use systematic ways to speed up the innovation process as much as possible. Speed yields competitive advantages: being the first to market can result in a quicker realisation of profit, and there will be a lower risk that the competitive situation or market has changed before the new product can be launched (Steinfeld and Beltoft, 2014). These kinds of structures are being overhauled to allow faster approvals, an overall corporate culture based on speed in everything, an organisation that is lean and flat but that stresses training and giving workers motivation and reward systems that include equity positions if possible, as well as less structure in the operation (Crawford, 1992; Chen et al., 2010). For example, one highly publicised example fitting this description is the autonomous NPD team, which typically involves a strong leader and little formality and structure in decision-making processes such as manufacturing, engineering, marketing, distribution, and purchasing (Li et al., 2009). Autonomy means allowing R&D team members a high level of freedom to make decisions by themselves in their workplace. It also implies that project teams work in parallel, rather than sequentially. At each stage of a project, many activities take place concurrently and involve different functions of the firm. By doing this, the so-called innovation 'assembly line' can be accelerated and results can be delivered quickly.

The second thread is associated with the involvement of customers. The current approaches to NPD pay more attention to good connections with customers so as to understand customers better and gather feedback quickly for continuous improvement (Bohlmann et al., 2012; Mahr et al., 2014). A thorough connection with and understanding of customers is significant: the more the customer is understood, and the more that understanding is implemented in product design, the more positive the impact will be on market share, revenues and margins (Evanschitzky et al., 2012; Bohlmann et al., 2013). Innovation can be facilitated by evolving ideas while listening to the voice of customers; the product is better when potential customers can be identified and their needs satisfied (Prahalad and Ramaswamy, 2013; Steinfeld and Cooper, 2014). Many projects have poor customer connections, which results in a series of problems: customer requirements and problems are vaguely defined; the product's functions and features are fuzzy; and the target customers are not well understood (Dunn and Dahl, 2012). Therefore, a strong customer connection is critical to success. It also involves data analytics such as computer aided engineering, artificial intelligence and integrated information systems, plus information communication technologies to increase quality and quantity of communication (Thomke, 2003; Bosch-Sijtsema and Bosch, 2015).

The third thread focuses on building an innovation ecosystem to support NPD. It stresses going outside for all resources possible – R&D consortiums of several types, alliances with vendors, customers and third parties and use of new product development consultants and suppliers (Christensen and Overforf, 2000; Chesbrough 2006; Colombo et al., 2014). This view is changing to include seeking more incremental innovation, replacing products more frequently than demanded by the market, reducing capital investments as much as possible and demanding quick response to changes in the marketplace (Crawford, 1992; Hagel and Brown, 2011; McKinsey, 2013). Adner (2006) points out that innovation ecosystem have become a core element in the growth strategies of organisations in a wide range of industries. Thus, ecosystems play an important role in product innovation, i.e. innovation and market testing environments to develop new products at dramatically faster speeds and lower costs. It bridges the gap between the need for the new product definitions and the changeable market conditions as development proceeds (Gupta, 2013). Also, the ecosystem indicates that the company network is used to acquire new requirements and the components of product development process externally or from intermediates, in order to create a fast launch-and-improve environment that is able to launch a product quickly and cheaper.

2.6 Big Data

Many countries are now aware of the importance of the Digital Economy, and the phrase big data is increasingly fashionable. Wong (2012) states that the key factor to gaining competitive advantage in today's rapidly changing business environment is the ability to extract big data to gain helpful business insights. Being able to use big data allows firms to achieve outstanding performance against their competitors (Oh, 2012). With big data, firms can gain a better understanding of their products, customers and markets, and this is crucial to NPD (McKinsey, 2013; Wong, 2012; Salehan and Kim, 2016). However, the main challenge to firms is how to use big data to improve NPD by making the development of new products faster and less costly. This research next reviews the relevant literature on big data to assist our understanding of how accelerated product innovation can be facilitated in a big data environment.

In tracing the origins of the term 'big data', some authors only mention the words (Tilly, 1984; Eric-Larson, 1989). However, other articles appear with a clear awareness of the big data phenomenon (Mashey, 1988; Weiss and Indurkhya, 1998; Diebold, 2003). In the early stages, all the authors agreed that big data involves having a very large volume of data. All of them only mentioned the focus on quantity of data and the technological difficulty of dealing with it. As Diebold (2003) states, big data refers to the large quantity of currently available and potentially relevant future data, and the sample sizes should be measured in megabytes in this new world. He pointed out the difficulties of recording and storage techniques in dealing with the data explosion. However, nowadays big data not only involves data volume, but has other characteristics.

There are a variety of definitions of big data, which can be referred to in articles or books. According to Lynch (2008), big data is the progress of the human cognitive processes that contain oversized data, which cannot be captured and managed within an acceptable time by current technology. Snijders and Matzat (2012) also propose that big data includes oversized data that is difficult to capture, manage and process with the commonly used software tools. Similarly, other authors define the term big data as applying to information that exceeds processing or analysing capacity using traditional processes or tools (Dumbill, 2012; Zikopoulos and Eaton, 2011). The definition of big data can be interpreted in different ways, but the majority of the definitions focus on large data size, the difficulties of data storage, the value of usage and data analytical capabilities. McKinsey Global Institute's (McKinsey, 2011) definition of big data is probably the most suitable and precise *"Datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse"*.

Although the original definition of big data only refers to its volume, it is not only about volume; big data can also be described in terms of variety, velocity and complexity. Laney (2012) produced significant work about big data. He was the first to highlight the three Vs in interpreting big data – that is volume, velocity and variety (Laney, 2012). The three Vs identified the characteristics clearly and have been quoted to describe big data by many companies and academic papers. Academics such as Ohlhorst (2013) described big data as having an immeasurable size, where the scale of data is too varied and the growth of the data is extremely quick, so that conventional information technologies cannot deal with the data efficiently. Gartner (2012) modified the definition as *"big data has three Vs characteristics that require new forms of processing to enable enhanced decision-making, insight discovery and process optimisation"*. In particular, while volume shows the growth of data, variety indicates the kinds of data, such as sensor logs, and velocity interprets the source speed of data flowing into one's enterprise (Zikopoulos and Eaton, 2011). In addition, some authors would like to supplement more characteristics based on these three dimensions. Veracity and value have been added to describe big data by IDC Company, so updating from 3Vs to 5Vs (Gantz and Reinsel, 2011). Veracity means trustworthy data and value focuses on the benefits it may obtain.

2.6.1 The Characteristics of Big Data

Big firms have dealt with a large volume of transactional data for many years, but as the global trend of using social media and smartphones increases, the types of data are becoming more varied and with changes in velocity that happen in unexpected ways. The three Vs of volume, velocity and variety are commonly used to characterize different aspects of big data. Figure 2.9 shows the basic components of

3Vs. They are a helpful lens through which to view and understand the nature of the data and the software platforms available to exploit them (Dumbill, 2012). The 3Vs make big data analytics extremely complex by using the current platform, data management and analytics technology (Minelli et al., 2012).

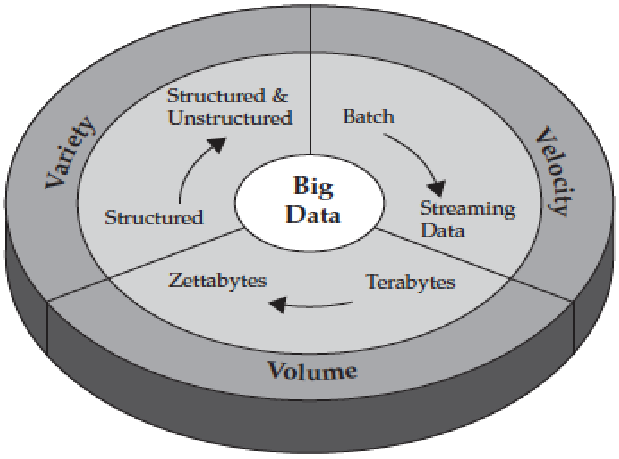


Figure 2.9: IBM Characterizes big data by its Volume, Velocity, and Variety (Source: Zikopolos and Eaton, 2011)

Volume

The size of data continues to increase from terabytes (1 terabyte = 1000 gigabytes) to zettabytes (1 zettabyte = 1 billion terabytes), but the percentage of data that our tools can process does not increase. There are figures to prove this; for example, in the year 2000, 800,000 petabytes (1 petabyte = 1000 terabytes) of data were stored in the world. It is expected this number will reach 35 zettabytes by 2020. Data is not only generated by traditional systems, but is also generated in our daily lives. Everyone has sensors to send information every second via their smartphone or computer. For example, Twitter by itself can generate more than 7 terabytes of data every day, Facebook 10 terabytes, and some enterprises generate terabytes of data every hour of every day of the year (Zikopoulos and Eaton, 2011). The data volumes have changed from terabytes to petabytes, and have then exploded to zettabytes of data. The explosion of data leads to difficulty for traditional systems to store and analyse it.

Organisations lack the technology to process, understand and analyse the increasing data. If the organisations can sufficiently use the raw material in meaningful ways or translate the data into a few humanly comprehensible pieces of information, then it will be easier for organisations to make decisions and take actions (Henson et al., 2012). For example, knowing how to use the sensor data in a plant can help to identify the status of jet engines and flight control surfaces; or using sensors on a smartphone in order to monitor the spread of infectious diseases.

Variety

Variety represents all types of data and contains structured and unstructured, semi-structured, traditional and non-traditional data. There are many different types of data, such as texts, weblogs, GPS location information, sensor data, graphs, videos, audio and more online data. This variety of data requires different equipment and technology to handle and store it. Moreover, data has become complex because the variety has shifted from traditional structured data to more semi-structured and unstructured data, from search indexes, emails, log files, social media forums, sensor data from systems, and so on (Zikopoulos and Eaton, 2012).

The problem is that the traditional analytical technologies cannot deal with the variety. According to Wong (2012), "*Eighty percent of data is now unstructured or semi-structured so that we cannot analyse it*". However, an organisation's success will rely on its ability to draw insights from the various kinds of data available to it, which includes both traditional and non-traditional. The ability to analyse all types of data can create more opportunity and more value for an enterprise. For example, the video data from surveillance cameras is one data type; police can use it to identify criminal suspects or to predict the crime location, then they can prevent the crime in advance (McKinsey, 2011). However, not all unstructured data is useful and much data is noise data without meaning. There are still huge potential values hidden inside big data, so differentiating between the useful data and the noise data is also a challenge (Minelli, 2012).

Velocity

Velocity means the frequency of data generated and updated. Data is arriving continuously as streams, and we are interested in obtaining useful information from it in real time. Huge amounts of data are generated every second and increasing amounts of data have a very short life. So organisations must be able to analyse this data in near real time if they hope to find insights within the data (Zikopoulos and Eaton, 2012). Also, today's enterprises are dealing with petabytes of data instead of terabytes, and the increase in Radio-Frequency Identification (RFID) sensors and other information streams has led to a constant flow of data at a pace that is impossible for traditional systems to handle.

Data velocity leads to the increased demand of businesses to make more real-time responses and decisions (Minelli, 2012). Because of that, velocity is often time sensitive, and big data must be used as it is streaming into the enterprise in order to maximize its value to the business, but it must also still be available from the archival sources (Ohlhorst, 2013). The big data analytical approach requires different knowledge, skills and culture for firms to translate data into useful information (Cerra et al., 2012).

2.6.2 Drivers of the Big Data Era

IBM (2013) reports that 90% of the data that exists in the world today was created in the last two years, and some projections estimate that the total amount of data in the world will reach 35 zettabytes by 2020 (Wong, 2012; Gantz and Reinsel, 2012). This is therefore the era of "big data" (Wong, 2012). Sathi (2012) argues that there are primarily three reasons behind the big data era: consumers, automation, and monetization. A more detailed explanation mentions sophisticated consumers, describing the generation of substantial information usage. The information usage enables insights about the market, as well as interactions in social media to exchange opinions and reviews. Such digital interactions go beyond pictures and text, and include videos, sound clips and several multimedia tools which in many cases involve expert opinions and quality rating. The term automation refers to all digitised means, such as mobile phone services, emails, social networks, as well as the modernization of older media, which are capturing and providing an enormous pool of data for analysis. As a generalised source of data, Sathi (2012) categorizes it into three groups: the first group encloses physical electronic products, which are characterised as 'smart' since they have the ability to retrieve data about various usage parameters. The second category is the electronic touch points of mobile devices, computers and other electronic devices. The last group is including all the components that are offering services or act as routes for the movement of data.

Another important driver, which paves the way for the big data era, is monetization – the ability and incentive to gather process and trade data for the use of potential new business development. Packages of data can be sold to interested parties and their value can change or even create a new market in creating collection value. Most valuable attributes lie within personal location data, cookies, user behaviour and usage data (Sathi, 2012).

A fairly new phenomenon which enables further growth of big data is called "Internet of Things (IoT)". IoT mainly describes machine intelligence, where networked technologies or smart devices (products and services that are used on daily basis) are interconnected and communicate through software and sensors (RFID). IoT enables fast and continuous exchange of real-time data for improving functionality, processes, and discovering new and improved products or services (Xia et al., 2012; Kopetz, 2011; Gubbi et al., 2013).

2.6.3 Values of Big Data

Literature indicates that big data can unlock plenty of new opportunities, and deliver operational and financial value (Ohlhorst, 2013; Morabito, 2015; Sathi, 2012). For that reasons, companies are devoting their resources and efforts to gain greater results by leveraging big data. Davenport (2014) describes three main benefits of big data: 1) cost efficiency and effectiveness, 2) enhanced decision-making, and 3) exploring new opportunities.

By implementing big data technologies (such as free open-source software, inexpensive servers and cloud-based analytics) companies can support their already existing data processing tools, which will result in cost reductions (Davenport, 2014). Sathi (2012) illustrates that an implementation of big data technologies would eventually lead to reduced latency, and require less administrators, hence supporting cutbacks in resources. Previous empirical research reveals that large organisations adopt big data technologies with the objective to strengthen their traditional technologies, not to replace them (Davenport, 2014). McKinsey (2011) suggests that big data significantly improves efficiency by allowing companies to raise productivity or enhance product quality by increasing its value. For example, the analysis of product data can result in an optimised use of resources such as time, human resources and raw materials. Ohlhorst (2013) argues that big data could also improve the stages before and after the production of the supply chain. Furthermore, Feinleib (2014) adds that combining production data with big data from different functions can provide analysts with vital information on how to improve efficiency and effectiveness.

Another benefit of big data analytics is focused on improving and enhancing decision-making. McAfee and Brynjolfsson (2012) argue that data-driven decisions seem to be more informed and effective. Organisations can leverage big data analytics to be more effective and faster in their decision-making, as well as to acquire new capabilities to make evidence-based decisions. However, Ross et al. (2013) suggest that adjustments of current processes and corporate cultures have to be considered for a positive effect.

Lastly, Davenport (2014) argues that the most interesting use of big data is for new business development, in other words to improve and create new products and services across the value chain. For example, data-intensive companies such as Google, eBay, Amazon and Facebook are continuously uncovering additional revenue and new value streams through utilising big consumer data. However, not only IT and data-intensive companies engage in harvesting big data for value. Strong focus on big data is also obvious across more traditional sectors. Moreover, research conducted by Capgemini (2015) shows that the majority (53%) of large established companies anticipate an increased competition in the future from start-ups enabled by big data. Research shows that large data sets can bring transformation to business models, enhance innovation capabilities and productivity, and enable companies to discover new markets by data-driven market learning (Gobble, 2013; O’Connor, 1998; Chen et al., 2012).

2.6.4 Big Data in Product Innovation

In terms of product innovation, Gandomi and Haider (2015) define big data as a kind of information asset that can be transformed into value by certain technological and analytical methods. On the basis of the above definitions, this study takes the view that big data is a kind of information resource that could apply analytical results in product innovation fields and then realise its value with new techniques and approaches.

Tan et al. (2015) define big data as a holistic approach to managing process; they analyse the 3Vs (volume, variety, velocity) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages. In 2000, only 800,000 petabytes (PB) of data were stored in the world (IBM, 2013). It is expected this number will reach 35 zettabytes (ZB) by 2020 (Wong, 2012). The explosion of data is a natural tendency and, if harvested properly, can provide companies with better product innovation. For example, Dell initiated the development of a database that includes 1.5 million records related to sales and advertisements (Davenport, 2006) and Tesco generates more than 1.5 billion new items of data every month to support their new product development (McKinsey, 2011). Thus, product innovation can be facilitated by acquiring amounts of information from different sources to develop better innovation processes, and to quickly discover the market acceptance of new products, customers' needs or even competitors' market movements. It also provides organisations with big ideas which could lead to big concepts and big solutions – the growth engines of the future (Li et al., 2015; Wamba, 2015). In short, it helps organisations to generate valuable insights, to make better decisions and finally achieve competitive advantage co-creation and realisation.

Moreover, there are many different types of data, such as texts, weblogs, GPS location information, sensor data, graphs, videos, audio data and more online data. Data has become complex because the variety has shifted from traditional structured data to more semi-structured and unstructured data – from search indexes, emails, log files, social media forums, sensor data from systems, and so on (Zikopoulos and Eaton, 2012). In the digital economy, a firm's success will rely on its ability to draw insights from the various kinds of data available to it, which includes both traditional and non-traditional. The ability to analyse all types of data will create more opportunity and more value for an enterprise (Dijcks, 2013; IBM, 2013). Big data analytics can integrate heterogeneous resources and tools from multi-disciplines to gain great advantages; these include increasing operational efficiency, informing strategic direction, developing better customer service, identifying and developing new products and services, identifying new customers and markets, etc. (Zhang et al., 2011; Chen et al., 2012; Lohr, 2012; Demirkan and Delen, 2013). For example, Tata Motors analyse 4 million text messages every month, spanning everything from product complaints to reminders about service appointments to announcements about new models, as well as connecting these with customer satisfaction polling (Agarwal and Weill, 2012); Procter and Gamble created a group consisting of more than 100 analysts from such functions as operations, supply chain, sales, consumer research and marketing to improve total business performance by analysing interrelationships among functional areas (Davenport, 2006). Therefore, big data is pushing traditional operations and product innovation to a higher generation, which can be more adaptable to complex situations, and also self-adjusted to changing conditions and unstable information to satisfy a wide range of customers (Zhong et al., 2015). Instead of collecting customer feedback via formal questionnaires, new product innovation relies more on mobile devices, social media platforms – including YouTube, Facebook and Twitter – and the internet in order to build better customer connections and get feedback quickly at a reduced cost.

In terms of velocity, huge amounts of data are generated every second and increasingly have a very short life (Xu et al., 2013; Zhong et al., 2015). In 2011, about 4 billion mobile phone users were identified worldwide; about 12% of them using smartphones and having the capability of turning themselves into data streams. Meanwhile, the video platform YouTube received 24 hours of video every 60 seconds (The Economist, 2011). On Facebook alone we send 10 billion messages including photos and videos per day; we click the ‘share’ button 4.5 billion times and upload 350 million new pictures each and every day (Thibeault and Wadsworth, 2014). In these circumstances, firms can easily track customers’ data, including clickstream data from the Web, and can leverage details from their behavioural analysis to better support their new product innovations. For example, Amazon manages a constant flow of new products, suppliers, customers and promotions without compromising guaranteed delivery dates (Davenport, 2006). The velocity of big data can drive new product development dramatically faster and at less cost through responding to market feedback in a short time. Firms are now capable of gathering users' feedback in near real time to track changes in customer behaviour and rapidly communicating this to the R&D team to ensure that a newly launched product is sufficiently flexible to incorporate new functionality quickly.

By summarising the literature, we have further identified three stages that big data can be used to support in NPD: generation of ideas and concepts; design and engineering; and test and launch. Potential roles and tasks that can be transferred to customers are demonstrated in each of these stages.

Generation of ideas and concepts

The initial stage is centred on the recognition and creation of opportunities, novel ideas and new product concepts (Can Kleef et al., 2005; Cooper, 2014). Big data can be engaged in supporting this stage through the collection of huge amounts of external information to offer managers supportive product ideas (Gantz and Reinsel, 2012; Tsai et al., 2013). Noteworthy here is the group of inventive customers categorised as 'lead users' (Bharadwaj et al., 2012). The information generated can be incorporated in proposals from the firm's NPD teams (Davenport, 2009; Füller et al., 2014). For instance, Lenovo set up a competition for its customers that involved online services, telematics as well as future PC online assistance systems (Moorhead, 2015). Novel ideas generation by the customers has been endorsed by an interactive multimedia tool for services, as well as assessing ideas generated by others. During the initial stage of NPD process, big data enables the integration of customers and turns them into valuable sources to support companies in ideas generation and evaluation (McAfee et al., 2012; Tsai et al., 2013).

Design and engineering

In the design and engineering stage, the term 'co-creator' (Dahan and Hauser, 2002; Shu-Chuan and Kim, 2011; Roberts and Candi, 2014) indicates the customer's role more precisely. Six web-based approaches have been proposed by Dahan and Hauser (2002) that seek the engagement of the Internet users in a more enhanced approach than the conventional market research approaches. For instance, a web-based approach can enable customers to design individual products that will meet their particular needs and wants (Schaarschmidt and Killan, 2014).

With such techniques, the advantage of using big data in customer involvement (assessed against conventional market research) is that customers are not only asked about their needs, opinions and wants. They can, rather, exhibit their creativity and competence by deriving and assessing new product ideas; they can challenge, explain and enhance detailed solutions; they can identify and individualise virtual prototypes, experimenting with and embracing the novel product features (Blazevic and Lievens, 2008; Hoyer et al., 2010; Zhang et al., 2011; Chen et al., 2012). This can be achieved by conducting simulations, or by acquiring information from different sources regarding a novel product (Chen et al., 2012; Füller et al., 2014). For instance, Chow Tai Fook Company (a Chinese company engaged in diversified businesses such as jewellery, property and casinos) instituted an internet-based design and launch competition; primarily, customers assessed Chow Tai Fook's idea of 'Forevermark magic', a novel type of jewellery. Subsequently, an internet-based toolkit enhanced customers' individual 'Forevermark magic' design. Within a timeframe of a single month, thousands of customers engaged in virtual dialogue and stated their personal preferences. The sampled individuals were able to create hundreds of appealing designs, which motivated Chow Tai Fook's NPD teams in addition to aiding the assessment of customers' latent needs.

Test and launch

In the test and launch stage, big data allows companies to transfer individuals from different sources (e.g. web-based communities, websites and platforms) into the roles of end customers or buyers (McKinsey, 2011; McAfee et al., 2012; Wong, 2012; Wamba et al., 2015). Previous studies have illustrated how customers can represent important resources for a company's development of new products and services (Payne et al., 2008; Blazevic and Lievens, 2008; Hoyer et al., 2010; Ahmad et al., 2013; Cooper, 2014). Conventional, manufacture-centric innovation greatly limits the role of the customer (Wong, 2012). For instance, previously customers (termed 'eventual evaluators') were often used to support companies in fixing bugs, (Brown et al., 2002; Fuchs and Schreier, 2011). Otherwise, customers were lucky to have any role at all. In contrast, customers can be seen as co-creators or co-developers in a big data environment (Prahalad and Ramaswamy, 2002; Robert and Candi, 2014). For example, Xuancai Company (a leading Chinese game company), in cooperation with China Telecom (one of the largest telecommunication SOEs in China), constructed a customer-friendly online platform (PLAY.CN) to enable customers to compose and download their individual internet mobile Java games without any special skills (e.g., programming). Enthusiasts of mobile gaming are acquainted with the novel service, platform testing, as well as downloading their self-designed games for their smartphones (ChinaTechNews, 2008). As a consequence, more than a million customers have offered their feedback regarding acceptance, usability, intention to play and willingness to pay. In this way, the customers were able to come up with numerous ideas for improvement supporting a company's NPD.

2.6.5 Implementation of Big Data

The purpose of all big data initiatives is to exploit valuable combinations of large structured and unstructured data, being both internal and external (Bloem et al., 2013). As an example, the data gathered from a telecom firm and financial services establishment could through a trans-sectorial connection enable a new type of product or service suitable for a totally different market. Integration of data pools is therefore required for significant potential, however this does not solely focus on trans-sectorial data pools as mentioned above, but also the integration of internal cross-functional data pools (McKinsey, 2011).

To enable big data, potential organisations need to coordinate and collaborate with other major big data actors and users. Accordingly, organisations will assist each other in the development of their data intelligence, together with IT partners, active suppliers and analytical-tool firms of large data sets (Bloem et al., 2013). Further, Bloem et al. (2013) explain that selecting the big data network has to reflect the strategic decisions and the long-term vision of engaging in big data activities. Additionally, organisational transformation is essential in accordance wit the ability to process big data with regards to technological capacity, the potential of big data platforms to comprehend and make use of incoming external and unstructured data. This combination of technological capacity and organisational change or transformation is a major and important factor of accessing big data potential (Bloem et al., 2013).

Data

Data is a broad term which incorporates various factors such as quality, reliability, availability, accessibility, as well as relevance, governance, and security, of unstructured, semi-structured, and structured data and its information (please refer to Table 2.2 as an example of different types of data and data sources).

Types of Data	**Example of Data Sources**
Structured Data	• Table and Records
Unstructured Data	• Human Language, Audio and Video
Semi Structured Data	• XML and Similar Standards
Event Data	• Messages (usually in Real Time)
Complex Data	• Hierarchical or Legacy Sources
Spatial Data	• Long/Lat Coordinates and GPS Output
Social Media Data	• Blogs, Tweets and Social Networks
Web Logs & Clickstreams	
Scientific Data	• Astronomy, Genomes and Physics
Machine-Generated Data	• Sensors, RFID and Devices
Metadata	• Data that describes the content of other data

Table 2.2: Types of Data and Data Sources (Chen and Zhang 2014; Lavalle et al., 2011; Zikopoulos and Eaton, 2011)

According to DiFilippo and Blase (2014), big data has changed the decision-making process. Changes in decision-making are connected to intensified usage of analytical technologies and techniques. Further, companies are establishing supportive data insight functions within their organisations to inform decision-making. Thus, strategic, operational, and tactical decisions are relying to a greater extent on increased data analysis and predictive analytics through real-time data.

Real-time data refers to streams of data that are delivered directly after data collection. In short, there exists no delay in the transition from raw data collection to the information provided from real-time data (Wong, 2012). Aside from real-time data, companies further commit resources to extract value from current and historical data. Excessive emphasis on real-time data can result in complications and failure of data-driven decision-making. Wu et al. (2014) argue that availability of current and historical data is necessary to position real-time data into the context of patterns and trends. Further, “right-time data” and actionable data needs to be provided to support decision-making (Wu et al., 2014). Hence, relevant data needs to be gathered and integrated for specific requirements or scenarios.

Staff

Staff refers to technology and analytical skills within the organisation’s human resources, the presence and function of internal collaborative networks, as well as overall organisational structures and culture that serve to enable big data potential. According to McKinsey (2011), a major challenge for organisations is the lack of analytical and technology skills to make use of big data. However, McKinsey (2011) acknowledges that the most significant barrier to overcome is to establish a data-driven culture and organisational structure.

According to Galbraith (2014), before organisations can entirely employ, accept and extract value from the big data platform, they are required to empower and embed the data personnel into decision processes. Galbraith (2014) argues that for organisations to be able to achieve this will require a shift in power from current decision makers to data decision makers. In addition, there is a need to strengthen the data acceptance, data reliance and analytical capabilities within the organisation to achieve a data-driven culture. A data-driven culture sees data and analytics as a central function, and by promoting a cross-functional distribution of data it allows for more fact-based decision-making (Parmar et al., 2014).

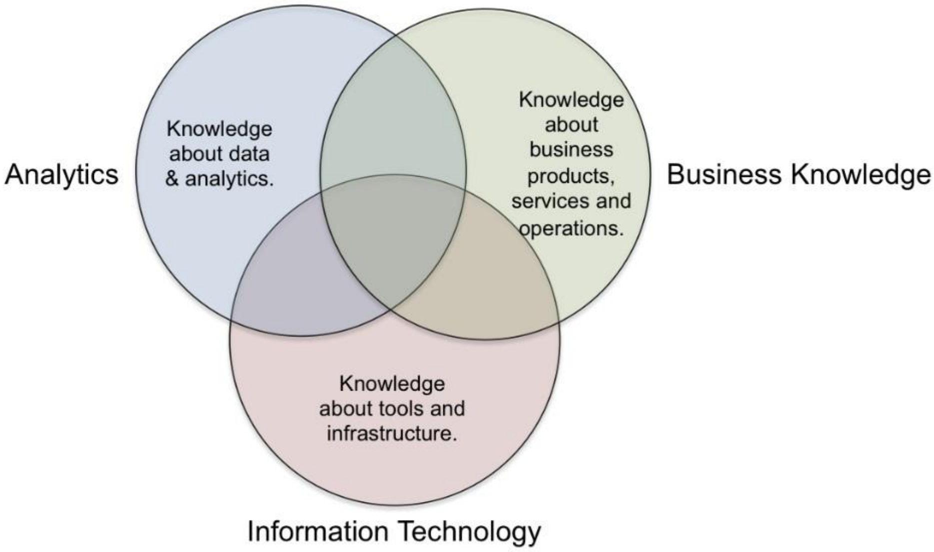


Figure 2.10: Knowledge Fusion in a Data-Driven Organisation

As shown in Figure 2.10, Grossman and Siegel (2014) suggest that organisations have to unite information technology, analytics, and business knowledge. Also, organisations need to possess 'a critical mass' of data scientists, with deep enough knowledge within the domain. Further, data scientists are required to have adequate business knowledge and understanding to be able to construct models that will generate business value. Lake and Drake (2014) and Harris et al., (2013) argue that the shortage of data scientists is due to the lack of required skill combinations for modern data objectives. For that reason, it is suggested for organisations to form big data analytical teams that include a mixture of data scientists, both generalists and specialists, with different skill combinations (Grossman and Siegel, 2014; Lake and Drake, 2014). Lake and Drake (2014) compare the current situation with the late 1980s and the advent of the hybrid manager, a combination of a business manager with extended technical knowledge.

One of the challenges in human resources is presented by Barlow (2013) that organisations need to find solutions for integrating new talent into their current structures or re-inventing structures to allow new talent to generate value.

Technologies and techniques

The data needs to be organised to transform the countless bits and bytes into actionable information – the sheer abundance of data won't be helpful unless we have ways to make sense out of it (Davenport and Patil, 2012; Louridas and Ebert, 2013). In order to harvest big data to produce such information, there are several existing big data techniques which involve a number of disciplines, including statistics, data mining, machine learning and visualisation approaches (Dumbill, 2012; Minelli et al., 2012; Gaynor, 2013; Tan et al., 2015). For example, lots of specific software in these disciplines (see Appendix I) is available. They differ in the statistical sophistication required from their users and statistical capabilities.

However, due to the characteristics of big data, it is extremely hard for traditional software to analyse it in real time and produce useful information (Bisson et al., 2010; Marchand and Peppard, 2013; Louridas and Ebert, 2013; Mishra et al., 2013; Chen and Zhang, 2014). Although such software might help managers to produce a lot of information, they are unfocused, and hence inefficient. A lot of effort and time is needed to sort out the competence-sets-related information generated and to identify those that are relevant and viable. For example, software such as Microsoft Office, SPSS, Matlab, Mathematica Stata and so on are usually not well suited to manage big data, most of them rely on analysing a certain amount of samples of big data, and varying in how the sample-based results are used to derive a partition for the overall data. Machine learning software (i.e. Weka) in neural networks over big data is severely time and memory consuming; software based on visualization (i.e. D3) has limited capacity to handle big volumes of data.

Therefore, traditional software is not sophisticated enough to capture the value from big data and it is necessary to develop new techniques and technologies for big data analysing (Cohen, 2009; Zikopoulos and Eaton, 2011; Davenport and Patil, 2012). Until now, scientists have developed a wide variety of modern techniques and technologies to capture, curate, analyse and visualize big data (see Tables 2.3 and 2.4 below). These techniques and technologies cut across a number of disciplines, including computer science, economics, mathematics, statistics and other expertise. Multidisciplinary methods are needed to discover the valuable information from big data. Even so, they are far away from meeting the wide variety of needs (Barton and Court, 2012; McAfee and Brynjolfsson, 2012; Wu et al., 2014).

Generally, big data tools can be divided into three classes: batch processing tools, stream processing tools, and interactive analysis tools. Most batch processing tools are based on the Apache Hadoop infrastructure, such as Mahout and Dryad (Kadlec et al., 2009; Wang et al., 2012). The latter is for real-time analysis of stream data applications (Zikopoulos and Eaton, 2011; Zaharia et al., 2012). S4 and Storm are good examples for large scale streaming big data analytical tools. The interactive analysis processes the data in an interactive environment, allowing users to undertake their own analysis of information (Chen et al., 2012; Liu et al., 2013). The user is directly connected to the computer and hence can interact with it in real time. The data can be reviewed, compared and analysed in tabular or graphic format or both at the same time. Goole's Dremel and Apache Drill are big data tools based on interactive analysis.

Batch Processing Tools				
Tools	***Developer***	***Main Functions***	***Main Challenges of This Type of Tools***	***Examples***
Apache Hadoop	Apache Software	Infrastructure and platform	• High latency • Depending on the data size and computational power of the system • Could provide an incomplete intelligence picture	• Common business processes (i.e., billing) • Monthly billing processes of credit card companies • Parts of online systems (i.e., Information updating tasks within deadlines)
Apache Mahout	Apache Software	Machine learning algorithms in business		
Disco	Nokia	Distributed MapReduce framework		
Tableau	Tableau Software	Data visualisation, business analytics		
Spark	UC Berkeley AMPLab	In-memory data sets and resiliency platform		
Skytree Server	Skytree Inc	Machine learning and advanced analytics		
Jaspersoft BI Suite	Jaspersoft	Business intelligence software		
Dryad	Microsoft	Infrastructure and platform		
HPCC	LexisNexis	Cluster for big data		
Pentaho Business Analytics	Pentaho Corporation	Business analytics platform		
Karmasphere Studio and Analyst	Karmasphere	Big data Workspace		
Talend Open Studio	Talend	Data management and application integration		

Table 2.3: An Overview of Current Big Data Technologies and Techniques (Morabito, 2015; Ohlhorst, 2013; Sathi, 2012; Wong, 2012)

Tools	*Developer*	*Main Functions*	*Main Challenges of This Type of Tools*	*Examples*
		Stream Processing Tools		
Storm	Twitter	Real-time computation system	• Increased data involved • Lack of processing power • Memory alignment problems • Synchronization issues • Limited parallelism	• Radar systems • Customer services • Bank ATMs • Retail dynamic pricing
Splunk	Splunk	Collect and harness machine data		
StreamReduce	Nodeable	Cloud infrastructure for big data		
S4	Yahoo!	Processing continuous unbounded streams of data		
InfoSphere	IBM	Data integration and management		
SAP Hana	SAP HANA	Platform for real-time business		
SQLstream s-Sever	SQLstream	Sensor, M2M, and telematics applications		
Apache Kafka	Apache Kafka	Distributed publish-subscribe messaging system		
		Interactive Analysis Tools		
Apache Drill	Apache Software	Distributed big data interactive analysis system	• Requires input data • Lack of processing power • Too much information involved • Interface complicated problem	• Handling bank accounts • Online booking and ordering
Dremel	GOOGLE	Nested data processing system		

Table 2.4: An Overview of Current Big Data Technologies and Techniques (Ohlhorst, 2013; Sathi, 2012; Wong, 2012; Zikopoulos and Eaton, 2011)

Batch processing indicates that jobs are configured to run without manual intervention in order to produce outputs in the form of computational analyses and data files (Zhou, 2013). One of the most famous and powerful batch-process-based big data tools is Apache Hadoop. It provides infrastructures and platforms for other specific big data applications (Kumar and Pandey, 2013). A number of specified big data systems (see Table 2.3) are built on Hadoop, and have special usages in different domains, for example, data mining and machine learning used in business and commerce. Batch data processing is an efficient way of processing high volumes of data where a group of transactions is collected over a period of time (Ge et al., 2011). However, although the batch processing tool does well in processing a large amount of data in parallel, it cannot process real-time data with high performance. For example, in the general Map/Reduce framework, the Reduce phase starts to work only after the Map phase finishes and this leads to significant latency of the processing. The high latency characteristic of the batch processing tool makes it almost impossible for real-time analytics. Worse, it could provide an incomplete intelligence picture (Yin et al., 2013).

For certain stream data applications, such as processing log files, industry with sensor, machine-to-machine (M2M) and telematics requires real-time response for processing a large amount of stream data. In those applications, several big data tools based on stream processing have been developed. Stream big data has high volume, high velocity and complex data types (Wang et al., 2012). One of the most famous platforms is Storm, and others include Splunk, Apache Kafka, S4, SAP Hana and SQLstream (see Table 2.4). Stream processing allows an organisation the ability to take immediate action for those times when acting within seconds or minutes is significant (Chen and Zhang, 2014). However, considering a variety of data sets in big data problems, it is still a big challenge for these tools to perform efficient representation, access, and analysis of unstructured or semi-structured data in the research (Zikopoulos and Eaton, 2011; Hirzel et al., 2013).

In recent years, open source big data systems have emerged to address the need not only for scalable batch processing and stream processing, but also interactive analysis processing. Interactive processing involves the exchange of information between a user and the computer (Arenas-Márquez et al., 2012; Chen et al., 2012; Gaffar, 2014). This information is passed on in the form of instructions which are then used to do tasks. The interactive analysis presents the data in an interactive environment, allowing users to undertake their own analysis of information. Users are directly connected to the computer and hence can interact with it in real time. However, due the large size and high dimension of big data, current interactive big data tools are difficult to use to conduct data visualisation and mostly have poor performance in functionality, scalability and response time (Barnett et al., 2013). In addition, interactive processing tools require users to input data but it is hard to ensure that the data is correct and accurate.

Data management process

Synthesising the prior literature in big data management process, there are four main steps that can link useful quantitative information generated from analytics to support a firm's decision making:

- Data capturing and management – Data sets grow in size because they are increasingly being gathered by ubiquitous information-sensing mobile devices, wireless sensor networks, microphones, software logs, radio-frequency identification readers, cameras, remote sensing, aerial sensory technologies, and so on (Chen and Zhang, 2014). These valuable data are created and captured at high cost, but most of them are ignored in the end. Data capturing and management is the process of generating data with the use of digital means, e.g. by monitoring activities through sensors (OECD, 2014). In this step, it is essential for organisations to understand what information they need in order to create as much value as possible. Thus, it is significant to meet their bulk storage requirements in big data capturing and management steps for experimental databases, array storage for large-scale scientific computations, and large output files. Requirements could be different due to different organisations' needs and problems. Morabito (2015) explains that an important organisational barrier is in the process of collecting data. Data collected from different sources or different timing could be inconsistent due to a malfunctioning source. Furthermore, it is vital to generate the metadata in order to register the type and the method of measurement (Ohlhorst, 2013). Due to the growth of the volume of data, organisations are challenged to acquire new storage platforms and engage in intelligent data collection (European Commission, 2013). Lowering the cost of data collection is assisting in the establishment of better means for data processing (Feinleib, 2014). However, a major concern that organisations need to be aware of during data collection is privacy (European Commission, 2013).

- Data cleaning and integration – As the sizes of data set are often huge in big data analysis, sometimes several gigabytes or more, and their origin from heterogeneous sources, current real-world databases are severely susceptible to inconsistent, incomplete and noisy data (Davenport, 2012; Zhou et al., 2014). Therefore, a number of data pre-processing techniques, including data cleaning, data integration, data transformation and data reduction, can be applied to remove noise and correct inconsistencies.
- Data analytics – Gathering and storing data into a database that no one will be able to access or combine is unproductive. Data aggregation requires an automatic process in order to manage a wide and efficient analysis (Morabito, 2015; Ohlhorst, 2013). It is crucial that data formation should be readable and resolvable by analytical systems in order to be queried, modelled and finally analysed. Big data has an unreliable, dynamic and diverse nature, therefore for the analysis and mining it requires to be accessible and integrated (Ohlhorst, 2013). *"It is easy to see how big data can enable the next generation of interactive data analysis, which by using automation can deliver real-time answers*" (Ohlhorst, 2013). Ohlhorst shows that computer intelligence can be used to create queries to analyse and sort out big data, thus increasing data value.
- Data interpretation and decision making – Following the analysis part of the process comes the interpretation of the results. This step is expected to generate most of the value of the process, by providing insight, assisting decision making or information in the form of patterns (Feinleib, 2014). An effective interpretation requires the user to comprehend the results, assisted by the analytics platform tools. It is possible to automate a procedure and interpret the data with little or no human supervision. Ohlhorst (2013) explains that the normal process connected with the interpretation of data is the data provenance.

> Users add extra information about the nature of the data and the results in order to enhance the process which can be used repeatedly for analysis, with different questions, factors or data sets.

The outcome of capturing, integrating, analysing and interpreting the results is generation of and access to information. Just as with data, firms have to establish an effective control over information in order to survive and compete (Laudon and Laudon, 2011). Furthermore, there are two perspectives of information systems' necessity: the technical and the business perspectives. The technical perspective has to do with information management and assisting the process of input, process and output. The business perspective is dealing with the organisational challenges such as decision-making support, strategy and the firm's culture. It is essential for organisations to implement a strategy regarding the management of information, in alignment with their level of maturity, which includes size, operation width, and integration level (Laudon and Laudon, 2011).

Organisational intent

McKinsey (2011) suggests that organisational intent should be to implement several new technologies and techniques, in accordance with the big data strategy, in order to extract value from their data. The level of technological adaption and big data platform selection will be affected by the data maturity of the organisation, while technological innovation could have a key role in managing the constantly increasing volume of big data. Sathi (2012) adds that the approach that each organisation will choose is influenced by the size, limited capabilities and the urgency of each organisation to evolve and transform by forming a competitive strategy.

However, adopting a big data analytics platform can cause three significant operational impacts. It has the ability reduce the latency of moving and processing data, extend the storage capacity thus the potential to acquire more data, and consequently reduce the cost of acquiring and managing data (Sathi, 2012). Each organisation has to decide the approach regarding the implementation of big data technologies. Sathi (2012) suggests three different strategies are: a) the revolutionary, b) the evolutionary, and c) the hybrid approach.

Organisations choose the revolutionary approach in order to install a completely new big data analytics unit. This requires the organisation to transfer the data to a new environment and fuse them with business processes. The revolutionary approach is adopted by data-driven companies, and while it is very effective, it is also costly and demands high technical capabilities (Sathi, 2012).

In the evolutionary approach, big data is inserted into the current Business Intelligence platform. This method is used by mature Business Intelligence companies, it has limitations regarding the process of data and the impact of their results, but it’s operating with a lower cost (Sathi, 2012).

The final approach, the hybrid approach, is described by Sathi (2012) as an addition of new technologies into the already existing Business Intelligence tools. The outcome of the merge is a parallel operation of the analytics units, which enables a high-performance of both of them in their own environment. The hybrid proposal is regarded as an efficient way to gradually transform current technologies.

2.6.6 Big Data Challenges

There are many opportunities linked to big data and implementation of big data analytics into concurrent business activities of organisations. In order to harvest real value from extremely large data sets, organisations have to address and overcome decisive obstacles, connected to both managerial and technological contexts.

Morabito (2015) addresses the technological challenges of using and implementing big data to create actual business value. One of the main issues is the incompatible IT infrastructures and data architectures. IT systems and software should be able to store, analyse, and derive useful information from datasets, composed of structured, semi-structured and unstructured data. Further, Morabito (2014) argues that an enterprise-wide platform of sharing big data and its analytics within the organisation and its sectoral system imposes challenges due to incompatible technologies. McKinsey (2011) additionally indicates that a key obstacle is the consistency of internal and external databases, implying that there is a challenge in integrating and standardising data of constructing formats to enable valuable information flows.

Moreover, accessing the required data could be a difficult task for a number of organisations and it is common that the acquisition of data stems from external sources, such as third parties. The SAS Institute Report (2013) describes a number of barriers in regards to the use of big data, after its acquisition. In particular, it emphasises the time and speed in which data should be acquired and processed to avoid being outdated and have their value diminished. Furthermore, it is crucial to ensure that datasets are complying with two important criteria: understanding and quality. The first refers to the ability to comprehend and separate useful as well as relevant data, which will form the information we seek, rather than including unconnected and misleading data. Data quality could affect the final outcome in a similar way by providing disorienting information which is not transformed into the desired value. Consequently, the decision-making process could be negatively affected.

An additional challenge of big data usage is output information management. Simon (2013) claims that the outcome of big data analytics should be meaningful information. The challenge lies in the ability to extract useful and targeted clusters of information out of the information pool, which require an urgent utilisation.

Besides the many technological challenges, big data also brings managerial challenges that need to be considered. Morabito (2015) argues that a major obstacle to overcome is management's lack of understanding of the potential value big data can bring to the business. McKinsey (2011) states "*organisational leaders need to understand that big data can unlock value – and how to use it to that effect*" (McKinsey, 2011, p. 108). At the same time, data scientists need to recognise the business aspects to be able to bring valuable information to the business (Harris et al., 2013). In consequence, there is a lack of resources in the form of technical expertise combined with business understanding to position favourable big data structures and generate value. However, an existing problem is the shortage of deep analytical and technical talent needed to leverage big data. According to a report conducted by Accenture, *"the U.S. is expected to create around 400,000 new data science jobs* *between 2010 and 2015, but is likely to produce only about 140,000 qualified graduates to fill them"* (Harris et al., 2013, p.4).

Another significant barrier, according to Morabito (2015), is related to the funding of an analytics unit for big data analytics. The cost of establishing advanced tools in order to sustain a data processing department could be excessive. Therefore, IT and business executives should determine what the real needs for analytics are, settle on a budget agreement, and provide the funds for these specific functions.

Also, firms are required to deal with several legal issues to be able to seize the full potential of big data. Extremely large amounts of data are being transferred across both public and private networks, resulting in the establishment of various data policies. Data policies address mainly legal concerns of intellectual property, liability, security and privacy. McKinsey (2011) emphasises the issues related to privacy and usage of personal data such as medical and financial records. Personal data is considered as valuable insight form increasing utility, however the specific category of data is viewed as sensitive and corporations need to comply with data policies. Kerr and Earle (2013) are examining Google's plan to enhance its search engine with predictive algorithms based on big data. The 'intelligent' search will display results to users even before they know they need it. They raise the concern that this use of big data promises efficiency and profits but they are sceptical that is might be used as a justification for shifting policies. As a result of big data technologies and corporate objectives, society will have to position itself in the trade-off between privacy and utility (McKinsey, 2011; Kerr and Earle, 2013).

Additionally, Morabito (2014) states that security is a barrier for big data technology. The law requests that customer data needs to be protected and sets a limitation on which personal data can be acquired and used. In some particular cases, policies can be extensively strict, such as medical and financial records (Ohlhorst, 2013). The challenge for organisations handling big data has to do with liability, in other words the constant danger of security breaches and the unauthorised use of data. There have been several cases of data hacking in the past and, according to Morabito (2014), several organisations are reluctant to report online attacks, driven by the fear of public image damage.

Last but not least, Vare and Mattioli (2014) bring attention towards another challenge of big data, which is Intellectual Property (IP). In their article "*big business, big government and big legal questions*", they explain the limitations on big data usage under the current IP legal system. Although the effectiveness of big data lies in the availability and transferability of data throughout organisations and systems, there is interference from privacy and IP legal frameworks. Moreover, understanding the legal rights of single strings of data and larger datasets are additional challenges which have to be addressed. Data is not patentable and copyrightable, however can be protectable trade secrets if they bring economic value (Vare and Mattioli, 2014).

2.7 Summary

Fink (1998) provides the following definition: "A literature review is a systematic, explicit, and reproducible design for identifying, evaluating, and interpreting the existing body of recorded documents". The analysis of documents pursues the aim of opening up material that does not have to be created on the basis of a data collection by the researcher. Literature reviews usually aim at two objectives: first, they summarise existing research by identifying patterns, themes and issues. Second, this helps to identify the conceptual content of the field (Meredith, 1993) and can contribute to theory development. One problem derives from the challenge that it is impractical to read everything (Seuring and Müller, 2008). Only for emerging or narrowly defined issues might it be possible to provide complete reviews.

For a literature reiew, it is particularly important to define clear boundaries to delimitate the research. In this content, this analysis aimed only at papers in peer-reviewed scientific journals in Enlish with a management focus. This excludes papers in other languages as well as those with, e.g., a technical or political science focues. The search for related publications was mainly conducted as a structured keyword search. Major databses were used to search for realted articles, such as those provided by major publishers, Elsevier (www.sciencedirect.com), Emerald (www.emeraldinsight.com), Springer (www.springerlink.com), Wiley (www.wiley.com) or library services (e.g., Ebsco, Scopus, Metapress, or subito).

After a first quick content check, identified articles were in- or exluded from the analysis. To increase the reliability of the research, databanks and journals as well as the individual papers were checked by a second researcher. Reading the papers, cited references were used as a secondary source, but did not yield many additonal papers, which can be taken as an indication of the validity of the literature study.

Based on the literature study, a review of existing product innovation and big data literature indicates that little is available on: a) what is accelerated product innovation, and b) how could managers attain accelerated product innovation in today's big data environment. Many sophisticated innovation processes have been described, and indeed successfully applied, all over the world (Cooper, 1994; 2008; 2012; Christensen and Overdorf, 2000; Mann, 2002; Chesbrough, 2003; Hansen and Birkinshaw, 2007; Sheu and Lee, 2009; Casadesus-Masanell and Zhu, 2011; Williamson and Yin, 2014). Nonetheless, what is required today is a framework to guide the product innovation process in a big data environment, one which can accelerate the problem-solving element, and shorten the overall process, in part through effective connection to customers, as well as ensuring low cost (especially when limited resources are available).

By studying accelerated product innovation literature, we found that different terms such as time-to-market (Chen et al., 2005), cycle time (Ittner and Larcker, 1997), innovation speed (Kessler and Chakrabarti, 1996), and speed to market (Meyer and Utterback, 1995) have been used to refer to accelerated product innovation of new product development. As noted by Kessler and Bierly (2002), and Chen et al. (2005), most studies on accelerated product innovation focus on its antecedents. However, the larger number of prior studies focused on the impact of speed on performance outcomes (i.e., profit and quality) have not been consistent in their findings, with studies finding positive (Ali et al., 1995; Chen et al., 2005; Cooper and Kleinschmidt, 1994; Kessler and Bierly, 2002; Langerak and Hultink, 2005), negative (Crawford, 1992; Karau and Kelly, 1992; Sethi, 2000), nonsignificant (Meyer and Utterback, 1995; Ittner and Larcker, 1997; Davis et al., 2002; Griffin, 2002), and U-shaped relationship (Lukas and Menon, 2004; Langerak and Hultink, 2006). This research takes a different angle by attributing the conflicting results of accelerated product innovation to several integrated threads that most prior studies have identified and supported.

By studying big data literature, although big data can offer much more useful production innovation and can gain great competitive advantages, there are no methods for managers to support organisations' product innovation from idea through to launch based on the values captured from big data. With big data, firms can gain a better understanding of their products, customers and markets – and this is crucial to innovation (McKinsey, 2011; Wong, 2012). However, the main challenge for firms is how to use big data to hasten the development of new products and to make them less costly. Therefore, instead of just generating vast amounts of information from big data, managers need a framework as guidelines to structure and utilise the information captured from big data to support their product innovation systematically, so that a better insight into the issue being analysed can be gained.

In short, this chapter has provided the backgroud to this research by reviewing the relevant literature and the review has led the research to focus on developing a framework to assist managers in attaining accelerated product innovation in a big data environment. It is worth pointing out that this research is not a data analytical study. It aims to extend the innovation and big data literature by clearly defining the concept of accelerated product innovation, and by developing a conceptual framework about how, specifically, big data and ICTs can contribute to accelerated product innovation in real company cases. Chapter 3 will descibe and justify the research methodology used to achieve the research aims.

CHAPTER 3.0 RESEARCH METHODOLOGY

Chapter 2 critically reviewed the literature on product innovation and big data, and focused this research on developing a framework to assist managers in attaining accelerated product innovation in a big data environment.

This chapter describes the research methodology taken to fulfil the research aims. Section 3.1 discusses the theoretical foundation, Section 3.2 describes the research design, and Sections 3.3 and 3.4 explain in detail the activities involved in each research stage. Finally, Section 3.5 provides a brief summary of this chapter.

3.1 Theoretical Foundation

Flynn et al. (1990) propose a six-step systematic approach for conducting research in production/operations management. Table 3.1 shows that the first stage of empirical study is to establish the theoretical foundation for the research. It is important to understand the philosophical issues underlying management research before proceeding further. Easterby-Smith et al. (1997) point out that failure to consider philosophical issues can seriously affect the quality of management research.

Research Stages	Description
1. Establish the theoretical foundation	• Positivism • Phenomenological
2. Select a research design	• Single case study • Multiple case study • Survey • Action research
3. Select a data collection method	• Historical archive analysis • Participant observation • Interviews • Questionnaires
4. Implementation	
5. Data analysis	
6. Publication	

Table 3.1: A Systematic Approach for Empirical Research (Source: Flynn et al., 1990)

Philosophers of science and methodologists have long debated how best to conduct research. The debate has centred on two fundamentally different and competing enquiry paradigms:

1) Logical positivism, which uses quantitative and experimental methods to test hypothetical deductive generalisations.
2) Phenomenological enquiry, using qualitative and naturalistic approaches to inductively and holistically understand human experience in context-specific settings (Patton, 1990).

A summary of the key features of positivist and phenomenological paradigms is presented in Table 3.2.

	Positivist Paradigm	**Phenomenological Paradigm**
Basic beliefs	• The world is external and objective • Observer is independent • Science is value-free	• The world is socially constructed and subjective • Observer is part of what is observed • Science is driven by human interests
Researchers should	• Focus on fact • Look for causality and fundamental laws • Reduce phenomena to simplest elements • Formulate hypotheses and then test them	• Focus on meanings • Try to understand what is happening • Look at the totality of each situation • Develop ideas through induction from data
Preferred methods include	• Operationalising concepts so that they can be measured • Taking large samples	• Using multiple methods to establish different views of phenomena • Small samples investigated in depth or over time

Table 3.2: Key Features of Positivist and Phenomenological Paradigms (Source: Easterby-Smith et al., 1997)

Qualitative methods are preferred when 'how' or 'why' questions are being posed, when the researcher has little control over the events being studied, and when the focus is on a contemporary phenomenon within some real-life context (Yin, 1994; Meredith, 1998). Easterby-Smith et al. (1997) pointed out that although quantitative methods can provide wider coverage of a range of situations, they tend to be inflexible and 'artificial'. Table 3.3 presents the comparison of qualitative and quantitative approaches.

	Qualitative Methods	**Quantitative Methods**
Strengths	• Ability to observe processes • Can understand people's meanings • Can adjust to new issues and ideas as they emerge • Contribute to evolution of new theories	• Provide wide coverage of the range of situations • Fast and economical • Good credibility
Weaknesses	• Difficulties in gaining access • Time and resource consuming • Data analysis may be difficult • Low credibility	• Inflexible and artificial • Ineffective in understanding processes • Not helpful in generating theories

Table 3.3: Comparison of Qualitative and Quantitative Methods (Source: Easterby-Smith et al., 1997)

This research aims to develop and verify a framework that can be used to assist managers in attaining accelerated product innovation in a big data environment. In order to achieve this research purpose, it is important to consider the following issues when setting the research design and data collection method:

- To study the practicality of the framework proposed in this research, it is important to interview different people in different fields.
- To further improve the framework, it is essential that the researcher is involved with the verifications of the developed framework in different companies.
- It is important to investigate what types of benefits and managerial challenges exist in using big data in product innovation activities, as well as what approaches of accelerated product innovation lie within the organisation to extract value from big data.

What is more, product innovations are processes that cannot be detached from reality and tested in a 'laboratory'. Therefore, the approaches for accelerated product innovation cannot be detached from the context in which the products are made. In addition, this research studies how companies utilise big data and apply it to facilitate the product innovation process. Thus, for this research, the phenomenological approach using qualitative methods will be most appropriate in meeting the research objectives.

3.2 Research Design

The research focuses not on the development of descriptive theory but on the development of a structured framework which would provide managers with better approaches for accelerated product innovation in a big data environment.

In order to achieve the research objectives, the research design was divided into two main stages, which are depicted in Figure 3.1. Stage 1 consists of identifying and refining the key approaches for accelerated product innovation in a big data environment from theory and practice, while stage 2 relates to the development and verification of a framework through conducting in-company case studies.

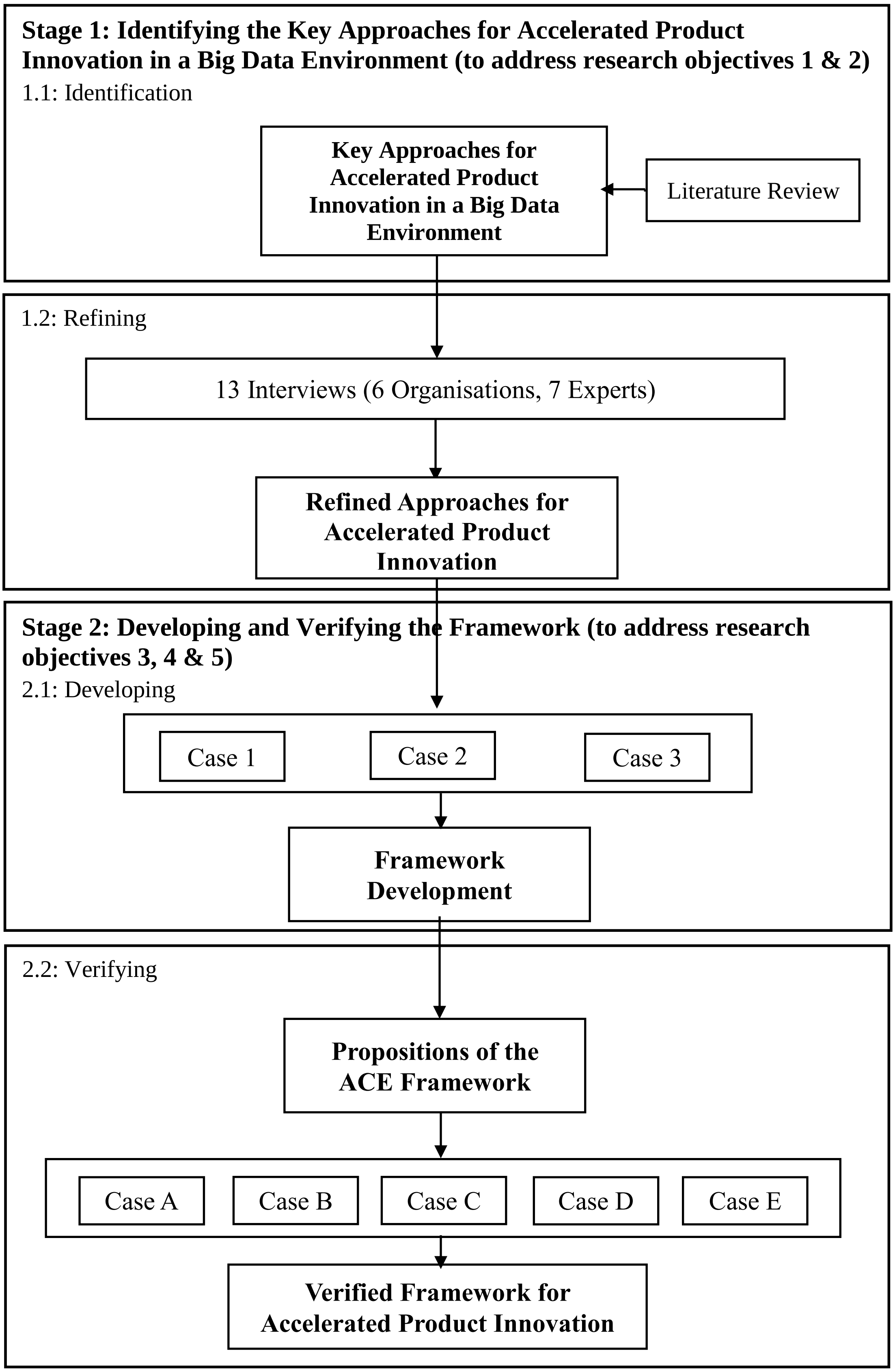


Figure 3.1: Updated Research Flow Chart

3.3 Stage 1: Identifying and Refining the Key Approaches for Accelerated Product Innovation in a Big Data Environment

The key approaches for accelerated product innovation in a big data environment were exploratory in nature and developed in phases. This was a substantial part of the overall research programme and involved the acquisition and synthesis of information from empirical research. After identifying the key approaches for accelerated product innovation from a comprehensive literature study, the empirical research consisted of interviews with academics and industrialists. The interviews enabled insight on strategies, capabilities, resources and processes used to successfully incorporate big data and analytics into the product innovation process. Figure 3.2 illustrates the components of the empirical research involved in the development of the key approaches.

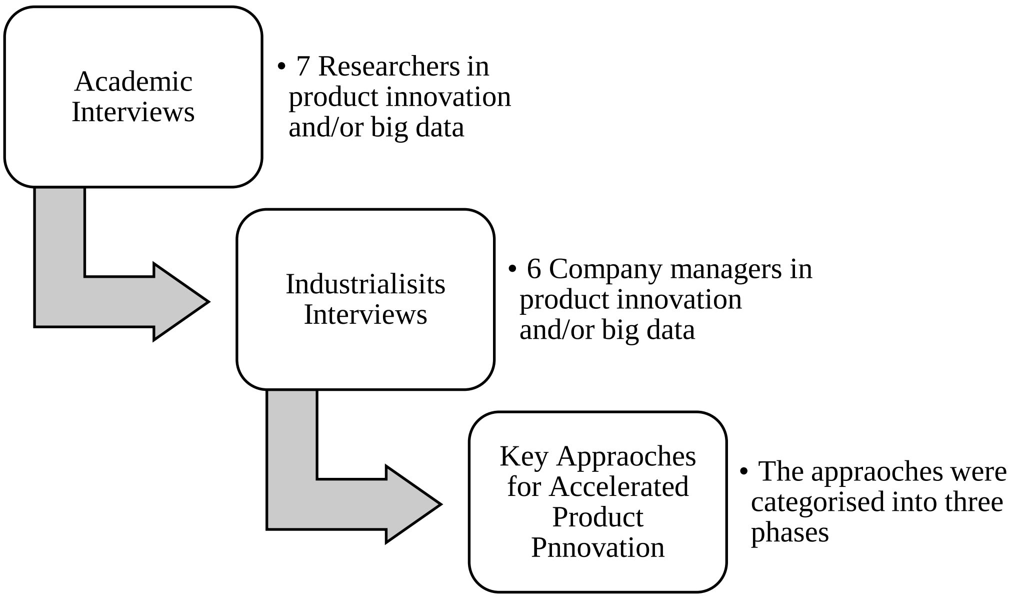


Figure 3.2: Case Interviews for Key Approaches

There are two main reasons for interviewing 7 researchers and 6 company managers. On the one hand, I personally had the opportunity to know and meet these people at different events (e.g., International Conferences, Seminars, Workshops, Company Visiting). Also, all these people were keen to support my research. The researchers were interested in my research topic and the company managers were keen to tap into new ideas to enhance their current product innovation approaches. On the other hand, according to the theoretical saturation phase (Bowen, 2008; Francis et al., 2010), we keep interviewing and analysing data until no new information appears. In this way, 7 researchers and 6 company managers indicate a sufficient sample that all concepts are well-developed.

3.3.1 Interviews with Academics

The literature survey was used to identify gaps in current research work. Further discussions with academic researchers who are active in and have experience in this area were needed to broaden the view on product innovation and big data issues. Interviews lasted from 30 to 90 minutes each and the areas covered are shown in Appendix A. Table 3.4 summarises the background of the 7 researchers; for more detailed interview analysis please see Appendix C.

Academics	Job Title	Institution	Location
Researcher A	Technology and Innovation Manager	Big Innovation Centre	UK
Researcher B	Researcher in Data Science	Imperial College London	UK
Researcher C	Senior Lecturer in Business Management	Oxford Brookes University	UK
Researcher D	Associate Professor in Faculty of Software and Information Science	Iwate Prefectural University	Japan
Researcher E	Associate Dean and Professor of Operations Management	University of Nevada, Las Vegas	USA
Researcher F	Professor of Supply Chain Management	University of Hull	UK
Researcher G	Professor in Systematic Innovation and Manufacturing Management	National Tsing Hua University	Taiwan

Table 3.4: Summary of Researcher Background

3.3.2 Interviews with Industrialists

Having surveyed and researched the key approaches for accelerated product innovation issues from academics' perspectives, it was then necessary to understand and take account of current industrial practice. This was ensuring that the proposed research was relevant to industry. To achieve this, a number of industrial interviews were conducted as in Appendix B.

In order to gain a broad insight into accelerated product innovation, interviews were conducted in 6 companies from different industries such as logistics, e-commerce and pharmaceuticals (Table 3.5 shows a summary of company backgrounds). For more detailed interview results please refer to Appendix D.

Company	Industry	Products	Revenue (£)	Location	Employees
A(CEVA Logistics)	Logistics	Distribution, transportation management, etc.	50b	UK	44,000
B(Unilever)	Consumer goods	Foods, beverages, cleaning agents, etc.	45b	UK	172,000
C(GSK)	Pharmaceuticals and consumer goods	Pharmaceuticals, vaccines, oral healthcare products, etc.	23b	UK	100,000
D(VIP.COM)	E-commercial	Clothing, cosmetics, furniture, etc.	11b	China	21,000
E(DB Schenker)	Logistics	Transportation and logistics	13b	Germany	95,000
F (Rolls-Royce)	Aerospace and power systems	Aerospace engines and related equipment	13.7b	UK	54,100

Table 3.5: Summary of Company Background

3.3.3 Industrial Interviews Setup

Interviews with industrialists were needed to explore the research issues further and address the gaps identified in the literature. Research in operations management needs to be developed with the input of practising managers (Buffa, 1980). The interviewees were selected based on their involvement in product innovation and big data within the company. Interviews were conducted with manufacturing directors or operations managers who had an understanding of the overall performance of the company.

Semi-structured interviews were used. This process was useful in maintaining in-depth discussion of the topic and it ensured that the questions were well understood. The first part of the interview addressed general questions and common problems encountered. The second part focused on generation and evaluation of key approaches. The interviewees were asked to explain current practice and the difficulties faced, their expectations of the approaches to facilitate product innovation in the big data environment, to give examples of the usage of big data in product innovation, and to provide suggestions for developing a framework for attaining accelerated product innovation in a big data environment.

3.3.4 Data Analysis

Both the academic and industrial interviews were audio-recorded, enabling the interviewer to work back and forth between interview notes and sections of the tape for better analysis. Attention was given to the aspects of the approaches for accelerated product innovation (the data analytics applied, and their effectiveness). To avoid 're-inventing the wheel', interviews with industrialists aimed to understand the existing processes used by the companies. The interviews also enabled the researcher to understand the difficulties and challenges faced by industrialists related to accelerated product innovation in a big data environment.

Analysis of interviews was based on the overall product innovation process, strength and weaknesses of current approaches, and the big data analytics applied. A matrix was used to categorise these issues and the information from each interview was entered (see Appendix C and Appendix D). Emphasis was placed on identifying the desirable approaches for accelerated product innovation. These criteria were then used for the refinement of the key approaches identified.

It is worth to mention that the initial objective of this PhD research is to develop an analytic infrastructure which can be used to support firms to harvest potential values from big data and achieve supply chain innovation. However, despite its potential contributions, feedback from interviews suggest that this research should change its research focus away from developing an big data analytic infrastructure to achieve supply chain innovation, and focus more on developing a framework to facilitate product innovation for several reasons: first of all, many researchers imply that the development of a big data analytic infrastructure is a very big subject. And also, it sounds like a research topic belongs to information system and data science but not a decent topic in operations management. Therefore, the focus of big data analytic infrastructure in management perspective is relatively weak. Second, participants argue that the supply chain innovation objective is too broad to achieve, the current research is more like to develop an infrastructure to provide organisations with optimal supply chain decisions. And also, as a student who has limited time to complete their PhD, the research topic should be narrowed down in order to contribute to a specific problem. Most importantly, the interview results from the industrialists indicate that most of the companies already have their own big data analytic techniques and different versions of innovation approach. Therefore, instead of developing an big data analytic infrastructure to achieve supply chain innovation, what firms requires is a big data framework that could tap into new ideas captured from big data to facilitate their current product innovation.

In summary, 13 worldwide interviews with academics and industrialists were undertaken in order to gain a sound understanding of product innovation and big data. The interview feedback leads to a narrowed of the research focus on leading companies in China. In particular, the approaches identified were categorised into three phases. The interviews provided useful suggestions for the refinement and improvement of the phases as well as the approaches for accelerated product innovation in a big data environment.

3.4 Stage 2: Developing and Verification of the Framework

3.4.1 Developing the Framework

The empirical research from the previous stage provided a relevant account of the criteria to be considered for the development of a framework for accelerated product innovation in a big data environment. However, this input was not sufficient. According to Wong (2012), while stochastic theories and industrial economics shed light on some phenomena of interest, they are far from full explanations of the use of big data to facilitate product innovation. Therefore, in order to build a 'robust' framework further information from real in-company cases were considered. In particular, three cases of emergent leading companies in China were selected to refine the identified key approaches in product innovation: (1) Xiaomi, a manufacturer of smartphones; (2) Lenovo, a computer hardware and electronics company; and (3) Didi Dache, a taxi service company. Brief outlines of the three firms are provided in Table 3.6.

Company	**Industry**	**Position of Interviewees**	**Revenue (£)**	**Position of Participants**
Xiaomi	Consumer Electronics and Computer Hardware	Smartphones, Tablet Computers and Home Devices	8b	Project Manager; Accessories Programme Manager
Lenovo	Computer Hardware and Electronics	Smartphones, Computers and Storage Devices	27b	Marketing Manager; Product Manager
Didi Dache	Software Company	Smartphone Applications	2b	Executive Assistant; Technicians

Table 3.6: Summary of Company Background and Interviewed Industrialists

Following a qualitative research strategy, building theory from case studies will be the main approach in the current research. In contrast to other qualitative research approaches, the case study focuses on understanding the dynamics present within single settings (Eisenhardt, 1989), and significantly emphasises the implementation of this new approach (Yin, 2011). In the current research, the reasons for choosing case study design are based on the theory-driven research questions, which are attempting to yield theories which are not dealt with in depth by other researchers

(Eisenhardt and Graebner, 2007; Denzin and Lincoln, 2011). Moreover, this research is generating theory from an external perspective, and for most of the time the study cannot have control of any behavioural events (Yin, 2009). All of the above considerations have led to the utilisation of case study research as the research design in this study. Other research approaches for building theories, such as experiment and some statistical methods could also answer similar research questions posed by this PhD research. However, experiment needs the researcher to be a participant (Yin, 2009); and statistical methods can answer a research question in breadth but not in depth; it very much relies on numeric data but not qualitative data (Denzin and Lincoln, 2011). Accordingly, theory-building from a case study approach is appropriate research for this study. There are two main reasons for conducting three cases. On the one hand, I personally had the opportunity to know and meet the senior managers of these companies. Also, all these people were keen to support my research. The company managers were interested in my research topic and were keen to tap into new ideas to enhance their current product innovation approaches. On the other hand, according to theoretical saturation phase, we keep investigating and analysing data until no new information appear (we investigated more than three cases). In this way, the three cases presented are the best samples for using big data to accelerate product innovation and indicate a sufficient sample that all concepts are well-developed.

The objective is to understand their main innovation approaches and big data activities to facilitate the product innovation process, that is, how they integrate big data to increase efficiency and reduce the cost and cycle time in product innovation. I am concerned with dynamic phenomena so I have used different data collection methods and different data sources (Eisenhardt, 1989). In particular, the data collection resorted to multiple sources of evidence, which allowed us to increase the validity of our constructs (Yin, 1994). Each company case took approximately one week and was recorded. According to Yin (1994), a richer portrait of any particular case can be acquired by using multiple sources of information and by mitigating bias in historical data interpretation. Information and comments gathered from the cases were then used to devise the framework development. Please refer to Appendix E for the analysis of big data initiatives in the three cases.

According to McDonald (2005), participated observation can provide unique insights into day-to-day working practices because they shift the emphasis to the direct study of contextualised actions. The author had full access as an observer to most of the teams during a period of product innovation or while the teams applied big data. Therefore, I was able to observe the teams in their natural setting (Schultze, 2000) to understand how they work. In particular, to avoid distortion of past facts and written reports were used to support observations. Starting 2015, the data collection consisted of 1 month research in real time (one week for each company), meaning that the researcher lives with the organisations over time or carries out periodic interviews. This involved: on-site observations, semi-structured interviews, discussions with the NPD team members, analysing internal documents (industrial reports, strategic planning reports, annual reports, newsletters, technical or non-technical documents and project reports).

As mentioned, semi-structured interviews were used. An interview guide (see Appendix B) assisted the semi-structured interviews by providing coordination and a frame of reference with mainly open and general questions connected to specific topics: accelerated product innovation approaches, and big data in new product development. This process was useful in maintaining in-depth discussion of the topic and it ensured that the questions were well understood. The first part of the interview addressed general questions and common problems encountered. The second part focused on generation and evaluation of key approaches. The interviewees were asked to explain current practice and the difficulties faced, their expectations of the approaches to facilitate product innovation in the big data environment, to give examples of the usage of big data in product innovation, and to provide suggestions for developing a framework for attaining accelerated product innovation in a big data environment.

3.4.2 Verifying the Framework

As this research aims to develop a practical framework for accelerated product innovation in a big data environment, the verification of the framework involves its implementation in 'real' companies. Our qualitative analysis followed the general strategy of "relying on theoretical propositions" which is preferred in our case according to Yin (2011).

Empirical case research (Yin, 1994) was selected as an appropriate research methodology given the specific context of this study and research questions to be investigated (Meredith, 1998). Yin (1994) suggests that case study can be used for theory testing, and it has been used in the marketing and operations management field in order to test complicated issues such as product development and innovation (Hoffman et al., 1993; Boyer and McDermott, 1999; Closs et al., 2008; Done et al., 2011). In particular, we followed Done et al. (2011) and conducted a comparative case study. The main reason for the comparative case study is the novelty of the research topic on accelerated product innovation approaches and how big data is managed and organised to facilitate the product innovation process. According to Dane (1990), descriptive research involves examining a phenomenon to define it more fully or to differentiate it from other phenomena. The examination of a contemporary phenomenon in a specific context, such as this study on accelerated product innovation in a big data environment, is well suited for case study research (Dubois and Gadde, 2002; Yin, 1994).

It is worth pointing out that this is not an action research study. According to Avison et al. (1999), action research is unique in the way it associates research and practice, so research informs practice and practice informs research synergistically. Also, it encourages researchers to experiment through intervention and to reflect on the effects of their intervention and the implication of their theories (Brydon-Miller et al., 2003). However, the main sets of questions during the cases were: a) what are the key approaches for accelerated product innovation?; and b) how can big data be applied to support these approaches? Rather than implementing a completely new framework or interventions with the cases, this research is trying to explore a specific topic that investigates the accelerated product innovation approaches and the big data practices applied within the case companies. During the cases, the researcher played facilitator roles (i.e., interviewing and observing people in different situations, providing clarifications and guidance to the NPD team when needed) without the insight associated with any interventions. In addition, rather than applying participated collaboration which is emphasised by action research, this study verifies the framework developed through reporting what practitioners say they do. For example, the NPD team was asked to comment on the approaches in terms of its feasibility for leveraging big data to accelerate the development of a new product/function. In short, the main purpose of his research is to generate theory from an external perspective, and for most of the time, the study cannot have control of any behavioural events (Yin, 2011). Therefore, this research is described instead as case study research.

The comparative design incorporates the logic of comparison, which implies that we can understand the utilization, benefits and challenges of accelerated product innovation in a big data environment better when comparing multiple cases (Bryman and Bell, 2015). Also, conducting multiple case studies, an extensive understanding will be obtained to guide a comparative analysis. The comparative design will outline the data collection in a cross-sectional design format with the intention of better comparing different corporate settings; in addition, to better understand how big data is being used in different settings, exploring similarities and differences. Moreover, it will further allow comparison to comprehend specific organisational behaviour and structures for accelerated product innovation in a big data environment. Further, creating categories of qualitative data will ensure comparability of findings. The multiple-case study improves theory generation. By comparing qualitative cases, the comparison will suggest relevant concepts for emerging theory (Bryman and Bell, 2015).

According to the literature review, there is a lack of research on accelerated product innovation connected to big data which in turn provides solid reasons to conduct research of multiple cases. The decision to focus on multiple cases rather than a single in-depth case is grounded in the aim to acquire a wider understanding of how to attain accelerated product innovation in a big data environment. Subject to time constraints, the aim will be to examine five case studies. The research approach in this study is akin to Popper’s (1968) approach – using a proposition under consideration to predict outcomes for specific cases and subsequently investigate these cases to see whether the theory holds true for them (Hillebrand et al., 2001). This pattern-matching technique (Campbell, 1966; Yin, 1994) allows for outcome evaluation on multiple dimensions, where as little as one actual observation for a given dimension is available (Bitektine, 2008).

According to Yin (2009), when designing case study research, five components are significant, including a study's question, propositions, the unit of analysis, the logic linking data to propositions, and the criteria for interpreting findings. Based on these five components, there can be four stages in the case study process. They are conducting constructs, identifying cases, data collection, and data analysis (Eisenhardt, 1989; Eisenhardt and Graebner, 2007; Yin, 2009).

Conducting constructs

According to Eisenhardt (1989), in the case study design process, a research question and some potentially relevant variables should be formulated with some references to the extant literature at the beginning of the case study, but these variables should not have any specific relationship with the theories. Following Esienhardt's approach, based on the research purpose, six propositions of the framework were identified for the proposed contributions of this PhD study. These propositions are helpful to shape the initial design of the current research, and they can also be further developed via the case studies. If these propositions prove indispensable as the study progresses, then this research will have a firmer empirical grounding for emergent theory (Eisenhardt, 1989).

Identifying cases

In order to address research questions, this study applies case-based research. Before identifying the cases to be studied, the case companies to be researched were considered first. Chinese companies were chosen as the research population for this investigation for three reasons. Firstly, several Chinese companies – like, for example, Xiaomi, the second largest smartphone manufacturer in the country, or Tencent, a leading internet company – have been observed to be aggressively experimenting with data-intensive, novel innovation models that have demonstrably accelerated and achieved cost benefits in their product innovation activities (Williamson and Yin, 2014). In fact, the country's activities on this front have been so impressive that McKinsey (2015), the global consulting firm, has specifically called for other countries to take note of and learn from the Chinese accelerated product innovation model. Secondly, the Chinese economy has grown rapidly over the past several decades. The confluences of the world's largest population and the dramatic growth in per capita consumption have propelled China to become the second-largest economy by Gross Domestic Product in a relatively short period of time (BCG, 2015; McKinsey, 2015). As a result, Chinese organisations are operating in an increasingly demanding consumer market environment that is catalysing these types of innovation (McKinsey, 2015) as the country tries to meet its "innovation imperative". Thirdly, most research into new product development has focused on Western economies and companies (Stanko et al., 2012; Eling et al., 2013; Roberts and Candi, 2014). Because of the size and rapid growth rate of its economy, however, China has emerged as an important new context for new product development. The specific nuances of how accelerated product innovation occurs within the Chinese context are therefore extremely relevant on both a practical and theoretical level, but have been largely overlooked in the literature. In this way, this paper shines a useful amount of light on a knowledge gap that needs to be addressed (Wei and Morgan, 2004; Yang et al., 2012).

Researchers normally select cases using replication rather than sampling logic when building theory from case studies (Eisenhardt, 1989; Yin, 1994; Voss et al., 2002). But case selection ought to be used to provide the best opportunities to learn and extend theory. In the case study, all five companies selected were focusing on accelerated product innovation and using a variety of data sources in support. In particular, the first criterion for selection was evidence of practising accelerated product innovation to concepts, features, prototypes, or full products in NPD. All the selected companies were able to reengineer their R&D and innovation process to achieve improved speed to market with reduced new product costs and good enough quality across a wide range of industries. For example, Case A was able to launch a range of new products in less than five months, at a total cost of $2 million. The company estimated that competitors using traditional design approaches have to invest around $20 million over twelve months to complete a similar set of new designs. The second criterion was a presence of a large amount of data and data analytics applied to facilitate their product innovation. The case companies have a big data analytics team or information department looking beyond online; merging with any relevant data sources as necessary. Also, these big data analytics teams do not define themselves by the tools they use or the channels they analyse. Their role is closer to one of business analyst: given a business context and a hypothesis, they will work with business stakeholders and subject matter experts, seek out any relevant and valuable information to offer the most optimal and realistic insight and recommendations. The third criterion was evidence of the development and launch of new/improved products or services in the last calendar year, since the focus of this research is on the use of big data specifically for accelerated product innovation.

Access to companies was mainly through mailing although some were via the personal contacts of the researcher at the University of Nottingham. A letter outlining the research objectives, a brochure about the deployment process and a fax back form were sent to a group of targeted companies (the individuals we contacted all had a managerial role and involvement in accelerated product innovation, NPD, big data analytics, i.e. innovation managers, senior consultants, data scientists and business developers). A follow up phone call was then made to those companies that had expressed interest in the research to arrange a meeting. More than 30 companies were contacted and most indicated interest in the research. However, only a handful (7 companies) was able to participate and commit the time and human resources required for the research. We decided to not pursue two companies due to their inapplicability towards our research objective. Key characteristics of the five cases are shown in Table 3.7 below. Table 3.8 demonstrates the different innovation projects across the five case examples, with different activities and data analytics applied.

Case	**Industry**	**Scope**	**Size (2015)**	**Revenue (2015)**	**Profitable (2015)**	**Time period**
A.	Manufacturing	New product development	13,000	£7.6b	Yes	Spring 2016
B.	Telecommunications	New product development	310,000	£32b	Yes	Autumn 2014
C.	Software	New feature development	35,000	£6.3b	Yes	Summer 2015

D.	Electronics	New product development	8,000	£7.3b	Yes	Spring 2015
E.	Software	New feature development	27,000	£9.1b	Yes	Autumn 2015

Case A: Development of a new wearable mediation headset;

Case B: Development of a new service package;

Case C: Development of a tablet device with improved functions;

Case D: Development of a new smartphone;

Case E Development of a calendar application with improved functions.

Table 3.7: Overview of the Case Studies

Case	Scope	Activities	Types of Data	Data Analytics Supported
A. Development of a new wearable meditation headset	New product development	Autonomy; cross-functional teams; simultaneous processing; understanding customers' needs; interaction with customers; sharing information and gathering feedback	Structured and semi-structured	SAP BusinessObjects (BO); Natural language processing (NLP); Office Automation System (OA)
B. Development of a new service package	New product development	Cross-functional teams; simultaneous processing; understanding customers' needs; interaction with customers; customer co-creation; sharing information and gathering feedback	Structured, semi- and unstructured	IBM Anlytics; HP Vertica
C. Development of a tablet device with improved functions	New feature development	Simultaneous processing; customer understanding; interaction with customers; customer co-creation; sharing information and gathering feedback; product launch and improve; fast learning and improvement	Structured, semi- and unstructured	Spark SQL; Google Analytics (A/B testing and crowdsourcing); Hootsuite
D. Development of a new smartphone	New product development	Autonomy; cross-functional teams; simultaneous processing; understanding customers' needs; interaction with customers; customer co-creation; sharing information and gathering feedback; network development; product launch and improve; fast learning and improvement	Structured and unstructured	Microsoft SQL Server; Hubspot, Visible Technologies
E. Development of a calendar application with improved functions	New feature development	Autonomy; cross-functional teams; simultaneous processing; sharing information and gathering feedback; network development; product launch and improve; fast learning and improvement	Structured, semi- and unstructured	PLM; Microstrategy; Hadoop Cluster, Google Analytics

Table 3.8: Innovation Projects in the Five Case Studies

All five companies were keen to support our research because: (1) the timing was good – the companies were looking to develop a new product and were willing to better understand what approaches could help save time and cost in product innovation; (2) the companies had been searching for potential product ideas and markets, and so the proposed use of big data to support accelerated product innovation fitted their current practices well; and (3) although the companies had their own versions of accelerated product innovation approaches, they wanted to tap into new ideas to enhance their current practices.

Due to the rigorous restrictions on accessing the cases, and the limited time for the current PhD research, it was difficult to focus on all the cases from comprehensive perspectives. Therefore, in this study, the case study on Cases A and B were conducted as the main cases for this study, and more data collection time was spent on it. For the other cases, with guidelines from the main case study, only perspectives seeming to be different were concentrated on, which can be helpful in reducing data collection time and overcoming the challenge of limited access to the case companies, to a certain extent.

Data collection

Before deciding on which data collection methods were to be used in this study, the criteria for collecting data were considered first. Rather than focusing only on the R&D departments of the cases, data from other perspectives were also included in this study. Collecting data from different perspectives is important from two aspects: firstly, it can enhance the creative potential of the research, since different perspectives can increase opportunities to capitalise on any novel insights which are contained within the data; secondly, it can enhance confidence in findings, since the integration of data from different perspectives can avoid biased data to a certain extent (Eisenhardt, 1989). In the current research, besides collecting data from the R&D departments in the case companies, relevant information was also gathered from other departments within the case sites. Additionally, the partners of the selected companies and even their competitors in some specific industry segments were also the sources of data in the research.

On reviewing the literature (Eisenhardt, 1989; van de Ven et al., 1989; Yin, 2009), in case study research, four data collection methods are usually involved, including archival documents, interviews, direct observations, and participant observation. The comparisons between them are summarised in Table 3.9.

Data Collection Methods	**Advantages**	**Disadvantages**
Archival Documents	Stable, unobtrusive, exact, broad coverage, and precise	Retrievability, biased, and difficult to access
Interviews	Focuses directly on case study topics; provides perceived causal inferences and explanations	Biased, inaccuracies due to poor recall, and reflexivity
Direct Observation	Reality, and contextual	Time-consuming, selectivity, and reflexivity
Participant Observation	Reality, contextual, and insightful into interpersonal behaviour and motives	Time-consuming, selectivity, reflexivity, and biased

Table 3.9: Four Main Data Collection Methods for Case Study Research

Due to the rigorous restrictions on access, it was difficult to undertake archival document research and direct observation in the selected companies. Therefore, interviews and participant observation (PO) became the primary choices for considering data collection in this study. According to McDonald (2005), PO can provide unique insights into day-to-day working practices because they shift the emphasis to the direct study of contextualised actions. The author had full access as an observer to most of the teams during a period of product innovation or while the teams applied big data. Therefore, I were able to observe the teams in their natural setting (Schultze, 2000) to understand how they work. However, both interviews and PO have their individual limitations. According to van de Ven et al. (1989), to compensate for these potential limitations, a combination of various data collection methods is necessary. Moreover, for overcoming the common weaknesses of interviews and PO, such as biased and reflexive data, the data collection criteria mentioned in the early part of this section can help reduce their negative impact.

Table 3.10 and 3.11 summarises the data collection work of the current research. As addressed previously, among the cases, Cases A and B were selected as the main cases in this research, and more data was collected on it compared to the other cases. In Case A, PO was the primary data collection method where all the R&D department's product development activities were actively engaged and recorded. In addition to the data collected from PO, interviews were also supplemental conducted in order to understand the product development activities from different perspectives for overcoming the challenges brought by privacy issues. For the other cases in this research, most data was collected from interviews to the R&D staff within the case sites directly, and some supplementary interviews were also undertaken to third-party institutes such as partners and regulators for conducting these three case studies from different perspectives. For detailed interview questions, please see Appendix G which provides coordination and a frame of reference with mainly open and general questions connected to specific topics: accelerated product innovation approaches, and big data in new product development. The semi-structured interview approach provided us with a great amount of flexibility and allowed the interviewees to freely express their experiences and opinions, which enabled greater and broader coverage of the investigated topic. Due to the iterative attributes of semi-structured interviews, we were able to vary the sequence of the questions, as well as adapt and form follow-up questions as we saw fit or based on the direction of the replies (Bryman and Bell, 2015).

Case	Interviews					
	Institution Visited	Nature of the institution	Interviewee	Position	Time visited	Duration (hrs)
A.	Head-quarters	Case Site	Z^1	R&D Project Leader	1	1
			X^1	Project leader	2	3
			F^1	R&D team member	2	3
			B^1	R&D team member	1	2
	HTD	Industry association	D^1	Deputy CEO	1	1.5
			Z^2	Project leader	1	1
	ALB	Competitor	D^2	Leader of the R&D team	1	1
			L^1	CEO	1	1
			F^2	R&D team member	1	2
	VM	Partner	Y^1	Chairman	1	2
			P	R&D senior manager	1	1
			Q	Operations manager	1	3
	Formal Staff	Individual	H^1	Previous Dean of the R&D department	2	3
B.	Guangzhou Research Institute	Case Site	Z^3	Vice General Manager	1	1
			X^2	Professoriate Senior Engineer	2	3
			R^1	R&D Director	2	2
	Ub	Partner	M	R&D Project Manger	2	3
			T^1	CEO and Technical director	1	1
	MS	regulator	G^1	Organisers and Sponsors of the project	2	3
C.	Shenzhen Customer Centre	Case Site	F^3	R&D Director	1	1
			Y^2	R&D Project Leader	2	3
			Z^4	CEO and Technical director	1	2
	INT	Partner	L^3	Deputy CEO	1	2
			H^2	R&D team member	1	1
	Former Staff	Individual	R^2	Previous Vice General Manager	1	1
D.	Technology Department	Case Site	S	R&D Director	1	2
			G^2	Senior Engineer	1	1
			T^2	R&D team member	2	3
	GZ	Supplier	D^3	Operations of the R&D Department	1	2
	AN	Partner	G^3	Head of Business Engagement	1	1
E.	Head-quarters	Case Site	S	Open Innovation R&D	1	2
			H^3	Senior Manager of the R&D Department	3	3
			B^2	Vice General Manager	1	1
	Former Staff	Individual	L^4	Previous R&D Team Member	1	1

Table 3.10: Summary of the Interviews Undertaken in the Research

<table>
<tr><td rowspan="2">Case</td><td colspan="5">PO</td></tr>
<tr><td>Institution Visited</td><td>Nature of the institution</td><td>Form of the PO</td><td>Observed Contents</td><td>Duration (hrs)</td></tr>
<tr><td rowspan="2">A.</td><td>Head-quarters</td><td>Case Site</td><td>Full-time replacement</td><td>The R&D team members' daily actives on developing Case A (2 months in total)
12 weekly internal team meetings attended by all the R&D team members (24 hrs in total)
2 meetings with the top management team attended by the director of the R&D department, the Chef Scientist of the development, and some selected project leaders (5 hrs in total)
3 meetings with a law agency attended by some patent-filing experts and all the R&D team members (6 hrs in total)</td><td>260</td></tr>
<tr><td>R&D Centre</td><td>Industry Association</td><td>PO in two meetings</td><td>Internal meetings on discussing the collaboration with the R&D department of Case A attended by all the R&D team members of R&D Centre (8 hrs)</td><td>8</td></tr>
<tr><td>B.</td><td>ZS Branch</td><td>Case Site</td><td>Fulltime replacement</td><td>The NPD team members' daily actives on developing Case A (1 months in total)
4 weekly internal team meetings attended by all the R&D team members (8 hrs in total)</td><td>128</td></tr>
<tr><td>Sum</td><td colspan="4"></td><td>396</td></tr>
</table>

Table 3.11: Summary of the PO Undertaken in the Research

In order to deal with the conflicting views among interviewees within the case, interviews were conducted by two interviewers with both NPD teams (e.g. R&D managers, heads of innovation, senior managers, project managers, as well as with a selection of R&D team members). As Eisenhardt (1989) points out, the use of multiple investigators can enhance the creative potential of the teams and the convergence of observations increases confidence in the findings. Therefore, after the interviews notes could be compared and conflicting observations could be clarified. In addition, available documentation such as the external facilitators' reports was consulted where appropriate. All of the interviews are in the in-depth, face-to-face form, and last one to three hours, and during most of the interviews, with the permission of the interviewees, a tape recorder was used to record the entire conversation. However, due to the confidentiality policy of some cases, especially for product innovation projects, a tape recorder was forbidden (please see Appendix K for detailed information). In this situation, a written record was used instead. Moreover, for confidential reasons, the names of all the interviewees, and some of the institutions visited other than the case sites, remain anonymous, and they are coded as the initial letter of their family names and company names in this research.

Data analysis

Data analysing is the most important stage when building theory from a case study, however, since the qualitative data derived from PO and interviews usually come with plenty of unstructured textual materials, the analysis of data becomes the most difficult and the least codified part in the research process (Eisenhardt, 1989; Yin, 2009; Bryman, 2012). Unlike statistical analysis with fixed formulas to guide the analysis, in case study research, data analysis mostly depends on the researcher's own style of empirical thinking and evidence, without fixed analysis models (Bryman, 2012). However, some guidelines can genuinely help researchers to undertake their qualitative data analysis.

The first guideline is from the perspective of the data analysis strategy. According to Yin (2009), four strategies exist for analysing data in case study research, including relying on theoretical propositions, developing a case description, using both qualitative and quantitative data, and examining rival explanations. In this research, due to the constructs derived from the literature, and the qualitative data collected in the data collection phase, this research adopts the strategy of relying on theoretical propositions to guide the data analysis activities. Differently from the other three strategies, analysing the data relying on theoretical propositions can be helpful to ensure concentration on 'useful' data whilst ignoring the 'useless' data, and it also helps to organise the entire case study and to update the proposed framework to be employed (Yin, 2009).

The second guideline is from the perspective of data analysis technique. Based on the data analysis strategy, relying on theoretical propositions, pattern matching is the technique adopted in this study. According to Saunders et al. (2007, p. 489), pattern matching "*involves predicting a pattern of outcomes based on theoretical propositions to explain what you expect to find*". When adopting this data analysis technique, based on the constructs developed in the literature, the data are classified into patterns, and all these empirically-based patterns are compared with other researchers' existing findings (Yin, 2009). If the patterns of the data appear to match other research, the result will be helpful in strengthening the internal validity of the case study (Saunders et al., 2007).

The third guideline is from the perspective of data analysis methods. This study adopts within-case analysis to deal with the data as the first step. Since the research questions for a case study are usually open-ended, the research usually comes with a massive volume of data, which makes within-case analysis one of the key steps in the research process, to cope with the volume of data. With the help of within-case analysis, this study created familiarity with each case, and accelerated further cross-case comparison (Eisenhardt, 1989). The subsequent step in the data analysis work is cross-case analysis. For the data comparison, as previously mentioned in the case selection section, cases were selected from the case companies chosen for this research. According to Eisenhardt (1989), there are two strategies to undertaking cross-case analysis: firstly, dimensions are selected to look for within-group similarities as well as inter-group differences; secondly, different pairs of cases are chosen, and the similarities and differences between each pair are listed. Following the above data analysis methods, in the research, the key approaches of the framework developed were catalogued into each activity of the conceptual framework for the in-case analysis, and referring to Rohrbeck's (2011) research work, all the capabilities were marked from level 0 to level 3 in each case, where the general measurement criteria can be discussed as in Table 3.12.

Level	Characteristics
0	The NPD department did not concentrate on the proposition for developing its new product
1	The NPD department had some concentration on the proposition but not much
2	The NPD department concentrated on the proposition but neglected a few significant perspectives.
3	The NPD department concentrated on the proposition from all the significant perspectives.

Table 3.12: Factor Rating Level

Moreover, for the specific measurement criteria of each individual proposition, they are further developed in detail in the research for undertaking the cross-case analysis more efficiently (please see Appendix F for detailed information).

The fourth guideline is from the perspective of the data analysis process. Referring to Eisenhardt (1989), this research divides the case study data analysis into two steps. In the first step, the propositions are established, building evidence in each case. In the second step, this study verifies that the emergent relationships between propositions fits with the evidence in each case, and the cases that confirm the emergent relationships can enhance confidence in the validity of the relationship, whilst the cases that weaken the relationships can inspire an opportunity to refine and extend the theory.

The final guideline for data analysis in the case study research is from the perspective of comparing the proposition with the literature. In this study, when the research findings were proposed, the propositions of the framework in each product innovation activity were compared with the literature to find theoretical support from the sources used. According to Eisenhardt (1989), this perspective can be helpful in enhancing the emergent theory from the perspectives of internal validity, generalisability, and the theoretical level of theory building.

All the qualitative data were collected and systematically processed through the stages proposed by Lincoln and Guba (1985) and Locke (2001): data reduction, focused coding, and data display. In the first stage, we identified areas pertaining to the dominant themes: agile structure, customer involvement, ecosystem of innovation and big data practice. The themes were summarised from theory and practice (stage 1) and further improved through conducting three in-company cases (stage 2.1). In the second stage, we focused on coding extracted passages relating to the main themes as well as the sub-themes. In the final stage, data display, we made tables and lists of passages and monitored the internal cohesion of the codes. The coding was an iterative process which went through several rounds of coding, and after each coding round the data were compared and discussed. During this whole process, I found a few discrepancies between the codes. The themes found in the codes were also related to the observational data. An example of a set of codes applied to the data is presented in Table 3.13 below.

Examples (Quotes)	Themes and sub-themes coded
Case A:	Agile Structure
"By applying real-time communication (OA software used), different function departments are grouped together to work actively. It cuts across boundaries of different departments and every team member becomes involved in marketing, engineering, design, production or R&D."	• Cross-functional teams Big Data practice • Data analytics applied for supporting NPD
"Managers are engaged in conversations with each other: it would be so good if we could build partnership with…"	Innovation Ecosystem • Partnership with the others
Case C:	
"Customer feedback can save us a lot of time and has eliminated a vast amount of unnecessary double communication within various teams."	Customer Involvement • Understand customers' needs

Table 3.13: Examples of Coding

Qualitative social research relies on various methods for systematizing, organising, and analysing qualitative data. Today, researchers increasingly make use of computer software for their qualitative data analysis. Qualitative data analysis software is used in many academic fields, such as sociology, psychology, political science, medicine, and educational science, and it is also a popular tool for business and market researchers. Software tools for qualitative data and text analysis allow for easy sorting, structuring, and analysing of large amounts of text or other data and facilitate the management of the resulting interpretations and evaluations. Many qualitative software analysis tools can be used in conducting qualitative data analysis such as ATLAS.ti, MAXQDA, NVivo, QDA Miner, and CAQDAS. These tools enable researchers to conduct research using many methods of analysis, such as those used in Grounded Theory, qualitative content analysis, mixed methods analysis, and discourse analysis. Particularly, MAXQDA was used to support qualitative data analysis in this study. The central elements of MAXQDA are the systematic assignment (‘coding’) of data segments (text, tables, image, media) to major themes (‘codes’) and the possibility to take note of references, ideas, etc. directly in the text (‘memos’). In MAXQDA, analysis and evaluation can be done by sorting materials into groups, using a hierarchical coding system, defining variables, and assigning colours and weights to text segments. For example, Tables 3.14 and 3.15 show the document and coding system of MAXQDA applied in this research. Using MAXQDA can help to manage the company cases conducted during my entire PhD study effectively. In particular, text documents or PDF files can be imported and organised in different groups. Also, relevant quotes can be linked to each other and project-wide search makes it easy to find what you are looking for. Additionally, the coding system can be expanded or refined which makes each of the case analysis more flexible.

Figure 3.3: Examples of MAXQDA Document System (Cases of Year 1 to year 3)

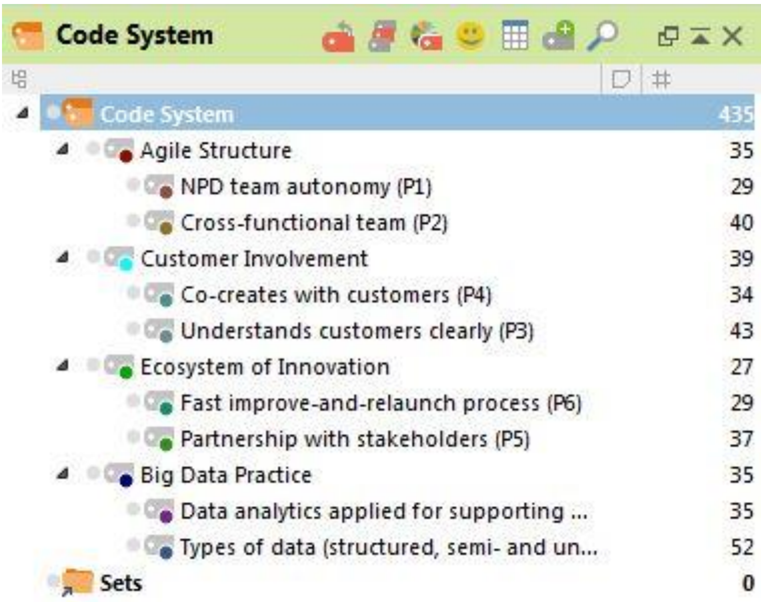


Figure 3.4: Examples of MAXQDA Coding System (Themes and sub-themes coded)

Table 3.16 illustrates the coding and retrieving functions of MAXQDA. During the data analysing, important information can be marked in specific databases with different codes through using regular codes, colours, symbols or emoticons.

Moreover, retrieving coded segments can help to find the relevant information quickly and efficiently with just one click.

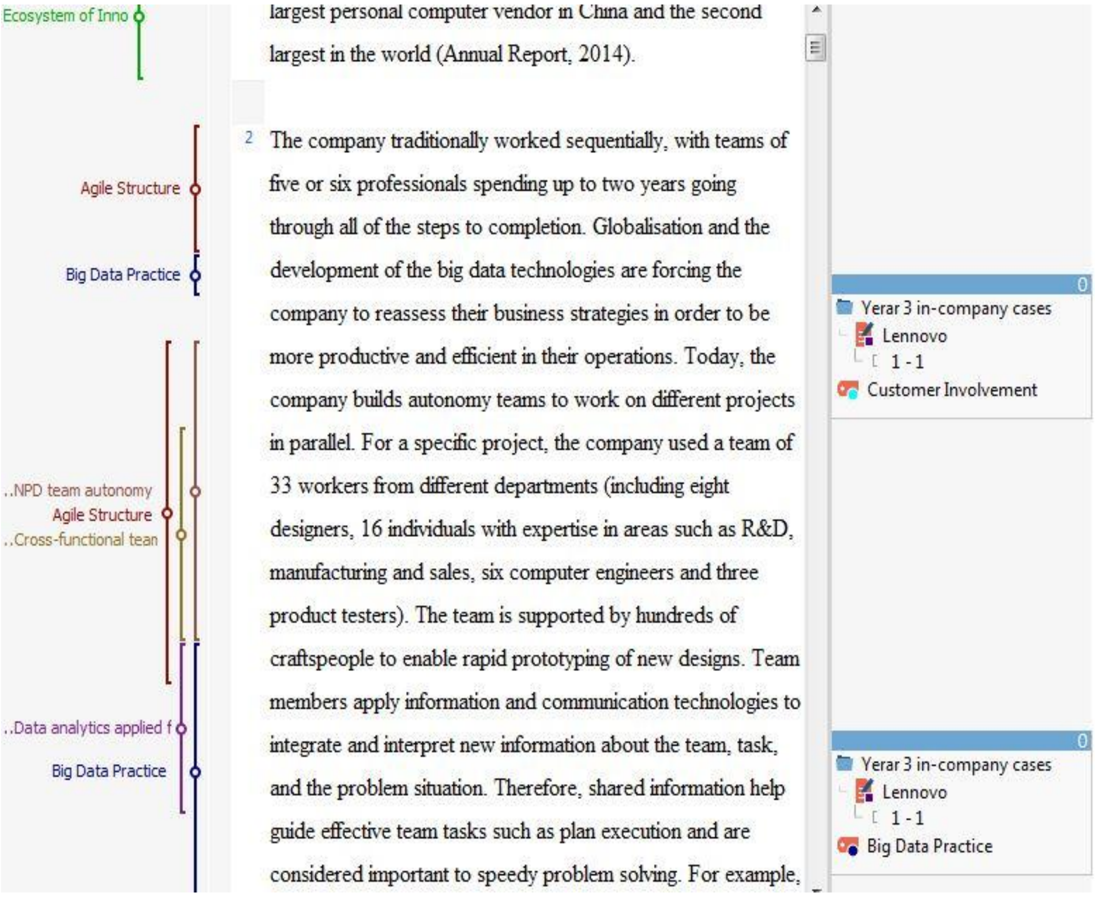


Figure 3.5: Examples of MAXQDA Coding and Retrieving

Validity

According to Bryman and Bell (2015), the validity of the research is a fundamental quality criterion, referring to how well research measures its main objective. Research does not aim at generalisation across all industries, but rather investigates a framework with the key approaches for accelerated product innovation in a big data environment, and how big data can be used to facilitate product innovation. In qualitative research, there is a risk of receiving wrong or fabricated answers upon which the empirical evidence is later based. This can be based on the fact that respondents are biased in their views of the potential of accelerated product innovation because people are not always willing to write their true views on a questionnaire or tell a stranger what they really think at interview. Observations in this study can be made in real life situations, allowing the researcher access to the context and meaning surrounding what people say and do. Therefore, it reduces bias during the interviews and provides a better chance to examine the propositions through investigating each case more comprehensively and deeply. Moreover, the strategy of semi-structured qualitative interviews allowed us to address difficulties, such as misinterpretations or insufficient answers by restating or reformulating questions. Thus, well formulated research questions also increased the internal validity. Furthermore, the interviews were conducted by two interviewers. According to Leonard-Barton (1990), multiple interviewers also guard against observer bias and increase research validity.

The external validity is increased due to the data collection from individuals at senior and managerial positions who are involved within accelerated product innovation or big data activities in a direct or indirect way. Further, Bryman and Bell (2015) argue that multiple case studies increase the external validity. In addition, transcribing the interviews as well as sharing the collected data for input with the interviewees also increased the external validity.

Reliability

On the one hand, Bryman and Bell (2015) state that ensuring external reliability in qualitative research is difficult since it requires reproducibility, hence often requiring the same conditions and settings during the research study. The reliability of this research is increased through grounded theory and a well-connected theoretical framework to the empirical evidence. Additionally, by doing tables and comparisons of the unique interviews we could observe distinctions. On the other hand, establishing a high level of internal reliability is tricky when conducting qualitative research since it is based on subjectivism and individual perception of what has been said. Since we were two interviewers during the interviews we could mitigate such difficulties and ensure internal reliability and inter-observer consistency (Bryman and Bell, 2015). Moreover, performing semi-structured interviews further enriched the reliability of the data collection and increased the reliability of our research. We aimed to spot areas within the answers of the interviewees and add or modify some questions in order to achieve a further exploration of our study.

3.5 Summary

We conducted a two-stage research process: identifying the key approaches, refining and examining in a number of interviews and company cases to develop a framework for accelerated product innovation in a big data environment. The framework was further verified in five comparative in-company cases.

In the first stage, careful attention was paid to identifying the key approaches for accelerated product innovation in a big data environment and then to incorporating, in addition to the literature, some of the knowledge of academics and industrialists.

In the second stage, careful attention was paid to the development and verification of the framework. The relevance of the research came from the direct applicability of the approaches identified to real product innovation projects that different companies face.

CHAPTER 4.0 APPROACHES FOR ACCELERATED PRODUCT INNOVATION IN A BIG DATA ENVIRONMENT

Chapter 2 illustrated that little is available in existing product innovation literature to assist managers in attaining accelerated product innovation in today's big data environment. Therefore, the aim of this research is to identify the key approaches and develop a framework for accelerated product innovation in a big data environment.

Chapter 3 described and justified the method of bridging such a gap, and explained the two main stages of the research design:

- the identification and refinement of the key approaches for accelerated product innovation in a big data environment
- the development and verification of the framework (incorporating the approaches identified)

This chapter reports on the first stage – that is to identify and refine the approaches for accelerated product innovation in a big data environment (Figure 4.1 illustrates this identification and refinement process). Section 4.1 describes the identification of the key approaches for accelerated product innovation. Section 4.2 presents the results of the empirical studies and the refined approaches. Section 4.3 discusses the learning gained. Section 4.4 presents the conclusions of this chapter.

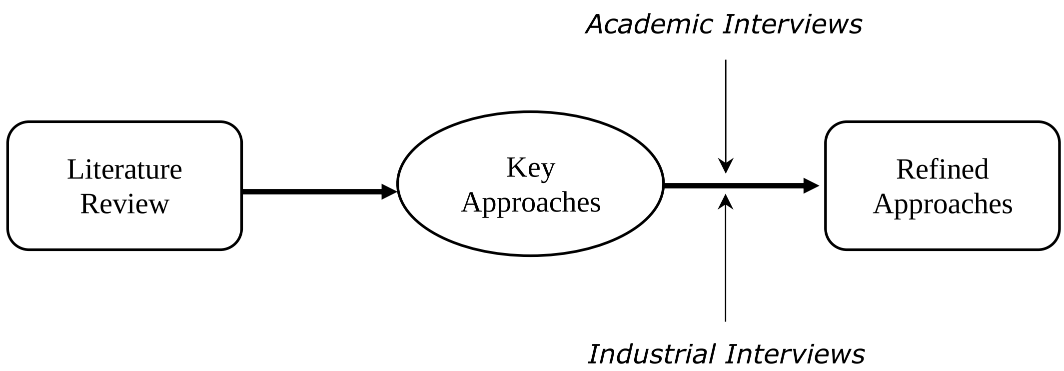


Figure 4.1: Identification and Refinement of the Approaches

4.1 Approaches for Accelerated Product Innovation

Many studies indicate that product innovation can potentially be more successful if a number of approaches are improved and implemented (Gold, 1987; Millson et al., 1992; Langerak et al., 1997; Chen et al., 2010; Eling et al., 2013; Williamson and Yin, 2014). Failing to do so can have disastrous results for a firm. As shown in Table 4.1, building on the considerable amount of literature, we identified various approaches that might contribute to accelerated product innovation. The approaches identified were summarised from prior studies and can be theoretically categorised into four different innovation phases as: pre-development research; accelerated product innovation process; customer connection; and an ecosystem of innovation. A series of interviews with leading academics and big data experts from a number of industries and disciplines were then conducted to examine and further improve the approaches as well as the phases.

Innovation Phase	Approach	Literature Support*
Pre-development research	Preliminary market assessment Detailed market study Financial analysis Well-defined product	1, 3, 5, 7, 8, 11, 12, 13, 15, 16, 17, 18, 19, 20, 22, 25, 26, 29, 30, 32, 34, 35, 38
Accelerated product innovation process	Systematic innovation process Autonomy management Cross-functional teams Simultaneous development	1, 2, 3, 4, 5, 8, 9, 10, 13, 14, 15, 18, 20, 21, 24, 26, 27, 30, 31, 32, 33, 34, 35, 36, 37, 38
Customer connection	Market orientation Customer communication Understanding of customers Good relationship with customers	1, 3, 4, 5, 6, 7, 9, 13, 16, 17, 18, 19, 20, 22, 24, 25, 26, 27, 28, 29, 30, 31, 33, 35, 37, 38
Ecosystem of innovation	Proficiency of marketing test Fast development and launch Quick response to market Market and partner tests	1, 2, 3, 4, 7, 11, 14, 15, 16, 18, 19, 23, 24, 26, 27, 29, 30, 31, 32, 33, 34, 36, 37, 38

*Notes: 1. Cooper (1980; 1996; 1999); 2. Mann and Jones (2002); 3. Lovelace et al. (2001); 4. Sethi et al. (2001); 5. Cooper and Kleinschmidt (2011); 6. Atuahene-Gima (1995); 7. Balbontin et al. (1999); 8. Barczak (1995); 9. De Brentani (1989); 10. Calantone and Di Benedetto (1988); 11. Calantone et al. (1997); 12. Dwyer and Mellor (1991); 13. Griffin (1997); 14. Al-Mashari and Zairi (1999); 15, Quesada and Gazo (2007); 16, Maidique and Zirger (1984); 17, Mishra et al., (1996); 18, Parry and Song (1994); 19. Rothwell et al. (1974); 20. Rubenstein et al. (1976); 21. Liao and Barnes (2015); 22. Song and Parry (1997); 23. Souder and Chakrabarti (1978); 24. Souder et al. (1997); 25. Utterback et al. (1976); 26. Evanschitzky et al. (2012); 27. Williamson and Yin (2014); 28. Lin et al. (2010); 29. Rese and Baier (2011); 30. Millson et al., (1992); 31. Langerak et al., (1999); 32. Barczak et al., (2008); 33. Callahan and Moretton, (2001); 34. Zirger and Hartley, (1996); 35. Ali et al., (1995); 36. Eisenhardt and Tabrizi, (1995); 37. Kessler and Chakrabarti, (1996); 38. Griffin, (2002).

Table 4.1: Approaches for Accelerated Product Innovation

In terms of the pre-development research, Cooper (1994) points out that the seeds of success or failure are sown in the first few steps of the process (the pre-development phase). The key approaches identified in this innovation phase are: preliminary market assessment, detailed market study, financial analysis, and well-defined product. The pre-development phase is important because it qualifies and defines the project. Many projects are poorly defined when they enter the development process. This is often the result of weak pre-development activities: the target user is not well understood, user needs and wants are vaguely defined and required product features and attributes are fuzzy. Those in R&D and design engineers are not mindreaders. With a poorly defined project, they waste considerable time seeking definition, often recycling back several times to get the product right. Better project definition, the result of sound pre-development research, actually speeds up development. What is more, pre-development research up front encourages changes to occur earlier in the process rather than later, when they are more costly. The result is considerable savings in time and money at the back end of the project and a more efficient product innovation process.

The accelerated product innovation process aims to use systematic methods to speed up the NPD process as much as possible. There are key approaches identified in this phase, as Table 4.1 shows: systematic innvoation process, autonomy management, cross-functional teams, and simultaneous development. Speed yields competitive advantages: being the first on the market can result in a quicker realisation of profit, and there will be a lower risk that the competitive situation or market would have changed before the new product can be launched (Steinfeld and Beltoft, 2014).

Systematic innovation approaches are significant in the product innovation process; it can create value and secure competitive advantage for organisations by generating a series of innovations, rather than unplanned or haphazard activities (Mann and Jones, 2002; Sheu and Lee, 2011). The autonomy management approach is based on guaranteeing the freedom of the individual groups of employees to decide on basic issues; it can improve efficiency and increase the effects of employee job satisfaction and motivation to work. Cross-functional teams can improve integration and coordination, span organisational boundaries, and reduce the production cycle time in new product development (Cooper and Kleinschmidt, 2011). What is more, bringing people together from different disciplines can improve problem solving and lead to more thorough decision making, which makes it easier to achieve corporate goals and customer satisfaction at the same time (Sethi et al., 2001). Simultaneous development is an approach of designing and developing products, in which the different stages run simultaneously, rather than consecutively. Applying such an approach can result in great benefits for organisations, such as reduced overall programme costs, lower manpower requirements, reduced potential risks, improved high-quality products and flexibility (Lovelace et al., 2001).

In terms of customer connection, a thorough connection with and understanding of customers is significant: the more the customer is understood, and the more that understanding is implemented in product innovation, the more positive the impact will be on market share, revenues and margins (Evanschitzky et al., 2012; Bohlmann et al., 2013). Therefore, a strong customer connection is critical for accelerating NPD in product innovation. With regard to customer connection, in terms of firms' value creation in product innovation, this research identified four key approaches from literature (as Table 4.1 shows): market orientation; customer communication; understanding of customers; and keeping good relationships with customers. According to Chesbrough (2003), companies are increasingly rethinking the fundamental ways in which they generate ideas and bring them to market. Because R&D has long been a costly and inexact process (Anders and Ali, 2004), customer connection has been widely acclaimed in management rhetoric as a means to tighten the feedback loop between the cycles of consumption and production (Lundkvist and Yakhlef, 2004). Underlying most such views is the assumption that customers are sources of information and knowledge (Lacity and Willcocks, 2014) and that customer connection can enhance product concept effectiveness (Anders and Ali, 2004).

Adner (2006) defines an ecosystem of innovation as the collaborative arrangements through which organisations combine their individual offerings into a coherent, customer-facing solution. As one of the identified phases for accelerated product innovation, an ecosystem of innovation refers to building an innovative and market-testing environment that can support organisations to develop new products at dramatically faster speeds and with lower expense. There are key approaches identified in this phase, as Table 1 shows: connection with customers and partners; proficiency of marketing tests; fast development and launch; quick response to markets; and market and partner tests. Bogel et al. (2014) point out that the ecosystem allows organisations to generate a greater value that no single firm could have generated alone. It also bridges the gap between the need for new product definitions and the changeable market conditions as development proceeds (Gupta, 2013). For each project, instead of focusing on R&D internally, allocating resources externally from partners (e.g. with customers, universities or companies) can be far more effective because critical bottlenecks may reside outside the company (Lacity and Willcocks, 2014). Especially when enabled by information technologies that have drastically reduced the costs of coordination, innovation ecosystems have become a significant innovation phase in the growth strategies of organisations in a wide range of industries (Adner, 2006).

4.2 Empirical Studies

In order to examine and refine the approaches and phases identified from literature, a number of interviews with academics and industrialists were conducted. This was to ensure that the proposed research was relevant to industry and take account of current research and development. The feedback from the interviews was used to refine the approaches and innovation phases involved in accelerated product innovation in today's big data environment. Particular attention was also paid to the current approaches used for accelerating product innovation, and their strengths and weaknesses. Details of the interview setup were presented in Chapter 3. A summary of the key learning points from the interviews is presented below.

4.2.1 Shortcomings of Current Approaches

Existing approaches to facilitate product innovation were mainly focused on the overall NPD process, but lacked sufficient detail on accelerated product innovation (in other words, how to facilitate product innovation to lead to it being faster and less costly in a big data environment). Based on the results of interviews (Appendix C and D), most academics point out that current innovation processes are focusefd on deployment process, most of them are lacking in market focus and some are too time-consuming and having too much cost ineffectiveness. Also, some of them are bureaucratic and have no provision for focus. Aditionally, the industrialists call attention to the structrual issues of the current innovation processes which are becoming too complex to manage efficiently and effecively. For exmaple, it is difficult to determine the approaches in different situations and hard to generate a feasible implementation approaches. Table 4.2 summarises the shortcomings higlighted by the academics and industrialists.

Academics	**Industrialists**
• Primarily focused on deployment process; • Lack of structured approach for facilitating product innovation; • Too time-consuming; • Long development cycle; • Lack of market focus; • Low commercial success rate, etc.	• Unstructured; • Difficult to determine the approaches in different innovation phases; • Hard to generate a feasible implementation approaches; • Relies on individual experience; • Lack of documentation capabilities,etc.

Table 4.2: Shortcomings of Current Approaches to Product Innovation

During the interviews, we received a vast amount of feedback on the identified approaches according to each of the phases and their potential implementation in product innovation in a big data context. We recorded both broad agreements and controversial opinions on the discussions. Table 4.2 summarises the feedback obtained from the interviews of different organisation executives and research experts about the identified innovation phases in facilitating product innovation in a big data environment.

	Pre-development Research	Accelerated Product Innovation Process	Customer Connection	Ecosystem of Innovation
Firm A	√		√	√
Firm B		√	√	√
Firm C	√	√	√	
Firm D		√	√	√
Firm E		√	√	√
Firm F		√	√	√
RSR a	√	√	√	√
RSR b		√	√	
RSR c	√	√	√	√
RSR d		√	√	√
RSR e	√		√	√
RSR f	√	√	√	
RSR g		√	√	√

(√ = Agree with the phase; RSR = Researcher)

Table 4.3: Summary of the Interview Results

4.2.2 Accelerated Product Innovation Process

Overall, the managers and researchers felt that the identified innovation approaches and phases are conceptually accurate in capturing the essence of product innovation in a big data environment. For the accelerated product innovation process, we observed broad acceptance among organisations and research experts. By applying this concept, self-directed teams emerge as the way to drive innovation and deliver great products, and we observed that it can create high velocity in product innovation projects. Most interviewees comment on autonomous teams as being more effective for addressing projects with high technological novelty or radical innovation, especially in a big data environment. Also, some interviewees found the cross-functional teams and simultaneous management to be very "*new to its produce development's culture*", and can help communication more broadly, gain alignment more easily and build better products in a short time. It was highlighted that the approaches included in this phase can provide a better big data-supported approach for accelerated product innovation:

Most of the interviewees believed that by implementing the accelerated product innovation process, people from different function departments are grouped together to work actively. It cuts across boundaries of different departments and there is no more marketing team or production team. Instead, every team member becomes involved in marketing, engineering, design, production or R&D. This movement can save us a lot of time and eliminate a vast number of unnecessary double communications within various teams.

In particular, according to the manager from Frim B, "*old, sequential method of design engineering, throwing the product design over the wall into manufacturing's domain is no longer acceptable. By harvesting big customer data allows previously unrecognised customer needs or combinations of needs to be identified".* Also, researcher G mentioned that *"risk and market uncertainties can be reduced by using big data analytics"*. Researcher D and F further pointed out that "*by applying big data analytics, it is possible to increase the number of test options and to institute parallel testing of product alternatives among a variety of customers; moreover, this can be done repeatedly throughout the different stages of NPD"*. The manager from Firm E also commented that "*the autonomy process takes some time to understand but okay afterward. It can save us a lot of time and has eliminated vast amount of unnecessary double communication within various teams".* Manager D felt that the process was very useful for them to develop an 'accelerated product innovation network' from a firm perspective. He further pointed out that "*each of us sees the factory operations through a unique set of lenses that is determined by our personal experiences, and our capabilities. Thus, none of us, as part of a functional group, have a good understanding of the innovation processes entirely. However, by implementing the cross-functional team, people from different function departments are grouped together to work actively".* All the participants agreed that in order to achieve the accelerated product innovation process, projects need to be divides into small elements (and applies autonomy and cross functional teams). Also, big data can be used to further facilitate communication and development process. The participants had high confidence in the refined approaches reached. This observation adds to the fact that the approaches of the accelerated product innovation process are commonly known and integrated in numerous business and theoretical concepts.

In addition, based on interview feedback, Table 4.4 shows the summary of refined approaches for accelerated product innovation in a big data environment. In particular, instead of applying a systematic innovation process, interviewees point out that systematic innovation processes are not necessary because current accelerated product innovation approaches tends to be more agile and flexible in order to adapt to today's fast changing situations while improving efficiency and effectiveness. Moreover, big data can be used in different approaches as a source to accelerated product innovation (e.g., facilitating team communication and development process).

Approach (Origin)	**Approach (Refined)**
• Systematic innovation process • Autonomy management • Cross-functional teams • Simultaneous development	• Divides the project into small elements • Autonomy management • Cross-functional teams • Simultaneous development • Uses big data to facilitate communication and development process

Table 4.4: Summary of Refined Approaches

4.2.3 Customer Connection

Most of the organisation experts and researchers concurred with the customer connection. They referred to various examples of their current projects addressing the importance of customer connection in product innovation. One organisation's marketing manager pointed out that the proposed customer connection phase provides more than merely an idea for product innovation. It supplies the firm with information on market needs or existing problems, product-related specifications or even a complete product design. It is generally believed by the interviewees that as one of the most important phases in product innovation, organisations need a process in place to pay close attention to their customers in every phase of the product innovation value chain, from idea generation to product development to marketing. According to the CEO of Firm F:

"Normally, companies just determine their main customers and potential customers, but big data will allow them to investigate more detailed aspects such as where they are, what problem they face, what they need, how they want to be contacted and when". The manager of Firm A explained that "*customer connection can be facilitated through utilising big data to provide new or more precise insights. The insights can be gained in a digital form, such as use tests, in order to understand the customers and adjust the decisions about the products accordingly. Therefore, big data allows users' behaviours to be examined and thus their demands can be fitted"*. Moreover, Researcher C pointed out that "*big data can be used to generate great ideas from a variety sources. Lead customers (or innovative users) often act as co-creators and support NPD managers in developing 'winning products' to the market"*.

The manager from Firm B and C agreed that "*gained a deeper understanding of customers' needs at the very beginning stages of the NPD".* The senior manager from Firm A further pointed out that "*by pushing core customers into the process early, and continuing to work with them in parallel, it is possible to avoid the pitfalls that are based on a one-shot market research project at the conceptual stage"*. The IT manager from Firm F stated that *"Normally we just determine our main customers and potential customers but the latest big data techniques allow us to investigate more detailed aspects, such as where they are, what problem they face, what they need, how they want to be contacted and when"*. Researcher D pointed out that "*the refined customer connection approach is partly to renew our customer connection and also to see what the customer really needs.*" In short, the observation shows that customer connection (including customer understanding, interaction and co-creation) is significant for every organisation to facilitate their product innovation, and it can be further enhanced by harvesting values from big data.

In terms of the customer connection phase, the key approaches were improved according to the feedback from the interviewees (as summarised in Table 4.5). Their feedback indicates that market orientation should be achieved through better understanding of customers. Also, the notion of customer interaction and co-creation is highly pertinent in the age of big data where emphasis is placed on the receiving and sharing of ideas and perceptions with customers. In addition, customer understanding and communication can be further enhanced through big data supported activities (e.g., customer interaction and customer co-creation). In this way, companies can achieve a win-win situation with their customers.

Approach (Origin)	**Approach (Refined)**
• Market orientation	• Customer understanding
• Customer communication	• Customer interaction
• Understanding of customers	• Customer co-creation
• Good relationships with customers	• Applies big data to gain better customer connection and market understanding

Table 4.5: Summary of Refined Approaches

4.2.4 Ecosystem of Innovation

There was broad agreement on the innovation ecosystem concept among business executives and researchers, which underlines this concept's high diffusion and acceptance. As a result, it costs the companies less time and money than would ordinarily be required, by concentrating on new product research and development rather than other non-value adding processes. According to the interviewees, by building a stable and diverse ecosystem of innovation, organisations can conduct product innovation and provide new products to meet their customers' requirements in a much more efficient and effective way. One organisation executive (Firm C) outlined the ecosystem of innovation as a major business opportunity:

"The company is already spending about a million dollars in cooperating with desirable partners among the entire supply chain to support its product innovation

ecosystem and it helps the company gain an outsized competitive advantage such as offering the consumer a greater value than the competitors, as well as providing better products and services". Researcher E further explained that *"if a certain competency has nothing to do with how you are positioning yourself in your market and creating value for your customers, then don't oversupply it. Put your energy elsewhere, where you are going to differentiate".*

Moreover, for competitive advantage, companies should identify their key components and all the intermediates within its networks involved in product development before a new product reaches the eventual customers. According to Researcher D and F *"gathers feedback quickly from customers and partners lends itself to customer loyalty and retention; for example, through using big data (such as online participation in NPD), customers gain a better understanding of a new product but also become attached to the product to which they have made a contribution*". The R&D manager of Firm D agreed the point by showing a real case that "*rather than spending time on internal R&D to make the product perfect, Didi Dache and Xiaomi tend to launch their new product ideas on the market quickly (and are able to do so through building strong networks with various partners) and then improve them through extremely fast and continuous rounds of commercial realisation and testing within their ecosystems. Hence, companies can earn a premium by staying abreast of competitors' innovations and by having up-to-date products available in volume at affordable prices. In the ecosystem, innovations are made from interrelated networks and these empower organisations to rapidly integrate useful feedback from customers and partners*".

Furthermore, Research F supported the innovation ecosystem by pointing out that "*By applying the fast improve-and relaunch process, what I see is a more agile, dynamic and flexible approach that is lean, rapid response and costs less*. *Through this repeated accelerated innovation cycles, project teams can iterate the product in sync with evolving market requirements and stay ahead of the competition".* Therefore, with the fast-improve-relaunch innovation ecosystems, firms are better able to respond to today's fluid, changeable information and evolving market conditions. However, a few academic experts criticised the innovation ecosystem concept as being too simple. For example, it was argued that the concept is based on successful examples of agglomeration, whether in industrial, entrepreneurial, economic or geographic terms. As such, there is relatively little new about the innovation ecosystem compared with earlier concepts like development clusters or blocks. These diverse and sometimes controversial viewpoints underline the difficulties when trying to operationalise the concept of innovation ecosystem.

In short, Table 4.6 shows the refined approaches according to the interviewees' comments. Their comments indicate that in order to establish an ecosystem of innovation for accelerated product innovation, it is essential to build strong networks with various partners. Additionally, big data can be used to connect with the partners and gather feedback quickly from partners and customers. Furthermore, they suggest a fast improve-and-relaunch process which indicates an innovation and market testing environment to develop new products at fast speeds and lower costs.

Approach (Origin)	**Approach (Refined)**
• Proficiency of marketing test • Fast development and launch • Quick response to market • Market and partner tests	• Builds strong networks with various partners • Gathers feedback quickly from customers and partners • A fast improve-and-relaunch process

Table 4.6: Summary of Refined Approaches

4.2.5 Pre-development Research

In terms of the pre-development research phase, most of the interviewees expressed dissatisfaction with the approaches toward accelerated product innovation in a big data environment. Although many researchers pointed out that pre-development research is key to success, most of the organisation experts in particular commented that time to market is widely recognised as one of the most important attributes of strong innovators to gain competitive advantages, particularly in high-tech industries in which product life cycles are often three years or less. In this context, pre-development research could be extremely time-consuming. Also, pre-development research can be achieved in the early stage of customer connection via harvesting information from big data. As an R&D manager points out:

Companies should not spend too much time on pre-development research because people don't know what they want until you show it to them.

Customers today are too sophisticated to satisfy because they always demand products with the latest technology, cutting-edge functionality, at an unprecedented low price, and immediate services. At the same time, they don't have much brand loyalty and keep comparing the product with others. Instead of spending a lot of time and resources on conducting pre-development research, big data can be used as the most important source in generating new ideas, capturing useful information, assessing target markets, introducing new product concepts and gathering feedback. Therefore, as pre-development research shall be included as part of customer connection and market understanding via big data, it was removed from the identified innovation phases.

4.2.6 Reflection and Learning

The main focus of this study is to investigate the approaches for accelerated product innovation in a big data environment. Because the real company situation is more than complicated, for different companies, they have different objectives, R&D focus, big data technology, available data and so on. Therefore, it is extremely difficult (and meaningless) to provide specific big data analytics for particular NPD projects. More importantly, the feedback from the industrialists indicates that most of the companies already have their own big data analytics and technologies. Therefore, instead of conducting a specific big data analysis, this research explores the approaches that could support organisations to tap into new ideas captured from big data to facilitate their accelerated product innovation in NPD.

During the interviews, the main problem companies faced was a lack of a framework with structured approaches for accelerated product innovation in a big data environment. The current approaches for product innovation were mainly identified based on their working experiences. Companies also found it difficult to apply due to many limitations (e.g., lack of structured approach for facilitating product innovation, too time-consuimg, and long development cycle). This created difficulties in attaining accelerated product innovation in today's big data era.

All interviewees outlined the advantages of the identified innovation approaches and phases for accelerated product innovation as an orientation framework for supporting product innovation in a big data context. Often, the phases for accelerated product innovation were considered particularly helpful in organisations when employees needed to be introduced or sensitised to the concepts, such as autonomy, cross-functional team, and ecosystem of innovation. Organisation experts initially criticised the lack of possibilities for quantitative methods/techniques to harvest big data, but later acknowledged the proposed phases' role as a meta-method (Paterson et al., 2001). These observations underscore two facts. On the one hand, businesses seek accurate amounts of valuable information from big data as a basis to facilitate their product innovation. On the other hand, large organisations may have already built up their big data toolbox of analytic techniques and methods to support product innovation, and hence they may not necessarily take advantage of the phases as a meta-method. Small and medium-sized enterprises (SMEs), conversely, might not have enough resources to engage in the field of big data analytics. Here, the developed innovation phases and approaches as a meta-method could significantly support organisations in providing guidelines for appropriate accelerated product innovation in a big data environment.

The academic highlighted the fact that research into developing a framework for accelerated product innovation in a big data environment was very much needed. All industrial interviewees expressed dissatisfaction with the current innovation approaches for NPD. This finding corresponds with the gaps identified in the literature review. In general, they believed that a framework with the following characteristics would be very helpful to them. It should:

- Be simple and easy to understand
- Flexible and can be generalised to different situations
- Generate feasible aproaches in different innovation phases
- Be particularly relevant in a big data environment

The industrial and academic interviews confirmed that this research is worth pursuing further, as it addressed a significant gap between the traditional product innovation approaches and the approaches for accelerated product innovation in a big data environment. In meeting this aim, more structured approaches and phases for accelerated product innovation in a big data environment were developed (see Table 4.7), which took account of the inputs from interviews.

Innovation Phase	**Approach**
Accelerated Product Innovation Process	• Divides the project into small elements • Autonomy management • Cross-functional teams • Simultaneous development • Uses big data to facilitate communication and development process
Customer Connection	• Customer understanding • Customer interaction • Customer co-creation • Keeps good market understanding and customer connection via big data
Ecosystem of Innovation	• Builds strong networks with various partners • Gathers feedback quickly from customers and partners • A fast improve-and-relaunch process

Table 4.7: Refined Approaches for Accelerated Product Innovation

To summarise, the developed phases for accelerated product innovation are: accelerated product innovation process, customer connection and innovation ecosystem, which gained significant support in all approaches for accelerated product innovation in a big data context. These phases with relevant approaches can be seen as an orientation framework and introduction to the field of big data, adding value to both product innovation and big data management.

4.3 Implications

The core competitive advantages of the approaches identified arise from the use of big data to attract and connect to a wide range of networks in each phase of product innovation. This might be through the presentation of mock-ups, images or videos of the new product to customers and thus the gathering of feedback early in the process of product innovation (Tuulenmäki and Välikangas, 2011). By applying the accelerated product innovation process, innovations are made from interrelated networks and these empower organisations to conduct their NPD rapidly and integrate useful feedback from customers and partners (Wang, 2009). Through big data supported customer connection, project teams can iterate the product in sync with evolving market requirements and stay ahead of the competition. With the innovation ecosystems, firms are better able to respond to today's fluid, changeable information and evolving market conditions (McAfee and Brynjolfsson, 2012).

Traditionally, the new product development process involved inefficient sequential processing of information between functional specialities. The ecosystem of innovation phase allows firms to adapt and respond rapidly to changing market needs and to develop innovative products in such an environment. Rather than spending years to exploit in-house capabilities, the approaches of ecosystem of innovation can be used to build a network to piece together production according to capabilities. Hence, it ensures the company remains at the cutting edge of product innovation. Proactive assessment of customer needs and behaviours is vital in today's competitive environment (Brown and Bessant, 2003). The demand for intelligence on product defects, improvements and usage has never been greater, especially in high technology firms in the electronic and manufacturing industries (Salge et al., 2013). The accelerated product innovation phase is meaningful for products and services with short product life cycles, notably the consumer electronics industry, where demand is driven mainly by lifestyle trends. Moreover, the empirical research highlights that achieving innovation and flexibility requires considerable planning and coordination through the various phases of development. Thus, top-level management support through a product champion and tight interfacing with social media and the target market are essential components of accelerated product innovation.

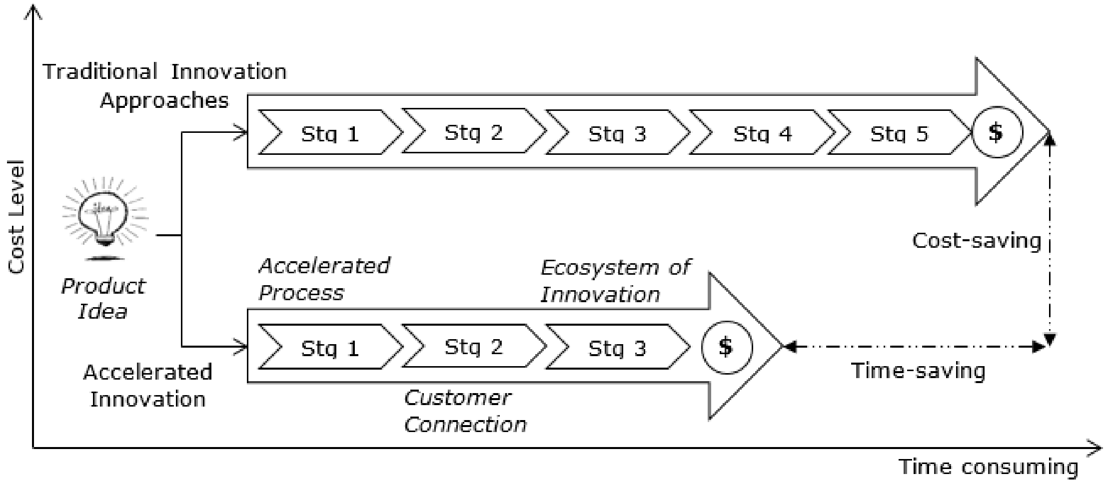


Figure 4.2: Comparison between Accelerated Product Innovation and Traditional Innovation (Millson et al., 1992; Williamson and Yin, 2014; McKinsey, 2015)

Traditionally, product innovation is viewed as firm-driven activities, with the firm being responsible for coming up with ideas for new products and deciding which should be commercialised and developed. As Figure 4.2 shows, compared with traditional innovation approaches, the approaches for accelerated product innovation places particular emphasis on efficiency and cost saving. There is no magic formula for innovation. However, firms could expand their existing innovation competence in many ways by tapping into the knowledge afforded by big data. The phases summarised provide a blueprint for accelerated product innovation in a big data environment. By adopting the approaches, firms are leveraging big data to embed customer sentiment in NPD. This enables firms to move away from product-focused innovation and to turn their attention to innovation around the customer experience. The proposed paradigm-shifting innovation phases enable firms to find ways to innovate – to make NPD faster and less costly.

4.4 Summary

The approaches in different phases for accelerated product innovation have been identified from a comprehensive literature study, and further refined with inputs from industrial and academic interviews. The summarised and refined innovation phases are: accelerated product innovation process, customer connection and innovation ecosystem. The next steps are:

- Developing a framework (incorporating the phases and approaches identified) to assist managers in attaining accelerated product innovation in a big data environment.
- Verifying the framework through establishing a set of propositions for attaining accelerated product innovation using five in-company case studies.

In the following Chapter 5.0, the development of the framework is illustrated. In Chapter 6.0, the detailed explanation that verifies the framework through case research is described.

CHAPTER 5.0 FRAMEWORK DEVELOPMENT

Chapter 4 discussed the empirical research results and described the identification and refinement of the approaches for accelerated product innovation in a big data environment.

This chapter describes the framework development process (Figure 5.1). Section 5.1 explains the results of the three in-company cases. Section 5.2 describes the development of the framework and explains its main phases. Section 5.3 discusses learning gained from the cases. Section 5.4 identifies the big data benefits gained from the cases to support the framework developed. Section 5.4 presents the conclusions of this chapter.

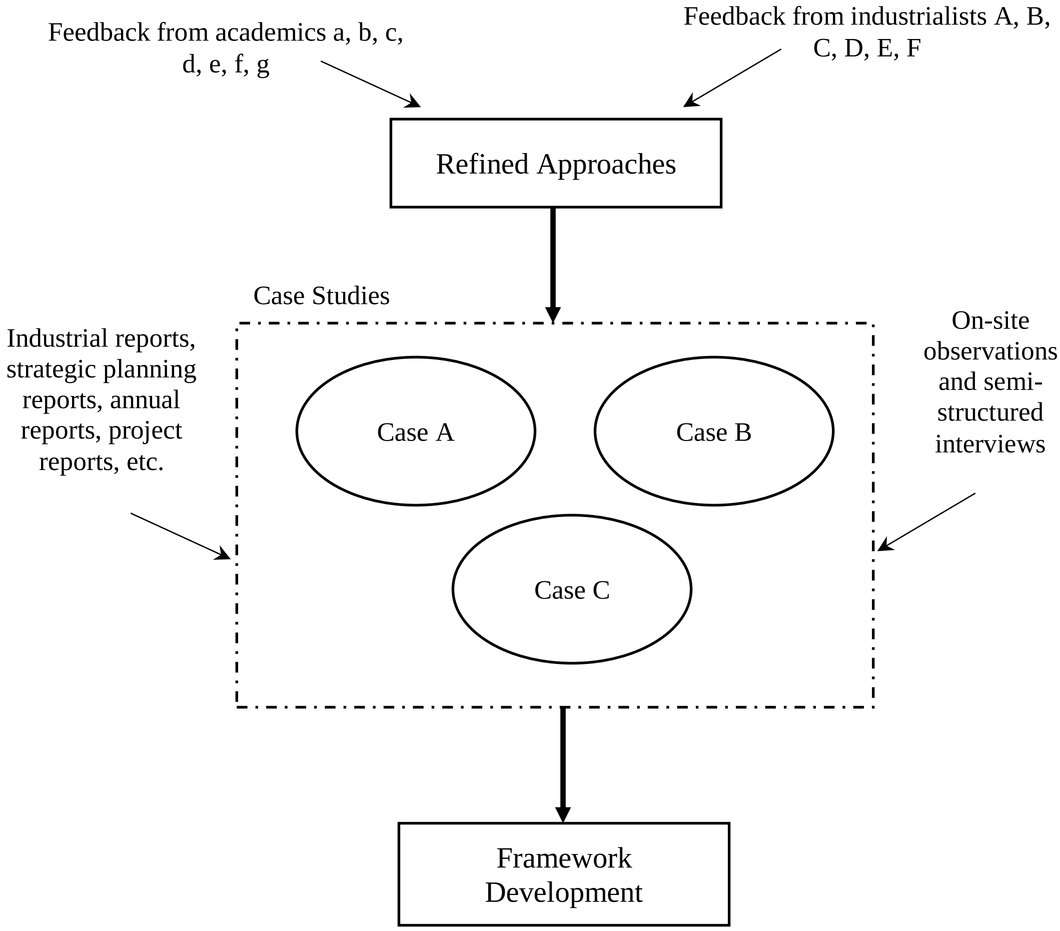


Figure 5.1: Framework Development Process

5.1 Results of Successful Firms

This research adopted an inductive approach (Yin, 1994) to study how firms incorporate big data to make product innovation faster and less costly. Three cases of emergent leading companies in China were selected: (1) Xiaomi, a manufacturer of smartphones; (2) Lenovo, a computer hardware and electronics company; and (3) Dididache, a taxi service company. Brief outlines of the three firms are provided in sections 5.1.1, 5.1.2 and 5.1.3. These cases were selected for a number of reasons. First, they have all used big data to speed up their product innovation process. According to Williamson and Yin (2014), the ability of Chinese firms to launch new products in rapid succession over short periods of time is worth worldwide attention, as this could inform the next generation of product innovation. Second, the three cases reflect certain aspects of the dynamism and rapid growth of Chinese companies in recent years. Third, the companies investigated all develop software-intensive or high-tech products. Fourth, they collectively provide coverage of different industries. Thus, the result may be generalizable to different industries.

In reviewing the product innovation approaches of these three leading Chinese companies, each of the cases can be seen as an independent part. The objective is to try to understand their main approaches for accelerated product innovation and involved big data activities, that is, how they integrate big data to increase efficiency of time-to-market and reduce the new product cost in NPD. The information presented here was collected from news, industrial reports, annual reports, newsletters and official websites. Yin (1994) argues that a richer portrait of any particular case can be acquired by using multiple sources of information and by mitigating bias in historical data interpretation. The next main section of this chapter then draws together some of the common findings from these three cases and suggests lessons for achieving accelerated product innovation in a big data environment.

5.1.1 Case 1: Xiaomi Inc.

Xiaomi Inc., a five year old Chinese mobile phone company, is now the world's third largest manufacturer of smartphones and is worth more than $46 billion (BloombergNews, 2014). Some 60 million Xiaomi smartphones were sold in 2014 and $1.1 billion of new funding from investors was received towards the end of December 2014 (BBC News, 2015), which made the company the world's most valuable technology start-up; at that time, its valuation exceeded $46 billion (Xiaomi, 2015) (see Table 5.1).

5.1.2 Case 2: Lenovo Group Ltd

Lenovo Group Ltd was founded as a Chinese computer technology company in 1984. It is currently valued at some $38.7 billion and has expanded its operations across more than 160 countries (Annual Report, 2014). There is deep integration across its 'Idea'-branded consumer PCs, 'Think'-branded commercial PCs, workstations, servers and mobile Internet devices, including tablets and smartphones. It is the largest personal computer vendor in China and the second largest in the world (Annual Report, 2014) (see Table 5.2).

5.1.3 Case 3: Dididache Inc.

Dididache, which means 'hire a taxi quickly', is a Chinese taxi services company founded in September 2012. It is among China's 13 most valuable start-ups and was valued at over $3 billion in April 2014 (Dididache, 2015). Currently, it has over 60 percent of the Chinese market, with over 154 million users, one million registered licensed taxi drivers, 5.2 million peak daily orders, and covers over 300 cities (Wang, 2014) (see Table 5.3).

Approach	Big Data Activities	Benefits
Teams work independently with Xiaomi customers	Cross-function teams are working independently as well as simultaneously with Xiaomi customers. Under this approach, Xiaomi develops new smartphones in 3 months on average. The collection and use of big data not only helps teams to communicate with each other (through Chinese communication services such as Wechat, QQ and Weibo), but also turns every customer into Xiaomi's source of information. Customers' suggestions and feedback are quickly rendered as inputs to Xiaomi's product improvement ideas.	• Fast product development • Lower development costs • Flexibility to incorporate new functionality quickly
The company connects and communicates with its customers	Xiaomi has forums across all the key social media platforms in China and leverages big data as its primary channel to interact with customers. For example, the main forum is called 'Xiaomi forum' on its official website. It posts (in different formats) more than 500,000 topics per day, including new product information, announcements, feedback and discussions. The core operating system of Xiaomi, MIUI, is highly customisable, allowing more than 85 million keen users upload their ideas and suggestions to facilitate the company's product innovation and invention of new features.	• Low research costs • Signals a firm commitment to improvement through co-creation • Gets feedback and ideas extremely quickly and effectively
Fast launch-and-improve ecosystem	Xiaomi collects feedback from customers and partners on a daily basis and updates its operating system on a weekly basis. The new features and functionalities are co-developed with various business partners. The ecosystem of Xiaomi involves app stores, games centre cloud storage services, theme stores, browsers, suppliers and intermediates. For example, one of the partners of Xiaomi is Tudou Youku, which has more than 500 million monthly users and the number of videos viewed on Tudou Youku have passed 800 million. Xiaomi gathers feedback and transfers the latest information on the most promising features quickly via its supportive ecosystem.	• Fast development and release • Turns feedback to advantage quickly • Increases brand and customer loyalty • Lower development and research costs

Table 5.1: Innovation Approaches of Xiaomi Inc. (Bai et al., 2015; BloombergNews, 2014; Li, 2014; BBC News, 2015; Stone, 2014; Xiaomi, 2015)

Approach	Big Data Activities	Benefits
Different cross-function teams work in parallel	Team members are from different departments and work together on different product development elements in parallel, but under one project leader's supervision. Research teams are encouraged to engage users independently, and as early as possible. Product concepts tend to go through dozens of labs/tests at the same time before being put on the market. The new product development cycle of Lenovo is about 6 months for a personal computer and 3 months for a smartphone, which is at least three times quicker than for comparable Chinese companies using other innovation approaches to their product development	• Low research and development costs • Fast NPD • Autonomy improves creativity as well as efficiency • Makes a large portion of the wide range of products the company produces compatible with each other
Connects customers promptly	The company connects with its customers through its own Talend big data platform. It understands customers' behaviours and needs better by acquiring datasets from about 300 processes that run simultaneously and come from sources including third parties, social networking feeds and Application Programming Interfaces (APIs).	• Faster and smarter decision making in product development • Cost saving • More flexible in making decisions/strategies toward the changing market
Customer feedback and improving network	Lenovo Group Ltd builds complex but powerful networks with thousands of partners in 44 different countries. It has launched a customer feedback programme to collect billions of pieces of information from its users and partners on a daily basis. For example, a thriving 'voice of the customer' programme gathers feedback from more than 30 million customers online per day to improve customers' experience and to facilitate product innovation.	• Low research costs • Understands customers better • Interprets data and reacts quickly to develop new products • Validates impact and monitors results over time

Table 5.2: Innovation Approaches of Lenovo Group Ltd. (Annual Report, 2014; Zhou and Huang, 2014; Gellert, 2016)

Approach	Big Data Activities	Benefits
Divides a project into small elements and groups work separately	Groups are drawn from different functions and work separately in parallel to accelerate the NPD process. For example, it took only 1 month to develop the first version of the Dididache app (excluding the time spent on market research). Big data is used to maintain connections and communication, such as idea exchanges between groups, market investigation of problems identified, as well as to characterise market size, competitors, etc.	• Low research and development costs • Fast NPD • Flexible and fast incorporation of new functionality
Build a terminal system that connects drivers and travellers	The Dididache app is a platform that connects to 100 million users, sending an average of 5 million customer orders a day. It uses real-time mobile internet data (text message, locations, voice message, images, etc.) to determine traffic conditions, connect to customers, redistribute taxi resources and gather feedback at the same time.	• Time saving for both taxi drivers and travellers • Improves traffic conditions • Cost saving
Fast launch-and-improve ecosystem	Dididache has a strong partnership with Tencent which is the largest and most used Chinese internet service company. After integrating with Tencent's Wechat service platform in Jan 2014, its registered users doubled from 20 million to 40 million within 3 weeks. Dididache creates a variety of channels to encourage feedback and rapidly communicate this to the R&D team. This informs the development of new versions, with better features and functionalities. For example, after the first release of the app, Dididache gathered feedback quickly and launched 3 new versions with new functions and capabilities over two months. More recently, the app has been updated approximately once per month.	• Low research and development costs • Interprets and reacts quickly to develop new products • Gains more market opportunities

Table 5.3: Innovation Approaches of Dididache Inc. (Mishkin, 2014; Wirtz and Tang, 2016; Wang, 2014; Dididache, 2015)

The three cases show a variety of approaches to the use of big data to accelerate product innovation. In summary, all three companies focus on establishing teams that can work both autonomously and simultaneously in order to speed up NPD. They also connect with their wide range of customers at the earliest stage possible of product innovation. They launch their new products as quickly as possible to gain market recognition as well as further feedback from customers to trigger further continuous innovation. In order for them to harvest big data to inform NPD, they identify and remove time and cost wasting processes during product innovation as much as possible, and they are adaptable enough to provide organisations with the ability to explore different possibilities in different situations. In short, all three companies are able to use big data to facilitate a more agile, lean, dynamic product innovation process that is faster and more adaptive. They also ensure that the product innovation is consistent with their company's strategic goals, and make necessary adjustments along the way. Based on the literature and empirical cases, key innovation phases to accelerated product innovation informed by big data can be summarised as: Accelerated Process (A); Customer Connection (C); and Ecosystem of Innovation (E). They are termed the ACE phases that allow firms to apply big data to accelerating their NPD.

5.2 Reflection and Learning

This part discusses the feedback obtained from the three cases, pertaining to the approaches for accelerating product innovation and big data activities. The discussions were based on the on-site observations, discussions with the participants and reflections gained from the case companies. The discussion will first focus on each of the innovation phases of the ACE phases. Then, a more detailed discussion is centred on big data benefits in supporting the product innovation process.

5.2.1 Accelerated Process

In terms of the accelerated process, this phase begins with a defined outcome of the product, and then all the development teams apply autonomy and/or cross-functional teams and focus their energies on achieving that outcome as soon as possible. At the beginning, Xiaomi found the autonomy approach very "new to its culture" of product development, and sought further clarification. After it applied autonomy management, the Xiaomi Company has developed an agile approach to product innovation to speed things up by tackling certain steps in parallel. The new product development teams organise simultaneous processing across the entire innovation process, beginning in R&D and continuing through design, manufacturing, engineering, quality control, procurement, marketing and service. For a specific project in Lenovo, the approach begins by dividing the NPD process (which normally includes the business case, development, testing and validation) into a large number of small steps and team members work on different elements in parallel, under the supervision of one manager. In this way, the company overcomes the usual problems of product innovation by: breaking down its product development into separate modules linked by standardised interfaces; redesigning its software to be compatible across all activities associated with the new product; establishing short lines of communication, where each team member can represent his or her respective functional department; and introducing open design processes, where information is shared with the entire team and their customers as early as possible. The Dididache Company also ensures a high degree of horizontal flexibility, allowing for smooth and rapid flows of resources and knowledge between peers in different teams and functions.

Big data plays a significant role. In terms of traditional product innovation approaches, the Lenovo Company found it hard to implement the autonomy among NPD teams, because of barriers such as unwillingness by engineers to release information early and difficulties in coordinating multidisciplinary teams. The company can now rely directly on big data (the company is currently using Google Analytics as a web-based technology for website customer behaviour analysing and social media marketing) to gather the latest information. Different function teams contact each other via ICT-enabled inter-team communication (such as information uploaded to the cloud or posted online, OA messages, app mentions, etc). Team members are now working and living in a big data environment (e.g. social media, Internet of Things, sensors, transaction information, location data), which ensures their communication and knowledge sharing are both effective and efficient. In this way, team collaboration can be enhanced by applying unified communications data analytics. According to the managers of Xiaomi "*When an innovation initiative* *encounters a problem, it supports the project team to quickly gather everyone together (the 'huddle') from different functions, who can help them find a solution*". This social dimension has the added benefit that once the outline of a solution is agreed, individuals from across the company feel a strong duty to implement their part of the answer quickly, so as not to let the team down.

Overall, the accelerated process can help the Dididache Company reduce the influence of and roadblocks created by functional fiefdoms while big data can be used to facilitate product innovation. By implementing autonomy team management, people from different function departments are grouped together to work actively. This cuts across boundaries of different departments and there is no more marketing team or production team. Instead, every team member becomes involved in marketing, engineering, design, production or R&D. In this way, this approach helped the company to save a lot of time and eliminated a vast number of unnecessary double communications within various teams.

5.2.2 Customer Connection

Currently, Xiaomi has little direct feedback from customers. Only recently did Xiaomi start to monitor consumer comments on the social media about its products. By applying the customer connection phase, the company has developed an application which is highly customisable. It allows its partners as well as customers to upload their ideas and suggestions to facilitate the company's NPD and invention of new features. Therefore, the new features and functionalities are co-developed with various customers based on the feedback collected. Moreover, Xiaomi connects to customers through a wide range of sources at low cost (e.g. official forum, mobile app platforms, popular websites) where customers can interact with the company and each other. The latest product information is updated to the difference sources on a daily basis, as well as to attract more customers and gain feedback for further developments. In this way, the company collects a wide range of customer feedback from different channels and platforms extremely quickly. For Lenovo Company, a thriving "voice of the customer" programme gathers feedback from more than a million customers online per day, and this information is used to improve customers' experience and to facilitate product innovation. There needs to be continual feedback from users of big data to improve its potential and Lenovo Company can better understand its customers by analysing the data collected, and gather feedback quickly to inform further product innovation. Therefore, big data in the form of feedback can be an important source of useful information and new ideas. Additionally, big data solutions enable Lenovo Company to meet the challenges of gaining insights from this data deluge and achieve competitive advantage through improved customer experience.

To achieve better management of its big data, Dididache pointed out that a number of different data platforms can be used (e.g. Hadoop, Tableau and SAP's enterprise resources planning). Dididache recently ditched a Microsoft system which it claims became too expensive to scale as data volume increased. Currently, Dididache collects information such as customer feedback, market preferences and competitors' information. The firm is also using a data management and processing tool, namely SAP's enterprise resources planning, to schedule data-crunching tasks more effectively when it is ready to release a new product on time. The platform enables Dididache to quantify its customer and marketing spend. The company now can merge data from apps, forums, the website, video and market research to analyse whether a new product has achieved market acceptance. Dididache is developing a sophisticated customer predictive data analysis tool to keep a close watch on customers; it could then work out the needs of its customers even before they have decided to buy the product.

Engagement with big customer data helps the company to better understand its customers as well as the market. In this situation, big data supports both the company's customer connection by discovering the factors that could influence customer loyalty and how to keep customers coming back again and again. With big data, the company now can determine the optimal marketing investment across multiple channels, and keep optimising its marketing strategies through analysis, measurement and testing.

5.2.3 Ecosystem of Innovation

The core competitive advantage of the ecosystem of innovation phase arises from the use of big data to attract and connect to a wide range of networks in each step of product innovation. This might be through the presentation of mock-ups, images or videos of the new product to customers and thus the gathering of feedback early in the process of NPD. On the one hand, the emergence of big data and the Internet allow for the combination of organisations' business strategies and those of outside suppliers within an ecosystem. For competitive advantage, Xiaomi Company identified the key components and all the intermediates within its networks involved in product development before a new product reaches the eventual customers. As a result, it costs Xiaomi Company less time and money than would ordinarily be required, concentrating on new product research and development rather than other time-wasting processes. Therefore, Xiaomi can provide new products to meet its customers' requirements in a much more efficient and effective way. On the other hand, enormous cost advantages can be acquired from big data by supporting the firm to identify the key competencies of their components and focus on them, and acquire the less important components from the ecosystem. A fast launch-and-improve system is not a totally new concept to Dididache. In order to support its ecosystem, Dididache invested half a million US dollars in online video content partners with iQiyi (a large internet TV company in China) to provide an platform for better customer and supplier interactions. In such a situation, product innovation is made from interrelated networks and these empower organisations to rapidly integrate useful information from customers and partners. Through repeated product innovation cycles, NPD teams can iterate the product in sync with evolving market requirements and stay ahead of the competition. This rapid launch-and-improve process has now become the company's core approach for accelerating product innovation.

To speed up the product innovation process, Lenovo built a customer feedback centre service as a marketing tool to encourage user feedback and to rapidly communicate this to its R&D teams. The main task of the customer feedback centre is deriving useful information from big data and to provide feedback as an input to the relevant project teams. Inputs from the centre can be channelled to relevant autonomy NPD teams in order to transfer the new market requirements into feasible functions, and thus quickly develop a new version of a product, with improved functions and features. By doing this, each successive version of the product comes closer to the customers' ideal, and therefore closer to being a market-winning product.

5.2.4 Phases Improvement

The case studies' results indicate that the phases were feasible to serve their task for accelerating product innovation in a big data environment. However, some shortcomings of the current approaches and innovation phases were identified. In order to address these shortcomings, the following modifications and changes were made to further improve the phases identified.

In terms of the accelerated process, the manager of Xiaomi points out that "*the term accelerated process is bit confusing since it is actually a part of accelerated product innovation*". Also, different companies have different objectives (e.g. new product development, new feature development), R&D focus (e.g. focus on fast launch of their new products, focus on customers' requirements), organisational structures (e.g. flat structure and multiple levels of hierarchical structure), corporate cultures and so on. Therefore, the manager of Xiaomi further points out that *"there is no exact process for attaining accelerated product innovation because different companies may face different situations"*. Instead, he referred to the innovation process as an agile structure because the process is a group of product development approaches based on iterative and incremental development, where requirements and solutions evolve through collaboration between self-autonomy and cross-functional NPD teams. It promotes adaptive planning, evolutionary development and delivery, a time-boxed iterative approach, and encourages rapid and flexible response to change. It is a conceptual structure that promotes foreseen interactions throughout the development cycle.

The interviewees from Lenovo and Dididache Company both agreed with the agile structure concept and believe it is more accurate in representing an innovation phase of accelerated product innovation in a big data environment than accelerated process. The managers from Lenovo further pointed out that "*after applied the agile structure,* *the company has speed things up by tackling certain steps in parallel. For a specific project, the approach begins by dividing the NPD process (which normally includes the business case, development, testing and validation) into a large number of small steps and team members work on different elements in parallel, under the supervision of one manager. In this way, the company overcomes the usual problems of product innovation by: breaking down its product development into separate modules linked by standardised interfaces; redesigning its software to be compatible across all activities associated with the new product; establishing short lines of communication, where each team member can represent his or her respective functional department; and introducing open design processes, where information is shared with the entire team and their customers as early as possible".* According to the managers of Xiaomi "*When an innovation initiative encounters a problem, the agile structure can support the project team to quickly gather everyone together (the 'huddle') from different functions, who can help them find a solution*". Therefore, we modified the innovation phase from accelerated process to agile structure to reduce confusion and improve language accuracy and proficiency. Moreover, the interviewees point out that NPD team autonomy implies that project teams work in parallel, rather than sequentially. In other words, NPD autonomy includes the process 'divides the project into small elements' and 'simultaneous development'. Therefore, it is not necessary for the 'Divides the project into small elements' and 'simultaneous development' approaches. Please refer to Table 5.4 for detailed information towards modifications and improvements.

Accelerated Process (origin)	**Agile Structure (improved)**
• Divides the project into small elements • Autonomy management • Cross-functional teams • Simultaneous development	• NPD autonomy • Cross-functional team

Table 5.4: Summary of Improved Agile Structure

In terms of customer connection, the managers from Lenovo and Xiaomi comment that "*customer connection is an outdated term. Nowadays, everything is changing so* *rapidly and it is really hard for companies to connect with and understand their customers"*. They further point out that "*Customers today are too sophisticated to satisfy because they always demand products with the latest technology, cutting-edge functionality, at an unprecedented low price, and immediate services. At the same time, they don't have much brand loyalty and keep comparing the product with others"*. Instead, customer involvement becomes more and more important especially in today's fast changing environment. It is a marketing management approach that takes customer orientation further than customer connection or customer relationship management. Customer involvement identifies and develops ways to involve customers in the business and product innovation process, such as design, marketing, sales, customer service, etc. All the interviews with three companies agreed with the customer involvement idea for further customer oriented innovation. According to the manager from Xiaomi "*by adopting customer involvement, the Xiaomi Company has developed an application which is highly customisable. It allows its partners as well as customers to upload their ideas and suggestions to facilitate the company's NPD and invention of new features. Therefore, the new features and functionalities are co-developed with various customers based on the feedback collected"*. Moreover, the managers from Lenovo company mentioned that "*the company is applying a thriving voice of the customer programme which gathers feedback from more than a million customers online per day, and this information can be used to improve customers' experience and to facilitate product innovation"*. Therefore, we changed the term 'customer connection' to 'customer involvement' which represents a better customer and market interaction and understanding for accelerating product innovation in a big data environment.

In addition, the approaches for customer involvement have been improved according to the companies' feedback (see Table 5.5). In particular, company managers from Lennovo and Dididache believe that approaches such as "market orientation", "customer communication", and "understanding of customers" overlap to some extent. For example, the managers from Dididache pointed out that '*there are a number of different ways can be used to improve market orientation and customer communication. However, the main purpose is to determine the optimal marketing investment across multiple channels, and keep optimising its marketing strategies through better understanding their market and co-creates with their customers'*.

Also, the managers from Lenovo further suggested that '*the co-creation with and feedback from customers provided the NPD teams with opportunities to gain a better understanding of customers' needs, and caused them to focus on the right aspects of the solution immediately'*. Therefore, they suggested two narrow sets of approaches focused on accelerated product innovation (understand customer and market clearly, and co-creates with customers) that are particularly relevant in a big data environment.

Customer Connection (origin)	**Customer Involvement (improved)**
• Market orientation	• Understands customers and market clearly
• Customer communication	• Co-creates with customers
• Understanding of customers	
• Good relationship with customers	

Table 5.5: Summary of Improved Customer Involvement

In terms of ecosystem of innovation, most of the participating company managers were satisfied with this innovation ecosystem phase. Although few managers required further definition and justification of the concept ecosystem of innovation, they agreed with the basic idea of this innovation phase. According to the interviews' feedback, both of the companies were looking for product innovation practices that could enhance their capabilities for speed in development, speed to market and reducing new product costs.

According to one of the managers from Dididache, "*Rather than spending time on internal R&D to make the product perfect, the Dididache Company tend to launch their new product ideas on the market quickly (and are able to do so through implementation of the agile structure) and then improve them through extremely fast and continuous rounds of commercial realisation and testing within their ecosystems*". Moreover, managers from Lenovo mentioned that "*the core competitive advantage of the ecosystem arises from the use of big data to attract and connect to a wide range of networks in each step of product development*". The emergence of big data and the internet allow for the combination of organisations' business strategies and those of outside suppliers (stakeholders) within an ecosystem.

"For competitive advantage, the company identified the key components and all the intermediates within its networks involved in product development before a new product reaches the eventual customers. As a result, it costs the company less time and money than would ordinarily be required, concentrating on new product research and development rather than other time-wasting processes". Managers from Xiaomi further supported by pointing out that "*based on customer feedback the NPD teams continue to iterate the design. This rapid improve-and-relaunch process has now become the company's core approach to NPD"*.

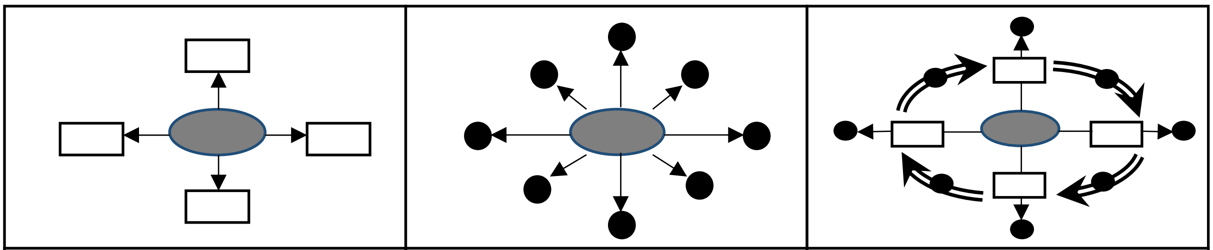
Hence, companies can earn a premium by staying abreast of competitors' innovations and by having up-to-date products available in volume at affordable prices. Moreover, nurturing interactions and establishing partnership with stakeholders in the proposed ecosystem improves efficiency and creativity, and also makes product innovation a cycle of continuous improvement and information transformation. Based on the interview feedback, the improved approaches for an ecosystem of innovation are: 'partnership with stakeholders' and 'fast improve-and-relaunch process' (see Table 5.6).

Ecosystem of Innovation (origin)	**Ecosystem of Innovation (improved)**
• Builds strong networks with various partners • Gathers feedback quickly from customers and partners • A fast improve-and-relaunch process	• Partnership with stakeholders • Fast improve-and-relaunch process

Table 5.6: Summary of Improved Ecosystem of Innovation Approaches

5.3 Framework Development

Based on the literature and three empirical cases, these approaches for accelerating product innovation informed by big data can be summarised as a framework with three innovation phases (see Figure 5.2): Agile Structure (A); Customer Involvement (C); and Ecosystem of Innovation (E). It is termed the ACE framework which we believe represents a paradigm shift to help firms to achieve accelerated product innovation in a big data environment. The framework allows firms to unlock the power of big data and make product innovation faster and less costly.



Agile Structure	Customer Involvement	Ecosystem of Innovation

Figure 5.2: Framework for Accelerated Product Innovation

5.3.1 Agile Structure

One of the key approaches of the agile structure is autonomy. According to Wynen et al. (2014), autonomy is the mother of motivation and creativity. This means allowing R&D team members a high level of freedom to make decisions by themselves in their workplace. For example, the project leader of Xiaomi who grants teams autonomy briefly introduces the teams to the final goal of a project or product then lets the teams make their own choices in achieving that goal.

Autonomy here also implies that project teams work in parallel, rather than sequentially. At each stage of a project, many activities take place concurrently and involve different functions of the firm. Under autonomy management, a group leader is allocated to supervise the output of the project. The project approach begins with dividing the innovation process into many small elements. After that, the divided project activities are undertaken by cross-function teams (which mean a team of people from different functional areas) and work on different elements in parallel. By doing this, the so-called innovation 'assembly line' can be accelerated and results can be delivered quickly (Davenport, 2013; Nordigården et al., 2014). Autonomy does not mean being separate: project teams need alignment with the core, using big data to share innovation portfolios as well as to cultivate a network of peers and relationships to facilitate innovation (Yalabik et al., 2012; Chen et al., 2015).

In this situation, the innovation process has been industrialised by assigning more people to the many small steps and project activities (Williamson and Yin, 2014). The total outlays for a given project can nonetheless be reduced, as these people are less highly trained than traditional R&D staff and are generally therefore paid less (Davenport, 2013; McNeish and Hazra, 2014). For example, Lenovo overcomes the usual problems of implementation by: breaking down its product designs into separate modules linked by standardised interfaces; redesigning its software to be compatible across all activities associated with the new product; establishing short lines of communication where each team member can represent his or her respective functional department; and introducing open design processes where information is shared with the entire team as early as possible.

Big data plays a significant role. In terms of traditional innovation approaches, many companies have found it hard to implement autonomy among NPD teams because of barriers such as unwillingness by engineers to release information early and difficulties in coordinating multidisciplinary teams (Berglund and Sandström, 2013; Li et al., 2014). Companies now can rely directly on big data to gather the latest information; team members are now working and living in a big data environment which ensures their communication and knowledge sharing are both effective and efficient.

5.3.2 Customer Involvement

In addition to being able to develop new products rapidly, product innovation has to be close to the market to stay abreast of the evolving needs for functionality, which in turn are driven by quickly evolving customers' taste (Prahalad and Ramaswamy, 2013; Steinfeld and Beltoft, 2014). A strong customer involvement is therefore critical to success. Barwise and Meehan (2012) believe that Apple has built its success not as a pioneer, but as a good follower of its customers. The second innovation phase of the ACE framework is customer involvement, i.e. a focus on building a close partnership with customers via big data.

Innovation can be facilitated by evolving ideas while listening to the voice of customers; the product is better when potential customers can be identified and their needs satisfied (Prahalad and Ramaswamy, 2013; Steinfeld and Beltoft, 2014; Cooper, 2014). Many projects have poor customer involvement, which results in a series of problems: customer requirements and problems are vaguely defined; the product's functions and features are fuzzy; and the target customers are not well understood (Dunn and Dahl, 2012). Engineers and R&D teams are not mind readers. With poor customer involvement, they often have to back-track to make the product right. Thus, they waste considerable time in defining projects appropriately. This product innovation process can be speeded up by building better customer involvement. What is more, instead of making changes late in the project, customer involvement encourages changes to occur earlier, when they are less expensive (Williamson and Yin, 2014). For example, Xiaomi's MIUI system and Lenovo's Talend big data platform are both good ways to build close interaction with customers. Additionally, Didi Dache spent a lot of time building various platforms to connect to its users as well as the market (including using big data to clarify its product definition and to identify its main competitors, market size and customers' problems and needs).

The involvement of customers is an emerging trend (Cooper, 2011; 2014; Dunn and Dahl, 2012; Williamson and Yin, 2014; Steinfeld and Beltoft, 2014). The innovation process can be dramatically accelerated by using big data in the form of, for example, usage information, which is much more rapidly available than, say, the results of market surveys (Li et al., 2014). Big data in the form of feedback can be an important source of useful information and new ideas. Key questions need to be focused at this stage, such as: Who exactly is the target customer? What functionalities and features should be developed to give the product a differential advantage? What exactly should the product be to make it a winner? How should the product be positioned? By answering such questions, companies can gain a better understanding of their customers, products, and markets.

5.3.3 Ecosystem of Innovation

Ecosystem of innovation is the third phase of the ACE framework. Ecosystem of innovation represents an innovation and market-testing environment to develop new products at dramatically faster speeds and lower costs. It bridges the gap between the need for the new product definitions and the changeable market conditions as development proceeds (Gupta, 2013). Adner (2006) argues that innovation ecosystems have become a core element in the growth strategies of organisations in a wide range of industries. The ecosystem of innovation phase of the ACE framework indicates that the company network is used to acquire new requirements and the components of product innovation process externally or from intermediates, in order to create a fast launch-and-improve environment that is able to launch a new product with reduced time-to-market and new product costs. A fast launch-and-improve ecosystem involves the phases of agile structure and customer involvement. It helps the NPD teams to move quickly to a market-winning product through a series of iterations: new product ideas; fast launch; gather feedback; fast improvement; re-launch.

Gawer and Cusumano (2014) point out that the ecosystem of innovation allows organisations to generate great value that no single firm could have generated alone. For each project, instead of focusing on R&D internally, allocating resources externally from partners (e.g. with customer, with universities or with companies) can be far more effective because critical bottlenecks may reside outside the company (Adner, 2006; Azadegan et al., 2013; Tavani et al., 2014; Nordigården et al., 2014). In particular, the emergence of big data and the Internet allows for the combination of organisations' business strategies and those of outside suppliers within an ecosystem (Shih, 2014). For example, in order to further enhance its smartphone ecosystem and take ownership of the future products roadmap, in 2014, Lenovo Group acquired world-renowned Motorola Mobility from Google, including the Motorola brand and Motorola Mobility's portfolio of innovative smartphones. The acquisition of such an iconic brand immediately made Lenovo a powerful global competitor in smartphones through scaling Motorola Mobility into a major player within its existing Android ecosystem and facilitating the new product innovation across the new Android ecosystem (Google, 2015).

Enormous cost advantages can be acquired from the ecosystem and companies should identify the key competencies of their components and focus on it, and acquire the less important components from the ecosystem (Horn, 2005). Companies can greatly reduce costs by concentrating on their core functions and let others do the rest. For example, due to its supportive ecosystem, Xiaomi is able to sell its products and a wide range of accessories at near-production cost to keep prices competitive and sell a large volume of goods. By integrating a range of key components and technologies, many high-class products can be invented and created. Producing such products in an open innovation ecosystem depends on contributions from across the network of suppliers and creates value for the eventual buyer (Boer et al., 2001; West and Wood, 2008). In the ecosystem, innovations are made from interrelated networks (Ogle, 2007; Wang 2009) and these empower organisations to rapidly integrate useful feedback from customers and partners. Through repeated accelerated product innovation cycles, NPD teams can iterate the product in sync with evolving market requirements and stay ahead of the competition. With the innovation ecosystems, firms are better able to respond to today's fluid, changeable information and evolving market conditions.

5.4 Implications

From the cases, we have evidence to indicate that the developed ACE framework appropriately reflects the smooth integration of accelerated product innovation in a big data environment. In general, the case supports the fundamental conceptual aspects of the ACE framework and endorses many of the suggested guidelines in each of the phases. For example, the ACE framework reflects what is "happening in Xiaomi" and incorporates the pillars of accelerated product innovation in today's dynamic and evolving marketplace. Proactive assessment of customer needs and behaviours is vital in today's competitive environment (Narasimhan et al., 2006; Mahr and Lievens, 2012). The factor of customer involvement (i.e. establishing interaction with consumers as early as possible) is vital for product innovation because developers should observe and communicate meaningfully with customers and work with them to design product features. Overall, the ACE framework is conceptually accurate in capturing the essence of accelerated product innovation in a big data environment, especially in the consumer electronics industry. According to Salge et al. (2013), the demand for intelligence on product defects, improvements and usage has never been greater, especially in high-technology firms in the healthcare and telecommunications industries. The proposed framework is suitable for industries which evolve rapidly. However, the exact implementation of the ACE framework may differ from one firm to another, and is dependent to some extent on the operational environment of the firm under consideration. Thus, it may meet with differing degrees of success and lead to different outcomes.

Traditionally, the product innovation process has involved inefficient sequential processing of information between functional specialities. According to the cases, the ACE framework allows firms to adapt and respond rapidly to changing market needs and to develop innovative products in such an environment. Rather than spending years to exploit in-house capabilities, the ACE framework can be used to build a network to piece together production capabilities. Hence, it ensures the company remains on the cutting edge of product innovation. Today, many customers are too sophisticated to satisfy because they always demand products with the latest technology, cutting-edge functionality, at an unprecedented low price, and immediate services. At the same time, they don't have much brand loyalty and keep comparing the product with others. The proposed ACE framework can provide companies with the ability to take a product to market as fast as possible, to capture increased margins over a narrow time frame and to gather feedback from customers. It is meaningful for products and services with short product life cycles, notably the consumer electronics industry and social media applications, where demand is driven mainly by lifestyle trends. In particular, by applying the fast improve-and-relaunch ecosystem, the Xiaomi Company can see the benefits to be gained from the approach. Compared with the traditional product innovation approach, Xiaomi was able to launch a range of new products in less than five months, at a total cost of $2 million. The company estimates that competitors using traditional design approaches have to invest around $20 million over twelve months to complete a similar set of new designs. Nonetheless, the challenges Xiaomi faced in implementing the ecosystem approach were identified, such as IT infrastructure, managing relationships with intermediates, and the culture shift from product focus to customer focus.

5.4.1 Big Data Benefits

The empirical findings appear to agree to a large degree with the framework developed. Specifically, the main benefits of utilising big data for accelerating product innovation were placed into three categories: cost efficiency and effectiveness, enhanced decision making, and new product development.

Cost efficiency and effectiveness

Regarding the cost reduction and effectiveness of production, participants at Xiaomi and Dididache who engaged in agile structure activities suggested that big data could be used to improve the efficiency of existing products. Ohlhorst (2013) and Feinleib (2014) suggest that combining production data with data from different functions can strengthen efficiency and effectiveness in several stages within the NPD process, as well as optimise functions outside the NPD such as supply chain management. Through applying cross-functional teams, participants from Lenovo explained that big data implementation could improve effectiveness by reducing time-to-market. Additionally, they point out that the fast-launch-and-improve innovation ecosystem is a good way to accomplish cost reduction and increase productivity.

Enhanced decision-making

McAfee and Brynjolfsson (2012) argue that data-driven decisions are more effective, since they are based on evidence provided by data. The empirical results describe the possibilities of how the framework can be enhanced in a big data environment by improving the precision and validity of decision-making. These opportunities were grouped under two categories: insights and predictions.

Participants at Dididache explained that customer involvement can be facilitated through utilising big data to provide new or more precise insights. Big data allows users' behaviours to be examined and thus their demands can be met. Interviewees from Xiaomi added that insight can be gained in a digital form, such as use tests, in order to understand the customers and adjust the decisions about the products accordingly. Further, they suggested that new insights from customers can be used in the process of product innovation for personalised products and prevision, but also to enhance different stages of the whole value chain. The insights can also be used to organise predictions in the market or in different sectors, and uncover hidden data patterns to use for commercial or social purposes. In addition, interviewees from Lenovo said that they considered big data as a way of confirming expectations and decisions that organisations were already considering with the use of descriptive analytics.

The second label includes the responses from participants regarding predictions which can assist the process of product innovation by changing it into a data-driven product innovation process. Through customer involvement, interviewees from Lenovo argued that big data-based predictions can provide evidence for product innovation decision-making, and improve a product, which would be impossible to do so without using it. After gathering information from different autonomy NPD teams and customers, interviewees at Xiaomi added that big data predictions could offer accuracy in sales, understanding what qualities users value and adjust products accordingly. Furthermore, after establishing a fast-improve-and-relaunch innovation ecosystem, individuals from Dididache emphasised that big data can assist in the development of predictive, contextualised and automated solutions. They also explained that the data-driven fast-improve-and-relaunch ecosystem could enhance decision making by predicting and suggesting actions but that it is currently in its infancy stage.

New product development

All case study companies referred to the NPD process and how big data can complete the objectives set, when utilised in it. The information extracted from interviews was in accordance with the framework developed for this research.

In particular, Lenovo participants suggested that utilising big data in order to support the NPD process is a valuable approach to exploit business opportunities and re-invent business models. Additionally, it suggested that big data can be used to facilitate communications between autonomous cross-functional teams. Thus, it offers more accurate observation and prediction in product performance or its parameters, and avoids malfunctions or downtime. Chen et al. (2012) suggest that insights provided by big data can transform business models and enhance the process of NPD. Xiaomi believed that big data in NPD can lead to a greater understanding of how products or users behave, and enable accurate recommendations for existing or new products. Further, they explained that big data comprise a key element of some of their products. By gathering relevant data, the agile structure is able to determine product features and customise them accordingly. Davenport (2014) described the use of big data in the NPD process as the most interesting, since it enables products and services across the value chain. Dididache argued that big data contribute to the NPD process by extending product features and life, as well as improvements in quality for customer involvement. Finally, they suggested that big data products could significantly impact societies, by offering products such as smart cities concepts of connectivity and optimisation.

Several interviewees identified the field of marketing as another area of contribution of adopting a big data unit in NPD. Xiaomi suggests that big-data-supported customer involvement and co-creation can enhance market research, target consumers and the results can be translated into precision for creating more personalised products. Furthermore, contributors at Lenovo explained how big data can identify trends and customer demands, and use their analysis to create and promote new product innovations. Dididache added that by using different big data analytics, Dididache can encourage customer co-creation during the connection with customers.

Furthermore, one of the benefits of using big data in NPD is the ability to acquire information about their innovation ecosystems. Interviewees at Lenovo described that they are analysing big data in order to monitor and determine potential need for new suppliers. After the examination of the results, the management team recommends whether the organisation should partnership with the suppliers and create new innovative products. In addition, Xiaomi explained that they are exploiting big data in order to discover new markets and to explore whether these opportunities have the necessary investment potential. Finally, Dididache interviewees argued that big data is a unique opportunity to strategically position inside emerging innovation ecosystems and forge new value networks that could provide a competitive advantage.

5.5 Summary

There is no magic formula for product innovation. However, firms could expand their existing competence to achieve accelerated product innovation in many ways by tapping into the knowledge afforded by big data. The developed ACE framework is based on information elicited from the literature, refined from interviews with academics and industrialists, and further improved from the unique product innovation approaches adopted by three successful companies. It provides a blueprint for companies to achieve accelerated product innovation in a big data environment, through making NPD with reduced time-to-market and new product costs. Compared with existing product innovation processes, the framework gives particular emphasis to efficiency and cost saving.

Having developed the framework, the next step was to verify it. Chapter 6 verifies the framework through establishing a set of propositions concerning the key factors of the ACE framework. The propositions were verified through five leading comparative company cases.

CHAPTER 6.0 FRAMEWORK VERIFICATION

Chapter 5 discussed the empirical research results, explained the improvements carried out on the identified approaches, and described development of an ACE framework for accelerated product innovation in a big data environment. The implications of big data for accelerated product innovation were explored and the main benefits were placed into three categories: cost efficiency and effectiveness, enhanced decision making and NPD.

Chapter 6 describes the process which was developed to verify the framework through establishing a set of propositions concerning the main approaches identified and improved in Chapters 4 and 5. This chapter has three sections. Section 6.1 briefly explains the development of the propositions. Section 6.2 describes the results and feedback gained from the five cases. A summary of each case is shown in Appendix E. In Section 6.3, the summary from this chapter is explained and discussed.

6.1 Development of Research Propositions

It is worth mentioning the reasons for choosing proposition testing as the best method for verifying the framework developed. Initially, I planned to examine the framework through implementing it in different case companies. In order to understand whether the developed ACE framework could really help firms in achieving accelerated product innovation in a big data environment, I developed a workbook for the framework implementation. The workbook was planned to be implemented in different companies to test and further develop the ACE framework. In total, I have developed the workbook in three different versions (focusing on different ways to help companies in achieving the main innovation phases of the ACE framework). However, we found problems during the implementation of the workbook. First of all, the real company situation is more complicated. For different companies, they have different objectives (e.g. new product development, new feature development), R&D focus (e.g. focus on fast launch of their new products, focus on customers' requirements), organisational structures (e.g. flat structure and multiple levels of hierarchical structure), corporate cultures and so on. Therefore, it is extremely difficult to provide particular guidelines for companies in implementing the key innovation phases in different situations. Secondly, the three innovation phases are too broad to be implemented. For example, the phase agile structure involves many R&D activities such as applying autonomous new product development teams to improve motivation and creativity, conducting simultaneous processing to speed up new product development progress, and establishing cross-functional teams to further enhance the efficiency and effectiveness of the new product development process. Therefore, it is hard to test the phases without addressing them clearly in specific propositions/elements. Thirdly, the test of the framework implementation could take several month or years for companies to develop a new product or service. However, as a student who has limited time to complete their PhD study, testing the ACE framework implementation is therefore not feasible. Fourthly, the result measurement could be a major concern since the ACE framework aims to support firms to achieve accelerated product innovation, by shortening the time to market, improving customers' product adoption and reducing new product costs. However, it is difficult to measure the outcomes for implementing the ACE framework. For example, after we found the result shows a significant reduction in new product cost in NPD, we cannot say that the cost reduction is because of the ACE framework since the costs could be completely different in different companies and projects (there is no comparison). Therefore, instead of implementing and testing the developed ACE framework, this study verifies the ACE framework through establishing a set of propositions concerning the key approaches of the ACE framework. The propositions were verified through five leading comparative company cases.

Building on the earlier discussion in Chapters 4 and 5, a framework was developed that included three sets of innovation phases that potentially contribute to accelerated product innovation in a big data environment. The first set of categories, 'agile structure' relates to the different processes that go into NPD. In this phase, these kinds of structures are being overhauled to allow: (1) faster approvals; (2) an overall corporate culture based on doing everything more efficiently and quickly; (3) an organisation that is lean and flat but that stresses training and giving workers motivation and reward systems that include equity positions if possible; and (4) less structure in the operations of the organisation (Crawford, 1992; Chen et al., 2010). One highly publicised example fitting this description is the autonomous NPD team, which typically involves a strong leader and little formality and structure in decision-making processes such as manufacturing, engineering, marketing, distribution, and purchasing (Li et al., 2009).

The second broad set of phases, 'customer involvement' is associated with cultivating and maintaining high-quality information and feedback links with customers. This new accelerated product innovation approach to NPD entails paying more attention to connections with customers so as to understand them better and gather feedback quickly for continuous improvement (Mahr et al., 2014). It also involves data analytics such as computer-aided engineering, artificial intelligence and integrated information systems, and real-time ICTs to increase the quality and quantity of communication (Thomke, 2003; Bosch-Sijtsema and Bosch, 2015).

The third set of phases, 'ecosystem of innovation' focuses on building an innovation ecosystem to support NPD. It stresses going outside the boundaries of the organisation to foster the innovation process. This could potentially include external linkages such as R&D consortia, alliances with vendors and customers, linkages with third parties, and the use of NPD consultants and suppliers (Christensen and Overforf, 2000; Chesbrough 2006; Colombo et al., 2014). This view is changing to include seeking more incremental innovation, replacing products more frequently than demanded by the market, reducing capital investments as much as possible and demanding quick response to changes in the marketplace (Crawford, 1992; Hagel and Brown, 2011; McKinsey, 2013). The following parts define each of the phase terms and formulate propositions.

6.1.1 Agile Structure

The ability to innovate quickly has become an increasingly significant factor in recent years in determining a firm's competitiveness, especially in industries where product cycles are short and the pace of technological change is fast (Cooper, 1994; 2014; McKinsey, 2009; Rese and Baier, 2011; Bharadwaj and Noble, 2015). The 'agile structure' has emerged as one type of organisational design that seems well suited to helping some companies deal with this accelerated rate of product innovation. Agile structure problem solving coexists with an organisation's formal operational design, but is structured as a highly flexible "organic-adaptive" system (Kilmann, 1982; Singh, 2005; Lyer and Davenport, 2009; Google, 2011; Davenport, 2013). As shown in Figure 6.1 below, this phase is underpinned by NPD team autonomy and cross-functional teams.

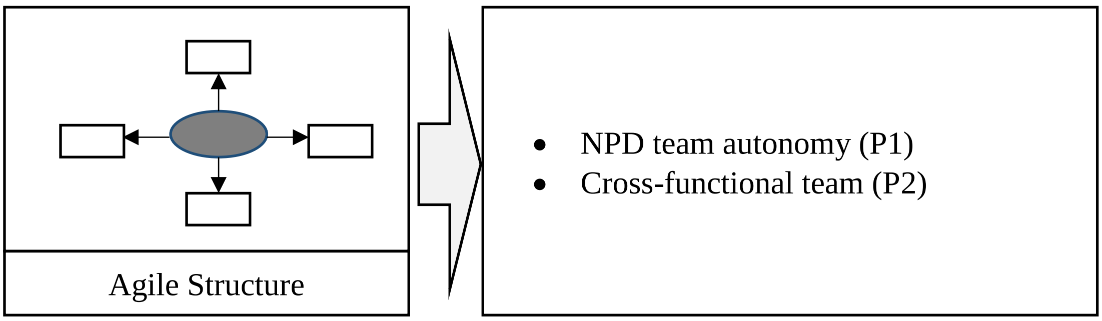


Figure 6.1: Agile Structure

NPD team autonomy

Several prior investigations in this area suggest that greater autonomy for NPD teams – which is characterised by a high degree of independence, dedication, leadership, and collaboration (Patanakul et al., 2012) – can play a material role in stimulating strategic innovation (Govindarajan and Trimble, 2005), radical or discontinuous innovation (Rice et al., 1998; O'Connor, 2008), or disruptive technological change (Gassmann and Enkel, 2004; Hagel and Brown, 2011). A recurring theme within these contributions is that NPD teams should have the freedom to be entrepreneurial and innovative. By giving these teams a high degree of autonomy, projects tend to be implemented by different NPD teams in parallel, with each team pursuing different approaches and technologies but all sharing information with each other (Millson, 1992; Patanakul et al., 2012). Despite the potential redundancies and inefficiencies that this multi-pathway approach to solving problems might create, NPD teams given this higher degree of autonomy have been found to ship new products more quickly than competitor companies whose NPD teams were less autonomous (Sarin and O'Conner, 2009).

However, IT resources have been found to improve the connectivity within and between organisations (Patanakul et al., 2012), which could in turn make it even easier for highly autonomous teams to succeed. Whereas many NPD teams have historically struggled to take full advantage of autonomy because of difficulties in coordinating multidisciplinary teams and an unwillingness by engineers to release information (Menon et al., 2002), today's teams can share information, knowledge, and analytical capabilities more readily (LaValle et al., 2011; Chen et al., 2012). In this way, team collaboration can be enhanced by applying unified big data analytics and communication technologies to accelerate innovation, reduce uncertainty, and form more accurate interpretations (McKinsey, 2011; Wong, 2012; Patanakul et al., 2012). We therefore make the following proposition:

P1: NPD team autonomy will lead to accelerated product innovation in a big data environment

Cross-functional teams

The use of cross-functional teams has also been closely linked to the fostering of team autonomy and the acceleration of NPD processes (Clark and Fujimoto, 1991; Eisenhardt and Tabrizi, 1995). These kinds of teams make it possible for development to connect technical, marketing, and manufacturing perspectives throughout the entire NPD process (Deshpande, 2013; Sarin and O'Connor, 2009). This more integrated approach makes it possible to move faster because they do not need to wait for or rely on external sources or other departments (Sarin and O'Connor, 2009). In many cases, cross-functional teams include members from different functional areas of an organisation, thereby increasing the team's coordination requirements (Deshpande, 2013). Customers, vendors, and other business partners may also contribute to these cross-functional teams, further increasing their diversity and their communication and coordination requirements (Peng et al., 2014). Teams exhibiting higher levels of cross-functional cooperation have a significantly higher incidence of project success than those teams with low cross-functional cooperation (Menon et al., 2002; Deshpande, 2013; Noble et al., 2013).

With the advent of worldwide connectivity through the Internet and other telecommunications technologies, organisations are increasingly adopting cross-functional teams that operate more independently of time and cost than traditional organisations (Menon et al., 2002). These kinds of interconnected and big data environment markedly improve an NPD team's ability to integrate different information sources across functional and organisational boundaries, thereby making them more productive (Peng et al., 2014) and delivering more value (Mishra and Shah, 2009). A more cross-functional team approach enables internal and external stakeholders to share data, information, and knowledge (Majchrzak et al., 2012). For example, advanced ICTs and big data technologies can be used to facilitate collaboration and communication within cross-functional teams, which enables intra- and inter-firm knowledge sharing, which in turn improves problem-solving capabilities (Dewett and Jones, 2001). We accordingly put forward the following proposition:

P2: The establishment of cross-functional teams will lead to accelerated product innovation in a big data environment.

6.1.2 Customer Involvement

The involvement of customers in NPD processes has also resulted in superior performance in terms of values and sales growth, profitability, and new product success (Henard and Szymansk, 2001; Brown et al., 2002; Blazevic and Lievens, 2008; Franke et al., 2009; Bharadwaj et al., 2012; Noble et al., 2012; Cooper, 2014). But prior investigations in this area also note that too much of this involvement can become unhelpful, with customer involvement being curvilinearly – that is, taking an inverted U-shape – related to innovation performance (Laursen and Salter 2006, Belderbos et al., 2010; Salge et al., 2013). As shown in Figure 6.2, the larger issue of customer involvement manifests itself in two principal ways: the ability to understand customers clearly, and the ability to co-create with customers.

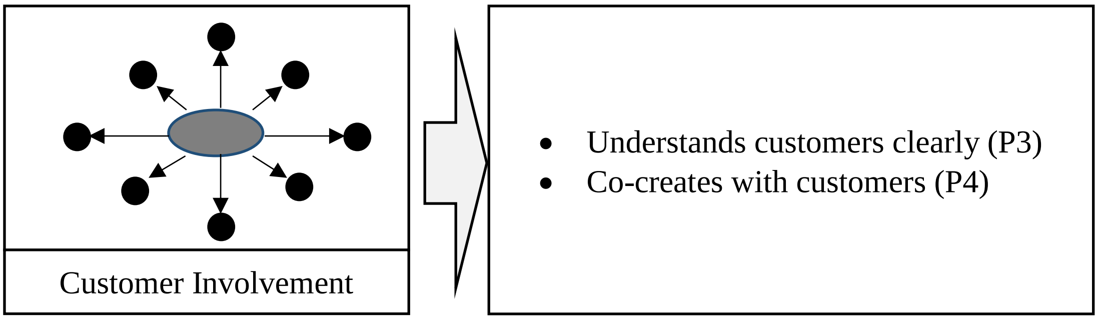


Figure 6.2: Customer Involvement

Understanding customers' needs

Customers are one of the key sources for product innovation, and a good understanding of their needs is therefore required to maximise the probability of NPD success (Blazevic and Lievens, 2008; Bharadwaj et al., 2012). An inadequate understanding of customer requirements is a recurring reason for failure in the NPD domain, especially in high-technology and industrial-product firms (Cooper and Kleinschmidt, 2011; Copper, 2014; 2016).

Here, too, an increase in data availability can positively impact the NPD process. Compared with traditional methods of acquiring information and generating customer insight for NPD, new technology and big data analytics provide a broader range of conduits through which NPD teams can glean valuable information and market research data, making it possible to understand customers in ways that were not previously possible (Shu-Chuan and Kim, 2011; Capgemini, 2012; Ahmad et al., 2013). For example, filling in questionnaires and conducting interviews have traditionally been popular ways for assessing customers' needs. But it is very difficult for enterprises to accurately capture consumer preferences with survey data that is static and highly structured because the real needs of consumers are very often private, complex, and steadily changing (Ahmad et al., 2015).

Via the Internet – and, as the Internet begins to expand its reach into the physical domain, the Internet of Things (IoTs) – today's firms can have relatively easy access to behavioural data, environmental information, and the geographical position of consumers. By combining these data sources and applying the new types of big data analytics capabilities that are increasingly available in the marketplace, firms can get a good grasp of the real needs of consumers, and can optimise product innovation processes by deepening their understanding of the technology level of companies and their research and development capabilities (Prahalad and Ramaswamy, 2004). Several firms have successfully applied big data analytics in this way to capture information from web-based platforms for market understanding, reducing costs, and accelerating NPD (Mckinsey, 2009; Noble et al., 2012; Bharadwah and Dong, 2014). Thus, we put forward the following proposition:

> *P3: A deeper understanding of customers' needs based on an increase in the amount and kinds of data will accelerate the innovation process.*

Customer co-creation

Beyond merely understanding customer needs, there is also growing evidence that having customers actively participate in the NPD process can deliver significant value (Hoyer et al., 2010; Shu-Chuan and Kim, 2011; Roberts and Candi, 2014; Schaarschmidt and Killan, 2014). Early customers of prototypes have, for example, been a source of novel ideas and valuable feedback about new products (Roberts and Candi, 2014). The observed benefits of co-creation with customers includes increased efficiency, innovativeness, cost minimisation and quality, and overall process effectiveness (Blazevic and Lievens, 2008; Hoyer et al., 2010). Products that are co-developed with customers have also been found to possess a higher degree of novelty, thus enhancing their attractiveness (Franke et al., 2009).

Big Data and ICT-enabled connectivity are well positioned to positively impact organisations' ability to co-create with customers insofar as these new resources will facilitate the capturing and sharing of the customers' ideas and perceptions (Chen et al., 2012). Customers can engage in ongoing dialogues and interact with firms during each stage of the NPD process (Hoyer et al., 2010; Roberts and Candi, 2014). Businesses can also use these digital resources to identify opportunities and problems throughout the NPD process that they might otherwise not have discovered (Franke et al., 2009). Several companies, like eBay (Davenport, 2009) and Microsoft (Kohavi et al., 2009), have built customer co-creation platforms that they have used to gain insights into the amount of time a user spends using a particular feature, the relative frequency of feature selections, and the path that users take while accessing different functions. This more direct connection with the NPD process has accelerated development cycle times and led to products with strong market appeal (Prahalad and Ramaswamy, 2004) and word-of-mouth advocacy for the new products being developed (Rohrbeck, 2010). We therefore propose:

> *P4: Big data market environments*[2] *will lead to accelerated product innovation via customer co-creation.*

6.1.3 Ecosystem of Innovation

Most breakthrough innovations do not succeed in isolation (Moore, 1993; Adner, 2006; Google, 2013); instead, they frequently need complementary innovations to deliver useful functionality to customers (Cooper, 1994; 2016; Gawer and Cusumano, 2014). These complementary goods and the core products that they fit are often developed by innovation ecosystems, which are the collaborative arrangements through which firms combine their individual offerings into a coherent, customer-facing solution (Adner, 2006). Big data and ICTs can drastically reduce the costs of

[2] Big data market environment refers to a business environment that presences of a large amount of data and data analytics applied to facilitate its day-to-day business operations (Chen et al., 2012). In such an environment, big data can be defied as multimedia-rich and interactive low-cost information resulting from mass communication (Zhan et al., 2017).

coordination throughout this multi-firm innovation process and, as a result, innovation ecosystems have become a core element in the growth strategies of firms in a wide range of industries (Majchrzak et al., 2012). The benefits of these systems – which have been discussed in the literature under a variety of conceptually connected labels such as “open innovation”, “platform leadership”, “hyperlinked organisations”, “value networks”, and “keystone strategies” – have been realised across a broad number of sectors and market conditions (Gassmann and Enkel, 2004; Rese and Baier, 2011; Rohrbeck, 2010; Gawer and Cusumano, 2014). As shown in Figure 6.3, two defining approaches of innovation ecosystems are at the core of the propositions put forward in this research: 1) partnership with stakeholders, and 2) the fast improve-and-relaunch process.

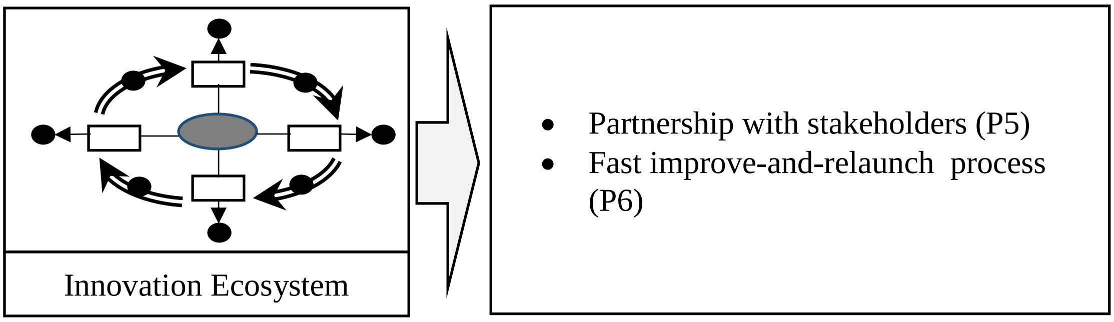


Figure 6.3: Innovation Ecosystem

Partnership with stakeholders

Unlike early approaches to product innovation that mainly relied on information from internal research (Rothwell, 1994; Niosi, 1999), current approaches such as open innovation involves building networks of cooperative product market relationships (Kessler and Chakrabarti, 1996; Adner and Kapoor, 2010; Gassmann and Enkel, 2004; Hagel and Brown, 2011; McKinsey, 2013; 2015). This change has largely been driven by shorter innovation cycles (Karagozoglu and Brown, 1993), the escalating costs of industrial research and development, and the scarcity of resources required to support R&D and innovation (Chesbrough, 2006).

Modern data analytics and big data capabilities can help firms to improve these external relationships even more by helping them to better understand stakeholders such as suppliers and customers in a way that more traditional means did not (Wong, 2012; Tan et al., 2015). Specifically, knowledge sharing in the era of big data has been found to positively affect innovation performance (Chen and Wang, 2015), and the application of big data has been used to improve problem solving and reduce the inefficiency associated with re-inventing already existing solutions (Xu et al., 2016). Moreover, effective interactions among stakeholders stimulate better quality solutions and reduce costs in the NPD process (Mangold and Faulds, 2009; Roberts and Candi, 2014). We accordingly propose:

P5: Big data market environments will lead to accelerated product innovation via stronger partnerships with stakeholders.

Fast improve-and-relaunch process

Successfully launching and commercialising new services and products is an important driver of performance for many businesses (Hultink et al., 2000; Mangold and Faulds, 2009). But how these launches happen is being impacted by ICTs and big data. Rather than developing a fully-fledged product before launch, companies today routinely launch new products as quickly as possible, and then pay close attention to the feedback that they receive from their partners and customers so that they can improve the product (Floricel and Dougherty, 2007; Williamson and Yin, 2014). The product can then be quickly relaunched, and this feedback loop can happen over and over again in an iterative cycle (Hultink et al., 2000; Cooper, 2014). This strategy has proven to be especially effective in market segments that are fast-growing and fluid, which are populated with many open-minded consumers and first-time buyers, and for which there are relatively few regulatory hurdles to clear before new products can be launched (Williamson and Yin, 2014).

The increasing availability of extensive data and a large improvement in connectivity between the innovating firm and these external stakeholders will enhance the fast improve-and-relaunch process as ICTs offer a low-cost means of communicating a new product launch to a wide audience, and feedback can easily be transmitted to and from a larger radius of prospective customers (Kohavi et al., 2009; Cooper, 2011; Bharadwaj et al., 2012; Noble et al., 2012; Wong, 2012; Storbacka and Nenonen, 2015). Droge et al. (2010) describe how firms can use social media such as blogs, Facebook, and Twitter as part of formal public relations or advertising campaigns. By applying big data analytics, feedback from partners as well as customers can be collected quickly via different data sources, and analysed in near real-time to shed valuable light on critical junctures of the NPD process (Chen et al., 2012; IBM, 2013; Bosch-Sijtsema and Bosch, 2015). R&D teams can relaunch the product quickly and trigger further innovation, leading us to:

P6: Big data market environments will lead to accelerated product innovation via faster improve-and-relaunch cycles in the NPD process.

6.2 Findings

Here we assess the five cases with regard to each of the propositions put forward in Section 6.1. The results are summarised in Table 6.1. We discuss the types of innovation approaches with the different data analytics applied. The results can be summarised by the three dominant phases: (1) agile structure; (2) customer involvement; (3) ecosystem of innovation. All three core phases represent an accelerated product innovation strategy in a big data environment, but not all three were equally important for every company.

	Case				
	A	B	C	D	E
Agile Structure					
NPD team autonomy (P1)	+			+	+
Cross-functional team (P2)	+	+		+	+
Customer Involvement					
Understands customers clearly (P3)	+	+	+	+	+
Co-creates with customers (P4)	+	+	+	+	
Innovation Ecosystem					
Partnership with stakeholders (P5)				+	+
Fast improve-and-relaunch process (P6)			+	+	+

+ *indicates approach clearly present/strong (level 3 and level 2)*

Table 6.1: Summary of Results

6.2.1 Agile Structure

Agile structure has been acclaimed as a core structural approach to catalysing effective and accelerated NPD (Crawford, 1992; Chen et al., 2010; Google, 2011; Liao and Barnes, 2015). Among the cases, this approach begins with a defined outcome for the product, and then the development teams are drawn from different functions and work autonomously to accelerate the innovation process.

In Case A, the company traditionally worked sequentially, with teams of five or six professionals spending up to two years going through all of the steps to completion. Globalisation and the development of ICTs are forcing the company to reassess their business strategies in order to be more productive and efficient in their operations. Today, the company builds autonomous teams to work on different projects in parallel. For a specific project, the company used a team of 33 workers from different departments (including eight designers, 16 individuals with expertise in areas such as R&D, manufacturing and sales, six computer engineers and three product testers). The team is supported by hundreds of craftspeople to enable rapid prototyping of new designs. Team members apply different data analytics (e.g., SAP BusinessObjects) to integrate and interpret new information about the team, task, and the problem situation. Therefore, shared information helps guide effective team tasks such as plan execution and is considered important to speedy problem solving. For example, through the use of Office Automation System, team members can collaborate instantaneously and continuously by making the most of hidden manpower dispersed throughout an organisation. As the cost of modern networking technologies falls and the reality of globalization transform business practices, autonomous teams are becoming increasingly more appealing to organisations. During an interview, one of the team members pointed out that the "*old, sequential method of design engineering, throwing the product design over the wall into manufacturing's domain, is no longer acceptable*". The industrial process with a cross-functional team and team autonomy produced a magic triangle linking time, costs and quality in the product development process. Consequently, autonomous teams have begun to emerge as the best alternative to meet the challenges of a new work context surrounded by sophisticated big data analytics and information technologies.

In Case D, the company gives teams the freedom to set their own level of responsibility and schedule to achieve it. According to the project manager, "*they don't sign up for a move they don't want to do*". In this way, teams are formed to exploit complementary skills in the pursuit of common strategic objectives, operating remotely from each other and from managers, and relying heavily on information technology to accomplish their tasks. For example, Microsoft SQL Server provides real-time insights across the transactional and analytical data among team members, rather than back-and-forth emails which can lead to confusion and frustration. The project is then divided into a large number of small elements (which include the business case, development, testing and validation) and undertaken by cross-functional teams working in parallel to facilitate product development. In this way, big data analytics such as Visible Technologies can enable teams to make data-driven decisions and share the latest information and communicate effectively, speed up problem solving and reduce development costs. It also allows disparate groups of people with different schedules and locations to work more effectively together by decreasing project completion times and costs. In addition, one of our findings was that implementation of this processing made employees feel more valued and trusted. The NPD teams agreed that "*It not only improves the output but may also encourage creativity during the approaches*." Through applying big data analytics, the talents and abilities of individuals are no longer constrained to organisations' branches, divisions, or offices, but can be mutually employed for the benefit of the entire organisation.

In Case E, the company applies autonomy and builds virtual teams that work independently and closely with strategy, technology, engineering, marketing, purchasing, and production. A virtual team is a group of people that uses electronic means to communicate with each other more often than face-to-face meetings. The company allows each team to decide how they will reach the target and gives them the right to tailor their approach to their preferences and abilities. Team members use the internet, intranets, and other networks to communicate, coordinate and collaborate with each other on tasks and projects even though they may work in different geographical locations and for different departments. Managers can enhance teams' ability to monitor and track a project as it progresses using PLM and Microstrategy. It allows managers to enter estimating, budgeting, scheduling and other aspects of the process. Thus, NPD teams can communicate synchronously or asynchronously; they may be located together or remotely; and the big data analytics (e.g., Hadoop Cluster and Google Analytics), can provide the support and challenge required to keep team members engaged and motivated and empower them to reach their potential. According to the interviews, the team manager highly valued the virtual teamwork for autonomy. They mentioned that "*by implementing the autonomy, people from different function departments are grouped together to work actively. It cuts across boundaries of different departments and there is no more marketing team or production team. Instead, every team member becomes involved in marketing, engineering, design, production or R&D*". The senior manager further pointed out that "*big data analytics can save us a lot of time and has eliminated a vast amount of unnecessary double communication within various teams*".

All these cases apply agile structure for accelerating their NPD, including NPD team autonomy and cross-functional teams. In particular, we also found that middle managers play an important role in cross-functional teams (Pich et al., 2002). In the cases (A, D and E), only one manager was charged with the task of directing team members of various disciplines. Cicmil et al. (2006) point out that team and project management skills are critical for project success. By comparing the cases, managers with better team and project management skills are able to transform different variations of input into one cohesive final output more efficiently.

6.2.2 Customer Involvement

Today, customers are increasingly regarded not just as passive adopters of innovations, but they may rather develop their own innovations and support producers for accelerating their innovation (Von Hippel, 2005). This approach to NPD pays more attention to connect with a wide range of customers through establishing information platforms at the earliest stage possible of product development to gain a deeper understanding of their needs and of the market.

In Case A, the company used to have little direct feedback from customers. Only recently did the company start to monitor consumer comments about its products on social media. In particular, the Company-Fans Club was a very important channel; until Sep 1, 2015, the total number of posts has over 16 million and registered users had reached 2.6 million. In this open community, there are tens of thousands of posts fed back by users every week, from which some deep reports of product usage were created. By the way of integrating and analysing information of those posts through to using NLP to unstructured contents, the company can acquire users' demand information with low costs and high efficiency, providing innovative ideas for research and development of new products. According to the marketing manager, "*big social data provides more than merely an idea for product innovation. It supplies the firm with information on market needs or existing problems, product-related specifications, or even a complete product design*". Connecting with customers through big social data helps the company better understand its customers by analysing the data collected; it gathers feedback quickly to inform further product information. To fully involve customers, the company has cultivated many active web-based platforms at low cost (e.g. official web forum, mobile apps, popular websites) where customers can interact with the company and each other. The latest product information can be updated to the forums on a daily basis, partly to attract more customers and to gain feedback for further developments.

In Case B, the company captures different sources of data such as videos, photos, number of comments and number of followers from the most popular websites by using Web Page Cleaning, Web Crawler and HTML parsing technologies. Big data analytics such as IBM Analytics and HP Vertica play an important role in supporting product innovation through the analysis of a huge amount of external information to offer managers supportive product ideas. For example, customers have a discussion of new ideas of certain functions, then a multidimensional scaling diagram (MDS) can be generated by applying IBM Analytics which illustrates the clustering results of different opinion groups in the discussion. Therefore, it is a useful approach to gain better customer understanding and uncover information since people will use similar wordings but different sentence structures to express their ideas. Moreover, the company differentiated 'core customer units' from 'normal customers' (i.e., through RFM analysis which is a data mining technique qualifying customer value by examining how recent recency, frequency and monetary a customer purchases) and keep in close connection with the 'core customer units' as early as possible. The company set up a competition for its 'core customers' that involved online services, telematics as well as future PC online assistance systems. Novel ideas generation by the customers has been endorsed by an interactive multimedia tool for services, as well as assessing ideas generated by others. During the initial stage of NPD process, the data generated enables the integration of customers and turns them into valuable sources to support companies in idea generation and evaluation. The senior manager pointed out that "*by pushing core customers into the process early, and continuing to work with them, it is possible to avoid the pitfalls that are based on a one-shot market research project at the conceptual stage.*"

In Case C, the company focused on collecting and analysing information from customers, market and competitors to gain competitive advantages and a deeper understanding of both their customers and their competitors. The advantage of using big data analytics (such as Hootsuite and Google Analytics) in customer understanding assessed against conventional market research is that customers are not only asked about their needs, opinions and wants. They can, rather, exhibit their creativity and competence by deriving and assessing new product ideas; they can challenge, explain and enhance detailed solutions; they can identify and individualise virtual prototypes, experimenting with and embracing the novel product features. This can be achieved by conducting simulations, or by acquiring information from different sources regarding a novel product. The IT manager stated that "*Normally we just determine our main customers and potential customers but the latest big data analytics allow us to investigate more detailed aspects, such as where they are, what problem they face, what they need, how they want to be contacted and when.*" The company is now developing a sophisticated customer predictive big data tool to keep a close watch on customers' activities; it should then be able to work out the needs of its customers even before they have decided to buy the product.

In Case D, to acquire a better understanding of their customers and to integrate with customers, the company has implemented a product innovation strategy of 'Customer Demand-Orientation' and analysed customers' behaviour by machine-style learning using both qualitative and quantitative data. The company installs feedback software and sensors into its new smartphone product in combination with the advantages of technology and hardware. According to various data transmitted from users' smartphones, functional design to products can be made appropriately so that smartphones in line with users' demands can be launched. As a consequence, more than a million customers have offered their feedback regarding acceptance, usability, intention to buy and willingness to try. In this way, the company was able to come up numerous improvement ideas though applying Google Analytics for A/B testing and Visible Technologies for big data visualisation to support their NPD faster and less costly. An R&D manager pointed out that "*this is partly to renew our customer involvement and also to see what the customer really needs.*" The NPD teams highly valued the customer feedback and engagement. R&D team members also mentioned that "*customers were able to experiment with and examine features early on, and [we] discussed the positive responses from customers to the developed solutions as validation and motivation for [our] work.*"

Overall, there was clear evidence of good development of customer involvement in cases A, B, C and D. In these cases, customer involvement plays an important part throughout the NPD process. However, we found that personality issues can arise. For instance, some employees have personalities that hinder customer involvement. According to Brown et al. (2002), employee personality traits are important in involvements with customers and these in turn relate directly to customer satisfaction. In Cases B and D, we found that employees with positive personality traits (e.g. positive attitude, warmth, enthusiasm and conscientious) were particularly helpful in customer involvement (Liao and Chuang, 2004). They were more likely to gather useful feedback and to get a higher service rating from customers than those without these positive personality traits.

6.2.3 Ecosystem of Innovation

Scholars and practitioners increasingly identify the usefulness of the innovation ecosystem concept for explaining cooperative innovative activities (Cooper, 2011; 2014; Leavy, 2012). The thinking behind what is termed the 'ecosystem of innovation' is that the capabilities of one actor can be expanded through collaboration with others (Adner, 2006). This innovation phase involves agile structure and customer involvement. It enables NPD teams to move to market-winning products quickly and cheaply through a series of iterations: new product ideas, fast launch, feedback gathering, fast improvement and re-launch.

In Case D, the company epitomizes a capabilities-driven innovation strategy and focuses its portfolio and its capabilities on providing products and services to create maximum competitive advantage. The company identifies the key components and all the intermediates within its networks involved in product development before a new product reaches the eventual customers. According to the NPD manager, "*the company is already spending millions of dollars in cooperating with desirable partners among the entire supply chain to support its product development ecosystem*." For example, the company and leading telecommunication operators all over the world set up over ten joint innovation centres and laboratories. Therefore, they can acquire a huge users' data source including data of consumption and personal attributes from operators by means of the cooperation agreement, so as to broaden channels of data acquisition and acquire data of target users, which help it to transform advanced technology into competitive advantages. In particular, different big data analytics were applied to harvest useful information from the acquired data (e.g., Microsoft SQL for relational database management, Hubspot for marketing and sales). As a result, it costs the company less time and money than would ordinarily be required. Also, it enables the company to concentrate on new product research and development rather than other time-wasting processes. Therefore, the company can launch new products to meet its customers' requirements in a much more efficient and effective way.

Cases C and E applied a 'voice of customer' programme which provided valuable inputs from customers for product ideas, market understanding, core competencies of components, as well as the benefits sought in a new product. As data emerged gradually and data volume increased consistently, the companies developed a customer feedback centre (in Case E) and a product improvement centre (in Case C) to encourage feedback from partners and customers and to rapidly communicate this to the R&D teams. The centres serve as a marketing tool and their main task is deriving useful information from data collected and to provide feedback as input to the relevant project teams. The companies have grasped the core big data technologies (e.g., Spark SQL, and Hadoop Cluster). Therefore, the companies were able to apply Hootsuite and Google Analytics, and react quickly to acquire a large number of loyal customers by adopting reasonable product portfolio, accurate market orientation and perfect function design. These inputs (essentially market requirements) also allow R&D teams to quickly develop a new version of a product, with improved functions and features. The marketing manager in Case E stated during an interview that "*many customers are too sophisticated to satisfy because they always demand products with the latest technology, cutting-edge functionality, at an unprecedented low price, and immediate services. At the same time, they don't have much brand loyalty and keep comparing the product with others*." By applying this fast improve-and-relaunch process, each successive version of the product comes closer to the customers' ideal, and therefore closer to being a market-leading product.

6.2.4 Big Data Efforts

The empirical findings manifest that investigated case companies are focusing their efforts on being more agile and accelerated in product innovation. The ACE framework developed is grounded on three phases with the objective to speed up product innovation through reduced time-to-market and new product costs. Findings from five leading Chinese companies show accelerated product innovation in a big data environment as an iterative process of repeating activities and adjusting products based on the large amount of product relative data.

Data collection

According to Morabito (2015), data collection is currently a limitation for several big data companies. Therefore, company participants were asked to describe how they collect and evaluate the data gathered. In particular, Case A identified the primary sources of data collection for the project as operations data, specifically logs and machine-generated data, but it argued that it is insufficient due to law restrictions. Case B mentioned product data, field data and social media data as the primary sources of collection. Interviewees from Case B emphasised the important big data source from social media that can create relations and provide a better understanding of the customers and their product usage and in that way improve the development.

Case C suggested a different approach regarding data collection, specifically, they believed that organisations should collect data they have not thought of in the past, in order to combine and correlate with data they already possess. Case D described the data sources as own machine-generated data, social media, open and external data provided by customers for certain product use and sensor data. Case E described the same sources with the addition that selective data brokering can occur selectively.

Data quality

Furthermore, the accuracy and validity of the captured data is another challenging aspect that organisations need to address (Ohlhorst, 2013). Therefore, each organisation should select and implement the effective tools, suitable for their purpose. Case A explained that the quality of data is connected with the anticipated results and based purely on an application basis. As an illustration, Case A described a situation where data quality is sufficient but not for the purpose for which it was acquired by the organisation. Case B pointed out that the challenge of data quality is related to missing values and data has to be sorted with the usage of robust techniques and scripts. Case C and Case D suggested that data quality can be verified by complete and accurate data which includes values and variables relevant to the purpose of collecting them. Finally, Case E connected the reliability with the accuracy of the past predictions, therefore it suggested as a method of accuracy improvement to correlate data in production in order to further connect it with quality.

Data usefulness

Morabito (2015) suggests that in order for a process of data gathering to produce value, data is required to be actionable. Thus, each organisation should seek data in accordance with the needs of its operations and goals. Case A suggested that it considers three types of data useful: production data, data influencing the development process anyhow, and undiscovered data that no one thought of but with value or an effect to the operations. Case B argued that there are two schools of thought regarding data usefulness: the first suggests that all data are considered useful, and the second suggests that organisations should acquire only the data that is directly valuable. Case C explained that the usefulness of data is determined by the analytic or business objective and if data is suitable for the right questions to be answered. Furthermore, Case D believed that all available data connected in any way with operations and products are useful, while any other kind of data is excluded. Finally, Case E explained that they consider all data useful as long as they are reliable and do not violate privacy regulations.

Big data in NPD

The role of big data in the NPD process is directly affected by how data-driven the organisation is overall. According to the theory and empirical findings, the ACE framework is the most utilised and preferred model within the product innovation process in a big data environment. Both the cases focus on specific approaches/phases of the ACE framework for developing high-tech products, but not all were equally important for every company. In particular, as seen in Case A, their product and solution indicates that big data can add value and be applied to facilitate every phase/stage of the NPD process. Central data collected from the company's own production lines or products' inter-connectivity is used in the formal development phase. However, each case or purpose of big data implementation requires a different approach and strategy. Case B suggested that their product development process is highly dependent on the collection and processing of large customer data sets. Case C emphasised that big data is more used for enhancing products and reducing cost than providing greater dynamics to the NPD process.

During our research, we noticed that many companies are focusing on more flexible innovation approaches, such as the approaches identified in the ACE framework for accelerated product innovation. In particular, interviewees in Case A explained how the experimentation with data can enhance the accelerated product innovation approaches in the framework: *"We believe that big data have the ability to be used and transform all stages of the NPD process. However, we would suggest organisations adopt flexible approaches or phrases such as the developed framework for accelerated product innovation in a big data environment in order to benefit even more. Linear models do not easily offer the ability to go backwards and redesign or implement changes. The more data-dependant a product is, the more it requires cyclical models to constantly improve. Feedback data is a continuous* *source of improvement, insights, and enhanced decision-making. To illustrate with an example, we can mention most fast-cycle products that need to be updated constantly*". Interviewees in Case B proposed that utilising data in the fast improve-and-relaunch process offers the ability to identify new customer needs and generate new ideas through market research and behaviours analysis. And also, the framework developed can take advantage of big data implementation benefits to a higher degree, since its non-linear structure allows feedback loops and data-gained insights to be implemented as fast as possible. Case C, D and E argued that the initial goal of a new software product development is to receive customer insights by launching a minimum viable product, a process which aligns with the framework developed.

Besides the framework, interviewees from Cases A and B explained that a data-driven culture is the key for enhancing the accelerated product innovation in a big data environment, and in several cases has a greater impact than factors such as the big data technology itself. In particular, interviewees from Case A argued that a data-driven culture could promote the adoption of accelerated product innovation in the new product development process by encouraging experimentation with data and encouraging a mental model for data innovation. Moreover, interviewees of Case B suggested that social actors should position themselves in the changing reality of big data in order to promote good use of analytics and data innovation. Therefore, the challenge lies in encouraging the adoption of modern laws with achieve both successful data commercialisation and respect the privacy of sensitive user-data. Furthermore, contributors from Cases C, D and E suggested the importance of setting a data-driven strategy in order to unlock data opportunities. Thus, collaborating with stakeholders with shared objectives and interests offers an excellent prospect of expanding data-operations, rather than just focusing on data management.

All cases referred to the organisational capabilities for big data implementation in the product innovation process. Bloem et al. (2013) emphasised the significance of organisational transformation in order to access big data potential. A crucial decision for the management team is to determine the information system strategy, according to the organisation's level of maturity (Laudon and Laudon, 2011). Interviewees from Cases A and B explained that accessibility and connectivity to all departments are able to increase effectiveness in collaboration and facilitate NPD. Also, they suggested that apart from the people, organisations should make structural changes and implement the right approaches and culture to enable big data capabilities. Therefore, centralised platforms can possibly prevent data-application elimination or critical delays caused by decentralisation of information systems, and no one supposed a decentralised model. In addition, interviewees from Case C argued that designing autonomous departments and teams provides the necessary flexibility to support data experimentation and accelerated product innovation. Interviewees from Cases D and E suggested the further involvement of data scientists within the organisation in order to unlock competencies and enhance data processes.

6.2.5 Factors for Successful Implementation of Big Data

Based on the literature and empirical studies, this section summarises the factors for successful implementation of big data for accelerated product innovation. Interviewees were asked to identify which are the factors – if any – for successful implementation of big data into product innovation. Therefore, in order to determine the specific area of impact of each factor, the classification of the factors was grouped in eight categories: Data, Technology, Organisational, Process, Culture, Intent, Staff and Privacy.

Data

Much of the literature describes how data have changed the decision-making process and unlocked new product innovation opportunities (Tan et al., 2015; DiFilippo and Blasé, 2014; Ohlhorst, 2013). Wengler (2001) further argues that having access to data enables the emergence of patterns and trends. An interviewee in Case A believes that expanding data collection to external sources will improve insights gained and promotes data experiments. Participants from Cases B and C suggested a similar approach, obtaining the right data and experimenting with them in order to explore new opportunities and to create a sense of urgency. Finally, Cases D and E added that collaboration with different stakeholders with combined ambitions and goals will set the base for strategic data sharing.

Technology

According to the empirical study, technological adoption is one of the significant factors for an effective commercial use of big data, especially regarding real-time decision making (Morabito, 2015; Sathi, 2013; Ohlhorst, 2013). Despite this reference in the literature, both the cases emphasised the importance of technology as an important factor. Specifically, Cases A and C suggested that in several innovation projects it is crucial to analyse the data and draw conclusions as fast as possible, in order to exploit possible market opportunities.

Organisational

McKinsey (2011) argues that organisations need to change to adapt to big data requirements, while they should perceive and design the business process of implementing a data strategy. Both the Case companies suggested that organisations should build and understand the business case when managing data. Therefore, it is vital to promote connections with their customers, data scientists and managers for an effective collaboration. Interviews in Cases B, C and D further added the value of speed in hyper-connectivity within the organisation regarding the use of data and achieving the goals.

Process

The process of organising the information systems and the data inside them is determined by the data-maturity of an organisation in accordance with the strategy (Laudon and Laudon, 2011). Participants in Case A highlighted that having centralised data which is accessible to everyone is a key factor of success, and could significantly promote project management and several other processes. The rest of the cases described similar approaches of centralised and accessible data, which could enable a combination of data.

Culture

All case companies referred to the significance of a data-driven culture and the impact upon the connected operations. Parmar et al. (2014) explain that in a data-driven culture, data holds a central function and promotes a fact-based decision-making process, while data-driven decisions are more informed and effective (McAfee and Brynjolfsson, 2012). Interviewees in Case A suggested that organisations using data should encourage the acceptance of big data in their product innovation process. In order to do so, organisations should cultivate a data-driven culture and promote a simple but structured framework (as the ACE framework developed) for product innovation in a big data environment. Case B argued that a data-driven culture is more important than big data technology, since this is where limitations often occur. Interviewees in Case C added that a culture to involve data in every process could improve functions such as decision-making. Furthermore, Case D connected the data-driven culture with the openness of experimenting and exploring new things with the use of data, as an important process for product innovation. Finally, interviews in Case E emphasised the importance of data-driven culture and explained that organisations should understand that handling data has both direct and indirect influences.

Intent

The factor of intent is referring to the organisation’s actions to design and implement a big data strategy by choosing the suitable technologies and techniques according to their requirements (McKinsey, 2011; Sathi, 2013). Case A suggested that it is essential for organisations to have set their objectives as well as data strategy in order to successfully manage big data. Further, Cases B and C believe that a strategic collaboration with different customers with common goals and ambitions could unlock data sharing opportunities. Additionally, interviewees in Cases D and E explained that organisations should oversee the interests of stakeholders in the data, rather than focusing only on handling data.

Staff

The empirical cases indicated the factor of having a well-trained staff as necessary to successfully organise big data. McKinsey (2011) includes the urgency of acquiring skilled human resources and believes that it will be a decisive factor that it will become a challenge due to a shortage. Interviews in Case A suggested that teams should be multidisciplinary and composed by specialists. Generalists-engineers should oversee the entire scope, operationally, tactically, and politically to ensure that the staff working with big data should have the necessary competencies, both in technical and commercial aspects, in order to achieve the goals set. Moreover, Case B argued that there is insufficient specialised human resources, and believes that organisations might need to start training their own staff. Another factor was highlighted by Case E which stressed the importance to have sufficient human resources but also have early adopters within the organisation.

Privacy

Cases A and Case B stressed the necessity for data-driven organisations to act in order to promote legislation enabling big data activities, and cope with that limitation. According to McKinsey (2011) and Kerr and Earle (2013), organisations and societies will have to position themselves and choose between privacy and efficiency in several market segments currently unavailable due to privacy laws. Interviewees in Case A urged organisations to ensure that future legislation will not prohibit the good use of big data that will benefit both societies and companies. Further, Cases C, D and E suggested that privacy laws must be addressed in order to allow the expansion of data-driven innovation, but in order to materialise, organisations should choose the right framing and timing.

6.3 Summary

This chapter examining the framework by studying specific innovation projects within the five case companies. From the cases, the approaches identified in the framework can be applied throughout all the phases of product innovation. Also, all five companies in the present case study were applying approaches in NPD for accelerating product innovation, better understanding of customers' needs, lower new product costs, and faster launch of new products to market. Moreover, in a big data environment, firms can make use of different technology-based or online data analytics to enhance their accelerated product innovation approaches identified in the framework. Examples are: methods of crowdsourcing and A/B testing in cases C and E, which could be viewed as testing or experimentation methods that are now applied to acquire customer feedback to support NPD; OA, to enhance real-time communication between R&D teams in case A; and the use of an SQL Server, used to build data platforms in case D. The next chapter will discuss the findings of this data analysis in relation to each of the innovation phases developed in turn.

Chapter 7.0 Discussion

This chapter reviews the findings of the data analysis presented in Chapter 5 and 6. These will be discussed in relation to each of the innovation phase for achieving accelerated product innovation in a big data environment. This chapter is divided into three sections.

Section 7.1 summarises the main findings gained from the empirical study and discusses its links and contrasts with external theories. In particular, it discusses the contributions of developed innovation phases: agile structure, customer involvement and innovation ecosystem to research and practice. It further discusses the knowledge of applying big data in facilitating product innovation. Section 7.2 discusses the main challenges that are essential to address when using or implementing big data for accelerating product innovation. Section 7.3 summarises the key points from this discussion chapter.

7.1 Discussion of the Main Findings

The study set out to investigate two research questions: first, what are the best approaches for accelerated product innovation in a big data environment?; second, how can big data be applied to support accelerated product innovation? The propositions based on case evidence are summarised in Table 7.1. A confirmatory contribution of this research to existing literature is specifying an ACE framework and identifying the approaches for accelerated product innovation in world leading companies. Although prior research has examined different antecedents or success factors associated with various aspects of the NPD speed, these contributions had not specifically examined the role that big data could play in these processes. Therefore, the fact that many companies today have not identified these approaches systematically indicates that this is not common knowledge, and that practitioners and academics could benefit from applying this framework to similar accelerated product innovation in today's big data environment.

Proposition	Support	Additional comments
Agile Structure		
NPD team autonomy (P1)	Yes	More top management support can be acquired from non-state-owned companies
Cross-functional team (P2)	Yes	*Team and project management skills positively contribute to building cross-functional teams*
Customer Involvement		
Understands customers clearly (P3)	Yes	Big data analytic skills are a necessary but not sufficient condition for success
Co-creates with customers (P4)	Yes	*Positive personality traits can make customer involvement more effective*
Innovation Ecosystem		
Partnership with stakeholders (P5)	Yes	Financial inadequacy may limit the ability to develop partnerships with stakeholders
Fast improve-and-relaunch process (P6)	Yes	Appropriate processes for both innovation and customer involvement are needed

Yes = clear support for proposition

Table 7.1: Summary of Support for Propositions

The traditional role of innovation in competitive success has been redefined to reflect a time-based requirement (Karagozoglu and Brown, 1993). Accordingly, accelerated product innovation is associated with maximisation of the product success rates, higher profitability and competitive advantage (Menon et al., 2002; Greve, 2011; Williamson and Yin, 2014; Gawer and Cusumano, 2014). All five companies in the present case study were applying approaches in product innovation for accelerating their NPD, better understanding of customers' needs, lower new product costs, and faster launch of new products to market. Some of the methods reported here have been discussed in the literature, such as autonomy (Patanakul et al., 2012) and cross-functional teams (Chen et al., 2010; Cooper and Kleinschmidt, 2011). However, the case study companies jointly implement other types of methods as well as big data to generate an integrated framework for accelerated product innovation. The literature on R&D research shows existing approaches to achieve fast NPD (Markman et al., 2005; Greve, 2011), or to develop involvement and co-creation with customers (Brown, 2002; O'Hern and Rindfleisch, 2009; Schaarschmidt and Kilian, 2014). However, identifying suitable approaches for accelerated product innovation throughout the whole innovation phase has been more difficult, as many approaches have focused on the early innovation stages in terms of collaboration (Shu-Chuan and Kim, 2011; Blazevic and Lievens, 2008; Fuchs and Schreier, 2011). Moreover, in a big data environment, firms can make use of different technology-based or online data analytics to enhance their innovation approaches. Examples are: methods of crowdsourcing and A/B testing in Cases C and E, which could be viewed as testing or experimentation methods that are now applied to acquire customer feedback to support NPD; OA, to enhance real-time communication between R&D teams in Case A; and the use of an SQL Server, used to build data platforms in Case D.

7.1.1 Agile Structure

The evidence from the five cases illustrates how R&D teams change their processes to accelerate product innovation in a big data environment. In order to speed up their NPD, Cases A, D and E focus on establishing cross-functional teams that can work both autonomously and simultaneously. Based on our cases, we found that the innovation process can be industrialised by assigning cross-functional teams to the many small steps and project activities. Thus, the total outlays for a given project can be reduced, as these people are less highly trained than traditional R&D staff and are generally therefore paid less (Markman et al., 2005; Schaarchmidt and Kilian, 2014). For example, Cases A and E overcame the usual problems of process innovation by: breaking down product designs into separate modules linked by standardised interfaces; redesigning software to be compatible across all activities associated with the new product; establishing short lines of communication where each team member can represent his or her respective functional department; and introducing open design processes where information is shared with the entire team as early as possible.

Moreover, advanced big data analytics and ICTs can be used to facilitate the process of boundary-crossing to overcome the challenges presented by remote and culturally diverse team members (Shachaf, 2008). Our study shows that it can also be used to support the creation and maintenance of team identity by the use of big data that decrease distorted communication (by capturing decisions in a shared database) while increasing team cohesiveness, inclusion, and common ground. With the cases, we found that the agile structure developed supports the more collaborative approach in the early, conceptual phases of product innovation, and the data and information collection approach through experiments and testing in the later phases.

7.1.2 Customer Involvement

The cases indicate that customer involvement is applicable throughout the whole of the innovation cycle. In many previous studies, customer involvement was primarily implemented in the early, conceptual phases of product development (Van Kleef et al., 2005; Shu-Chuan and Kim, 2011), although in some instances it was also applied in the deployment phases (Schaarschmidt and Kilian, 2014), but few studies have examined big data for customer involvement in the product development phases, after a product has been launched. Notably, the customer has been viewed as an active co-creator in, for example, agile software development (Blazevic and Lievens, 2008; O’Hern and Rindfleisch, 2009), or the customer supports innovation through data optimisation experiments after product deployment (Fuchs and Schreier, 2011;

Davenport, 2013). However, few studies have looked at customers providing input throughout the whole of the innovation phase. We found in our case studies that customer involvement can take place at different phases of the innovation process for acceleration of NPD. For example, the companies (cases B and D) connect with their wide range of customers at the earliest stage possible of product development to gain a deeper understanding of their needs and of the market, and they collect feedback after launches of the product to trigger further continuous innovation.

7.1.3 Innovation Ecosystem

The cases show that successful companies aim to build an innovation ecosystem, that is, an innovation and market-testing environment (Gawer and Cusumano, 2014), to develop and launch new products at fast speed to market and low new product costs (Leavy, 2012). The environment being like an ecosystem indicates that the company network is used to acquire new requirements and components of product development processes externally or from intermediates (Ernst, 2002; Berends et al., 2014), in order to create such an environment that is able to launch a product quickly with less cost (Nambisan, 2002; Carbonell et al., 2009). Moore (1993) proclaimed the end of 'industry' as a useful concept in contemplating business and urged the adoption of the concept of the business ecosystem as a more insightful alternative. Gawer and Cusumano (2014) argued that in the evolving competitive landscape, the crucial battle is no longer between individual firms but among networks of firms. Many scholars today use the concept of the innovation ecosystem to explain cooperative innovative activities (Gassmann and Enkel, 2004; Adner and Kapoor, 2010; Gawer and Cusumano, 2014). However, the innovation ecosystem, as a very broad concept, can be used only once there is a relatively mature implementation of the product or feature available. In the cases, we found that Cases C, D and E aimed to build partnerships with stakeholders and leading customers that can support the launch of their new products as quickly as possible to gain market recognition as well as feedback from customers to trigger further continuous innovation. In particular, a fast improve-and-relaunch process requires the appropriate agile structure and customer involvement can help the product team to move quickly to a market-winning product through a series of iterations: new product ideas, fast launch, gathering feedback, fast improvement and relaunch.

7.1.4 Implications of Big Data for Accelerated product innovation

The different big data and information technologies applied offer unstructured, semi-structured, and structured input to the R&D teams. Among the cases, structured and rich data were gathered during earlier innovation phases in order to gain more insight into customer contexts and needs by conducting dialogues, collaboration and online surveys. For example, Cases B and C utilise customer dialogue to shape their NPD process through customer data capture, and crowdsourcing from various online forums. Case D builds a targeted ongoing customer advisory group to interact with customers. This structured feedback was often based on customer stories or dialogues, and customers were able to consciously and actively help the development of new products and functionalities. Semi-structured and unstructured large-scale data sets were captured in the later phases of innovation, when a feature or product had been launched on the market, and customers were able to use the particular feature or product. For instance, Case A applies natural language processing (NLP) to unstructured content (captured from apps and social networks) to identify customer satisfaction and preferences. The large-scale set of data from different sources provided a different kind of feedback to the innovation process, but could provide more reliable, real behavioural data based on the click behaviour of customers using a system, for example. Case E predicts customer behaviour by applying Google Analytics to analyse customers' post-click data. In such circumstances, the customer was not actively involved in giving feedback, but feedback was automatically generated through online behaviour. More and more organisations are collecting this kind of data, to the extent that discussions are arising in social media about ethics and customer privacy (Bosch-Sijtsema and Bosch, 2015). This is an element that needs to be taken into account when focusing on capturing customer data for innovation. Structured, semi-structured and unstructured data are common in customer input studies in all phases of product development (Sood and Tellis, 2005; McKinsey, 2009; Capgemini, 2012). However, through the use of big data in the cases studied, the data in earlier phases are more connected to feedback, while in later phases larger amounts of data are captured through actual usage and customer behaviour.

7.2 Managerial Challenges

The empirical findings acknowledged several significant challenges that are essential to address when using or implementing big data for accelerating product innovation. The obstacles that need to be overcome are presented and divided into two categories: technical and managerial (see Table 7.2). The technical challenges presented by theory and empirics are more concerned with technical ability and functionality, which lands outside the scope of this research. However, to wholly understand what hurdles organisations face, we cannot disregard crucial technical challenges that possess a direct impact of the utilisation of big data for accelerating product innovation.

Technical	**Managerial**
• Incompatible IT • Access to Data • Meaningful Output	• Understanding Data Value • Corporate Culture Change • Human and Financial Resources • Legal and Security

Table 7.2: Summary of Big Data Managerial Challenges

7.2.1 Incompatible technologies

Theory in the area of big data mainly presented technological challenges of using and implementing big data. Morabito (2015) stated that an essential obstacle to overcome is to solve incompatible technologies, IT infrastructures and data architectures. He further argued that incompatible technologies offset the initiatives of sharing data across internal and external platforms. Cases A and C referred to the challenge of integrating data silos into centralised systems. Accordingly, McKinsey (2011) pointed out the technological challenge of integrating and standardising data of distinct formats. So, ensuring format consistency of internal and external databases is a challenge that needs to be addressed. According to the empirical findings, the implementation of technologies has to be compatible with the specific task, since some technologies are more suitable for certain objectives and goals. Cases B and E expressed that the organisation needs to adapt the necessary technologies based on the task and fit the implementation accordingly. However, this technological adaptation is subjected to the data maturity of the organisation (McKinsey, 2011). Moreover, Case D emphasises that legacy systems (outdated technologies) form obstacles and organisations are required to possess sufficient resources, capabilities and agility to successfully deal with such technological challenges.

7.2.2 Access to data and gain values

Regarding access to data, we are referring to two different categories. The first category is describing the organisation's ability to acquire data from internal and external sources. OECD (2014) and Morabito (2015) highlight the importance of being able to collect data. Case A considered the access to right data as a key component of experimentation with data, and therefore a major success factor for the NPD. Cases B and C highlighted the importance of establishing external sources of data for product innovation. While Cases D and E believe that stakeholders with shared goals might be the key for data sharing.

The second category concerns access to data by the organisation's employees. Cases A and B stressed the importance of having data centralised in order to provide the ability to all interested actors within the company to access and process it. In the developed framework, we explained some of the approaches regarding agile structure. We believe that in order to organise and successfully manage big data, most organisations should have an agile structure. Further, we recognise the importance of acquiring data, therefore we would suggest organisations establish an innovation ecosystem and build 'data-alliances' with stakeholders including customers, partners, suppliers and other actors with common interests.

Organisations should be aware that output from data is useful and efficient only if it encloses value. Tan et al. (2015) and Ohlhorst (2013) suggest that collecting data does not provide any value unless crucial information is extracted. In order to be classified as important information, the result must be valid and accurate (Ohlhorst, 2013). Our empirical findings suggested that understanding the value of data is one of the initial steps of success. All the case companies argued that it is vital to build and understand their business case with data, by combining managers and data scientists to examine the data offered and determine its potential. According to the manager of Case A, *"We understand the importance of extracting value information but we also understand the nature of new discoveries. In some cases, in order to acquire a valuable output, it is necessary to experiment and reveal new methods, processes and results".*

7.2.3 Anchoring change in the corporate culture

A major managerial challenge of using big data for accelerating product innovation recognised by most of the case companies was linked to anchoring change in the corporate culture. Case A stressed that a significant obstacle faced by many that are trying to implement big data into their processes is that the corporate culture is not data-driven. Further, interviewees in Case B emphasised that cultural change is often being neglected by domain experts who are too sceptical about what value big data can bring, as well as changing the already established processes. In the literature, McKinsey (2011) argue that the most crucial barrier to overcome is the establishment of a data-driven culture and structure. Case C presented a concurring opinion and reasoned that the challenge lies in employees being reluctant to change, which creates significant hurdles since big data implementation is a prolonged and continuous process. Another managerial challenge mentioned by Cases D and E, which further incorporates the corporate culture, is the challenge of internal competition and unwillingness to share data, information or knowledge across departments, thus disabling a successful big data implementation. The findings were in line with the reasoning of Parmar et al. (2014), placing data and analytics as the central function for achieving a data-driven culture, hence the need for a cross-functional distribution of data.

Interviewees of Case A presented another cultural aspect as a managerial challenge. They argued that the main challenge of implementing big data into product innovation is the cultural clash between different types of key staff necessary for such implementation. The cultural clash is the inability of data experts and business managers to understand the common objectives. Galbraith (2014) emphasised the need to strengthen the data acceptance, data reliance and analytic capabilities within the organisations to achieve a data-driven culture. At Case B, it was vital to establish an interactive culture and attitude so the cultural clash can be minimised by the staff being knowledgeable about the applications to ensure good interaction with data scientists and engineers. However, Cases C and E also pointed out the importance of addressing the challenge of having or acquiring individuals that possess the right soft skills to be able to interact across their competence fields.

7.2.4 Human and financial resources

In order to establish an analytics unit which will support big data processing, interested parties should be able to ensure that they hold the resources for the implementation. All the case companies referred to the necessity of securing the required resources. They argued that employees should be more involved with data procedures. Further, literature emphasised the importance of resource acquisition and management in order to successfully complete such a project (Morabito, 2015; Harris et al., 2013; Grossman and Siegel, 2014; Lake and Drake, 2014). While examining the literature and during our empirical findings, we realised that the hardest resources to acquire are human resources. Therefore, we propose organisations to train their employees or alternatively, create cross-functional teams composed of individuals who possess the necessary skills to manage big data as well as generalists. Regarding the financial resources, we suggest interested parties to determine the level of engagement of their organisation and invest accordingly. By doing so, budget teams will control the cost of the analytics project, and they will be able to compare the initial investment with the value of the information gained at later stages, before deciding on further investments for big data.

7.2.5 Legal and security

A significant limitation of using big data which is not affected by the organisation is within the privacy and legislation context. McKinsey and Ohlhorst (2013) emphasis the policies regarding medical and financial records. In some countries, the limitation includes more categories of private data protected by laws. Further, there have been incidents in the past of organisations suffering security breaches and the loss of important private information. Morabito (2015) explains that in some cases the organisations responsible for securing the data were hiding the truth in fear of their public, corporate image.

All the case companies highlighted the need for legislative reform to allow the positive use of big data to benefit both organisations and society by promoting innovation. Further, they agreed with the legislation change and added that organisations should encourage the right metal model for the acceptance of big data supported innovation. In order to achieve that, they should pick the right timing and the right framing. We believe that it is time for organisations and society to start a constructive dialogue regarding big data and privacy. Companies should approach government and society and agree on a reform which will be accepted by all interested groups.

7.3 Managerial Challenges

This chapter illustrated how each of the two research questions was addressed by drawing on the previous data analysis chapter, to investigate each of the innovation phase developed for achieving accelerated product innovation in a big data environment. It summarises the main findings gained from the empirical study and discusses its links and contrasts with external theories. It further discusses the main challenges that are essential to address when using or implementing big data for accelerating product innovation.

The next chapter will conclude this thesis by presenting the research contributions, the limitations of the current research, areas for further research and concluding remarks.

CHAPTER 8.0 CONCLUSION

This chapter discusses and summarises the knowledge gained from this research and indicates where further research might be undertaken. This chapter is divided into five sections.

Section 8.1 explains the results gained from the empirical study and describes the contributions to knowledge. Section 8.2 describes contributions to research and practice. Section 8.3 indicates the limitations of this research. Section 8.4 describes the areas for further research. Section 8.5 concludes the dissertation by summarising the main learning outcomes of this research.

8.1 Summary of Main Findings

In conclusion, based on the two research conversations – accelerated product innovation, and big data that facilitates accelerated product innovation – this research has contributed to filling a gap in the current innovation literature, namely how to achieve accelerated product innovation in a big data environment. By comparing the aim of the current research with other researchers' findings on relevant topics, two research questions were raised in the research, as follows.

1. What are the best approaches for accelerated product innovation in a big data environment?
2. How can big data be applied to support accelerated product innovation?

In order to satisfy the needs for the research questions. Five research objectives were identified:

a. To identify the best approaches for accelerated product innovation in a big data environment.
b. To determine the role and benefits of using big data in product innovation.
c. To develop a framework to assist managers in achieving accelerated product innovation in a big data environment.
d. To examine the framework using in-company case studies.
e. To identify how can big data be applied to support accelerated product innovation.

In particular, the first objective aims to fulfil the research question 1, while the second objective pays particular attention to address the research question 2. Moreover, by studying the literature of the approaches for accelerated product innovation, we find out that even as more and more firms begin to acknowledge the significance of accelerated product innovation, they still suffer from a lack of knowledge about how to attain it (see chapter 2). On the other hand, we also identified that although many researchers have pointed out the great values of big data in product innovation, to the best of our knowledge, none of them explained how big data can be applied by organisations to accelerate the product innovation in NPD (see chapter 2). Therefore, in order to support organisations in attaining accelerated product innovation (research question 1) as well as harvest the values of big data in product innovation (research question 2), there is lack of a bridge to connect there two issues and develop a framework for accelerated product innovation in a big data environment. Therefore, the research objectives from c to e were focused on developing and verifying of the framework.

Following the research objectives, the phenomenological approach using qualitative methods was applied to guide the research design. Based on the data collected from interviews with academics and industrialists, the approaches were identified for accelerated product innovation in a big data environment (see chapter 4). Through further investigation of the approaches in three company cases, a three-phase framework was developed (see chapter 5). Following this, a set of propositions concerning the best approaches to innovation and big data in supporting accelerated product innovation are proposed. Five in-company cases were then conducted to verify the propositions (see chapter 6). By comparing the five cases, the two research questions (the company's uses of approaches for accelerated product innovation and how big data can be used to facilitate accelerated product innovation) were addressed.

In short, the main outcome of this research has been the development and verification of a framework which helps managers in attaining accelerated product innovation in a big data environment. Results from the case studies demonstrated that the approaches included in the framework were highly rated by industrialists. Also, the implications of big data for product innovation were explored and the main efforts, success factors as well as managerial challenges were clearly summarised and identified. In the following sections, the findings from the case studies pertaining to the accelerated product innovation framework and big data are described.

8.1.1 An ACE Accelerated Product Innovation Framework

A three-phase ACE framework for accelerated product innovation in a big data environment was developed and verified in two stages. In the first stage, the key approaches for accelerated product innovation in a big data environment were identified and refined in 7 academics and 6 industrialists; the refined approaches were further applied in three case companies to address real manufacturing concerns. The results and feedback from the case companies were used to refine and develop the final framework. In the second stage, the framework developed was verified in five comparative cases through establishing a set of relevant propositions. The main outcomes were:

- *An ACE framework based on prior studies and empirical research was developed and verified* – the cases demonstrated that the framework provided practical approaches for managers to attain accelerated product innovation in a big data environment. For example, Case A was able to launch a range of new products in less than five months, at a total cost of $2 million. The company estimated that competitors using traditional design approaches have to invest around $20 million over twelve months to complete a similar set of new designs. The interview feedback indicated that the framework was easy to understand and the approaches identified were valuable to implement.
- *The framework provided benefits by increasing customer involvement and understanding in the product innovation process* – in each case, the framework can provide companies with the guidance to handle data from various sources and formats, as well as to push intelligence from these data to various channels so as to support product innovation. The interviews indicate that the framework developed can be used to increase both the understanding and involvement of customers in different phases of product innovation.
- *The proposition based in-company case research proved to be useful and helpful to draw good support and rich information* – the cases demonstrated that the established propositions were useful to facilitate understanding and group discussion. It predicts outcomes for specific cases and subsequently investigates these cases to see whether the theory holds true for them. The accelerated product innovation enabled variable information to be captured, while at the same time the interviewees could continue their discussion and be aware of issues being discussed.
- *There are indications that the framework may be better than existing approaches for product innovation* – although prior research has examined different antecedents or success factors associated with various aspects of the NPD speed, no studies have investigated the approaches for accelerating innovation in today's big data environment. Therefore, the fact that many companies today have not identified these approaches systematically

indicates that this is not 'common knowledge' and that practitioners and academics could benefit from applying this framework to similar accelerated innovation. The interviews conducted in cases indicated that the approaches identified were more effective, structured and educative than many traditional product innovation approaches in use at many Chinese companies.

- *The fast improve-and-relaunch approach was shown to be useful for accelerated product innovation* – the cases demonstrated that the fast improve-and-relaunch approach for product innovation was effective and useful. It allows companies to earn a premium by staying abreast of competitors' innovation and by having up-to-date products available in volume at affordable prices. Moreover, nurturing interactions in the proposed ecosystem of innovation improves efficiency and creativity, and also makes product innovation a cycle of continuous improvement and information transformation. Overall, the interviewees felt that the fast improve-and-relaunch approach enables firms to find ways to innovate – to make product innovation faster and less costly.
- *The framework development process was shown to be a useful way of enlarging individual knowledge of accelerated product innovation in a big data environment and avoiding 'experience bias'* – the cases indicate that the interview processes during framework development and verification enabled everyone to have their knowledge brought into the open and their assumptions challenged. Using the process, the interviewees also pointed out that they could take wider aspects of accelerated product innovation approaches into consideration.

8.1.2 Approaches for Accelerated Product Innovation

In order to development a framework, a number of approaches for accelerated product innovation in a big data environment was identified and refined (the approaches were categorised into three innovation phases). In particular, the identification and refinement processes were mainly in three stages. Stage one summarised the key approaches from prior studies for accelerating product innovation in a big data environment. Stage two consisted of 13 interviews (with 7 academics and 6 industrialists) to explore its validity and applicability. Stage three consisted of three successful case studies to further investigate its feasibility in product innovation. The main outcomes were:

- *A guide for operating accelerated product innovation* – the cases support the fundamental conceptual aspects of the innovation approaches and endorsed many of the suggested guidelines in each of the approaches. In general, the innovation phases identified included a set of approaches which were demonstrated to be capable of supporting and operating accelerated product innovation in different circumstances.
- *A guide for assisting managers in attaining accelerated product innovation in a big data environment* – the industrial cases demonstrated that the phases were practical and useful for their intended function in attaining accelerated product innovation in a big data environment. From the case, we have evidence to indicate that the identified approaches appropriately reflect the smooth integration of product innovation and big data.
- *The structure of three phases was shown to be feasible for organising companies' information* – the interviewees felt that the three phases were useful and easy to understand. In addition, the innovation phases, together with the approaches identified, are conceptually accurate in capturing the essence of product innovation in a big data environment.
- *A guide for accelerated product innovation framework building* – a significant outcome of this study is identifying the approaches and specifying a framework to attain accelerated product innovation in world leading companies. The cases demonstrated that the refined phases provided practical approaches for structuring a framework and enabled information on accelerated product innovation and big data to be included in a framework.
- *Besides its application for accelerated product innovation, the approaches were shown to have potential as a product innovation knowledge management tool* – the approaches identified help managers to decompose the complexity of accelerated product innovation into manageable approaches, and help them to crystallise thoughts at each approach of the phase. Thus, the interviewees felt that the approaches were useful to capture organisational memory and could be utilised for product innovation knowledge management.

8.1.3 Big Data in Product Innovation

This study explores and provides an understanding of how to apply big data successfully in facilitating product innovation. Furthermore, this study examines perceived benefits, the success factors for implementation and managerial challenges linked with big data in accelerated product innovation.

- In the cases, big data enables the possibility for organisations to gain significant benefits, which can result in a competitive advantage. In particular, benefits extending to a large spectrum of business activities can be translated into cost efficiency, insights or predictions, but also act as the key for product innovation possibilities. Also, advanced big data analytics can offer the opportunity for organisations to manage large datasets to some extent, similar to economies of scale. Therefore, the more data the organisation acquires, the cheaper it will become to store and analyse per data unit. With the increased data volume, organisations are able to expand the possibilities of market research and customer targeting more effectively, and support product innovation. In this way, a less expected outcome of big data is caused by its disruptive action, and the ability to unlock and compete in new non-core markets that otherwise would be impossible without the role of big data.
- What is more, the process of using collected data to extract insights and value is not new, but due to the exponential growth of data volume and its variety, organisations are required to implement new analytics. The empirical findings from the cases conclude that the role of big data is widespread within product innovation. However, its influence is more likely to be aimed at supporting already employed product innovation structures than enabling novel ones. For the objective of this study, the developed accelerated product innovation framework was investigated and proved to be mostly employed by the case companies.
- Moreover, the cases illustrated that the big data enabled fast launch-and-improve innovation ecosystem is a critical component of product innovation success. In particular, flexible product innovation processes such as agile structure can draw more benefits from big data activities, because of their

dynamic nature of swift implementation of new changes. Also, in order to enable effective accelerated product innovation and enhance the value generation throughout the chain, organisations should collect data according to their needs. Some cases require all the possible available data, while others demand a targeted acquisition of datasets. In addition, organisations have to ensure the high quality of the data before they base their business and operational decisions on them. Further, to accelerate product innovation through big data there is a need for alignment between big data strategies and overall business strategies to ensure effectiveness. In other words, top management has to continuously provide clear guidelines and present an enterprise-wide business case that can effectively be solved through the means of big data.

- Furthermore, the successful implementation of big data requires organisations to be prepared to address some – significant for succeeding – challenges. In the cases, apart from solving technical challenges, it is vital for data-driven organisations to focus on managing the managerial dimension of these obstacles. The first limitation to overcome is connected with securing the resources (human and financial) required for the transition into a data-driven organisation. But perhaps the most important step is the design and implementation of a data-driven culture, which requires employees to understand the important role of data as well as to have centralized and clear access to it.

In summary, among the cases, the benefits of using big data to support product innovation are identified as follows. First, risk and market uncertainties can be reduced by using big data analytics. Market feedback in a variety formats and from different sources can be acquired in the early development stages. Second, harvesting big customer data allows previously unrecognised customer needs or combinations of needs to be identified. Market share will go to ‘first mover’ firms which can respond to customers quickly and meet their needs. Thirdly, big data can be used to generate great ideas from a variety sources. Lead customers (or innovative users) often act as co-creators and support product innovation managers in developing and bringing ‘winning products’ to the market. Fourthly, big data enables a company to contact potential customers in different ways. Fifthly, it also lends itself to customer loyalty and retention; for example, through online participation in product innovation, customers gain a better understanding of a new product but also become attached to the product to which they have made a contribution. It is a compelling experience which creates commitment and trust. Customer involvement in product innovation not only improves a company's product performance, but also serves as a means of building and enhancing relationships with both potential and existing customers. Finally, big data can provide product innovation teams with a broader basis for their decisions. By applying big data analytics, it is possible to increase the number of test options and to institute parallel testing of product alternatives among a variety of customers; moreover, this can be done repeatedly throughout the different phases of product innovation.

8.2 Contributions

Rather than attempting to build a theory about the whole product innovation process, this research stood in the position of the high-tech industries and specifically concentrated on incremental innovation in Chinese companies, in order to develop a better understanding of the research topic. This study contributes to the innovation literature by clearly defining the concept of accelerated product innovation. It further develops a framework with different approaches for accelerated product innovation in a big data environment. The framework can be applied throughout all the phases of product innovation, based on the framework developed this research contributes to existing research in several ways.

8.2.1 Contributions to Research

The major contribution of this research is that it usefully extends the innovation literature by clearly defining the concept of accelerated product innovation, and by developing a conceptual framework with six propositions about how, specifically, big data and ICTs can contribute to accelerated product innovation. Then it offers qualitative evidence from five case studies involving world-leading firms, and explaining how innovation can most appropriately be accelerated in a big data environment.

This research develops and demonstrates a distinct theoretical lens – a framework for accelerated product innovation in a big data environment – allowing for the new perspective on accelerated product innovation to be applied in empirical studies. There is no magic formula for accelerated product innovation. However, firms could expand their existing competence in many ways by tapping into the knowledge afforded by big data. The developed framework is based on information elicited from the literature and the unique product innovation approaches adopted by five successful Chinese firms. It provides a blueprint for using big data to make product innovation faster and less costly. Compared with existing product innovation approaches, the framework developed places particular emphasis on efficiency and cost saving (particularly in time-to-market and new product costs). It demonstrated that it can facilitate better planning and organisation of parallel work teams and groups that may be involved in accelerated product innovation.

This study extends the accelerated product innovation boundaries pointed out by Williamson and Yin (2014), and provides further evidence to ascertain the vital role of the fast improve-and-relaunch process within an innovation ecosystem in product innovation. More specifically, this framework contributes to an increasingly vital body of literature discussing the importance of accelerated product innovation (Day and Wensley, 1988; Stanko et al., 2012; Williamson and Yin, 2014; McKinsey, 2015) and big data (McKinsey, 2011; Tan et al., 2015). Firms are leveraging big data to embed customer sentiment in product innovation. To stay competitive, Cooper (2014) points out that the next generation of product innovation process should be leaner, faster, adaptive and flexible. This research extends the traditional product innovation boundaries by providing a clear definition of accelerated product innovation and provides evidence of the vital role of accelerated product innovation in a big data environment. This enables firms to move away from product-focused innovation and to turn their attention to innovation around the customer experience. For example, the paradigm-shifting customer involvement innovation phase enables firms to find ways to innovate – unlocking the power of big data to improve customer understanding and make product innovation faster and less costly.

Besides, the developed framework makes a contribution to several subsets of the literature. On a general level, it can be viewed as a response to different calls in big data literature seeking to understand how big data can be used to facilitate product innovation (Chen et al., 2015; Xu et al., 2015; Davenport, 2014, McAfee and Brynjolfsson, 2012). In this discourse, the framework offers a new way for understanding and conceptualizing the mutual entanglement of technology and human action, frequently studied in operations, business, innovation, and contemporary information system research (Kallinikos, 2006; Latham and Sassen, 2005; Orlikowski, 2007; Orlikowski and Scott, 2008). Particularly, the evidence from the cases illustrates how agile structure, customer involvement and innovation ecosystem change their processes to accelerate product innovation in a big data environment. Moreover, from the case evidence, firm can make use of different technology-based or data analytics to enhance their product innovation in a big data environment.

To our knowledge, this is the first attempt that incorporates the big data initiatives and applies it in a synergistic fashion with accelerated product innovation. Although the term big data is not new (Cecere, 2013; Zhou et al., 2014), the application of big data in facilitating accelerated product innovation is a relatively new area. The evidence provided in the research reveals the promise of this combinatorial approach, which we believe is worth further developmental efforts from product innovation and big data scholars. However, the implementation of the framework may put considerable strain on an organisation. We posit that any stress presented by the introduction of these approaches will be more than compensated for by the time and cost reductions achieved in the modification of the product innovation process.

8.2.2 Contributions to Practice

In addition to the theoretical contributions as discussed above, practically, the findings of this research could also guide company managers and strategy people on how to achieve accelerated product innovation in a big data environment, and how to apply big data to facilitate accelerated product innovation, using the prior experience of the case studies. The study is intended as a framework for R&D innovation managers to apply their resources to feature and product innovation in a fast and effective way through reducing the time-to-market and new product costs. Based on the examples in the case study, company managers can maximise positive outcomes from the approaches identified in the framework. Our study shows that managers agreed with the developed framework that enables them to capture the logic behind the variety of decisions made over the course of the accelerated product innovation process. Although the specific problem might be unique, they felt reassured that an approach to addressing it was well known. Also, the incorporation of big data into the fast improve-and-relaunch ecosystem can be significant. We identified a number of implications of implementing a customer-supported fast improve-and-relaunch process in the cases, including a decrease in new product costs, an increase in speed to market, better understanding of customers' needs (and connection with customers), and a change in leadership and team organisation. The managers commented that the framework developed captures the main features for accelerated product innovation in a big data environment.

Moreover, the approaches identified in the framework are recommended by company managers, as they can allow managers to arrange their resources in order to develop new features and new products in a fast and effective manner. From the examples in the case study, company managers can maximise positive outcomes from the approaches of the developed framework. In the company cases, implementing the customer-centred approaches allowed a decrease in new product costs, to increase the speed of product innovation, to gain a better understanding of customers' needs (and interaction with customers), and a change in leadership and team organisation. Compared with the traditional product innovation approach, Case A was able to launch a range of new products in less than five months, at a total cost of $2 million. The company estimates that competitors using traditional design approaches have to invest around $20 million over twelve months to complete a similar set of product innovation in NPD. Nonetheless, the challenges the company faced in implementing the customer involvement approach were identified, such as IT infrastructure, managing relationships with intermediates, and the culture shift from product focus to customer focus.

In addition, the empirical findings show that the approaches of the developed framework are undoubtedly the most useful approaches for accelerated product innovation in high-tech industries, especially those that require big investments and a high degree of formalisation. The role of big data in the developed framework was found to strengthen important activity approaches and segments. The effect of influential innovation phases streaming in to the framework, from external and internal sources, increases with big data due to informationalisation. However, the empirical study as well as the theory (Keon et al., 2001) highlight that the embedded corporate culture, governance and strategies directly influence the role of big data within the process. Nonetheless, the circular accelerated product innovation framework is more flexible than more sequential processes, thus better suited to adopt big data into its process of generating concepts in NPD.

Furthermore, this research points to the vital role of big data in helping firms to enhance product innovation (Davenport, 2014). First of all, it allows organisations to launch new products to market as quickly as possible. Secondly, it helps organisations to determine the weaknesses of the product earlier in the development cycle. Thirdly, it allows functionalities to be added to a product that customers are willing to pay a premium for, while eliminating features they don’t want. Last but not least, it identifies and then prioritises customer needs for specific markets. To stay competitive, Cooper (2014) points out that the next generation of product innovation process should be leaner, faster, adaptive and flexible. This study shows how firms could utilise big data to achieve that. However, the ACE framework developed is impossible in the absence of a strong leader, who can establish autonomous organisational structures that recognise and support product innovation. Thus, managers need to adopt a strong business orientation toward product innovation and embed this orientation in their organisation's operating systems and cultural values (Verganti, 1997; Sarpong and Maclean, 2012).

8.3 Limitations

Despite the above theoretical and practical contributions, limitations still exist in the current research that have not yet been fully addressed, and more research effort is required. This part summarises these limitations.

The primary limitation of the current research, commonly raised in relation to qualitative case study research design, is from the perspective of generalising and expanding the research findings (Flyvbjerg, 2006). In this research, we have only verified the framework by studying specific innovation projects within the five case companies. Although the findings are drawn from comprehensive data collection processes, the limited access to large companies (the case companies are very large corporations operating globally or nationally) means that using several specific innovation projects represents accelerated product innovation in the entire Chinese companies. In addition, the framework was focused on high-tech industries, which could raise the question of the reliability and validity of the research findings. Therefore, it is not known to what extent the approach can be generalised beyond the high-tech industry and Chinese context.

Moreover, when conducting comparative case studies, in the current research the concentration on data collection work in the five case companies was different. Among the cases, due to limited research time and access to the companies, only Cases A and B were selected as key, and most of the interviews and participated observations were conducted on this. However, in Cases A and B the data on the companies' exploiting stage during the exploiting cycle was missing, since the project was still in development when the data collection work for this study ended. In the other cases, this research concentrated only on the accelerated product innovation development activities that were different from the key cases, and fewer interviews were undertaken with these others. Despite some researchers conducting research with the same data collection portal (Rohrbeck, 2010), questions could be raised about neglecting some significant perspectives in this study.

It is worth mentioning that the main focus of this study is to investigate the approaches for accelerated product innovation in a big data environment. The real company situation is more complicated – different companies have different objectives, R&D focus, big data technology, available data and so on. More importantly, the feedback from the industrialists indicates that most of the companies already have their own big data analytics and technologies. Therefore, instead of conducting specific big data analyses, this research only explores the approaches that could support organisations tapping into new ideas captured from big data to facilitate their accelerated product innovation in NPD.

So far, the development of a high-level framework for such a complicated phenomenon as accelerated product innovation may highlight some obvious connections while failing to capture others. The framework developed is mainly focused on investigating approaches for accelerated product innovation, where different data analytics were applied to support each of them. Therefore, the framework may not work where there is no data or data analytics to support it. We are hopeful, though, that this broad framework will provide a means to help integrate the wealth of research on innovation in order to advance both research and practice.

8.4 Future Research

To overcome the above limitations and to enhance the findings of this study, future research needs to be conducted as follows:

Enhance the framework through revisiting some cases for interviews – when revisiting these cases, referring to the findings of this research, some specific interview questions could be designed which focus on the missing data from the cases. For example, by revisiting the case companies, the missing data in the exploiting stage could be collected via further interviews with NPD team members. The newly-collected data could be compared with the findings of this study, and then verified.

Conduct additional cases for enhancing the findings – some international companies or other industries could be visited to conduct more case studies to enhance the findings of this research. The findings of this research could be taken to the proposed cases in order to gain access, and some qualitative data collection methods, such as interviews, could be undertaken within these companies. If the data from these proposed case studies proves consistent with what has been found in this study, the findings of this research would be enhanced. If the data in these further studies cannot match what has been found, the reasons for the differences could be analysed and the findings of the current study would then be extended.

Investigate the framework at organisational level – the current research studies the framework at project level, while Frambach and Schillewaert (2002) point out that studies of organisational adoption of the framework in different disciplines can provide a better identification of factors to influence the acceptance of new products by organisations.

Investigate the enhancement to the innovation phases identified for accelerated product innovation in a big data environment – the three innovation phases have been shown to be useful for supporting managers in attaining accelerated product innovation in a big data environment. Further research could be carried out to test new phases (including big data techniques and technologies) and to update the information and approaches identified.

Create a workbook – a workbook giving guidelines on implementation of the framework and the functions of the approaches can be created. The workbook could be used to facilitate further testing and refinement of the framework in a broader industrial context. This is likely to enhance the dissemination of the developed framework to industrialists and academics.

Investigate the framework with additional features – feedback from the interviewees showed that more features could be built into the framework to enhance its application. For instance, relevant business models as well as strategies need to be developed to support accelerated product innovation and the fast improve-and-relaunch process within an innovation ecosystem.

Investigate further the effect of 'learning' in applying the approaches – further studies might be carried out to study the effect of 'learning' in using different approaches.

Collaborate with industrialists and academics to have more independent verification of the framework – more research could be carried out to verify the application of the framework without the facilitation of the researcher. Furthermore, it could also help to identify the wider applicability of the approaches in broader industrial contexts.

8.5 Summary

In short, this research has shown that it was feasible to attain accelerated product innovation in a big data environment through three innovation phases, incorporating the use of both the approaches and big data. The determined phases are: Agile Structure (A); Customer Involvement (C); and Ecosystem of Innovation (E). It is termed the ACE framework which we believe represents a paradigm shift to help firms to achieve accelerated product innovation in a big data environment. The three phases identified were shown to be useful for framing the approaches for accelerated product innovation and big data was applicable to further facilitate the innovation process. The case study result shows that the framework developed was very useful in attaining accelerated product innovation in a big data environment. It allows firms to unlock the power of big data and make product innovation faster and less costly.

Overall, the results of the case studies indicated that the developed framework provided the following benefits to managers:

- *Collective understanding* – through conducting accelerated product innovation in a big data environment which enables everyone to have their knowledge brought into the open and their assumptions challenged. Managers agreed that such a big data environment is useful to enhance their understanding of an issue, as well as to facilitate organisational learning. Moreover, the framework assists in avoiding individual 'experience bias' in making decisions. One of the senior managers commented that "the framework encourages people to take a broader view and also helps them understand the implications and effects of each approach for accelerated product innovation".
- *Innovation support* – the three phases of the framework – a) Agile structure; b) Customer involvement; and c) Ecosystem of innovation – support managers to address accelerating problems right from problem framing and understanding to making decisions. The innovation phases identified help managers to decompose the complexity of accelerated product innovation into manageable approaches, and help them to crystallise thoughts at each approach of the phase.

- *Facilitate discussion* – the approaches identified help managers to increase both the depth and breadth of participation in the discussion of accelerated product innovation and evaluation issues. The approaches recognise the importance of assisting the evolution of the managers' ability to deal with the innovation problems confronting them through increasing their understanding of accelerated product innovation and big data. The approaches provide a structured framework of the environment from which a manager can develop insights into the effects of his actions on progress towards accelerated product innovation.
- *Organisational learning* – the building of a framework for accelerated product innovation in a big data environment allows information to be passed, assessed and updated, so that the ideas and beliefs contained within the framework can be altered or modified at will. Moreover, the framework provides the main innovation phases and approaches which are relatively easily adopted, examined, explored, and, if appropriate, changed. People often have difficulty perceiving the dependencies among innovation actions. The framework provides a useful overview. Managers can step back and see the structured phases and approaches in a global way which often stimulates fresh thinking.

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10. APPENDICES

Appendix A: Guidelines for interviews with academics

Aim of Interviews

- To discuss the key approaches and the latest developments in big data and product innovation (e.g., what are the current approaches for product innovation? What are the current big data practices in the company during the product innovation?).
- To discuss current approaches for accelerated product innovation in a big data environment (e.g., what is the company structure during the product innovation? When developing new products, how did the company build the innovation networks?).
- To identify the shortcomings of current product innovation approaches (e.g., have you met any challenges in product innovation? Can any big data technology be used to improve the current approaches?).
- To acquire new ideas for the development of a framework for accelerated product innovation in a big data environment (e.g., do you like the approaches of accelerated product innovation? What are the challenges in using the approaches in your company?).

Guidelines for Interviews

- ➢ Background of academics
- ➢ Satisfaction of the proposed approaches in product innovation
- ➢ Current models/approaches to support product innovation (eg. Stage-gate, TRIZE)
- ➢ Strengths and weaknesses of current approaches
- ➢ Big data applications in product innovation
- ➢ Suggestions for developing a practical framework for accelerated product innovation in a big data environment

Appendix B: Guidelines for interviews with industrialists

Aim of Interviews

- To discuss the key approaches and the latest developments in big data and product innovation (e.g., what are the current approaches for product innovation? What are the current big data practices in the company during the product innovation?).
- To understand the approaches carried out in practice for accelerated product innovation in today's big data environment (e.g., what is the company structure during the product innovation? When developing new products, how did the company build the innovation networks?).
- To understand the current big data activities which can be used to support product innovation in practice (e.g., could you provide me with some examples of big data application in product innovation? Could you tell me your expectations for using big data for product innovation?).
- To identify the shortcomings of current product innovation approaches (e.g., have you met any challenges in product innovation? Can any big data technology be used to improve the current approaches?).
- To understand the industrial needs for accelerated product innovation (e.g., what are the main characteristics required? Do you like the approaches of accelerated product innovation? What are the challenges in using the approaches in your company?).

Guidelines for Interviews

- ➢ Details of company (industry, personnel, turnover)
- ➢ What is your product innovation problem?
- ➢ What are big data activities in your company?
- ➢ What are some of the challenges among the various innovation approaches?
- ➢ Is there an industrial need that justifies the development of a framework for accelerated product innovation in a big data environment?
- ➢ What are the main characteristics required for an accelerated product innovation framework?

Appendix C: Analysis of Interviews with Academics

Academics	**University**	**Areas of research**	**Objective Innovation Approaches**	**Weaknesses of current approaches**	**Suggestions for creating a practical framework**
Academic A	*David Wong* Cambridge University	Big data analytics, product innovation and innovation strategy	Using open innovation to facilitate product development	Unstructured. The product developed may not be necessary.	Holistic and easy to use and understand for firm managers
Academic B	*David Johnson* Imperial College London	Computing and data science	Quantitative strategic manufacturing decision support model for product innovation	Not applicable in dealing with big data and the application in management is weak	Big data focused and structured framework to support product innovation
Academic C	*Kevin Maynard* Oxford Brookes University	New Product Development, Business Management and Legal Services	System dynamics approach for product innovation	Unstructured and too many factors need to be taken into account	Practical. Step-by-step process to support firm managers to apply
Academic D	*Takeo Takeno* Iwate Prefectural University	Information Science and Software Development	Quantitative-based information science perspectives on product innovation	Primary focused on overall product development and decision making	Simple and easy to customise to company specific requirement
Academic E	*Keah-Choon Tan* University of Nevada	Operations Management, Supply Chain Innovation	Creative problem solving techniques for managers	Unstructured. The outputs could be too complicated	Input based on different firms and provide systematic easy to follow stages
Academic F	*Chandra S Lalwani* University of Hull	Innovative manufacturing research, Supply Chain Management	Using in-house developed tools and techniques, coupled with the managers' experience	Dependent on experience and unable to avoid bias	Consider a methodology that incorporates product innovation
Academic G	*Dongliang Daniel Sheu* National Tsing Hua University	Systematic Innovation, Design and Manufacturing Management	TRIZ and TRIZ related methods to support product innovation	The application of TRIZ in management perspective is relatively weak	Combine big data with management to facilitate product innovation

Analysis of Interviews with Academics

Appendix D: Analysis of Interviews with Industrialists

Company	Position of Interviewee	Involved Data	Techniques/Approaches used in NPD	Shortcomings	Relevance of having a structured framework?	Desirable Characteristics
Company A	*Senior Manager*	• Consumers' data • Retailers' data • Report of daily claims • Transportation data, etc.	SAP database service including warehouse and daily claim management	Lack of supporting techniques for decision making	Yes, more informed process for product innovation	• Consider a tool that incorporate knowledge management features • Practical
Company B	*Open Innovation R&D*	• Product Information • Selling Records • Manufacturers' data, etc.	Established an Open Innovation Unit to work with outside partners	Unstructured. The ideas generated may not be relevant	Yes, provide visualisation towards particular problem	• Easy to understand • Simple to customise to company specific situations
Company C	*Discovery Partnerships Leader*	• Consumer feedback • Industry groups and competitors, etc.	Fostering the Democratization of Innovation; Open Innovation	Applicability. Only can be used in particular situation	Yes, the developed infrastructure must be flexible.	• Easy to use • Flexible in different situations
Company D	*Project Manager*	• Financial data • Information from third-party data brokers, etc.	Stage-gate innovation approaches, fast launch project of new product	Highly rely on the managers' past experience	Yes, user friendly tools and regulations	• Simple and easy to use • Process view • Good generalisability
Company E	*Oil & Gas BD Manager*	• Government information • Map service data • Oil and gas well data	Finding the right talent, pursuing the right partners and getting the right metrics in place to measure their innovation process	Metric driven not flexible. Assorted tools and techniques required	Yes, more informed process for deployment	• Input from industrialists • Easy to follow • Flexible in different situation
Company F	*Research & Technology Programme Manager*	• Product information • Customer Information	Open innovation, autonomy management, cultivate innovation culture across the whole business	Unstructured. Too depended on experience	Yes, the developed framework should avoid rigid procedures	• Easy to customise to company specific requirement • Documentation

Analysis of Interviews with Industrialists

Appendix E: An Overview of Big Data Initiatives in Company Cases

Big Data Definition

During the qualitative interviews the participants were asked to define and share their understanding of the term big data. The following results within the empirical findings are based on their definitions, thoughts and comprehension of the term big data.

Case Company	Definition
Case 1: Xiaomi Inc.	➢ Amount of data is so large that it allows for complete coverage of all settings that can happen and creates useful combinations; ➢ Data that enables reliable predictions without knowing anything about the relation between input and output.
Case 2: Lenovo Group Ltd.	➢ Accurate predictions, understand what users value and build something tailored to that; ➢ Use data for discovering and developing new innovations.
Case 3: Dididache Inc.	➢ Extend products and services ➢ Ensure consumer satisfaction ➢ Improve product quality ➢ Cost and efficiency in production ➢ Discover new markets through data

Big Data Objective

The interview participants were asked about their organisations' objective of using big data and their expectations of the data initiative.

Case Company	**Objective**
Case 1: Xiaomi Inc.	➢ Unstructured raw data from production; ➢ Really unstructured data from a large set of applications – less accurate.
Case 2: Lenovo Group Ltd.	➢ Not just the amount but the difficulty in understanding of what is in the data; ➢ Complex with ambiguous, unstructured data from multiple sources
Case 3: Dididache Inc.	➢ Currently no formal big data objective; ➢ A general objective of having good products and getting development costs down, where big data could be a useful tool to do so.

Data Management

The empirical evidence describes the data management procedures such as collection, quality evaluation, utility and the assessment of what types of data are considered valuable.

Case Company	Data Management
Case 1: Xiaomi Inc.	➢ All available data is useful if it is connected to the objective; ➢ Streams of data from sensors, performance indicators and maintenance logs; ➢ Robust techniques and scripts to ensure data quality.
Case 2: Lenovo Group Ltd.	➢ Own machine-generated data; ➢ Open and external data provided by customers and suppliers; ➢ Social media data for trend analysis to capture moods, events and behaviours; ➢ Quality purely based on an application basis; ➢ Prioritizing data from trusted sources.
Case 3: Dididache Inc.	➢ The usefulness of data depends on the analytic or business objective; ➢ Data quality is established using complete and accurate data including all variables and aspects.

Organisational Setup

The interviewees were asked about the organisational setup for managing big data within their organisation.

Case Company	**Organisational Setup**
Case 1: Xiaomi Inc.	➢ Big data trend has increased the top management's awareness of data potential; ➢ Combining data is essential for value, but decentralised data is killing its applications; ➢ Accessible data and data analysis skills in all levels of the company for improved decision-making.
Case 2: Lenovo Group Ltd.	➢ Structured in such a way that collecting and sharing of data is promoted; ➢ Departments should have access to all data to enable data-driven culture; ➢ Designation of a Chief Data Officer – as a bridge between business and data technology; ➢ Top-down incentives.
Case 3: Dididache Inc.	➢ Big organisational changes, higher importance of offering consultancy services; ➢ Right people, right methods and right culture; ➢ Management boosting the data usage in cyber environments to proactively advise on threats.

Big Data in Product Innovation

The interviewees were asked if or how the case companies make use and implement big data into their current product innovation processes. In other words, what function does big data have throughout the process and in which phases is big data used? Participants were also asked to rate their utilization level of using big data in their product innovation process.

Case Company	Big Data in Product Innovation
Case 1: Xiaomi Inc.	➢ Product development dependent on data; ➢ Start from the end, identify the problem and evaluate the usefulness of solving it, then test with big data if valuable predictions can be made; ➢ More data equals better R&D.
Case 2: Lenovo Group Ltd.	➢ Big data can serve every phase of product innovation process, however requiring different approaches; ➢ The utilization of big data in product innovation depends on how data-driven the company is; ➢ Central data more used in the formal product development.
Case 3: Dididache Inc.	➢ Successful utilization and implementation into core products and markets; ➢ Not yet successful in utilizing big data for product innovation directed towards new and emerging markets.

Big Data Implementation

The interviewees were asked about what factors or criteria exist for successfully organising big data. Interviewees were asked to describe organisational and structural factors for successfully utilising and implementing big data, both in general and in the product innovation process.

Case Company	Data Implementation
Case 1: Xiaomi Inc.	➢ Having centralized data which can be easily accessed and combined; ➢ Acquiring external data sources; ➢ Training the staff to be more big data educated; ➢ Culture to involve data into every process in the organisation.
Case 2: Lenovo Group Ltd.	➢ Big data objective and strategy; ➢ Access to the data; ➢ Speed and hyper-connectivity; ➢ Cooperating with different stakeholders with shared ambition and goal to be able to share data.
Case 3: Dididache Inc.	➢ Trained staff need to understand the data being offered and what to do with it; ➢ Make sure that the legislation is not prohibiting the good use of big data; ➢ Faster analytics and conclusions from big data.

Managerial Challenges of Big Data

The interviewees were asked to explain and describe what managerial challenges of using big data exist, as well as what managerial challenges their own organisation is facing connected to big data.

Case Company	Managerial Challenges
Case 1: Xiaomi Inc.	➢ Acquire necessary resources and skills for managing big data; ➢ Understand the business case, and not see data as sole potential of value; ➢ Change to a data-driven culture; ➢ Have enough data to avoid cold-starts in the product innovation.
Case 2: Lenovo Group Ltd.	➢ Employees are reluctant to change; ➢ Departments' unwillingness to share disables data combination; ➢ Acquiring right expertise; ➢ Integrating data from silos and different departments into centralised systems.
Case 3: Dididache Inc.	➢ Big data challenges are also connected with IoTs and cyberspace; ➢ Challenges becoming more complex; ➢ To have a clear overview of decisions and impacts is more difficult; ➢ Scarce human resources for the big data objective.

Appendix F: The Measurement Criteria of the Company's Accelerated Product Innovation Propositions

Referring to Rohrbeck's research work (2010), the measurement criteria of the Company's accelerated product development propositions can be discussed as follows:

<u>NPD team autonomy</u>

- Level 0: The Company did not have team autonomy activities during the product innovation approaches.
- Level 1: The Company had some team autonomy activates during the product innovation approaches.
- Level 2: The Company placed significant emphasis on its team autonomy during the product innovation approaches.
- Level 3: The Company had applied autonomy activates from all the significant perspectives during the product innovation approaches.

<u>Cross-functional team</u>

- Level 0: The Company did not have any activates on establishing its cross-functional teams during the product innovation approaches.
- Level 1: The Company undertook a few activates on establishing its cross-functional teams during the product innovation approaches.
- Level 2: The Company concentrated on establishing cross-functional teams during the product innovation approaches but neglected a few significant perspectives.
- Level 3: The Company placed significant emphasis on establishing cross-functional teams from all the significant perspectives during the product innovation approaches.

<u>Simultaneous processing</u>

- Level 0: The Company did not have any simultaneous processing activates during the product innovation approaches.

- Level 1: The Company had few simultaneous processing activates during the product innovation approaches.
- Level 2: Most of the activities during the product innovation approaches were undertaken in simultaneous processing, but a few significant perspectives were neglected by the company.
- Level 3: All the activities during the product innovation approaches were undertaken in simultaneous processing.

Understanding customers' needs

- Level 0: The Company never pays attention to understanding of customers' needs during the product innovation approaches.
- Level 1: The Company pay some attention to gain understanding of customers' needs during the product innovation approaches.
- Level 2: Most of the activities during the product innovation approaches were undertaken to gain better understanding of customers' needs, but a few significant perspectives were neglected by the company.
- Level 3: All the activities during the product innovation approaches were undertaken to gain better understanding of customers' needs.

Customer interaction

- Level 0: The Company never interacted with customers during the product innovation approaches.
- Level 1: The Company had a few interactions with customers during the product innovation approaches.
- Level 2: Most of the activities during the product innovation approaches were undertaken with customer interaction, but a few significant perspectives were neglected.
- Level 3: All the activities during the product innovation approaches were undertaken with customer interaction.

Customer co-creation

- Level 0: The Company never co-created with customers during the product innovation approaches.

- Level 1: The Company had a few customer co-creation activities during the product innovation approaches.
- Level 2: Most of the activities during the product innovation approaches were undertaken with customer co-creation, but a few significant perspectives were neglected.
- Level 3: All the activities during the product innovation approaches were undertaken with customer co-creation.

<u>Partnerships with suppliers and customers</u>

- Level 0: The Company never paid attention to partnerships with suppliers and customers during product innovation approaches.
- Level 1: The Company paid some attention to build partnerships with suppliers and customers during the product innovation approaches.
- Level 2: The Company closely collaborated and had partnerships with suppliers and customers during the product innovation approaches but neglected a few significant perspectives.
- Level 3: The Company built all the important partnerships with suppliers and customers during the product innovation approaches.

<u>Rapid feedback from partners and customers</u>

- Level 0: The Company never paid attention to rapid feedback from partners and customers during the product innovation approaches.
- Level 1: The Company paid some attention to collect rapid feedback from partners and customers during the product innovation approaches.
- Level 2: Most of the activities during the product innovation approaches were undertaken with rapid feedback from partners and customers, but a few significant perspectives were neglected.
- Level 3: All the activities during the product innovation approaches were undertaken with rapid feedback from partners and customers.

<u>A fast improve-and-relaunch process</u>

- Level 0: The Company never paid attention to a fast improve-and-relaunch process during the product innovation approaches.

- Level 1: The Company paid some attention to establish a fast improve-and-relaunch process during the product innovation approaches.
- Level 2: Most of the activities during the product innovation approaches were undertaken with a fast improve-and-relaunch process, but a few significant perspectives were neglected.
- Level 3: All the activities during the product innovation approaches were undertaken with a fast improve-and-relaunch process.

Appendix G: Example of Interview Questions

<u>Product Innovation</u>

1) How did the company make the product innovation decisions?
2) What are the current approaches for product innovation? What are the pros and cons of current approaches in NPD (e.g. on its speed, data utilisation)?
3) Could you provide me with some product innovation/NPD cases (what are the key processes, activities and objectives in each phase of product innovation)?

<u>Innovation Structure</u>

4) Have you met any challenges when building the NPD teams? How did you overcome these challenges?
5) What is the company structure during the product innovation/NPD (e.g. hierarchical or flat)? Have you met any challenges during this process and how did you overcome them?
6) Did the NPD teams have any autonomy for the product innovation? Have you met any challenges during this process and how did you overcome them?
7) Did the NPD teams have any cross-functional teams for the product innovation? Have you met any challenges during this process and how did you overcome them?
8) Did the NPD teams have any simultaneous (or sequence) processing for the product innovation? Have you met any challenges during this process and how did you overcome them?
9) Can any big data technology or data analytics be used to improve the current product innovation approaches?

<u>Customer Involvement/Connection</u>

10) What was the role of customers during the product innovation processes?
11) Did the NPD teams have any customer interaction during the product innovation? Have you met any challenges during this process and how did you overcome them?

12) Did the NPD teams have any customer co-creation activities during the product innovation? Have you met any challenges during this process and how did you overcome them?
13) Which kinds of activities did the company undertake for collecting customer information? Have you met any challenges during this process and how did you overcome them?
14) How did the company keep connected to their customers during the product innovation? How did the company collect feedback from them and deal with the feedback collected?

<u>Ecosystem of Innovation</u>

15) When developing new products, how did the company build the innovation networks?
16) How did you build partnerships with stakeholders (e.g., suppliers, customers, and partners) during the product innovation? Which kinds of challenges did you meet? And how were these challenges overcome by the company?
17) What kind of activities did the company undertake for establishing partnerships with stakeholders?
18) How did the company collect the information during partnership selection?
19) How did the company keep connected with the partners (e.g. through what kind of methods? email, telephone or visiting)? How did the company collect feedback from their partners (e.g. how often, how was the feedback dealt with)?

<u>Big Data & Data Analytics</u>

20) What are the current big data practices in the company (what data they use, when they started, what software they apply, what they do with the data, challenges they face in using big data) during the product innovation processes?
21) Could you provide me with some examples of big data application in product innovation/NPD (if they don't use big data, ask why and collect examples of difficulties they face)?
22) Could you tell me your expectations for using big data for product innovation?

<u>The ACE Framework</u>

23) Could you please provide me with some comments on the ACE Framework developed (i.e., it could focus on the whole framework or specific innovation phases)?
24) Do you like the ACE framework (if yes, why? What in the ACE that they like, what in the ACE that trigger new ideas from them, etc.; if they don't like, why? What are the challenges in using the ACE in your company?)?

<u>Others</u>

25) In addition to the above interview questions, may I ask is there anything else you want to mention that either helped or hindered the project during the product innovation processes?
26) Do you wish to add anything else to our research?
27) Finally, could you please introduce one or two friends you know for me to visit?

Summary of connections between propositions and interview questions:

Proposition	Statements	Questions
NPD team autonomy (P1)	NPD team autonomy is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 5, 6, 9, 20, 21, 22, 23, 24, 25, 26
Cross-functional team (P2)	The establishment of a cross-functional team is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 5, 7, 9, 20, 21, 22, 23, 24, 25, 26
	Simultaneous processing is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 5, 8, 9, 20, 21, 22, 23, 24, 25, 26
Understands customers clearly (P3)	Understanding customers' needs is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 9, 10, 11, 12, 13, 14, 20, 21, 22, 23, 24, 25, 26
Co-creates with customers (P4)	Customer interaction is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 9, 10, 11, 12, 13, 14, 20, 21, 22, 23, 24, 25, 26
	Customer co-creation is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 9, 10, 11, 12, 13, 14, 20, 21, 22, 23, 24, 25, 26
Partnership with stakeholders (P5)	Establishing partnerships with suppliers and customers is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 9, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26
Fast improve-and-relaunch process (P6)	Product launches and rapid feedback from partners and customers is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 9, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26
	A fast improve-and-relaunch process is one of the key approaches to accelerated product innovation	1, 2, 3, 4, 9, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26

Appendix H: Summary of Case Studies

Case A

This is a Fortune 1000 company that develops wearable medical equipment. The company is best known for its wearable electronic headset, which can be used to monitor brain activity. The brain activity data is streamed to a smartphone or stored in the system. The data is then transmitted in real time to a receiver located up to 10 miles away. The company has stated that its main customers are patients in old age; the product can help doctors intervene earlier and avoid complications. However, since this market size is comparatively small and most doctors are not familiar with the product, sales were decreasing year by year. In addition, the company experienced challenges with a lack of understanding and customer empathy on the part of its engineering staff. In order to improve its market performance and gain competitive advantage, the company decided to innovate and to launch new products with improved functionality and a different market focus. The main objective of the product innovation project was to design and develop a new wearable electronic headset with a new virtual reality function for young people to better understand and control their minds. This is a monitoring device which users will wear while watching videos, searching the Internet or playing games. It provides users with accurate, real-time feedback on brain activities. In this way, users can have a better understanding of active areas of the brain in different situations, such as relaxation, improved mood and reduced stress.

In this study, data collection covered multiple sources of evidence, which allowed us to increase the validity of our constructs (Yin, 1994). Initially, a retrospective method (Miller et al., 1997) was applied to become familiar with the initial part of the project, when the concept took shape in 2014. To eliminate distortion, only written reports were drawn upon in this wave of data collection. Then, starting in 2016, the subsequent data collection included six months of research in real time. The aim was to record how researchers worked in the company (Pettigrew, 1990). For this wave of data collection, sources included: semi-structured interviews with key respondents, on-site observations, annual reports, industrial reports, technical or non-technical documents, newsletters, project reports, strategic planning reports, and discussions with the NPD teams. I was actively engaged in the project itself, in market research. This meant that every unit of market information was recorded in real time by one of the researchers. In total, 26 interviews were conducted, each lasting 1 to 3 hours. The initial interviews were kept broad in scope in an effort to cover a wide range of motivations, decisions and competences. As the research project progressed and the theory was refined, interview questions became more focused, in an effort to ascribe more details to the emerging patterns. The Company's CEO championed the project. The Company NPD team consisted of the CEO, NPD team manager, designers, functional specialists, electronics engineers, information analysts, researchers, and a marketing manager.

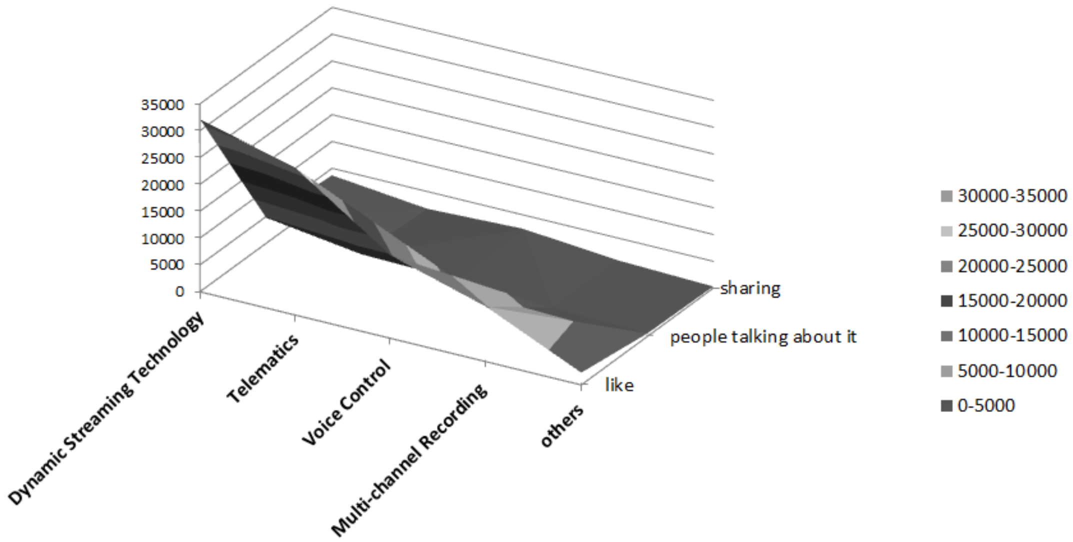
Change of product innovation process

The company is currently using big data for accelerated product innovation in NPD. By accelerating its product innovation processes, the company was able to launch a range of new products in less than five months, at a total cost of $20 million. The company executives estimate that competitors using traditional design approaches have to invest around $200 million over several years to complete a similar set of new designs. The company has applied an agile approach to product development to speed things up by tackling certain steps in parallel, an approach pioneered by NASA and now commonly referred to as simultaneous or concurrent processing. It helps the company to complete projects two to five times faster than comparable projects using conventional approaches that the company benchmarked in China. The NPD teams organise simultaneous processing across the entire innovation process, beginning in R&D and continuing through design, manufacturing, engineering, quality control, procurement, marketing and service. For the project, team members work on different elements in parallel, under the supervision of one leader. In this way, the company overcomes the usual problems of product innovation by: breaking down its product development into separate modules linked by standardised interfaces; redesigning its software to be compatible across all activities associated with the new product; establishing short lines of communication, where each team member can represent his or her respective functional department; and introducing open design processes, where information is shared with the entire team and their customers as early as possible.

Using big data to determine customer profile

The term 'big data' in this case refers typically to the following types of data: (a) traditional enterprise data, (b) social media data, and (c) machine-generated/sensor data (e.g. weblogs, cloud files, smart meters, manufacturing sensors, equipment logs). The company used to have little direct feedback from customers. Only recently did the company start to monitor customer comments on social media about its products. The company gathered feedback from their customers as well as partners about their preferences. In order to identify each wearable electronic headset product and generate new ideas, the company collected different source of data such as videos, photos, number of comments and number of followers from the most popular websites (i.e. Amazon, Facebook, eBay) by using Web Page Cleaning, Web Crawler and HTML parsing technologies. It is worth mentioning that all this collected information has vast amounts of data which people produce and share every second and most of the information is unstructured data (i.e. photos, videos or social media) which means it cannot easily be put into tables. Moreover, take Facebook posts as an example. The data quality and accuracy are less controllable. Thus, in order to harvest great values from big data, the trustworthiness of the data is a significant issue that the company needs to address. The company pointed out that data quality can be verified by complete and accurate data which includes values and variables relevant to the purpose of collecting them.

Additionally, the company has developed an application which is highly customisable. It allows its partners and customers to upload their ideas and suggestions to facilitate the company's product innovation and the invention of new features. In this way, potential targets were customers with an interest in becoming involved in developing the new wearable device. Some of these customers were highly innovative and able to offer valuable new product ideas. For example, by visualising the big customer data collected in the past three months, early adopters of the high-end wearable device requested functions like Dynamic Streaming Technology, Telematics, Multi-channel Recording, and Voice Control (see Figure below).



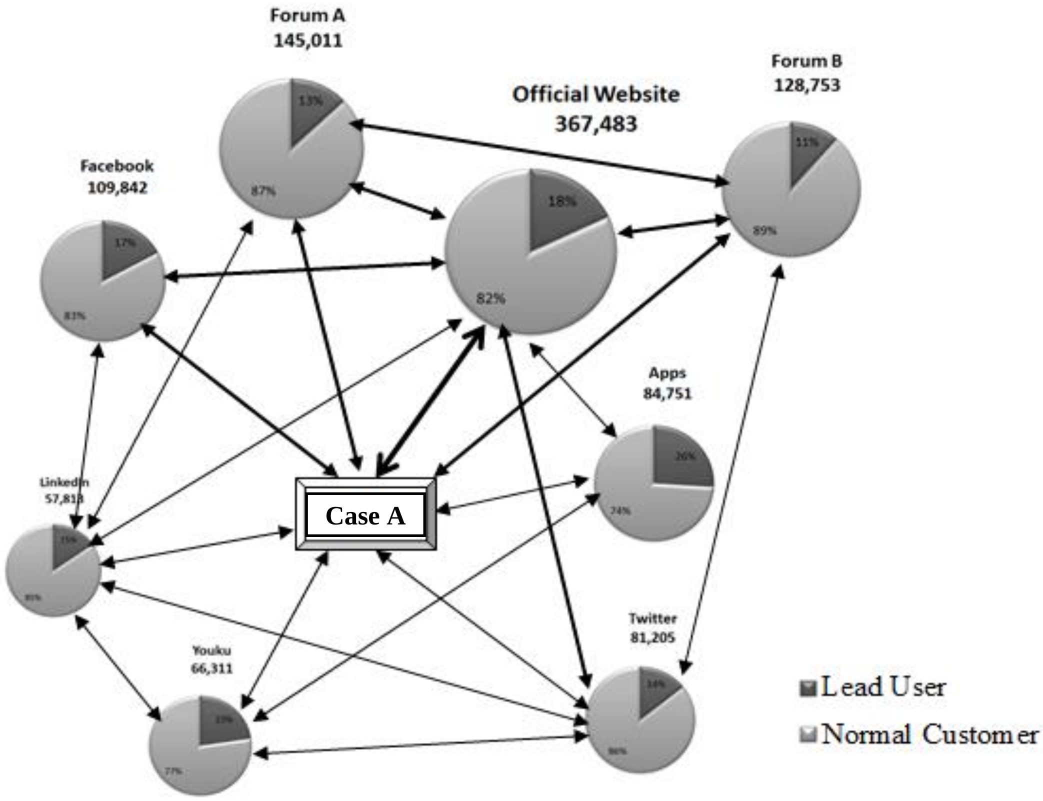
Levels of Customer Involvement for Each New Product Function

By making use of social data, the managers face challenges to extract the useful information from the terabytes of text data. Different from other data sources, data from social media is no second intent opinion, but the data density is extremely low, i.e. the useful information is buried in the unstructured massive data. In order to unravel the hidden information, data scientists need to adopt some data-mining techniques such as frequency analysis, cluster analysis, and sentiment analysis. For example, customers have a discussion of new ideas of certain functions; a multidimensional scaling diagram (MDS) can effectively illustrate the clustering results of different opinion groups in the discussion (Tse et al., 2016). It is a useful approach to uncover information since people will use similar wordings but different sentence structures to express their ideas. Thus, it is useful to use clustering analysis with MDS diagrams to identify major opinion groups from Facebook data. Also, username is another useful 'metadata' to identify gender of the post owner, so it will be easy to investigate different gender group towards the proposed NPD ideas. The company information department had the job of processing different customers' suggested attributes of a new product in parallel. In particular, it applies different conventional data techniques to harvest useful information from big data. For example, Apache Mahout for machine learning algorithms in business, Tableau for big data visualisation, Storm for analysing real-time computation systems and InfoSphere for big data mining and integration.

Using big data to identify information sources

The company's information department is able to analyse customer data captured from different sources. In particular, the company has set up innovation centres and research laboratories in different places. They can acquire huge customers' data source including data of consumption and personal attributes from operators by means of cooperation agreements, so as to broaden channels of data acquisition and acquire data of target customers, which help it to transform advanced technology into competitive advantages. Particularly, social media is a very important data source. For example, the main forum of the company on its official website posts (in different formats) more than 10,000 topics per day, including new product information, announcements, feedback and discussions. In this open community, there are tens of thousands of posts fed back by customers every week, from which some deep reports of product using came into being. By way of integrating and analysing information of those posts, the company can acquire demands information of customers with low costs and high efficiency, providing innovative ideas for research and development of new products.

The company emphasised the importance of big data sources from social media which can create relations and provide a better understanding of the customers and their product usage and in that way improve development. Particularly, 'lead users' can be differentiated from 'normal customers' by the information department through RFM analysis which is a data mining technique quantifying customer value by examining how recency, frequency and monetary a customer purchases (Hughes, 1996). The information department analysed the customer information and activities around the company brand (e.g. platform, communities, apps, and official websites). The figure below shows the company network for customer connection and interaction. The company connects to its customers through a wide range of sources at low cost (e.g. official web forums, mobile apps, website communities). Using the same means, customers can also interact with the company and each other in real-time. The latest product information is updated to these sources on a daily basis, partly to attract more customers and partly to gain feedback for further development. A vast number of these places were cultivated for different interested customers. In this way, the information department can collect a wide range of customer information from different channels and platforms extremely quickly. Data requirements could be different due to different organisations' needs and problems. Then, a number of data pre-processing techniques, including data cleaning, data integration, data transformation and data reduction, can be applied to remove noise and correct inconsistencies from data sets. After that, data mining techniques can be used to help managers generate lots of useful information.



The Company Network for Customer Involvement

Using big data to improve customer involvement in product design

To come up with a customer involvement process, their individual qualities as well as inspirations should be considered in the design. The best solution to customer involvement is dependent on the specific situation: the offered incentives (e.g. monetary compensation, supply of proprietary information, excitement factor, or even just the kudos of being called a 'co-developer'); the degree of use of multi-media data (e.g. virtual product presentations, short videos, animations); the intensity of interaction (e.g. duration, frequency and number of participants); the applied tools (e.g. open discussion forums, toolkits, virtual stock markets, virtual concept testing or competitions); and the communication style (e.g. anonymity of the interacting parties, informal/formal; uni-, bi- or multi-directional). In particular, the company installs feedback software and sensors into every new product in combination with the advantages of technology and hardware. According to various data transmitted from customers' smart devices, functional design to products can be made appropriate so that new products with improved features/functions in line with customers' demands can be launched. The company has grasped the core big data technology (e.g., Spark SQL, and Hadoop Cluster). Therefore, the company was able to apply data analytics with its big data technology, and react quickly to acquire a large number of loyal customers through adopting reasonable product portfolio, accurate market orientation and perfect function design. These inputs also allow R&D teams to quickly develop a new version of a product, with improved functions and features.

Using big data to enable customer access and participation

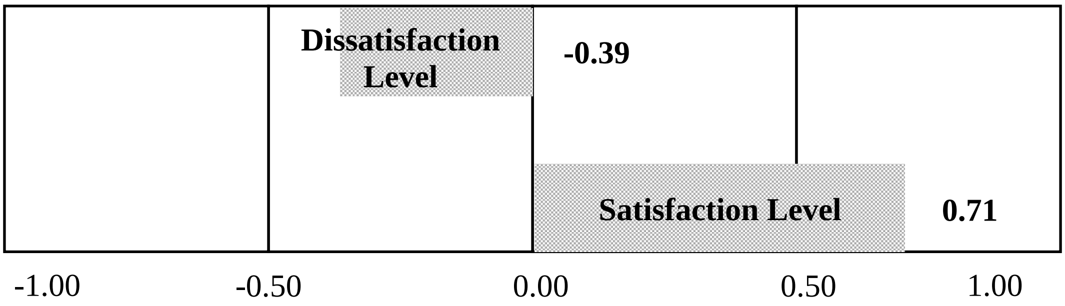
In the programming and testing of the customer involvement platform, customers were accessed (communicated with) by different means. The use of banners, emails, pop-up windows as well as short articles were considered in communicating with the customers encountered on the Internet and notifying them of their responsibility in the product innovation project. For example, an pop-up window invited every 50th online user to the Company official forums for 1 month. Email and app subscribers were recruited simultaneously.

Within the involvement process, the company connects with its customers through its own Talend big data platform. It understands customers' behaviours and needs better by acquiring datasets from 12 processes that run simultaneously and come from sources including third parties, social networking feeds and Application Programming Interfaces (APIs). The customers were asked for help or raising certain questions with the need for apt processing. A wide range of customers enjoyed giving direct feedback and expressed preferences in product innovation. Meanwhile, customer inputs can be analysed to initiate some improvement and to get first results in case the anticipated quantity or quality of customer information is insufficient, or the process of collecting it needs to be reconsidered. Customers engaging with the company for the first time should be assessed for background information on their preferences, their willingness to contribute again as well as their expectations regarding further product innovation projects. For those customers who have already engaged with the company several times, a relationship can be seen to have been established and company managers should consider creating a specific community for such customers.

Results

In Case A, overall, more than 26,000 customers participated in product innovation in some form. Over 13,700 new product ideas were recorded from different sources (e.g. images, text, video and voice mails), more than 127,400 comments were made on the specific functionalities required, and over 3,200 visions of future similar devices were gathered. A total of 15,943 customers participated (or around 61.2%) and would like to get involved in future product innovation projects.

As suggested by Matzler et al. (1996) and Füller and Matzler (2006), a functional/ dysfunctional examination was conducted to identify whether the new functions identified were considered exciting or simply basic. Take the function of Dynamic Streaming Technology as an example. According to the customers' answers to the question of how they would react if Dynamic Streaming Technology (high-quality videos in 360-degree virtual reality) was provided in the new device and how they would react if the function were not provided, then function/dysfunctional ratios were calculated which evidences whether the new function identified is an excitement or basic factor (Matzler et al., 1996). As the figure below shows, if Dynamic Streaming Technology were provided, it would have a significant impact (0.71) on overall satisfaction with the new device, more so than on dissatisfaction if the function were not provided (-0.39). Therefore, the finding shows that Dynamic Streaming Technology was identified as an excitement factor, and exceeding customer expectations. If Dynamic Streaming Technology is delivered to the new device it brings excitement, otherwise, there is a low dissatisfaction from the customers.



Dissatisfaction and Satisfaction Level Due to Absence or Presence of Dynamic Streaming Technology

To examine whether the customer involvement provided by Case A actually allows customers to better understand the value of the new products and to articulate their needs, several questions were asked. In particular, a five-point Likert scale (1 = very positive; 2 = positive; 3 = neither; 4 = negative; 5 = very negative) was used to identify the perceptions of customers. The result shows that most of the participating customers highly agreed with the statement that if Dynamic Streaming Technology was supported by the device, its functions and features would meet with satisfaction by customers (Mean = 1.23; Std. Dev. = 0.81). The functionality and interactivity of the information department also helped in the articulation of individual needs and wants (Mean = 1.96; Std. Dev. = 0.94). Overall, customers stated that they positively and actively made contributions to the NPD (Mean = 2.08; Std. Dev. = 0.78).

Engagement with customer-derived big customer data helps the company to understand its customers as well as the market. In this situation, big data supports the company's customer involvement by revealing the factors that might influence customer loyalty (i.e., how to keep customers coming back again and again). By applying big data analytics, the company can identify optimal investment opportunities across different information sources, and keep optimising its marketing strategies through analysis, measurement and testing. The different information and communication technologies applied offer unstructured, semi-structured, and structured input to the NPD teams. In the case study project, structured and large-scale data sets were gathered during the earlier product innovation phases, in order to attain more insight into customer contexts and needs, through dialogues, collaboration and online surveys. For example, the company utilises customer dialogue to shape its product innovation through customer data capture, crowdsourcing and large forums. This structured information was often based on customer stories or dialogues, and customers were able to consciously and actively support the development of new products and functionalities. Semi- and unstructured rich data were captured in the later phases of product innovation, when a feature or product had been launched on the market, and customers were able to use the particular product or feature. For instance, the company applies natural language processing (NLP) to unstructured content (captured from apps and social networks) to identify customer satisfaction and preferences. The rich data from a variety of sources provided a different type of information to the product innovation process, and included real behavioural data based on the click behaviour of customers using a system, for example. In such circumstances, the customer was not actively involved in giving feedback, but information was automatically captured through analysing customers' online behaviour. Organisations are paying more and more attention to gathering this type of data, to the extent that discussions are arising in social media about ethics and customer privacy. This is an aspect that requires to be taken into consideration when concentrating on capturing customer data for product innovation. Structured, semi-structured and unstructured data are common in customer involvement studies in all phases of product innovation (Sood and Tellis, 2005; McKinsey, 2009; IBM, 2013; Gantz and Reinsel, 2015). However, in the case study, the data in the first two phases (generation of idea and concepts; design and engineering) are more connected to feedback, while in the later phases of test and launch, larger amounts of data are captured through actual use and customer behaviour.

<u>Case B</u>

This is a Fortune 500 company in the telecommunications industry. It experienced challenges with the lack of understanding and user empathy of its engineering staff. In addition, it experienced a decrease in the 'innovativeness' of its main products. Its NPD teams work with large customers for whom they build customer-required features that extend the base product (which all customers receive). However, the product innovation process in the company was rather hierarchical, with little input from engineers, and the feedback loop between developed solutions and customer feedback was the length of a full product release cycle, which was too slow for learning. In order to accelerate the innovation process, the company has changed the interaction, which is in the form of a dialogue during the development of final products and new features. Recently, the company developed a new integrated package and Internet data service by assembling a team that included individuals from every function and speciality required to host, launch and service the new product. This allowed the company to coordinate all of the critical elements: the customer interface, the programming, the enhancement of the infrastructure and the development of maintenance and customer service protocols. By applying these processes, the company has managed to shorten the project development cycle from eight months to less than four months. For example, the company launched the first version of the product within 1 month. This first version was very light on features, but the team immediately started to collect customer feedback by studying customers using the available features, both in a simulator and in retrofitted versions of the subsystem in earlier releases of the same product. Within weeks, the company team released a new version that incorporated functions mentioned in the customer feedback. This rapid improve-and-relaunch process has now become the company's core approach to new product development.

In addition, the company explained that customer involvement can be facilitated through utilising big data to provide new or more precise insights. The insights can be gained in a digital form, such as use tests, in order to understand the customers and adjust the decisions about the products accordingly. Therefore, big data allows users' behaviours to be examined and thus their demands can be fitted. Since the recruitment of customers was conducted from diverse information sources, it was imperative for the design to align with corporate identity. In addition to this, the customers were led by the design to share their ideas and expertise in a simple and enjoyable approach.

Furthermore, the role of big data in the product innovation process is directly affected by how data-driven the organisation is overall. In particular, as seen in Case B, their product and solution, as well as product innovation is highly dependent on the collection and processing of large customer data sets. In order to handle the problem of difficult data storage, the company has set up a data centre of cloud computing specialising in storing and handling big data. By means of reconstructing decision making and an analysis system based on big data and establishing product innovation and a feedback mechanism based on big data and cloud computing, the company improved the competitiveness of products and satisfaction of customers. Furthermore, the company further explained the important of having data centralised in order to provide the ability to all interested actors within the company to access and process it. To organise and manage big data successfully, organisations should have an established ecosystem of innovation and build 'data-alliances' with stakeholders including partners, suppliers, customers, and other actors with common interests.

<u>Case C</u>

This is a Fortune 500 company that provides customised customer services and software. This case is about the introduction of new features for a mature product. The top management decided that it was important to meet customers' needs for improved commercialisation. The NPD team's project aims were to enhance the functionality and add some services to a calendar application. The company accelerated the innovation process by dividing the product innovation process into a series of eight steps, with dozens of people assigned to each. The initial creation of the 'reactive intermediates' required specialist staff with at least master's degrees and considerable research training, the other steps required 'R&D workers', who are graduates of trade colleges (the company hires thousands of such employees each year). Moreover, the company implemented a thriving 'voice of the customer' programme to gather feedback from more than 30 million customers online per day, and this information is used to improve customers' experience and to facilitate product innovation.

<u>Case D</u>

This is a Fortune 500 company in the electronic industry that designs and develops computers and electronic devices. In a project to develop a new tablet device with improved functions, research teams are encouraged to work independently and engage with customers as early as possible. The concepts of products tend to go through dozens of labs/tests at the same time before being put on the market. The company connects with its customers through its own data platforms (such as apps, forums, and Twitter). The company can collect a wide range of customer feedback from different channels and platforms extremely quickly. Based on customer feedback, the team continues to iterate the design. At the end of the development, all teams present their ideas to a panel, consisting of the head of product development, head of product management, head of IT, and a selection of customers. The panel decides on prioritisation of the proposed solutions. Throughout the development, the innovation processes are accelerated by fast doing, learning and improving from customers.

<u>Case E</u>

This is a Fortune 500 company that manufactures software and networking equipment. Usually, it took 12 months to develop new equipment to the point where it could be released on the market. In response, the company introduced team autonomy and multi-functional teams in a new project (development of a telecommunications equipment with improved functions) to enhance its product innovation and gain competitive advantages. In this approach, development groups are drawn from different functions and work separately in parallel to accelerate the innovation process. Whenever the company hits a roadblock in the course of creating a new product, it brings together experts across all the disciplines (industrial design, software, hardware, customer aesthetics and interfaces, procurement, testing and production). In this way, the company can initiate projects quickly, focused on joint rapid problem solving and immediate execution. The company has developed an application which is highly customisable. It allows its partners as well as customers to upload their ideas and suggestions to facilitate the company's product innovation and invention of new features. Therefore, the new features and functionalities are co-developed with various customers. With these approaches, the company can now develop new smartphones in two months on average.

Appendix I: An Overview of Existing Software for big data analysis

Software	Techniques	Operations Environment	Challenges
IBM SPSS	Statistics and data mining	Stand-alone	• Lag in newer techniques
Data Driver Documents (D3)	Visualization	Programming	• Doesn't have a widely accepted standard • Low SVG rendering performance
Weka	Machine learning	Programming	• Memory limitation • Low performance
Stata	Statistics and data mining	Stand-alone	• Complex when working with multiple datasets
Microsoft Office	Statistics	Stand-alone/programming via Visual Basic	• Not functional enough
Statistical Analysis System (SAS)	Statistics and data mining	Stand-alone	• Outdated programming language
R	Statistics and data mining	Programming	• Heavy program codes • Challenge learning curve
Python	Statistics and data mining	Programming	• Slow process performance • Nested functions can't modify variables in the outer scope • Missing useful features
Mathematica	Statistics and data mining	Stand-alone/programming	• Long learning curve • Hard to write modular code
Matlab	Statistics and data mining	Stand-alone/programming	• Slow interpreter • Lack of object orientated features

Appendix J: An Overview of Big Data Initiatives in Company Cases

Big Data Definition

During the qualitative interviews the participants were asked to define and share their understanding of the term big data. The following results within the empirical findings are based on their definitions, thoughts and comprehension of the term big data.

Case	Definition
Case A	➢ Big Data is just data that has increased in size, volume and velocity; ➢ Data that needs scaled up technologies, advanced techniques and tools to manage; ➢ All the data that is an important component of the product is big data.
Case B	➢ Combination of different internal and external data sources; ➢ Should be called mixed data; ➢ Any data-related problem where the size of the data also becomes a part of the problem.
Case C	➢ Big data stands for enormous amounts of data that is opening up; ➢ Exponential and a more complex data world.
Case D	➢ Data that allows you to see things on a larger scale; ➢ Do things with data that you could not do before.
Case E	➢ Number of tools, methods and approaches that enables us to do things with data which we were not able to do before; ➢ Definition changes when technology advances.

Big Data Objective

The interview participants were asked about their organisations' objective of using big data and their expectations on the data initiative.

Case	**Objective**
Case A	➢ Achieve internal and external security goals; ➢ Identify a potential and a need for data; ➢ Security, and data that needs to be protected; ➢ Data transformed in security products and solutions.
Case B	➢ Better understanding of how products behave; ➢ Drive recommendations for new concepts.
Case C	➢ Observe function, performance and predict failure; ➢ Improve products and projects, ensure that parameters are set.
Case D	➢ Personalized products and precision; ➢ More prediction, contextualization and automation; ➢ Forge new value networks.
Case E	➢ Uncover patterns that are hidden; ➢ Confirm the things you already know; ➢ Get insights and make predictions.

Data Management

The empirical evidence describes the data management procedures such as collection, quality evaluation, utility and the assessment of what types of data are considered valuable.

Case	Data Management
Case A	➢ All available data is useful if it is connected to the objective; ➢ Streams of data from sensors, performance indicators and maintenance logs; ➢ Robust techniques and scripts to ensure data quality; ➢ If you do not know what you are looking for, your big data project will fail; ➢ The gathering and usefulness of data needs to be based on the objective and purpose of the project; ➢ Prioritizing data from trusted sources.
Case B	➢ The usefulness of data depends on the analytic or business objective; ➢ Data quality is established using complete and accurate data including all variables and aspects; ➢ Poor quality of data or wrong algorithms leads to wrong insight; ➢ Collect external data or data you have not thought of, to correlate and combine with data you already have; ➢ Quality depends on application and requirements.
Case C	➢ Own machine-generated data; ➢ Open and external data provided by customers for specific products; ➢ Social media data for trend analysis to capture moods, events and behaviours; ➢ Quality purely based on an application basis.
Case D	➢ Data quality is connected to the limitation of data and the anticipated results; ➢ Linked data – combine different datasets in open-format; ➢ Metadata can describe the quality of the data.
Case E	➢ Open data from collaborators through agreements; ➢ One school of thought is to get all the data, and a second is to know what data you are looking for first; ➢ Production data, data influencing the development process and additional undiscovered data.

<u>Organisational Setup</u>

The interviewees were asked about the organisational setup for managing the big data within an organisation.

Case	Organisational Setup
Case A	➢ Connect globalized platforms with decentralized areas; ➢ Accessible data via visualization techniques and sandbox environments to staff without data knowledge; ➢ Teams with some autonomy, allowed to fail and break some process regulations; ➢ People with domain expertise need to be able to ask questions that can be answered with data.
Case B	➢ Flexible teams experimenting, testing and validating data; ➢ Internal and external digital connectivity; ➢ Departments have specific setups for using big data; ➢ Teams with application knowledge that are focusing on certain markets and collecting specific data; ➢ Data scientists and business individuals running the processes should change their thinking to common goals.
Case C	➢ Market intelligence for analysing and capturing trends and feelings; ➢ Architectural function to track requirements; ➢ No large formal functions to promote big data.
Case D	➢ Have a core entity managing the sales and market data; ➢ Installed department focusing on big data; ➢ Data scientists spread all over the organisation, enabling competencies.
Case E	➢ Data initiatives are based on a project basis for different objectives; ➢ Established electronics groups (to establish automated analysis systems) that have experience with big data will support and implement big data analytics.

Big Data in Product Innovation

The interviewees were asked if or how the case companies make use of and implement big data into their product innovation processes. In other words, they were asked what function big data has throughout the process and in which phases big data is used. Participants were also asked to rate their utilization level of using big data in their product innovation process.

Case	**Big Data in Product Innovation**
Case A	➢ Product connectivity enables data feedback loops, which improves product design, product development and maintenance; ➢ Products without big data elements can still use big data to enable innovation processes; ➢ When the data is part of the product you get different dynamics of using big data in R&D and NPD; ➢ More used for enhancing products and saving money than traditional product innovation approaches.
Case B	➢ For existing products, it can improve efficiency and effectiveness; ➢ For product innovation it is a process of discovery, what is the best way to implement it; ➢ R&D with big data from more sources, collectively discover innovations; ➢ Big data used in very early stage to give insights; ➢ Built-in feedback mechanisms for late-stage product innovation; ➢ Big data more valuable for technical applications rather than consumer applications; ➢ Big data in product innovation is great in theory, but no real examples in practice.
Case C	➢ Identify a new need or new clients for existing or new markets; ➢ Big data to track activity and other elements within the product; ➢ Optimize products and enable growth; ➢ Privacy laws restrict certain usage of big data in product innovation; ➢ Big data used in product innovation is not done on a large scale, still exploring the application of it.
Case D	➢ Big data just one element, the process will change a bit but in essence stay the same; ➢ Market data has been used for a long time, connected products that generate data and utilizing that data is new.
Case E	➢ Most used in the manufacturing or production phase; ➢ Big data is seen as a tool for analysis over many projects and serves decision making in the product innovation process; ➢ Many concepts will be in electronic parts and big data can set up the structure, especially if the concept has a data generating function.

Big Data Values

The interviewees were asked to explain what benefits or potential values are expected or experienced from using big data in the product innovation process.

Case	**Values**
Case A	➢ Efficiency and effectiveness for existing products; ➢ Enhanced market research and targeting of consumers; ➢ Create new products and improve the value chain with new insights; ➢ Cost efficiency, and targeting new partnerships; ➢ Strategic positioning in the new emerging value ecosystems.
Case B	➢ Get insights that help you make predictions; ➢ Cost reduction and efficiency from big data; ➢ Prescriptive analytics to improve decision-making; ➢ Validity through descriptive analytics.
Case C	➢ Exploring new opportunities; ➢ Using big data to make an impact and difference in society.
Case D	➢ Insights in digital form (user tests), understand what customers' feelings are etc.; ➢ Utilizing the potential of data to identify what you need to target.
Case E	➢ Big data has a lot of potential for products or development that can be easily tested in different circumstances; ➢ Potential only in the bigger context, if you can generate enough data.

Big Data Implementation

The interviewees were asked about what factors or criteria exist for successfully organising big data. Interviewees were asked to describe organisational and structural factors for successfully utilising and implementing big data, both in general and in the product innovation process.

Case	Managerial Implementation
Case A	➢ Multidisciplinary teams of specialists; ➢ Processes and project management, as well as experience using data in different projects; ➢ The right data and the ability to do sufficient data testing; ➢ Building and understanding the business case; ➢ Having a data-driven culture; ➢ Establishing connections between data and business professionals; ➢ Data which is centralized and accessible for everyone.
Case B	➢ Acceptance and adoption by the users and people that are expected to work with the outcomes of the big data analysis for product innovation; ➢ Engineers that can oversee the entire scope; ➢ Understand that handling data has both direct and indirect influences; ➢ Oversee all stakeholders and their interests in the data.
Case C	➢ Right timing and right framing; ➢ Privacy laws that allow big data supported innovation in NPD; ➢ Mental model for the acceptance of data innovation and data analysis.
Case D	➢ Sense of urgency in the organisation; ➢ The right data science competencies; ➢ Be able to build your first proof points early; ➢ Culture – openness to experiment and explore new things.
Case E	➢ Prove a success story and have early adopters in the development team; ➢ Efficient analysis – have good database access and reliable connections; ➢ Acquiring sufficient resources (human and technology); ➢ Identify if the big data approach is suitable for the problem you want to solve.

Managerial Challenges of Big Data in NPD

The interviewees were asked to explain and describe what managerial challenges of using big data exist, as well as what managerial challenges their own organisation is facing connected to big data.

Case	Managerial Challenges
Case A	➢ Have large amounts of data which is clean and well organised; ➢ Potential but at the same time resource consuming to clean out the data bases to measure and analyse relevant data in a systematic way; ➢ Staff need to work according to set procedures and the data needs to be clean; ➢ Need to have time and vision to implement the big data correctly into the process; ➢ Cultural issues need to be addressed.
Case B	➢ Getting the right data is the biggest challenge, often the data is not yet there and you have to generate it; ➢ Have an interactive attitude and culture; ➢ Accessing data from the eco-system of suppliers and users; ➢ Accessible and open information; ➢ Managers need to possess right soft skills.
Case C	➢ Scaling up new ideas is a challenge due to legacy systems; ➢ Change requires resources, agility and capabilities; ➢ Challenge of data ownership, interoperability issues, trust and privacy to share and connect data with external actors.
Case D	➢ Find the right and qualified resources; ➢ Top management needs to understand and possess basic knowledge about data technology and its processes; ➢ A main challenge is the cultural clash between data experts and managers.
Case E	➢ Big data is a relatively new concept; ➢ Other tools have to be used than those we have been using previously; ➢ How to find efficient methods in drawing conclusions and decisions.

Appendix K: Application for a restriction to be placed on a thesis

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Application for a Restriction to be placed on a thesis

In special cases the Senate may impose a restriction on the consultation of a thesis for a period of two years from the date the restriction is agreed and may extend this period up to a maximum of five years[1].

Restrictions will normally only be granted on the basis of the actual or potential confidentiality of the contents of the thesis, e.g. to protect a patent application.

Once the form is complete e-mail it to studentservices@nottingham.ac.uk (or alternatively you can take this in person or post to one of the Student Service Centres).

For completion by the student:

Full name of author of thesis: Yuanzhu Zhan

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Faculty: E07a, Yang

School/Division: Business School/Operations Management and Information Systems

Title of thesis: A Framework for Accelerated Product Innovation in a Big Data Environment

Degree for which submitted: Doctor of Philosophy

Year of award of degree: 2017

I request Senate to restrict consultation of the above named thesis for a period of TWO [2] years on the following grounds:

Reason for Restriction (please tick):

- Politically sensitive ☐
- Commercially sensitive ☒
- Industrially sensitive ☒

Supporting Statement: This research is done in the context of obtaining a PhD in Business and Management Degree at the University of Nottingham. As requires by the case companies, the case description contents (e.g., innovation processes, new product designs, advertising and marketing strategies) shall be qualified for intellectual property rights (IPRs) protection and keep confidential. Moreover, the names of the case companies, interviewees, and some of the institutions visited other than the case sites have been removed for confidentiality purposes.

Signature of student: Yuanzhu Zhan Date: 12/12/2016

[1] http://www.nottingham.ac.uk/academicservices/qualitymanual/researchdegreeprogrammes/application-for-a-restriction-to-be-placed-on-a-thesis.aspx
[2] State number of years

For completion by Supervisor

Supporting statement of Supervisor:

The case studies involves discussing a collection of sensitive data pertaining to case companies new product development that are commercially sensitive.

This application has also been discussed with any body[3] (e.g. Research Council, government Department, industrial concern) which has an interest in the thesis by virtue of its sponsorship of the Research:

Yes ☒

No ☐

Not applicable ☐

If yes or no, the following comments have been received:

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Research Project Number (if applicable): The Natural Science Foundation of China (71172075, 71371006, 71420107024), the Fundamental Research Funds for the Central Universities: SCUT (2015JCRC06), the National Planning Office of Philosophy and Social Science of China (14AGL015), the New Economic Models in the Digital Economy (RA2186), and the Marketing Science Institute, USA.

Name of Supervisor: Professor. Kim Hua Tan

Signature of Supervisor:

Date: 12/12/2016.

[3] If no other body is involved mark this section 'Not applicable'
Last updated 12/03/2014 LP