A Proposed Framework for Accelerated Innovation in Data-Driven Environments: Evidence and Emerging Trends from China

Purpose – In today's rapidly changing business environment, the case for accelerated innovation processes has become increasingly compelling at both a theoretical and practical level. Thus, the purpose of this paper is to propose a conceptual framework for accelerated innovation in a data-driven market environment.

Design/methodology/approach – Our research is based on a two-step approach. First, a set of propositions concerning the best approaches to accelerated innovation are put forward. Then it offers qualitative evidence from five case studies involving world-leading firms, and explains how innovation can be accelerated in different kinds of data-driven environments.

Findings – The key sets of factors for accelerated innovation are: a) collateral structure; b) customer involvement; and c) ecosystem of innovation. The proposed framework enables firms to find ways to innovate - specifically, to make product innovation faster and less costly.

Research Limitations/implications –The findings from this research focus on high-tech industries in China. Using several specific innovation projects to represent accelerated innovation could raise the problem of the reliability and validity of the research findings. Additional research will probably be required to adapt the proposed framework to accommodate the cultural nuances of other countries and business environments.

Practical Implications – The study is intended as a framework for managers to apply their resources to conduct product innovation in a fast and effective way. It developed six propositions about how, specifically, data analytics and ICTs can contribute to accelerated innovation.

Originality/value – The research shows that firms could harvest external knowledge and import ideas across organisational boundaries. An accelerated innovation framework is characterised by a multidimensional process involving intelligence efforts, relentless data collection and flexible working relationships with team members.

Key words: Accelerated Innovation; Innovation Approaches; Data-Driven; NPD

1.0 INTRODUCTION

The current state of business in the world is one of rapid change and companies are opening up a new front in global competition (McKinsey, 2015; Liu and Jiang, 2016). It centres on what we call accelerated innovation – that is, reengineering innovation processes and R&D to make new product development (NPD) dramatically faster and less costly (Hagel and Brown, 2011; Williamson and Yin, 2014). Any company that wishes to be proactive must master accelerated innovation (Stalk, 1988; Goktan and Miles, 2011). The market share advantages will go to "first mover" firms in terms of the pioneer's opportunity to create the rules for subsequent competition in its favour (Day and Wensley, 1988; McKinsey, 2015). In a highly competitive environment, to be first in the market demands short NPD times. Even to be a successful later entrant requires relatively fast NPD capabilities, to meet customer needs before they change (Ahmad et al., 2013). In addition, important cost benefits can be achieved by firms that learn to manage accelerated NPD (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).

Traditionally, NPD is viewed as a firm-driven activity, with the firm being responsible for coming up with ideas for new products and deciding which should be commercialised and developed (Van Kleef, 2005; Cooper, 2014; Barczak, 2012). Advances in information and communication technologies are enabling new initiatives to be explored and are transforming NPD (Bharadwaj and Noble, 2015; Liu and Jiang, 2016). In particular, data from different sources can be captured and used to improve NPD. IBM (2013) reports that 90% of the data that exists in the world today was created in the last two years and it is expected the global total of data will reach 35 zettabytes (ZB) by 2020 (Wong, 2012). This is therefore the era of "big data" (Chan et al., 2015). Firms now can access a variety sources of data, such as click streams, videos, tweets and other unstructured sources to extract new ideas or understanding about their products, customers and markets (Tan et al., 2015; Bharadwaj and Noble, 2015). According to Sanders (2014), data analytics (i.e. capturing useful information from data, to inform decision making) has given rise to intelligent product innovation and can help to enhance NPD in many ways.

However, embedding and sustaining accelerated innovation in a data-driven environment is not easily achieved. Few studies have explicitly explored approaches to accelerated

innovation. Findings from existing studies mainly suggest that most innovation approaches are based on changing technology in the firm's environment (Millson et al., 1992; Liu and Jiang, 2016). 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 papers that attempt to bring together data-driven initiatives on this increasingly important accelerated innovation approaches. The overwhelming majority of these earlier contributions in the area of accelerated innovation have sought to identify potential success factors by analysing relatively large samples and quantitative methodological approaches (Kessler and Chakrabarti, 1996; Callahan and Moretoon, 2001; Swink et al., 2006; 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 innovation in a data-driven environment. Therefore, a systematic study of the implications of data-supported accelerated innovation approaches on NPD could greatly extend knowledge in this respect (Bharadwaj and Noble, 2015).

Moreover, 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 data analytics to support accelerated innovation in new product development processes (Wong, 2012). Emerging evidence indicates that accelerated 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; 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 data analytics to realize these benefits. These problems and considerations lead to the following research questions concerning in NPD:

1. What are the best approaches to accelerated innovation?
2. In a data-driven environment, how can data analytics be applied to support accelerated innovation?

A previous study by Zhan et al. (2017) have proposed the earliest extant knowledge on the implementation of accelerated innovation in a big data environment by suggesting a preliminary framework to facilitate product innovation process. However, its key attention was paid to identifying the key approaches for accelerated product innovation in a data-driven environment and then to incorporating, in addition to the literature, some of the knowledge of academics and industrialists. As a result, it is not evident which approaches can be applied to facilitate different phases of product innovation. Also, it is impossible to determine how data analytics can be used to support product innovation. The main purpose of this research is to extend Zhan et al.'s (2017) big data framework by further recasting and augmenting the conceptual basis of the accelerated innovation and data analytic initiatives through conducting in-company cases. In particular, the relevance of this research came from the direct applicability of the approaches identified to real product innovation projects that different companies face. This paper is structured as follows. A set of propositions concerning the best approaches to innovation and data analytics in supporting accelerated innovation are proposed and examined. Then, we develop a framework for accelerated innovation in a data-driven environment that integrates data analytics and different types of information. The case study has been used to refine the framework and illustrate its applications.

2.0 LITERATURE REVIEW AND PROPOSITIONS

Building on the considerable amount of literature in this area, we propose that there are three sets of factors that might contribute to accelerated innovation in a data-driven environment. The three sets of factors were summarised from prior studies and were further improved by conducting a series of interviews with leading academics and data experts from a number of industries and disciplines, for further development and refinement of these sets of factors, please refer to the work of Zhan et al. (2017). The first set of factors relates to the different approaches in NPD (which we term the "collateral structure"). The second broad set of factors is associated with the involvement of customers. The third set of factors focuses on building an innovation ecosystem to support NPD. The following sections define each of the factor terms and formulate propositions.

2.1 Collateral Structure

The ability to innovate quickly has become an increasingly significant factor in recent years in determining competitiveness, especially in industries where product cycles are short and

technological change rates are high (Brown and Bessant, 2003; McKinsey, 2009; Rese and Baier, 2011). Collateral structure indicates a company structure for problem solving which coexists with the formal, operational design but structured as a flexible, open, loose, "organic-adaptive" system (Kilmann, 1982; Singh, 2005; Lyer and Davenport, 2008; Google, 2011). According to the literature, collateral structure in product innovation for NPD has been underpinned by NPD team autonomy and cross-functional teams (Kilmann, 1982; Lichtenthaler, 2009; Goktan and Miles, 2011; Bauer and Leker, 2013).

2.1.1 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 (O'Connor, 2008), or disruptive technological change (Gassmann and Enkel, 2004; Hagel and Brown, 2011). 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). Today, 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 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 innovation in a data-driven environment

2.1.2 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). 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 (O'Hern and Rindfleisch, 2009). Moreover, 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 data-driven environments 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). For example, advanced ICTs and data analytics 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 innovation in a data-driven environment

2.2 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 (Brown et al., 2002; Blazevic and Lievens, 2008; Franke et al., 2009; Cooper, 2014). Regarding accelerated innovation, 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 (Williamson and Yin, 2014; Abhair et al., 2017).

2.2.1 Understanding customers' needs

Customers are one of the key sources for product innovation, and a good understanding of their needs is required to ensure NPD success (Blazevic and Lievens, 2008). Compared with traditional methods of acquiring information and generating customer insight for NPD, new communication and data techniques provide a variety valuables source of information and a new dimension to market research; they represent new opportunities to understand customers (Shu-Chuan and Kim, 2011; Capgemini, 2012). It offers new ways to improve a firm's understanding of its customer and to conduct market research that can be utilised in the NPD

process. It has been reported that successful companies use data analytics to capture information from web-based platforms for market understanding and accelerating NPD (Mckinsey, 2011). Therefore, we put forward the following proposition:

P3: A deeper understanding of customers' needs will lead to accelerated innovation in a data-driven environment

2.2.2 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 (Shu-Chuan and Kim, 2011; Schaarschmidt and Killan, 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). The IoTs 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; Abhari et al., 2017). 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: Customer co-creation will lead to accelerated innovation in a data-driven environment

2.3 Innovation Ecosystem

Most breakthrough innovations do not succeed in isolation (Moore, 1993; Adner, 2006; Minguela-Rata et al., 2014); instead, they frequently need complementary innovations to deliver useful functionality to customers (Cooper, 2014; Gawer and Cusumano, 2014). The thinking behind what is termed the "innovation ecosystem" is that the capabilities of one actor can be expanded through collaboration with others (Adner, 2006). The benefits of these systems – discussed under such labels as "open innovation", "platform leadership", "value

networks", and "keystone strategies" – are well publicized and real (Gassmann and Enkel, 2004; Rese and Baier, 2011; Rohrbeck, 2010). Two defining features of innovation ecosystems are at the core of the propositions put forward in this paper: 1) partnership with stakeholders, and 2) the fast improve-and-relaunch process.

2.3.1 Partnership with stakeholders

Unlike early approaches to product innovation, which mainly relied on information from internal research, with very little use of external sources (e.g. market ideas, customer complaints) (Niosi, 1999), current approaches (e.g. open innovation) involve building networks of cooperative product market relationships (Adner and Kapoor, 2010; Christensen and Roynor, 2003; West et al., 2014). The reasons are to be found in shorter innovation cycles, the escalating costs of industrial research and development as well as in the dearth of resources (Chesbrough 2006; Minguela-Rata et al., 2014). Additionally, modern data analytics and ICTs can enable firms to improve their 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). Therefore, NPD today is more likely to succeed if the firm looks outside the company, for example to customers, suppliers and competitors, in order to find new partners; the building of such comprehensive networks will create both more value and greater competitive advantage (Gassmann and Enkel, 2004; Hagel and Brown, 2011; McKinsey, 2013; 2015). We therefore propose:

> *P5: Stronger partnerships with stakeholders will lead to accelerated innovation in a data-driven environment*

2.3.2 Fast improve-and-relaunch process

Rather than developing a fully-fledged product before launch, companies today routinely launch new products as quickly as possible and then harness feedback from their partners and customers to improve the product (Floricel and Dougherty, 2007; Williamson and Yin, 2014), which is then quickly relaunched, in an iterative cycle. 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; Wong, 2012). For example, by applying 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). This leads us to propose that:

P6: Faster improve-and-relaunch cycles in the NPD process will lead to accelerated innovation in a data-driven environment

3.0 METHODOLOGY

To study the approaches for accelerated innovation in a data-driven environment, this study follows a naturalistic approach and focuses more on "what" goes on in the research context, and less on "how" events are socially brought into being (Silverman, 2015). Our company cases are topical as they look for facts, descriptions, and examples that help answer a set of specific research questions (Rubin and Rubin, 2011). In Particular, comparative case study research (Yin, 2011) was selected as the most appropriate methodology for this investigation because of the expected context-specific nature of the phenomena and research questions being investigated. The method was applied in two stages: first, in-depth case studies were analysed; and second, the cases were compared. We applied qualitative methods (observations and interviews) to five case examples of accelerated innovation supported by data analytics in five world-leading companies in the manufacturing, telecommunication, electronics, and software sectors. The companies investigated were all high-tech companies and develop software-intensive or high-tech products. In total, we conducted 46 interviews (semi- and unstructured): 12 interviews for each case A and C; eight interviews each for cases B and D; and six interviews for case E.

Our qualitative analysis followed the general strategy of "replying in theoretical propositions" (Yin, 2011). In particular, we followed Done et al. (2011) and conducted a comparative case study. 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 innovation in a data-driven 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, 2011) allows for outcome evaluation

on multiple dimensions, where as little as one actual observation for a given dimension is available (Bitektine, 2008).

Interviews were conducted with both managers (e.g. R&D managers, heads of innovation, senior managers and project managers) as well as with a selection of R&D team members. In addition to the interviews, we observed these R&D teams, participated in internal presentations and workshops, and collected internal secondary material. According to McDonald (2005), observations can provide unique insights into day-to-day working practices because they shift the emphasis to the direct study of contextualised actions. One of the authors had full access as an observer to most of the teams during a period of product development or while the teams applied data analytics. Therefore, we were able to observe the teams in their natural setting (Schultze, 2000) to understand how they work.

Researchers normally select cases using replication rather than sampling logic when building theory from case studies (Eisenhardt, 1989; Yin, 2011; Voss et al., 2002). But case selection ought to be used to provide the best opportunities to learn and extend theory. In the study, all five companies selected for case study were focusing on accelerated innovation and using a variety of data sources in support. Accelerated innovation was being applied to concepts, features, prototypes, or full products. In summary, the selection criterion applied in the present study was the application of analytics in accelerated innovation, in support of product or service innovation. An overview of the case companies and the data collection in each case is presented in Table 1. For instance, Cases A and D are both consumer electronic companies and develop electronic equipment intended for everyday use.

Table 1. Overview of the case companies and data collection

Case	Industry	Size (2015)	Revenue (2015)	Profitable (2015)	Interviews	Data Collection
A	Electronics	13,000	£7.6b	Yes	12	Interviews, workshops, presentation, observations, secondary material
B	Telecommunications	310,000	£32b	Yes	8	Interviews, presentation, observations
C	Software	35,000	£6.3b	Yes	12	Interviews, observations, workshops, presentation, secondary material
D	Electronics	8,000	£7.3b	Yes	8	Interviews, workshops, presentation, secondary material, observations
E	Software	27,000	£9.1b	Yes	6	Interviews, workshops, presentation, secondary material, observations

Size indicates approximate number of employees

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: collateral structure, customer involvement, innovation ecosystem, and data analytics applied for supporting NPD. In the second stage, we focused on coding extracted passages relating to the main themes as well as the sub-themes (as set out in Section 2.0). 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 among the three authors which went through several rounds of coding, and after each coding round the data were compared and discussed among the authors. During this whole process, we found 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 2. Table 3 demonstrates the different innovation projects across the five case examples, with different activities and data

analytics applied. In a final step, the conclusions drawn from the study were presented to some of the firms from the case studies, for validation.

Table 2: Examples of coding

Examples (Quotes)	Themes and sub-themes coded
Case A: "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."	Collateral Structure • Cross-functional teams Data-driven 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…"	Ecosystem of innovation • Partnership with stakeholders
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: Innovation projects in the five case studies

Case	Scope	Activities	Types of Data Involved	Data Analytics
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); 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	SAP BusinessObjects (BO); 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	Semi- and unstructured	SAP BusinessObjects; 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; Google Analytics (A/B testing and crowdsourcing)

4.0 RESULTS

Here we assess the five cases with regard to each of the nine propositions put forward in Section 2. The results are summarised in Table 4. We discuss the types of innovation approaches with the different data analytics applied. The results can be summarised by the three dominant sets of factors: (1) collateral structure; (2) customer involvement; (3) innovation ecosystem. All three sets of factors represent an accelerated innovation strategy, but not all were equally important for every company. E.g., for different companies, they have different objectives, R&D focus, organisational structures, corporate cultures and so on. Therefore, they might focus on different strategies for accelerated innovation in their projects.

Table 4: Summary of results

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

+ indicates factor clearly present/strong

4.1 Collateral Structure

Collateral structure has been acclaimed as a core structural approach to catalysing effective and accelerated NPD (Chen et al., 2012; 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. Today, the company uses a more industrial process in NPD. The company builds teams to work on different projects in parallel. For a specific project, the company used a team of 33 workers from different departments (including 8 designers, 16 individuals with expertise in areas such

as R&D, manufacturing and sales, 6 computer engineers and 3 product testers). Instead of having work details controlled by senior management, the company gives the authority to teams to manage their own processes. 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.

In case D, the NPD teams were given autonomy to facilitate their innovation and development process. The company creates independent development teams and appoints one project leader to supervise the output of its product development. The company gives teams the freedom to set their own level of responsibility and schedule to achieve it. In particular, the approach begins by dividing the innovation process (which includes the business case, development, testing and validation) into a large number of small steps. One of our findings was that implementation of this processing made employees felt more valued and trusted. The R&D manager pointed out that "*What I see is a more agile, dynamic and flexible approach that is lean, rapid response and costs less*." The NPD teams agreed that "*It not only improves the output but may also encourage creativity during the approaches.*" In addition, they mentioned that data analytics and information technologies play a big role, in that they enable teams to share the latest information and communicate effectively, speed up problem solving and reduce development costs.

In case E, the company brings together top design, engineering, and business thinking in one holistic approach. It builds cross-functional teams that work independently and closely with strategy, technology, engineering, marketing, purchasing, and production. Particularly, 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. The company also invites the teams to attend weekly meetings, to improve communication and collaboration. Managers can enhance team's 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 data analytics, can provide the support and challenge required to keep team members engaged and motivated and empowers them to

reach their potential. According to the interviews, the NPD teams highly valued the cross-functional work and autonomy.

4.2 Customer Involvement

Today, customers are increasingly regarded not as just 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 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 on social media about its products. It connects to customers through a wide range of sources at low cost (e.g. official Web forum, mobile apps, popular websites). According to the marketing manager, "*customer connection 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 via social media 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 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 NPD teams keep in close connection with their core customer units as early as possible. A frequent dialogue between the customer and the R&D teams took place through the customer unit, first on the new feature requirements of new products, and in later stages on concept testing and prototypes before the new product was provided to particular customers. The engineers of the NPD team mentioned during the interviews 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.*" Moreover, the development teams were able to bring in their own knowledge of product development, and sometimes suggested alternative solutions that were more suitable and customer-friendly than the solution suggested by the customers.

In case C, the company focused on collecting and analysing information from customer, market and competitors to gain competitive advantages and a deeper understanding of both their customers and their competitors. The data analytics enabled the company to quantify its customer and marketing spend. The IT manager stated that ""*gained a deeper understanding of customers' needs at the very beginning stages of the NPD"* The company is now developing a sophisticated customer predictive data analysis 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 invites 50 customer representatives to reflection and discussion sessions (these are half-day events). During the events, customers' particular problems and issues which were found or stated earlier are become a starting point for discussions and reviews with the customers. The customer representatives are self-selected. In the research interviews, managers pointed out that this immediate interaction 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. 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.*"

4.3 Innovation Ecosystem

Scholars and practitioners increasingly identify the usefulness of the innovation ecosystem concept for explaining cooperative innovative activities (Cooper, 2014; Leavy, 2012). This approach involves collateral structure and customer involvement. It enables NPD teams to move to market-wining 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. In interview, one of the R&D managers mentioned 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, 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. The NPD manager stated that "*the company is already spending millions of dollars in cooperating with desirable partners among the entire supply chain to support its product development ecosystem.*" 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. Therefore, the company can launch new products to meet its customers' requirements in a much more efficient and effective way. Besides, the companies in case C and E aim to formulate their own innovation ecosystem by looking for partners and practices that could enhance their capabilities for speed in development, speed to market and speed in improvement. For instance, Case A Company invested half a million US in 2016 to online video content partners to provide a platform for better customer and supplier interactions. Thus, product innovation is made from interrelated networks and these empower organisations to rapidly integrate useful information from customers and partners.

To speed up the NPD process, in both case C and case E the companies 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. The companies also 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. These inputs allow 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.*" This fast-improve-and-relaunch process requires the appropriate collateral structure and customer involvement that can help the R&D team to move quickly to a market wining product through a series of iterations: new product ideas, fast launch, gathering feedback, fast improvement and relaunch.

5.0 DISCUSSION

The paper set out to investigate two research questions. First, what are the best approaches for accelerated innovation in a data-driven environment? And second, how can data analytics be applied to support accelerated innovation? The propositions based on case evidence are summarised in Table 5. A confirmatory contribution of this research to existing literature is identifying the approaches and specifying a framework to attain accelerated innovation in world leading companies. 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.

Table 5: Summary of support for propositions

Proposition	Support	Additional comments
Collateral 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	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

5.1 A Framework for Accelerated Innovation

Stalk (1988) pointed out in his works almost thirty years ago that "time-based competition" or the ability to innovate and produce ahead of competition is a key competitive strategy. Being the first to market with new products and technologies enable the firm to stay ahead of competition, and to enjoy a price premium on its products. World-class organizations such as Apple Inc., Microsoft, Intel, Advanced Micro Devices, and Samsung Electronics, have all been relying on accelerated innovation as their core competency to develop new products and technologies to compete in this fiercely competitive global market. Accordingly, accelerated

innovation is associated with maximisation of the product success rates, higher profitability and competitive advantage (Greve, 2011; Williamson and Yin, 2014). All five companies in the present case study were applying new approaches in product development to gain accelerated NPD, better understanding of customers' needs, higher revenue growth, 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). However, the case study companies jointly implement other types of methods as well as data analytics to generate an integrated approach for acceleration of NPD. The literature on R&D research shows existing approaches to achieve fast NPD (Markman et al., 2005; Greve, 2011), or to develop interaction and collaboration with customers (Brown, 2002; O'Hern and Rindfleisch, 2009; Schaarschmidt and Kilian, 2014). However, determining suitable approaches to 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), and more virtual customer co-creation (Blazevic and Lievens, 2008). Moreover, in a data-driven environment, firms can make use of different technology-based or online data analytics to enhance their innovation approaches. Examples are (see Table 3): 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; the use of an SQL Server, used to build data platforms in case D.

Figure 1 shows our proposed innovation framework, which is based on the literature as well as our findings from the cases. The framework consists of the following approaches: (1) Collateral Structure – refers to the different processes that go into NPD, (2) Customer Involvement – associates with the cultivation and maintaining of high-quality information and feedback links with wide range of customers, and (3) Innovation Ecosystem – focuses on building an innovative ecosystem to support product innovation in a fast-improve-and-relaunch process. Different companies might pay more attention to different approaches.
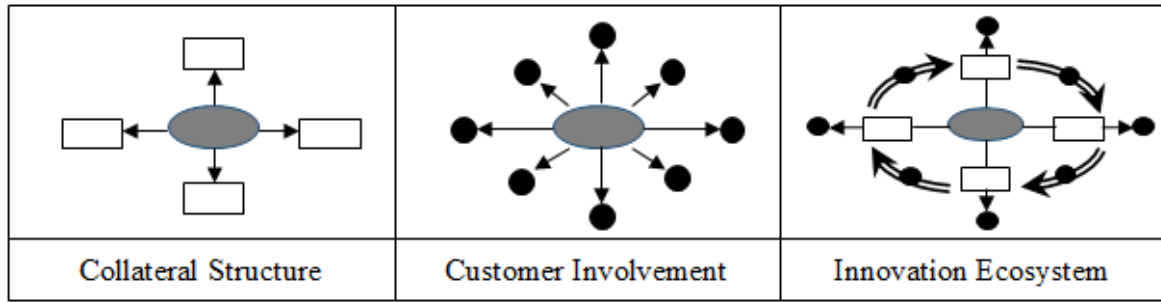
Figure 1. Framework for Accelerated Innovation

5.1.1 Collateral structure

The evidence from the five cases illustrates how R&D teams change their processes to accelerate NPD in a data-driven environment. In order to speed up product development, 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; 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.

Advanced 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 also can be used to support the creation and maintenance of team identity by the use of data analytics 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 collateral 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.

5.1.2 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 data analytics 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 (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.

5.1.3 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 is like an ecosystem indicates that the company network is used to acquire new requirements and components of product development processes externally or from intermediaries (Ernst, 2002), in order to create such an environment that is able to launch a product quickly with less cost (Adner and Kapoor, 2010). Many scholars today use the concept of the innovation ecosystem to explain cooperative innovative activities (Gassmann and Enkel, 2004; 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 collateral 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.

5.1.4 Implications of data analytics for accelerated innovation

The different data analytics and information technologies applied offer both of 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- 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 (McKinsey, 2013; 2015; Capgemini, 2012). However, through the use of data analytics 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.

5.2 Implications for Practice and Research

The major contribution of the paper is that it usefully extends the accelerated innovation literature by developing and refining a conceptual framework with how innovation can be accelerated in a data-driven environment. The developed framework is based on information elicited from the literature and the unique product innovation approaches adopted by five successful Chinese firms. It enable firms to find ways to innovate – to make NPD faster and less costly. Compared with existing product innovation approaches, the framework developed places particular emphasis on efficiency and cost saving. It investigates the approaches to accelerated innovation in a big data environment that may shorten the time to market, improve customers' product adoption and reduce new product costs. Although the term big data is not new, 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 the author believes is worth further developmental efforts from product innovation and big data scholars.

In terms of practical contributions, the study is intended as guidelines for R&D innovation managers to apply their resources to conduct product innovation in a fast and effective way. The findings of this research could 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. In the cases, we identified a number of implications of implementing a data-driven fast improve-and-relaunch process, 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.

This study also extends the accelerated product innovation boundaries pointed out by Williamson and Yin (2014), and 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 (Davenport, 2014; McAfee and Brynjolfsson, 2012). Moreover, this research further improved Zhan et al.'s (2017) big data framework by further recasting and augmenting the conceptual basis of the accelerated innovation and data analytic initiatives through conducting in-company cases. Firms are leveraging data analytics to embed customer sentiment in product development. 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 framework enables firms to find ways to innovate – to make NPD faster and less costly. However, the implementation of the NPD acceleration approaches 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 NPD process.

5.3 Limitations and Future Research

Since all the companies investigated are very large corporations operating globally or nationally, we have only examined our propositions 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. Moreover, the cases collectively provide coverage of different high tech companies. Therefore, we believe that the results can be generalized to different other projects or other high-tech companies. Besides, the suggested sets of factors are examined, but their results are measured only in the given cases. Future empirical studies can be conducted at the organisational level to compare the implications of the framework and enhance the findings of this research. Also, the cases were conducted on Chinese companies; it is not known to what extent the approaches for accelerated innovation can be generalised beyond the Chinese context. Thus, further research in other country contexts are required to enhance confidence in the generalisability of these findings. Although the findings of this research focus on high-tech industries (high-tech manufacturing, telecommunications, electronics and software), we believe they can be generalised to any industry that applies data analytics and employs R&D in its product development and enables their businesses to be connected to the Internet. Additionally, we pay attention to the approaches needed to achieve accelerated innovation in this research and we found that the fast improve-and-relaunch process can be generalised and applied to other properties of the service or product. So far, the development of a high-level framework for such a complicated phenomenon as accelerated innovation may highlight some obvious connections while failing to capture others. The developed framework is mainly focused on investigating approaches to accelerated 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.

However, action research can be conducted to further explore to what extent the proposed framework can facilitate product innovation under different circumstances. 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.

REFERENCES:

Abhari, K., Abhari, K., Davidson, E.J., Davidson, E.J., Xiao, B. and Xiao, B., 2017. Co-innovation platform affordances: Developing a conceptual model and measurement instrument. *Industrial Management & Data Systems*, 117(5), pp.873-895.

Adner, R. 2006. Match your innovation strategy to your innovation ecosystem. *Harvard business review* 84 (4): 98-109.

Adner, R., and R. Kapoor. 2010. Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic management journal 31*(3): 306-333.

Ahmad, S., D. N. Mallick, and R. G. Schroeder. 2013. New product development: impact of project characteristics and development practices on performance. *Journal of Product Innovation Management* 30(2): 331-348.

Barczak, G. 2012. The Future of NPD/Innovation Research. *Journal of Production innovation Management* 29 (3): 355-357.

Bauer, M., and J. Leker. 2013. Exploration and exploitation in product and process innovation in the chemical industry. *R&D Management* 43 (3): 196-212.

BCG, 2015. *The most innovative companies 2015*, The Boston Consulting Group.

Bharadwaj, N., and C. H. Noble. 2015. Call for Papers Innovation in Data-Rich Environments. *International Journal of Product Innovation Management* 32 (3): 476-78.

Bitektine, A. 2008. Prospective case study design qualitative method for deductive theory testing. *Organizational Research Methods* 11(1): 160–180.

Blazevic, V., and A. Lievens. 2008. Managing innovation through customer co-produced knowledge in electronic services: an exploratory study. *Journal of the Academy of Marketing Science* 36 (1): 138-51.

Bosch-Sijtsema, P. and J. Bosch. 2015. User Involvement throughout the Innovation Process in High Tech Industries. *Journal of Product Innovation Management* 32(5): 793-807.

Brown, S. and Bessant, J. (2003), "The manufacturing strategy-capabilities links in mass customisation and agile manufacturing – an exploratory study", *International Journal of Operations and Production Management*, Vol. 27 No. 4, pp. 346-370.

Brown, S., Squire, B. and Blackmon, K., 2007. The contribution of manufacturing strategy involvement and alignment to world-class manufacturing performance. *International Journal of Operations & Production Management*, 27(3), pp.282-302.

Brown, T.J., J. C. Mowen, D. T. Donavan, and J. W. Licata. 2002. The customer orientation of service workers: Personality trait effects on self-and supervisor performance ratings. *Journal of Marketing Research 39*(1):110-119.

Bryman, A. 2012. *Social Research Methods* 3rd ed., Oxford; New York: OUP Oxford.

Calder, B.J., Malthouse, E.C. and Maslowska, E., 2016. Brand marketing, big data and social innovation as future research directions for engagement. *Journal of Marketing Management*, 32(5-6): 579-585.

Callahan, J. and B. Moretton. 2001. Reducing software product development time. *International Journal of Project Management* 19(1): 59-70.

Campbell, D. T. 1966. Pattern matching as an essential in distal knowing. In: Hammond, K.R. (Ed.), The Psychology of Egon Brunswik. Holt, Rinehart & Winston, New York, pp. 81–106.

Capgemini. 2012. *Unlocking the Power of Data and Analytics: Transforming Insight into Income, Capgemini*, available at: http://www.uk.capgemini.com/resources/business-process-analytics-unlocking-the-power-of-data-and-analytics-transforming-insight (assessed Oct 08, 2015).

Chan, H. K, X. Wang, E. Lacka, and M. Zhang. 2015. A mixed-method approach to extracting the value of social media data. *Production and Operations Management*. Doi/10.1111/poms.12390

Chen, H., R. H. Chiang, and V. C. Storey. 2012. Business Intelligence and Analytics: From Big Data to Big Impact. *MIS quarterly* 36(4): 1165-1188.

Chen, J., F. Damanpour, and R. R. Reilly. 2010. Understanding antecedents of new product development speed: A meta-analysis. *Journal of Operations Management 28*(1):17-33.

Chen, J., R. Reilly, and G. Lynn. 2005. The impacts of speed-to-market on new product success: The moderating effects of uncertainty. *IEEE Transactions on Engineering Management* 52 (2): 199-212.

Chesbrough, H. W., 2006. *Open innovation: A new paradigm for understanding industrial innovation*, Oxford University press, Berkeley.

Christensen, C. M., and M. E. Raynor. 2003. The innovator's solution: creating and sustaining successful growth. Boston: Harvard Business School Press.

Clark, K. B., and T. Fujimoto. 1991. *Product development performance: strategy, organisation, and management in the world auto industry*. Boston: Harvard Business School Press.

Cooper, R.G. 2014. What's Next? After Stage-Gate. *Research Technology Management* 57 (1): 20-31.

Davenport, T. H. 2009. How to design smart business experiments. *Harvard Business Review* 87 (2): 68-76.

Davenport, T. H., 2013. *Process innovation: reengineering work through information technology*. Harvard Business Press.

Day, G. S., and R, Wensley. 1988. Assessing advantage: a framework for disposing competitive superiority. *Journal of Marketing*: 52-53.

Deshpande, A. 2013. Development and consequences of cross functional team performance in the concurrent engineering context: an integrated framework. *Journal of Applied Business and Economics* 14 (4): 24-36.

Dewett, T. and G. R. Jones. 2001. The role of information technology in the organization: a review, model, and assessment. *Journal of management* 27(3): 313-346.

Done, A., Voss, C. and Rytter, N.G., 2011. Best practice interventions: Short-term impact and long-term outcomes. *Journal of Operations Management*, 29(5), pp.500-513.

Eisenhardt, K. M. 1989. Building theories form case study research. *Academy of Management Review* 14: 532-50.

Eisenhardt, K., and B. Tabrizi. 1995. Accelerating adaptive processes: Product innovation in the global computer industry. *Administrative Science Quarterly* 40 (1): 84-110.

Eling, K., F. Langerak. and A. Griffin. 2013. A Stage-Wise Approach to Exploring Performance Effects of Cycle Time Reduction. *Journal of Product Innovation Management* 30(4): 626-641.

Ernst, H. 2002. Success Factors of New Product Development: A Review of the Empirical Literature. *International Journal of Management Reviews* 4 (1): 1-40.

Eui-Bang Lee, (2017) "The effect of technology innovation on mobile communication and mobile products", *Industrial Management & Data Systems*, Vol. 117 Issue: 8, pp.1707-1719.

Floricel, S., and D. Dougherty. 2007. Where do games of innovation come from? Explaining the persistence of dynamic innovation patterns. *International Journal of Innovation Management 11*(01): 65-91.

Franke, N., P. Keinz, and C. J. Steger. 2009. Testing the value of customisation: When do customers really prefer products tailored to their preferences?. *Journal of Marketing* 73 (5): 130-21.

Gassmann, O., and E. Enkel. 2004. Towards a theory of open innovation: three core process archetypes. In *R&D management conference* 6: 1-18.

Gawer, A., and M. A. Cusumano. 2014. Industry platforms and ecosystem innovation. *Journal of Product Innovation Managemen*t *31*(3): 417-433.

Goktan, A. B. and G. Miles. 2011. Innovation speed and radicalness: are they inversely related?. *Management Decision* 49 (4): 533-547.

Google. 2011. The Eight Pillars of Innovation. *Google.com.* Available at: https://www.thinkwithgoogle.com/articles/8-pillars-of-innovation.html (accessed Sep 09, 2015).

Govindarajan, V., and C. Trimble. 2005. Building breakthrough businesses within established organisations. *Harvard Business Review* 83 (5): 58-68.

Greve, H. R. 2011. Fast and expensive: the diffusion of a disappointing innovation. *Strategic Management Journal* 32 (9): 949-968.

Griffin, A. 2002. Product development cycle time for business-to-business products. *Industrial Marketing management* 31 (4): 291-304.

Guide, Jr, V.D.R., G.C. Souza, L.N. Van Wassenhove, and J.D. Blackburn. 2006. Time value of commercial product returns. *Management Science*, 52(8), pp.1200-1214.

Hagel, J., and J. S. Brown. 2011. Creation nets: harnessing the potential of open innovation. *Journal of Service Science (JSS) 1*(2): 27-40.

Hillebrand, B., R. A. W. Kok, W. G. Biemans. 2001. Theory-testing using case studies: a comment on Johnston, Leach, and Liu. *Industrial Marketing Management* 30 (8): 651–657.

Hoyer, W. D., R. Chandy, M. Dorotic, M. Krafft, and S. S. Singh. 2010. Consumer co-creation in NPD. *Journal of Service Research* 13 (3): 283-96.

IBM. 2013. What is big data? – Bringing big data to the enterprise. *IBM*, available at: www.IBM.com (accessed Mar 03, 2015).

Kessler E. H, Chakrabarti AK (1996) Innovation speed: A conceptual model of context, antecedents, and outcomes. *Academy of Management Review*. 21(4) 1143-1191.

Kilmann, R. H., 1982. Designing Collateral Organisations. *Human Systems Management* 3 (2): 66-76.

Kohavi, R., R. Longbotham, D. Sommerfield, and R. M. Henne. 2009. Controlled experiments on the web: survey and practical guide. *Data mining and Knowledge Discovery* 18 (1): 140-81.

Langerak, F., A. Griffin, and E. J. Hultink. 2010. Balancing development costs and sales to optimise the development time of product line additions. *Journal of Product Innovation Management* 27 (3): 336-48.

LaValle, S., E. Lesser, R. Shockley, M. S. Hopkins., and N. Kruschwitz. 2011. Big Data, analytics and the path from insights to value. *MIT sloan management review* 52(2): 21-23.

Leavy, B. 2012. Interview-Ron Adner: managing the interdependencies and risks of an innovation ecosystem. *Strategy & Leadership 40*(6):14-21.

Liao, Y. and J. Barnes. 2015. Knowledge acquisition and product innovation flexibility in SMEs. *Business Process Management Journal* 21(6):1257 – 1278.

Lichtenthaler, U., and E. Lichtenthaler. 2009. A capability-based framework for open innovation: Complementing absorptive capacity. *Journal of Management* 46(8): 1315-1338.

Lijun Liu, Zuhua Jiang, (2016) "Influence of technological innovation capabilities on product competitiveness", *Industrial Management & Data Systems*, Vol. 116 Issue: 5, pp.883-902.

Lincoln, Y. S., and E. G. Guba. 1985. *Naturalistic inquiry*. Beverly Hills. CA: Sage.

Locke, J. 2001. *Grounded theory in management research*. London: Sage.

Lyer, B., and T. H. Davenport. 2008. Reverse Engineering Google's Innovation Machine. *Harvard Business review* 86 (4): 58-68.

Markman, G. D., P. T. Gianiodis, P. H. Phan, and D. B. Balkin. 2005. Innovation speed: transferring university technology to market. *Research Policy* 34: 1058-1075.

McDonald, S. 2005. Studying actions in context: A qualitative shadowing method for organisational research. *Qualitative Research* 5: 455-73.

McKinsey. 2009. How companies are benefitting from Web 2.0. *The McKinsey Quarterly* 4: 84-85.

McKinsey. 2011. *Big Data: The Next Frontier for Innovation, Competition, and Productivity,* McKinsey Global Institute: 1-137.

McKinsey. 2015. *The china Effect on Global Innovation.* McKinsey Global Institute, October 2015.

Menon, A., J. Chowdhury, and B. Lukas. 2002. Antecedents and outcomes of new product development speed: An interdisciplinary conceptual framework. *Industrial Marketing Management* 31 (4): 317-28.

Millson, M. R., S. P. Raj, and D. Wilemon. 1992. A survey of major approaches for accelerating new product development. *Journal of Product Innovation Management* 9: 53-69.

Minguela-Rata, B., Fernández-Menéndez, J. and Fossas-Olalla, M., 2014. Cooperation with suppliers, firm size and product innovation. *Industrial Management & Data Systems*, 114(3), pp.438-455.

Mishra, A. A., R. Shah. 2009. In union lies strength: Collaborative competence in new product development and its performance effects. *Journal of Operations Management* 27(4): 324–338.

Moore, J. F. 1993. Predators and prey: a new ecology of competition. *Harvard business review 71*(3): 75-83.

Niosi, J. 1999. Fourth-Generation R&D: From Linear Models to Flexible Innovation. *Journal of Business Research* 45 (2): 111-117.

O'Hern, M. S., and A. Rindfleisch. 2009. *Customer co-creation: a typology and research agenda.* In Review of Marketing Research. New York: Armonk.

Patanakul, P., J. Chen, and G. S. Lynn. 2012. Autonomous teams and new product development. *Journal of product innovation management* 29 (5): 734-50.

Peng, D. X., G. R. Heim, and D. N. Mallick. 2014. Collaborative product development: The effect of project complexity on the use of information technology tools and new product development practices. *Production and Operations Management* 23(8): 1421-1438.

Popper, K. 1968. *The Logic of Scientific Discovery*. Harper Torchbooks, New York.

Prahalad, C. K., and V. Ramaswamy. 2004. Co-creation experiences: The next practice in value creation. *Journal of Interactive Marketing* 18 (3): 5-14.

Rese, A. and D. Baier. 2011. Success factors for innovation management in networks of small and medium enterprises. *R&D Management* 41 (2): 138-155.

Rohrbeck, R. 2010. Harnessing a network of experts for competitive advantage: technology scouting in the ICT industry. *R&D Management 40*(2): 169-180.

Rubin, H.J. and Rubin, I.S., 2011. *Qualitative interviewing: The art of hearing data*. Thousand Oaks, CA: Sage.

Sanders, N.R., 2014. Big data driven supply chain management: *A framework for implementing analytics and turning information into intelligence*. Pearson Education, New Jersey.

Schaarschmidt, M., and T. Kilian. 2014. Impediments to customer integration into the innovation process: A case study in the telecommunications industry. *European Management Journal 32*(2): 350-361.

Schultze, U. 2000. A confessional account of an ethnography about knowledge work. *MIS Quarterly* 24: 3-41.

Shachaf, P. 2008. Cultural diversity and information and communication technology impacts on global virtual teams: An exploratory study. *Information & Management* 45(2): 131-142.

Shu-Chuan, C., and Y. Kim. 2011. Determinants of customer engagement in electronic word-of-mouth in social networking sites. *International Journal of Advertising* 30 (1): 47-75.

Silverman, D., 2015. *Interpreting qualitative data*. London: Sage.

Singh, K. 2005. *Organisation Change and Development*. EXCEL BOOKS: New Delhi.

Stalk, G. (1988). 'Time: The next source of competitive advantage', *Harvard Business Review*, 66 (4), pp. 41–51.

Stanko, M. A., F. J. Molina-Castillo, J. L. Munuera-Aleman. 2012. Speed to Market for Innovative Products: Blessing or Curse? *Journal of Product Innovation Management* 29(5): 751-765.

Swink, M., S. Talluri. and T. Pandejpong. 2006. Faster, better, cheaper: A study of NPD project efficiency and performance tradeoffs. *Journal of Operations Management* 24(5): 542-562.

Tan, K. H., Y. Zhan, G. Ji, F. Ye, and C. Chang. 2015. Harvesting Big Data to enhance supply chain innovation capabilities: An analytic infrastructure based on deduction graph. *International Journal of Production Economics 165*: 223-233.

Tatikonda, M. V., and M. M. Monotoya-Weiss. 2001. Integrating operations and marketing perspectives of product innovation: the influence of organisational process factors and capabilities on development performance. *Management Science* 47 (1): 151-72.

The Economist. 2015. The Business of Data. *The Economist Intelligence Unit Limited*, available at: https://www.eiuperspectives.economist.com/sites/default/files/images/Business%20of%20Data%20briefing%20paper%20WEB.pdf (accessed Dec 21, 2015).

Tidd, J. and Trewhella, M.J., 1997. Organizational and technological antecedents for knowledge acquisition and learning. *R&D Management*, 27(4), pp.359-375.

Van Kleef, E., H. C. M. Can Trijp, and P. Luning. 2005. Consumer research in the early stages of new product development: A critical review of methods and techniques. *Food Quality and Preference* 16: 181-201.

Von Hippel, E. 2005. *Democratizing Innovation.* MIT Press, Cambridge, MA

Voss, C. A., N. Tsikriktsis, and M. Frohlich. 2002. Case research in operations management. *International Journal of Operations and Production Management* 22(2): 195-219.

West, J., A. Salter. W. Vanhaverbeke, and H. Chesbrough. 2014. Open innovation: The next decade. *Research Policy 43*(5): 805-811.

Williamson, P. J. and E. Yin. 2014. Accelerated Innovation: The New Challenge From China, *MITSloan Management Review* 55 (4): 27-34.

Wong, D. 2012. *Data is the Next Frontier, Analytics the New Tool: Five trends in big data and analytics, and their implications for innovation and organisations*. London: Big Innovation Centre.

Xiaojun Wang, Leroy White, Xu Chen, (2015) "Big data research for the knowledge economy: past, present, and future", *Industrial Management & Data Systems*, Vol. 115 Issue: 9.

Yin, R. K. 2011. *Applications of case study research.* Sage.

Zhan, Y., Tan, K.H., Ji, G., Chung, L. and Tseng, M., 2017. A big data framework for facilitating product innovation processes. *Business Process Management Journal*, 23(3), pp.518-536.

Zhan, Y., Tan, K.H., Li, Y. and Tse, Y.K., 2016. Unlocking the power of big data in new product development. *Annals of Operations Research*, pp.1-19.

Zirger, B. J. and J. L. Hartley. 1996. The effect of acceleration techniques on product development time. *IEEE Transactions on Engineering Management* 43 (2): 143-52.