New Product Success through Big Data Analytics: An Empirical Evidence From Iran

Purpose

Innovative firms leverage big data analytics benefits in optimising value creation, particularly in business-to-business (B2B) contexts. Examples of this are found in new product success and product innovation performance. However, knowledge of how innovative firms and their corporate customers generate insights from big data, develop new products, and gain higher quality service from intra- and inter organisations' resources is limited. This knowledge manifests in the form of opportunities available in big data analytics (BDA) and through the adoption of the co-creation approach to generate value in the form of new product innovation. BDA reflects an excellent means of enhancing a firm's customer agility, but how this is possible remains largely unknown.

Design

In this research, we hypothesise that new product success is a function of a firm's customer agility and product innovation performance moderated by environmental turbulences. In turn, the firm's customer agility is enhanced by the effect of big data aggregation and analytical tools. These hypotheses have been confirmed by a survey in an emerging market.

Findings

We use structural equation modelling to test our hypotheses. The main contribution of this research is the conceptualisation and test of an integrative framework identifying the links among a firm's customer agility, new product success, and big data analytics capabilities.

Practical implications

The study established that BDA tools—the effective use of data aggregation tools and the effective use of data analysis tools—shape customer agility in achieving new product success. This study contributes to our understanding of the relevance of BDA in B2B value creation contexts.

Originality

Our findings show that big data analytics shapes a firm's customer agility in achieving new product success.

Keywords: firm's customer agility, product innovation, new product success, big data analytics (BDA), dynamic capabilities

1.0 Introduction

Big data is generated from multiple sources, from scientific, industry, smart sensors, and social media. Big data offers characteristics known as 5Vs. This includes properties such a 1) Volume (large quantity of data), 2) Velocity (the speed at which the data is generated and processed), 3) Variety (different types of data in the form of a structured database or spreadsheet data, unstructured (text, voice, video and web objects, and semi-structured (files and documents), 4) Veracity (the quality of data), and 5) value (the richness of information and the knowledge acquired through processing and analysis of large datasets). Big data analytics (DBA) tools offer organisations a cost-effective multiplatform environment for data analysis, data visualisations, and user-friendly dashboards.

In this context, big data analytics have become an increasingly important component for firms to enhance business value and firm performance (Ren et al., 2017; Demchenko, De Laat & Membrey, 2014). Using real-time, multivendor, cross-domain data, BDA provides actionable insights about customer experience and behaviour that can automate actions and drive decisions across marketing, customer relationship performance, operations, and planning. BDA offers firms opportunities to predict, prioritise, and manage customers' demands in a real-time fashion, resulting in superior service, experience, customers' satisfaction, royalty, engagement, brand awareness and sales (Farrokhi et al., 2020; Erevelles et al., 2016). It also offers opportunities for new product development (Jagtap & Duong, 2019; Tan & Zhan, 2017; Zhan et al., 2016) and new product success and performance (Hajli et al., 2020; Johnson et al., 2017; Jain, 2016; Xu et al., 2015; Chen et al., 2005).

In B2B contexts, the organisational use of BDA illustrates the process of deploying a combination of skills, technologies, applications, and processes in the examination of big data to uncover useful information such as hidden patterns and unknown relationships. This process could result in achieving success in new product development (Kiron, 2017). It could also help make better decisions across business processes among intra functions or inter organisations (Chen, Preston, & Swink, 2015; Wiersema, 2013). One possible means of achieving this is through leveraging BDA capabilities.

Acquiring and deploying required BDA capabilities, technological developments, and their use, such as BDA in B2B contexts, could be pivotal to the timely development of business solutions of value to an innovative firm and its customers. This value could be in the form of new product success. There is consensus among practitioners and academics that BDA could help a firm manage customers' mounting pressure on productivity amidst limited and resource-rationing innovating strategies (Cuevas, 2018; Marcos-Cuevas, Nätti, Palo, & Baumann, 2016; Wiersema, 2013).

The use of BDA across areas of B2B, including product innovation, can enhance inter-organisational learning among firms in business relationships. For instance, innovative firms are increasingly interested in creating more market opportunities for lead time reduction and better product improvement, thereby increasing sales and patronage (Wiersema, 2013). BDA is relevant in a diverse range of B2B contexts and product innovation related studies, including a product portfolio, new product development, customer loyalty, acquisition, and retention (Wedel & Kannan, 2016); supply chain management (Chen et al., 2015), and the healthcare business (Wang & Hajli, 2017; Wang, Kung, Wang, & Cegielski, 2018). However, studies show that the role of BDA, particularly in product innovativeness success, such as new product success and product innovation performance, are still at the infancy stage or, at best, growing (Hajli et al., 2020; Troisi, et al., 2018).

Likewise, Mikalef et al. (2019) argue that knowledge is scarce about how firms transform potentials in big data to business value. Similarly, research inquiries into B2B contexts of big data such as processes, activities, and decisions remain underexplored (Braganza, Brooks, Nepelski, Ali, & Moro, 2017; Lilien, 2016; Wiersema, 2013). Although in their recent qualitative study conducted in three developed countries, Hajli et al. (2020) confirmed the link and role of big data analytics, big data aggregation tools, customer agility, organisational slack, and environmental turbulence in new product success. However, no empirical study is yet to explore these factors' moderating roles (customer agility and big data aggregation tools) in achieving new product success. This present study empirically investigates the significance and moderating roles of BDA capabilities, customer agility, and environmental turbulence in achieving new product success and product innovation performance in B2B contexts with evidence from an emerging market.

The study's motivation arises from the need to understand in what specific ways do BDA capabilities (i.e., big data aggregation tools) shape a firm's customer agility, culminating in product innovation (new product success). The research was conducted primarily in IT-related services and consulting firms. They include banking and insurance, ICT, healthcare, oil and gas training and consulting, transportation, and production and mining firms.

These BDA capabilities facilitate faster and more effective use of innovation and market opportunities in big data, leading to value creation that meets customers' needs. These research findings offer rare insights into how BDA capabilities shape customer agility in achieving new product success.

This study's structure is presented as follows; section two discusses the relevant literature review in both IT/IS and marketing literature. Section three discusses the theoretical framework adopted in the study. Section four examines BDA and dynamic capabilities including customer agility, new product success, and research hypotheses. This also covers the role of the moderating environment in new product success. Section five explains the methodology adopted in the study. Section six provides research findings and analyses. Finally, section seven presents a discussion of research limitations and the conclusion of the study.

2.0 Literature Review and Theoretical Development

There are interrelated concepts in product innovation through big data analytics. This section examines key themes of interest and how they are interlinked, specifically, how BDA shapes a firm's customer agility toward achieving new product success. The relevant themes examined in the literature are customer agility, environmental turbulence, new product success, big data, and big data analytics (BDA) capabilities.

2.1. Custome Agility

Customer agility captures the extent to which a firm can sense and respond quickly to customer-based opportunities for innovation and competitive action. Drawing from the dynamic capability and IT business value research streams, we propose that IT plays a vital role in facilitating a knowledge-creating synergy derived from the interaction between a firm's IT resources and its analytical ability. In this context, customer agility is the most commonly used operationalisation of agility (Sambamurthy, Bharadwaj, & Grover, 2003; Roberts & Grover, 2012a; Chatfield & Reddick, 2018; Zhou et al., 2018). Ericsson Telecom Company highlighted that customer agility involves leveraging big data to understand and predict customer needs, solve problems, and put customers in control. Organisations face an unprecedented explosion of big data. Big customer data generated by online users have important strategic value for product development through business analytics technologies (McAfee & Brynjolfsson, 2012; Turner, Schroeck & Shockley, 2013; Mayer-Schönberger & Cukier, 2014). In this context, the increasing digitisation of governments and businesses, the ubiquitous use of social media channels in society, and enterprise-level data-driven initiatives have contributed to this unprecedented explosion of big data and the rapidly changing analytical landscape (Davenport, 2006; Chatfeild & Reddick, 2018). Using real-time, multivendor, cross-domain data, big data analytics provides actionable insights about customer experience and behaviour that can automate actions and drive decisions across marketing, customer care, operations, and planning. In addition, one of the most important reasons business organisations utilises business intelligence and analytics to analyse big customer-related data is that absorbing customers' demand-side knowledge (customer agility) is useful for product development (Zhou et al., 2018).

2.2 Customer Agility and Environmental Turbulence

The business environment is often in a state of flux (Hajli et al., 2020). The link between customer agility and environmental turbulence readily manifests through the sensing and prompt responding to customer agility features, particularly in service-driven dynamic environments (Chatfield & Reddick, 2018). Sensing and timely responding to market opportunities are two central complementary capabilities of customer agility (Roberts & Grover, 2012a, 2012b). Contemporary firms operate in an environment characterised by a deluge of data and information, including changing customer tastes and preferences. This makes firms' ability to make sense of happenings around them of immense importance, and a firm may benefit from it by quickly responding to the emerging opportunities sensed in the environment. Customer agility in B2B manifests in various forms; these include quick and timely actions taken on insights gained from different customer engagement, buyer-seller processes, relationship marketing, and customer experiences (Zolkiewski et al., 2017; McColl-Kennedy et al., 2019).

2.3 New Product Success

In B2B contexts, New Product Success (NPS) has been linked to both proactive and responsive market insights (Narver, Slater, & MacLachlan, 2004; Slater & Narver, 2000a). A responsive market insight relates to a business' effort in understanding, and satisfying customers' expressed needs. These expressed needs (and expressed solutions) are understood to be the needs and solutions of which the customer is cognizant and can express. In B2B contexts, new products successes are outcomes of complex and iterative value processes between the innovative firm and the customer (Aarikka-Stenroos & Jaakkola, 2012; Dixon &

Tanner Jr, 2012). These products manifest in the form of customised product offerings or business solutions that in turn, contribute to the customer's value creation process.

In B2B, NPS could be associated with the time between generating an idea and introducing the product encapsulating that idea. It could connote marketing and sales teams working together with key customers' marketers and operations staff of the customer firm to co-design concepts and co-ideate new solutions. Innovation in these contexts does not just emerge solely from product innovation but through value co-creation and the adoption of a collaborative approach with the customer, drawn from relevant available data (Marcos-Cuevas et al., 2016).

2.4 Big Data

Big data represents a knowledge-generating pool, a valuable source of market insight that can facilitate a firm's ability to sense and respond to market opportunities. It provides a platform for real-time data analysis that allows responses to unexpected market threats (Farrokhi et al., 2020; Wedel & Kannan, 2016). It is a useful tool for analysing social media to comprehend current trends in a targeted market. Sound analysis of data and information could be a means of harnessing the economic benefits of big data. The proliferation of big data in the market place offers distinctive opportunities for firms to enhance their customer agility (Gupta & George, 2016). It is a resource landmine at a firm's disposal to generate the continuous flux of valuable knowledge available from both internal and external knowledge embedded in data and information (Wang & Hajli, 2017; Wang et al., 2018).

Big data offers innovative firms a unique opportunity in gaining insight into their customers' purchasing behaviour. It also offers them a rare avenue to constantly improve their skill sets in learning more effectively and efficiently the specifics of competitive solutions to meet their target customers' needs (Shirazi & Mohammadi, 2019). Through proper harvesting of potentials in big data, these firms are well placed to reap benefits in new product development and customer loyalty. It could also be in the form of product and service improvements made possible through harnessing the potentials embedded in big data (Mikalef, 2019). Harnessing the potentials of proactive market insight and other benefits inherent in big data give credence to the importance of big data analytics (Hajli, et al., 2020; Troisi et al., 2018).

2.5 Big Data Analytics (BDA)

BDA denotes the organisational ability to harness potential benefits in big data towards accessing novel insights for updating and improving quality decisions. Organisations achieve this feat by deploying BDA tools. These usually have enhanced improvement and immense organisational benefits (Baga, et al, 2020; Gunasekaran et al., 2017).

Technology choice and how a solution is built and how effective analytical tools are deployed influence how quickly an organisation can respond to the requirements and demands. Big data analytics has changed the paradigm of traditional local and service-based settings to data-centric architecture (Demchenko, De Laat & Membrey, 2014). The effective use of big data aggregation tools such as the open-source Apache Spark platform, with built-in architecture such as Extract, Transform, Load (ETL), and the effective use of big data analytics tools (e.g., Tableau) are potent tools required in today's value generation for new product/service success. For example, the current version of Tableau is integrated with R and Python script programming. Allowing business analysts the capability to not only leverage data visualization but also advanced business analytics features powered by R and Python.

Furthermore, The big data aggregation tools can take big data (BD)-competitive intelligence (CI) application. This constitutes an important platform for processing data into insightful forms, thereby creating novel growth opportunities for the organisation. It enhances prompt firm's responses to changes in the business environment as occasioned by competitor's activities. The BD-CI application also helps spot potential vulnerabilities and subsequent strategic plan improvements to curb the weaknesses (Ranjan and Foropon 2021). Big data analytics (e.g. Waymo) can take predictive analytics that attempts to highlight patterns and identify interconnectivity in data (Gandomi and Haider 2015).

Studies have highlighted different roles and applications of BDA in enabling organisational capabilities and performance in different contexts. Specifically, the significant role of BDA in the new product success contexts of small companies (Hajli et al, 2020). Big data has been implicated in business transformation as it acts as a cross-functional capability empowering business executives to achieve strategic fit between set strategies and decision making according to the market demands (Johnson, Friend, and Lee, 2017). Similarly, big data enhances the organisational ability to promptly adapt to a challenging business environment, thereby disrupting existing process in new product development (Wessel, 2016).

BDA in B2B contexts aims to create value for both parties in business relationships, including deciding how both firms engage and share value creation ideas such as new product success (Ward et al., 2014). BDA is a rich source of proactive market knowledge that could shape how firms make sense of and respond quickly to market opportunities (Wang & Hajli, 2017; Wedel & Kannan, 2016). It presents innovative firms with a novel means of addressing the increasing need to understand better customer needs and priorities (Wedel & Kannan, 2016; Wiersema, 2013). The increasing relevance of BDA in B2B marketing and the production of innovative products and services from various studies is presented in Table 1 below.

Insert Table 1

A conceptual framework (Figure 1) was developed to provide a better picture of this research. The theoretical base of this research is discussed in the following section of this paper.

Insert Figure 1: The conceptual model

3.0 Theoretical Foundation for Shaping Customer Agility in Achieving a New Product Success Through Big Data Analytics

Achieving new product success could be anchored to associated keys' organisational capabilities such as customer agility, market sensing capability, intra and inter-organisational processes performed by different actors, and big data analytics capabilities (Bharadwaj & Dong, 2014; Braganza et al., 2017; Chen et al., 2015). These themes (i.e., customer agility, market sensing capability, intra and inter-organisation processes, and BDA capabilities) are germane in value creation for innovative firms and their customers. This insight underscores the applicability of the BDA-BV (big data analytics-business value) model in this present study (Wang & Hajli, 2017). The model consists of two components: resource-based theory (RBT) and capability building view (Bharadwaj & Dong, 2014; Wang & Hajli, 2017). The underlying assumption of RBT is that a firm can generate revenue as long as it can harness a bundle of valuable, rare, inimitable, and non-substitutable (VRIN) resources in a highly competitive market (Barney, 1991). Various studies in IT and marketing have drawn on the RBT, eliciting different types of IT and marketing resources (e.g., tangible and intangible, including technical resources) that can add value to an inter-organisation value-creating processes (Bharadwaj, 2000; Braganza et al., 2017). Despite the wide acceptance of RBT in IT and marketing research, the theory has been criticised for its lack of explanatory power on how IT resources are constituted, how distinct IT systems can create specific and unique IT capabilities, and how they orchestrate competitive advantages (Melville, Kraemer, & Gurbaxani, 2004; Mukhopadhyay, Kekre, & Kalathur, 1995). However, RBT in IT and marketing research addresses resource ownership, resource attributes, and more importantly, it enables discourse on big data's contribution to strategic advantage (Braganza et al., 2017). Consistent is the view of capabilities as "teams of resources" and organisational routines (Braganza et al., 2017; Grant, 1999).

Dynamic capabilities describe ways in which organisations configure and continually reconfigure processes to achieve desired outcomes. It has been used to complement the limitations of RBT (Bharadwaj, 2000; Karimi, Somers, & Bhattacherjee, 2007). Capability building connotes "the ability of firms to build unique competencies that can leverage their resources" (Karimi et al., 2007). Thus, the capability building view articulates that firms have to develop capabilities by selecting and using resources and coupling them into synchronised combinations, thereby transforming resources into valuable products (Karimi et al., 2007; Wang & Hajli, 2017). Such capabilities are not easily bought; they must be built (Teece, Pisano, & Shuen, 1997). The capability building view has been extended to IS and marketing fields (Bharadwaj, 2000; Bharadwaj & Dong, 2014; Day, 1994). In IS, a firm's IT capability refers to its "ability to mobilise and deploy IT-based resources in combination or co-present with other resources and capabilities" (Bharadwaj, 2000). In innovative and marketing-driven firms, capabilities refer to "complex bundles of skills and collective learning, exercised through organisational processes that ensure superior coordination of functional activities" (Day, 1994). Examples of IS and marketing capabilities are market sensing capability, customer agility capability, and big data analytics capability.

However, there is a dearth of knowledge on how insights from these capabilities enhance a new product's success. Thus, building on the dynamic capability and RBT theoretical foundation, we articulate that BDA capability plays a fundamental role in shaping customer agility and achieving new product success. The theoretical foundation and research hypotheses are empirically tested through quantitative research methodology. Details of this quantitative research are discussed in the hypotheses development and methodology sections.

3.1 Hypothesis Development

Value creation is central to big data analytics, particularly for both parties in the B2B context. This could result in new product success and product innovation performance. This typifies a key difference between big data and big data analytics. Agile firms, therefore, need not only to collect heterogeneous data from multiple sources but use them promptly toward value creation, considering that big data analytics could be instrumental in shaping the direction and timely deployment of other firm's resources in the creation of customer's value (Kiron, 2017; Mikalef, 2019). The key focus here is the firm's ability (or inability) to effectively use the big data by acquiring and aggregating relevant data-generated insight in the creation of the firm and customers' value on time. A firm's ability to sense and respond in a timely manner to spotted market opportunities could be premised on insights gathered from aggregated data. The ability to sense and respond is based on information the firm has gathered and interpreted for relevant market opportunities. According to Côrte-Reala et al., (2019), skill sets required to detect value in a business context are difficult to acquire. This might not be unconnected to such skills' technicality, including problem-solving and people skills required in understanding the customer's problem and proffering needed solutions (Hajli, et al., 2020; Davenport & Dyché, 2013). Thus, an integral part of big data analytics would be a firm's ability to acquire, aggregate, store, and use relevant data for value creation (Ward et al., 2014; Kiron, 2017). Therefore, based on this logic, customer agility is premised on the effective use of data aggregation tools. This informs the first hypothesis:

H1: Effective use of data aggregation tools has a direct effect on customer agility.

Effective use of data aggregation tools refers to collecting heterogeneous but relevant data from multiple sources and transforming different data sources into certain data formats (Ward et al., 2014). Data aggregation is comprised of data acquisition, transformation, and storage (Raghupathi & Raghupathi, 2014; Ward et al., 2014). Data acquisition is focusing on the effective collection and extraction of data from all relevant units of the firm and external sources (Phillips-Wren et al., 2015). Data transformation deals with transformation tools with the ability to transfer, clean, split, decipher, sort, synthesise, and validate data. The transformation tools are also implicated in data consistency, visibility, and easy accessibility for analysis, while data storage is associated with adherence to relevant regulations, data procedures and policies, and access controls. Data storage tools can be executed and done in real-time or in phased processes. Building on previous studies on data aggregation (Ward et al., 2014; Raghupathi & Raghupathi, 2014), an important component that needs close consideration is the sharing and appropriation of aggregated data with relevant business units towards value creation. According to Ottum and Moore (1997), the understanding customer wants, and needs is linked to a firm's capabilities for gathering and appropriating the gathered market information. They posit that a new product's success or failure is linked to the integration of marketing, R&D, manufacturing units, and the firm's effectiveness in market information gathering, sharing, and use among the relevant units.

Further, drawing on Narver et al.'s (2004) work, proactive use of gathered market information would play a significant role in a firm's new product success. Thus, this research conceives effective use of data aggregation tools as the acquisition, transformation, and storage of data and its sharing and proactive deployment to relevant business units for new product success. Based on this logic, the second hypothesis emerges:

H2: Effective use of data aggregation tools is directly linked to new product success.

Agile firms create value through the ability to make sense of and respond swiftly to market opportunities (Chen et al., 2015; Gupta & George, 2016; Wang & Hajli, 2017). However, the ability to make sense of and respond swiftly to market opportunities is premised first on identifying possible latent and expressed customers' problems and plausible solutions. This ability to generate relevant insights would be germane to effective orchestration and deployment of data, technology, and other resources promptly. It constitutes an important milestone in which big data could be huge help rather than hurting firms (Kiron, 2017). As big data in itself does not translate to customers' value, effective use of data analysis tools, aggregation of the relevant customer and product data, data processing, and data visualisation would greatly benefit the firm (Wang & Hajli, 2017). The effective use of big data is activated such that data-generated insights help make sense of latent market intelligence inherent in big data. This could help in the transformation of firms and resulting in creating required business solutions. Thus, the effective use of big data analysis tools in generating competitive insights constitutes the starting point of customer agility. Increasingly, firms are expected to discover, interpret, and generate latent market intelligence (Narver et al., 2004; Slater & Narver, 2000a). They are considered germane to firm survival and success as they are linked to a firm's ability to make sense of and respond quickly to market opportunities (Roberts & Grover, 2012a). Implicitly, the ability to discover, interpret, and generate latent market intelligence and market opportunities relates to customer agility; a firm can only make sense of latent market intelligence inherent in big data through big data analytics. This reflects a key characteristic of a customer-agile firm’s ability to deploy business value inherent in big data through the effective use of big data analysis tools (Roberts & Grover, 2012a, 2012b). Based on this argument, the third hypothesis emerges:

H3: Effective use of data analysis tools has a direct effect on customer agility.

Achieving a firm’s competitive advantage will, among other things, be dependent on how the firm discovers, interprets, and generates a latent market-intelligence sense and quickly responds to changes in and understanding of customers’ needs and preferences (Narver et al., 2004; Roberts & Grover, 2012a, 2012b). It is not enough for innovative firms to only listen to their customers’ perceived needs; these firms should be able to analyse and make sense of both latent and expressed customers’ needs from big data. A firm’s ability to address this could sustain its leadership position in the industry as firms that only address customers’ expressed needs are more likely to lose their market leadership position (Narver et al., 2004; Christensen & Bower, 1996). Based on this logic, big data analytics inherently consist of big data analysis tools such as aggregation of the relevant customer and product data, data processing, and data visualisation (Wang & Hajli, 2017). Based on this logic, the fourth hypothesis emerges:

H4: The effective use of data analysis tools has a direct effect on new product success.

As agility is gaining importance as a dynamic capability in modern-day business environments (Roberts & Grover, 2012a), much more so is the need for firms to develop the effective use of big data analysis tools to discover new insights for value creation (Mikalef, 2019). A firm's customer agility relates to the sensing and responding (seizing opportunity) components of a firm's dynamic capabilities (Roberts & Grover, 2012a). Sensing new market opportunities involves scanning, learning, and interpreting activities (Rapp, Trainor, & Agnihotri, 2010; Teece, 2007). This implies that sensing activities could entail investment in research activities, fact-finding about customer needs, understanding the latent need, and evaluating probable supplier and competitor responses (Slater & Narver, 2000a, 2000b). Once an opportunity for new product development or competitive action is discovered, it must be addressed by mobilising a firm's existing processes or services (Jayachandran, Hewett, & Kaufman, 2004; Teece, 2007). In this sense, a firm can be agile by promoting higher-order activities that allow modifications to the firm's existing core capabilities, such as swift modification of its existing manufacturing capabilities to serve a new customer segment. Hence, through customer agility, a firm maintains competitiveness by enhancing, combining, and reconfiguring its intangible and tangible assets (Teece, 2007). This implies that through innovative or competitive activities, a firm can turn a new market opportunity into new product success. This leads to the next hypothesis:

H5: Customer agility has a direct effect on new product success.

According to Alegre et al. (2006), product innovation performance (PIP) is a construct comprising two distinct dimensions, namely: innovation efficacy and innovation efficiency. Innovation efficacy explains the level of success of an innovation. The innovation efficacy dimension is also referred to as innovation market performance (Valle & Avella, 2003; Atuanaheme-Gima, 1995). While innovation efficiency refers to the effort deployed in achieving that level of success, the level of success of an innovation is higher when innovative firms collaborate with customers. Except in few studies (e.g., Nieto & Santamaría 2007; Monjon & Waelbroeck 2003), collaborating with customers has been found to impact positively on product innovation performance (Faems et al. 2005; Miotti & Sachwald 2003; Li & Calantone, 1998; Souder et al., 1997; Tsai, 2009; Brockhoff, 2003). They are innovating in the B2B context results in a series of advantages such as spotting market opportunities for technology development and lessening the likelihood of poor design in the early development stage of a new product.

Further, firms could gain new insights about solutions through understanding the needs of valued customers (von Hippel et al., 1999; Tsai 2009). It could also lead to early identification of market trends, thus increasing the likelihood of new product development and success (Tsai 2009). Furthermore, collaborating could lead to the generation of comprehensive knowledge that may be critical to the new product's successful development. Both dimensions of product innovation performance have been implicated as strongly and positively linked to new-product success. Also, a significant relationship exists between both dimensions. This implies that innovating firms should simultaneously improve both dimensions to record product innovation performance success (Alegre et al., 2006). Based on this argument, the sixth hypothesis emerges:

H6: Product innovation performance (PIP) is directly linked to new product success.

However, the competitive environment influences how firms build, leverage, and reconfigure capabilities that allow them to develop competitive products, equalling new product success. Through sensing and responding to market opportunities in the competitive environment, firms both react to and proactively influence the competitive environment (Choo, 1996; Narver et al., 2004). The ability of firms to perform this capability lies in the moderating role of the environment in big data analytics. This is examined in the next section.

3.2 The Moderating Role of Environmental Turbulence in NPD

Building on the moderation (i.e., interaction) perspective (Venkatraman, 1989) which views moderators as types of environments (e.g., environmental turbulence in NPD), and depth of competitive intensity or degree of business relatedness (i.e., skills set for analytical professional a firm possesses (Roberts & Grover, 2012a) is, according to moderating variable influences, the direction or the strength of the relationship between a predictor variable (e.g., customer agility) and a dependent variable (e.g., new product success). This moderating perspective provides further insight into the relationship between a firm's customer agility and new product success in its dynamic capabilities of building, integrating, and reconfiguring existing functional competencies to manage turbulent environments. This could reflect the firm’s ability to sense new market opportunities and involve scanning, learning, and interpreting activities possible through big data analytics (BDA) capabilities (Gupta & George, 2016). As such, we argue that BDA offers firms the opportunities to react faster and efficiently to environmental turbulence due to unexpected and unpredictable market changes.

Similarly, the organisation uses information generated in three main areas: (1) to make sense of change in its business environment, (2) to develop novel knowledge for innovation, and (3) and to take action for the way forward. Through sense-making, employees give meaning to their environments, developing insight and knowledge to design new products. Organisations only act promptly based on their available resources and timely response to market opportunity (Choo, 1996; Roberts & Grover, 2012a). Building on this insight, big data analytics (BDA) capabilities shape a firm's customer agility to achieve new product success.

4.0 Methodology

In this section, we provide information about our research method. This includes data collection and sample, measurement items, deployed data analysis, reliability and validity, and the structural model.

4.1 Data Collection and Sample

An empirical survey has been built through Iranian industries to examine the research model and devise hypotheses. Considering that big data analytics is an emerging subject in firms, there were subject intuition limitations. Based on this insight, firms that were placed in the best rank in each industry were selected for this research. Firms in this category endeavour to find more efficient ways to exploit their growing data to get smart and get ahead of the competitors. Through the IMI-100 list (2018) of the Industrial Management Institute, where the top 500 Iranian companies, the target community, have been identified. These firms have sophisticated IT infrastructure and have large databases due to information systems implementation and software developments. Their industry type and the number of employees prove their need for data-oriented decision-making. Based on this capacity, the majority of them is moving on the trail of the business intelligence and data analytics roadmap, which means they had projects in data warehousing, data mining, dashboards, and visualisation fields. For instance, the Iranians selected banking and insurance companies, which, situated in enterprise levels, have a sustainable and automated process for data analytics-based product and service developments, and the current research has aimed to examine if the effective use of these data aggregation data analysis tools are important capabilities shaping the firm's customer agility and have a role in achieving new product success (NPS) or not.

From each of these samples, we tried all our best efforts to survey a wide range of decision-makers in order to reflect the firm's strategy and organisational performance related to big data analytics for product/service innovation. This makes sure that respondents do not overstate the competencies in response to survey questions, known as common method variance (CMV). We will discuss the CMV in detail in the next section.

We collect data by a survey sent out via mail and e-mail from October 2018 to April 2019. The survey questionnaire along with a cover letter was sent to the respondent of each firm. The letter served as a guide to filling out the questionnaire and highlighting the research rationale. About 310 surveys were sent to the firms' top managers, including CIOs. Table 4 in the Appendix A shows the distribution of positions held by our respondents. The returned questionnaires were 122, which showed a response rate of 39.5%. Two of the returned questionnaires were discarded due to incompleteness, so the number of valid questionnaires reduced to 120; that is, the response rate reached 38.7%. A detailed summary of the sample characteristics is shown in Table 2. The responders belong to banking and insurance, ICT, healthcare, oil and gas training, consulting, transportation, production and mining, and other service sectors.

Insert Table 2

Appendix A also shows six tables associated with the demographic data of this study.

4.2 Measurement Items

The items of measurement for this model are from the following sources, and two of them are new items developed by the authors. Data aggregation tools and effective use of data analysis tools are new items. Customer Agility has been adopted from research by Narver et al. (2004) and Slater and Narver (2000a). New product success has been adopted from Chen et al. (2005). Finally, product innovation performance is from De Luca and Atuahene-Gima (2007).

5.0 Data Analysis

In this research, we use structural equation modelling (SEM) for data analysis. SEM allows us to perform path analytic modelling for unobserved latent variables constructed through measured variables (Chin, 1998). It estimates the multiple and interrelated dependence in a single unified analysis indicating how constructs are related to each other (Kahn, 2006). Weston (2006) argues that one of SEM's main advantages is its capacity to estimate and test the relationships among constructs with multiple measurements or indicators while addressing the issues of measure-specific error. We used two popular statistical packages for this study, namely the STATA version 15.0 for SEM and SPSS version 25 for other measures described below.

Prior to estimating the research model, we went through multiple initial tests to ensure that the measured variables are reliable and the internal consistencies are assured. Also, we were interested to see if there are multicollinearity issues among latent variables.

5.1 Reliability and Validity

We started with Cronbach's alpha for internal consistency measures among our 33 observed items. We found two variables within NPS and product innovation performance (PIP) representing low factor loading of 0.361 and 0.495, respectively. The aim was to select measures with high internal consistency of 0.7 and above. The source of these issues were related to NPS's question, “Overall, our new products meet the senior management’s expectation,” and the PIP's question, “Profitability related to stated objectives.”

Table 1 in Appendix B provides descriptions of indicators and information about the construct reliability and validity results as described below. As shown in the above Table, all constructs' values exceeded the 0.70 criterion suggested by (Nunnally & Bernstein, 1994). The results show acceptable composite reliability (CR). To validate all constructs of this study, we deployed both congruent validity and discriminant validity.

Congruent validity was assessed by average variance extracted (AVE) and indicator loadings. As indicated, all AVE values are greater than the recommended level of 0.5 (Hair et al., 2006). All factor loadings are also highly significant, as indicated by their respective p-values, and the loading scores are all above the desired threshold of 0.70. In addition, we deployed three sets of tests for discriminant validity (DV). We accessed DV by estimating the Fornell-Lacker Criterion. According to Fornell and Larcker's (1981), AVEs should be greater than the squared correlation estimates involving the construct. As shown in Table 2 (Appendix B), all AVE values (bold numbers) met this criterion showing an acceptable discriminant validity.

The third criterion used for discriminant validity was by looking at the cross-loading values across all constructs. The factor loadings should be higher than all other constructs loading under the condition that the threshold value of 0.70 is met (Hair et al., 2006). Table 3 in Appendix B shows the cross-loading values across all constructs.

Finally, Table 3 below shows the constructs Cronbach's values. Cronbach's alpha defines whether indicators associated with a construct measure that specific construct. According to Koo and Li (2016), alpha values between 0.5 and 0.75 indicate moderate reliability, values between 0.75 and 0.9 indicate good reliability and values greater than 0.90 indicate excellent reliability. However, the rule of thumb suggests that a reliability coefficient of 0.7 or higher is considered "acceptable" in most social science research situations (UCLA STATA, 2020).

Insert Table 3

We also evaluated multicollinearity among the constructs. Multicollinearity is a problem linked to independent variables that are highly correlated with each other and may cause a wide swing in the estimate of parameters due to small changes in data. To test the multicollinearity issue (Gujarati, 2003), the Variance Inflation Factor (VIF) was estimated. It shows how multicollinearity has increased the instability of the coefficient estimates (Freund & Littell, 2000).

It is generally held that multicollinearity is present if there are tolerance values of < 0.2 or VIF values of > 5. As shown in Table 5.0, in this study there are no instances of either of these criteria for any of the constructs indicating that there are no multicollinearity issues among variables of this study.

Insert Table 4

Another issue addressed by this study is concerns related to Common Method Variance (CMV). Tehseen, Ramayah and Sajilan (2017) argue that related to the constructs developed by structural equation modeling, CMV may significantly influence the research findings if it is not appropriately controlled through procedural and statistical remedies. However, researchers usually do not use all procedural remedies to remove potential impacts of CMV (Tehseen, Ramayah & Sajilan, 2017). Therefore, it is strongly suggested that statistical procedures are followed to address CMV issues before a survey is distributed and/or to control and remove these effects from data analysis.

For instance, if the impacts of entrepreneurs' competencies on SMEs' growth are estimated using only entrepreneurs' perceptions of their competencies and their business growth performance, the estimated effects may be biased. For example, if some respondents overstate both competencies and growth performance due to the tendency to assess themselves positively or because of social desirability. In this case, a positive correlation is produced between variables when the same respondent is used as a source for obtaining both the independent and dependent measures. Therefore, the estimated impacts may suffer from common method bias (Tehseen, Ramayah & Sajilan, 2017). This study has considered the issues of CVM as we did not rely on a single view when answering our survey questions. We ensured that if a respondent is from the IT department or an executive branch, another manager, say from sales and marketing, gets an opportunity to answer the same questions. This is done to avoid the bias issues as discussed above.

5.2 Structural Model

The measurement model depicted in Figure 2.0 is set up to evaluate how well the observed (measured) variables combine to identify underlying hypothesised constructs. Confirmatory factor analysis is used in testing the measurement model, and the hypothesised factors are referred to as latent variables (Weston, 2006). Equations in our structural model specify the hypothesised relationships among latent variables. We include one hypothesised structural model in the composite model in Figure 2. In this model, we hypothesise that an NPS is a function of customer agility (CAG) and PIP, moderated by environmental turbulences (ENV). In turn, CAG is informed by the effect of big data aggregation and analytical tools. It is important to note that the role of moderating variables is widely discussed in the fields of psychology (Dakanalis et al., 2015; Tylka, 2004; Smyth, 1998), social behaviour (Dearing & Hamilton, 2006), and business research (Volle, 2001). We postulate that the environmental turbulences in NDP moderate the effects of the exogenous variable's dimensions (customer agility) on the endogenous variable (new product success). Also, the role of moderating factors and their effects on the success of new products has also not been examined.

Insert Figure 2

5.3 Structural Model

Similar to linear regression, we can describe relationships among latent variables as correlations or covariances of direct effects or indirect effects (Weston, 2006). The path coefficients are indications of the strength of relationships among latent variables. The z-values in parentheses show the significance of constructs at $p<0.05$ and $p<0.01$ levels. The results show that the effective use of big data aggregation and big data analytical tools have positive impacts on companies' customer agility, and this impact is statistically significant. Furthermore, the adjusted R-square shows that variations of big data tools explain 51% of the variation of customer agility. The same is true with variable NPS. The latent variables CAG and PIP moderated by ENV positive impacts on the success of a new product, and these impacts are statistically significant at 0.05 and 0.01 levels. Furthermore, the adjusted R-square shows a value of 0.732. Table 5 shows statistics about the fit model. Nevitt and Hancock (2000) argued that using structural equation modelling techniques have shown keen interest in evaluating the fit of a hypothesised model to sample data; however, the chi-square goodness-of-fit statistic has been criticised as not being the best approximation of real-world relations among a set of constructs especially with large models containing many indicators.

Insert Table 5

To address the sensitivity issues of the chi-square, the root mean square error of approximation (RMSEA) by Steiger and Lind (1980) has been proposed. The authors stress the fact that the RMSEA is tied closely to the noncentral chi-square distribution for evaluating structured models (Nevitt & Hancock, 2000). Any values lower than 0.08 (Browne & Chdeck, 1993) are an indication of a good fit. As shown in Table 5 above, our model's RMSEA's value is estimated at 0.074. Also, the Comparative Fit Index (CFI) analyses the model fit by examining the discrepancy between the data and the hypothesised model, while adjusting for the issues of sample size inherent in the chi-squared test of model fit (Gatignon, 2010) and the normed fit index (Bentler, 1990). CFI values range from 0 to 1, with larger values indicating a better fit. Previously, a CFI value of .90 or larger was considered to indicate acceptable model fit (Hu & Bentler, 1999). However, recent studies have indicated that a value greater than .90 is needed to ensure that misspecified models are not deemed acceptable (Hu & Bentler, 1999). Thus, a CFI value of .95 or higher is presently accepted as an indicator of a good fit (Hu & Bentler, 1999).

6.0 Discussion

Big data analytics (BDA) relevance is seen in alerting relevant business units and top management on areas to scale up or down for relevant resources required to achieve new product success for customers. BDA represents a powerful tool in achieving value co-creation in the form of new product success in a B2B context. BDA offers firms the opportunities for a wide range of business solutions through the values generated by big data. There is evidence that BDA enables faster and robust comprehension of information, including prompt data processing that enables innovative firms to co-create value with their customers. This may be pivotal in the value co-creation processes, which largely remains a rather abstract concept without copious empirical development and a scanty study illustrating its enactment in practice. Specifically, in this study of the effective use of data analysis tools and the effective use of data aggregation tools are found to be important BDA powerful tools required for achieving value co-creation in the form of new product success in B2B contexts. They form the basis of efficient use of data in creating value for businesses and customers. They are linked to improvement in customers' experiences, remodelling of firms' operational processes, and developing and implementing novel big-data-driven and profitable business models. The implications of the findings in this work for research and practice can be seen in different ways. For research, the findings in this work help in (i) gaining insights on how capabilities such as BDA and Customer Agility (CAG) enhance new product success (NPS) (ii) it helps in establishing BDA as a 'connector' and facilitator of other organisation's dynamic capabilities, activities and its influence on them. For example, this research enlightens us on the multiple interconnectedness between BDA, CAG, and organisation activities; (iii) insights from our research are consistent with Day (1994), who construe innovative organisations as complex bundles of skills and capabilities. Likewise, Wedel & Kannan, (2016); Wiersema, (2013) highlighted the importance of BDA in B2B, particularly in the product innovative contexts.

There are several implications for managerial practice, as well. (i) this research not only highlights the link between BDA, CAG and organisation activities but also establish the importance of other organisation capabilities/activities in the process of achieving new product success; (ii) organisations could improve their B2B product innovation by leveraging on BDA as this could help their understanding of customers' needs and in turn help shapes the deployment of Customer Agility CAG); (iii) BDA issues owing to its interconnectedness to other dynamic capabilities and activities should be considered as a strategic innovative process. This need to be understood first by the management team and its significance in ensuring new product success. Such insight may further enhance the organisational agility in the prompt deployment of required resources to respond to market opportunity (Roberts & Grover, 2012a). Lastly, this could be relevant in the industries primarily examined in this research. These industries are banking and insurance, ICT, healthcare, oil and gas training, consulting, transportation, production and mining, and service sectors. Lastly, (iv) BDA is equally important in B2B product innovative and value-creating processes in emerging markets such as Iran.

6.1 Theoretical Contribution and Practical Contribution

This research offers clear insights into how firms can harness the benefits in big data through the deployment of effective use of data analysis tools and effective use of data aggregation tools in new product success and product innovation performance. The study contributes to studies in B2B contexts by examining the effects of BDA on customer agility and new product success as well as the mediating effects of environmental turbulence. Primarily, the main contribution of this study is the conceptualisation and test of an integrative framework identifying the links among customer agility, new product success, and BDA capabilities. More importantly, the study established that BDA tools—effective use of data aggregation tools and effective use of data analysis tools—shape customer agility in achieving new product success. This study contributes to our understanding of the relevance of BDA in B2B value creation contexts. Specifically, empirical evidence from this investigation highlights the significance and moderating role of environmental turbulence in achieving new product success.

6.2 Limitation and Future Research Direction

This research has limitations like other research. The first issue is in the area of data collection. We spent many months collecting data in Iran. This was a difficult process to get access which enables us to supply only those samples. Considering big data analytics is an emerging subject in the firms in Iran, there were subject institution limitations. As a result, we had to select the firms that were placed in the best rank in each industry. Future research may consider this model for another setting or developed countries to test the research model. The other limitation of the study is reflected in the co-creation of intra-organization value processes. No individual party, neither innovative firm nor customer, can solely lay claim to achieving success in new product success. Although with BDA capability, an innovative firm may be able to scale up or down the required resources in new product development. An organisational and structural misfit may impede the effort. Finally, this study was limited to the Confirmatory Factor Analysis (CFA the future study should also investigate Exploratory Factor Analysis [EFA] to determine the underlying constructs for a set of measured variables).

7.0 Conclusion

Big data with advanced characteristics such as volume, variety, velocity, veracity, and value have changed the paradigm of traditional in-house, service-based analytics to data-centric architecture by offering firms great opportunities and capabilities to better understand customers and market demands for new and innovative products and services. In this context, the notion of customer agility involves leveraging big data to understand and predict customer needs. Our empirical analysis found that the effective use of big data aggregation tools (e.g., Apache Spark) and the effective use of big data analytics tools (e.g., Tableau) are potent tools required today's value generation for new product/service success. Using structural equation modelling with data from an emerging market, we argue that new product success (NPS) is a function of customer agility and product innovation performance. We also highlight the significant effect and moderating roles of big data aggregation and analytical tools on customers' agility. The study found positive impacts BDA on mediating effects of environmental turbulence. A survey in an emerging market has confirmed these hypotheses. The current research develops the theoretical foundation of BDA capabilities for product innovation.

References

Aarikka-Stenroos, L., & Jaakkola, E. (2012). Value co-creation in knowledge intensive business services: A dyadic perspective on the joint problem solving process. *Industrial marketing management*, *41*(1), 15-26.

Afthanorhan, W. M. A. B. W., & Ahmad, S. (2013). Modelling the Multimediator on Motivation Among Youth in Higher Education Institution Towards Volunteerism Program. *Mathematical Theory and Modeling*, 3(7), 64-70.

Alegre, J., Lapiedra, R., & Chiva, R. (2006). A Measurement Scale for Product Innovation Performance. European Journal of Innovation Management, 9(4), 333–346.

Atuanaheme-Gima, K. (1995), "An Exploratory Study of the Impact of Market Orientation on New Product Performance: A Contingency Approach", Journal of Product Innovation Management, Vol. 12, pp. 275-93.

Baga, S. Wood, L. C. Xu, L, Dhamijaf, P and Kayikci, Y. (2020). Big Data Analytics as An Operational Excellence Approach to Enhance Sustainable Supply Chain Performance, Resources, Conservation & Recycling, 153, 1 – 10.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management*, *17*(1), 99-120.

Bentler, P. M. (1990). Comparative fit indexes in structural models. Psychological Bulletin, 107(2), 238-46

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS quarterly*, 169-196.

Bharadwaj, N., & Dong, Y. (2014). Toward Further Understanding the Market-sensing Capability–Value Creation Relationship. *Journal of Product Innovation Management*, *31*(4), 799-813.

Braganza, A., Brooks, L., Nepelski, D., Ali, M., & Moro, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research*, *70*, 328-337.

Brockhoff, K. (2003) Customers` Perspectives of Involvement in New Product Development, International Journal of Technology Management, 26, 5/6, 464.

Browne, M.W. & Cudeck, R. (1993). Alternative ways of assessing model fit. In Bollen, K.A. & Long, J.S. [Eds.] *Testing structural equation models*. Newbury Park, CA: Sage, 136–162.

Chatfield, A. T., & Reddick, C. G. (2018). Customer Agility and Responsiveness Through Big Data Analytics for Public Value Creation: A Case Study of Houston 311 On-Demand Services. *Government Information Quarterly*, 32(2), 336–347.

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *Journal of Management Information Systems*, *32*(4), 4-39.

Chen, J., Reilly, R. R., & Lynn, G. S. (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

Chin, W. W. (1998). The Partial Least Squares Approach to Structural Equation Modeling. In: G. A. Marcoulides (Ed.), Modern Methods for Business Research (pp. 295–358). Mahwah, NJ: Lawrence Erlbaum Associates

Choo, C. W. (1996). The Knowing Organisation: How organisations use information to Construct Meaning, Create Knowledge and Make Decisions. *International Journal of Information Management*, *16*(5), 329-340.

Christensen, C. M, Bower, J. L. (1996). Customer Power, Strategic Investment, and the Failure of Leading Firms. Strategic Management Journal 17(3): 197–218.

Côrte-Real, N., Ruivo, P., & Oliveira, T. (2019). Leveraging Internet of Things and Big Data Analytics Initiatives in European and American Firms: Is Data Quality a Way to Extract Business Value?. Information & Management. https://doi.org/10.1016/j.im.2019.01.003.

Cuevas, J. M. (2018). The transformation of professional selling: Implications for leading the modern sales organisation. *Industrial Marketing Management*.

Dakanalis, A., Zanetti, A. M., Riva, G., Colmegna, F., Volpato, C., Madeddu, F., & Clerici, M. (2015). Male Body Dissatisfaction and Eating Disorder Symptomatology: Moderating Variables Among Men. Journal of Health Psychology, 20, 80-90. doi:10.1177/1359105313499198

Davenport, T. H. (2006). "Competing on Analytics," Harvard Business Review (84:1), p. 98-107.

Day, G. S. (1994). The capabilities of market-driven organisations. *the Journal of Marketing*, 37-52.

Dearing, E., & Hamilton, L. C. (2006). Contemporary Advances and Classic Advice for Analyzing Mediating and Moderating Variables. Monographs of the Society for Research in Child Development, 71, 88 –104.

De Luca, L. M., & Atuahene-Gima, K. (2007). Market knowledge dimensions and cross-functional collaboration: Examining the different routes to product innovation performance. Journal of Marketing 71 95–112.

Demchenko, Y., De Laat, C., & Membrey, P. (2014). Defining architecture components of the Big Data Ecosystem. In *2014 International Conference on Collaboration Technologies and Systems (CTS)* (pp. 104-112). IEEE.

Dixon, A. L., & Tanner Jr, J. F. (2012). Transforming selling: why it is time to think differently about sales research. *Journal of Personal Selling & Sales Management, 32*(1), 9-13.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data Consumer Analytics and the Transformation of Marketing. Journal of Business Research, 69(2), 897-904.

Eriksson, P. & Kovalainen, A. (2008). Qualitative Methods in Business Research. London: Sage

Farrokhi, A. Shirazi, F. Hajli, N. & Tajvidi, M. (2020). Using Artificial Intelligence to Detect Crisis Related to Events: Decision Making in B2B by Artificial Intelligence, Industrial Marketing Management, Vol. 91, 257 – 273.

Flora, D. B. & Curran, P. J. (2004). An Empirical Evaluation of Alternative Methods of Estimation for Confirmatory Factor Analysis With Ordinal Data" Psychological Methods. 9 (4), 466–491.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Freund, R. J, & Littell, R.C. (2000). SAS System for Regression. 2nd ed. Cary, NC: SAS Institute.

Gandomi, A., and Haider, M. (2015). Beyond the Hype: Big Data Concepts, Methods, and Analytics. International Journal of Information Management, 35, 137–145.

Gatignon, H. (2010). Confirmatory factor analysis. In Statistical analysis of management data (pp. 59-122). Springer, New York, NY.

Grant, R. M. (1999). The resource-based theory of competitive advantage: implications for strategy formulation. In *knowledge and strategy* (pp. 3-23): Elsevier.

Gujarati, D. N (2003). Basic Econometrics, fourth edition. McGrew-Hill, Inc. New York.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B., Akter, S., (2017). Big Data and Predictive Analytics for Supply Chain and Organizational Performance. Journal of Business Research, 70, 308–317.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049-1064.

Hajli, N. Tajvidi, M. Gbadamosi, A. and Nadeem, W. (2020). Understanding Market Agility for New Product Success with Big Data Analytics, *Industrial Marketing Management*, https://doi.org/10.1016/j.indmarman.2019.09.010

Hair, J. F. Jr., Anderson, R. E., Tatham, R. L. & Black, W. C. (1995). Multivariate Data Analysis (3rd ed). New York: Macmillan.

Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E.; and Tatham, R.L. (2006).Multivariate, Data Analysis, 6th ed. Upper Saddle River, NJ: Pearson Education.

Heinonen, K., Strandvik, T., Mickelsson, K.-J., Edvardsson, B., Sundström, E., & Andersson, P. (2010). A customer-dominant logic of service. *Journal of Service management*, *21*(4), 531-548.

Hu, L. & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal. 6 (1), 1–55.

Jagtap, S. & Duong, L. (2019). Improving the New Product Development Using Big Data: A Case Study of a Food Company. British. Food Journal. Vol. 121, 2835–2848.

Jain, C. L., (2016). "How to Use Big Data and Predictive Analytics to Improve the Success of New Products". Review of Business, 2016, 37(1), 48-55

Jayachandran, S., Hewett, K., & Kaufman, P. (2004). Customer response capability in a sense-and-respond era: the role of customer knowledge process. *Journal of the Academy of Marketing Science*, *32*(3), 219-233.

Johnson, J. S. Friend, S. B. and Lee, H. S. (2017). "Big Data Facilitation, Utilization, and Monetisation: Exploring the 3Vs in a New Product Development Process", Journal of Production Innovation Management, Vol. 34 (5), 640 - 658

Kahn, J. H. (2006). Factor Analysis in Counseling Psychology Research, Training, and Practice: Principles, Advances, and Applications. The Counseling Psychologist, 34, 684-718

Karimi, J., Somers, T. M., & Bhattacherjee, A. (2007). The role of information systems resources in ERP capability building and business process outcomes. *Journal of Management Information Systems*, *24*(2), 221-260.

Kennedy, P. (1992). A Guide to Econometrics. Oxford: Blackwell.

Kiron, D. (2017). Lessons from Becoming a Data-Driven Organization. MIT Sloan Management Review, 58(2).

Koo, T. K., & Li, M. Y. (2016). A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. Journal of Chiropractice Medicine, 15, 155–163. doi:10.1016/j.jcm. 2016.02.012

Li, T. and Calantone, R. J. (1998), "The Impact of Market Knowledge Competence on New Product Advantage: Conceptualization and Empirical Examination," Journal of Marketing, 62 (October), 13–29.

Lilien, G. L. (2016). The B2B Knowledge Gap. *International Journal of Research in Marketing*, *33*(3), 543-556.

Marcos-Cuevas, J., Nätti, S., Palo, T., & Baumann, J. (2016). Value co-creation practices and capabilities: Sustained purposeful engagement across B2B systems. *Industrial Marketing Management*, *56*, 97-107.

Marquardt, D. W. (1970). Generalised inverses, ridge regression, biased linear estimation, and nonlinear estimation. *Technometrics*, 12, 591–256.

Malhotra NK, Dash S (2011) Marketing Research an Applied Orientation. Pearson Publishing, London.
Mayer-Schönberger, V., & Cukier, K. (2014). Learning from Big Data: The Future of Education. New York: Houghton Mifflin Harcourt.
McAfee, A., & Brynjolfsson, E. (2012). Big Data: The Management Revolution. Harvard Business Review, 90(10), 60-68.
McColl-Kennedy, J.R., Zaki, M., Lemon, K. N., Urmetzer, F., & Neely, A. (2019). Gaining Customer Experience Insights That Matter. *Journal of Service Research*, https://doi.org/ 10.1177/1094670518812182.
Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Information technology and organisational performance: An integrative model of IT business value. *MIS quarterly*, *28*(2), 283-322.
Mikalef, P.; Boura, M.; Lekakos, G.; & Krogstie, J. (2019). Big Data Analytics and Firm Performance: Findings from a Mixed-Method Approach. Journal of Business Research, 98, 261–276
Miotti, L. and Sachwald, F. (2003) Co-operative R&D: Why and with Whom? An Integrated Framework of Analysis. Research Policy, 32, 8, 1481–1500
Monjon, S., & Waelbroeck, P., (2003). Assessing Spillovers from Universities to Firms: Evidence from French Firm Level Data. International Journal of Industrial Organization 21 (9), 1255 – 127
Mukhopadhyay, T., Kekre, S., & Kalathur, S. (1995). Business value of information technology: a study of electronic data interchange. *MIS quarterly*, 137-156.
Narver, J. C., Slater, S. F., & MacLachlan, D. L. (2004). Responsive and proactive market orientation and new-product success. *Journal of product innovation management, 21*(5), 334-347.
Neter, J., Wasserman, W. & Kutner, M. H. (1989). Applied Linear Regression Models. Homewood, IL: Irwin.
Nevitt, J., Hancock, R. G. (2000). Improving the Root Mean Square Error of Approximation for Nonnormal Conditions in Structural Equation Modeling, *The Joumul of Exverimental Education*, 68(3), 251-268.
Nieto, M.J, Santamaria, L. (2007). The Importance of Diverse Collaborative Networks for the Novelty of Product Innovation. Technovation, 27 (6-7): 367-377.
Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). New York: McGraw-Hill
O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. Quality & Quantity, 41, 673-690.
Ottum, B. D., & Moore, W. L. (1997). The Role of Market Information in New Product Success/Failure. Journal of Product Innovation Management, 14, 258 – 273
Pan, Y, & Jackson, R. T. (2008). Ethnic difference in the relationship between acute inflammation and and serum ferritin in US adult males. Epidemiology and Infection, 136, 421-431.
Phillips-Wren, G., Iyer, L.S., Kulkarni, U., & Ariyachandra, T., (2015). Business Analytics in the Context of Big Data: A Roadmap for Research. Comm. Assoc. Inf. Syst. 37 (1), 448–472.
Raghupathi, W., & Raghupathi, V., (2014). Big Data Analytics in Healthcare: Promise and Potential. Health Inf. Sci. Syst. 2 (1), 3.
Rapp, A., Trainor, K. J., & Agnihotri, R. (2010). Performance implications of customer-linking capabilities: Examining the complementary role of customer orientation and CRM technology. *Journal of Business Research, 63*(11), 1229-1236.

Ranjan, J. and Foropon, C. (2021). Big Data Analytics in Building the Competitive Intelligence of Organisations, International Journal of Information Management 56, 1 – 13.

Ren, S. J-F, Fosso Wamba, S., Akter, S., Dubey, R., & Childe, S. J. (2017). Modelling Quality Dynamics, Business Value and Firm Performance in a Big Data Analytics Environment. International Journal of Production Research, 55(17), 5011-5026.

Roberts, N., & Grover, V. (2012a). Investigating firm's customer agility and firm performance: The importance of aligning sense and respond capabilities. *Journal of Business Research*, *65*(5), 579-585.

Roberts, N., & Grover, V. (2012b). Leveraging information technology infrastructure to facilitate a firm's customer agility and competitive activity: An empirical investigation. *Journal of Management Information Systems*, *28*(4), 231-270.

Rogerson, P. A. (2001). Statistical methods for geography. London: Sage.

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). “Shaping Agility through Digital Options: Reconceptualizing the Role of IT in Contemporary Firms,” MIS Quarterly (27:2), pp. 237-263.

Shirazi, F., & Mohammadi, M. (2019). A Big Data Analytics Model for Customer Churn Prediction in the Retiree Segment. International Journal of Information Management. https://doi.org/10.1016/j.ijinfomgt.2018.10.005.

Slater, S. F., & Narver, J. C. (2000a). Intelligence generation and superior customer value. *Journal of the academy of marketing science*, *28*(1), 120.

Slater, S. F., & Narver, J. C. (2000b). The positive effect of a market orientation on business profitability: a balanced replication. *Journal of business research*, *48*(1), 69-73.

Smyth, J.M. (1998). Written Emotional Expression: Effect Sizes, Outcome Types, and Moderating Variables. Journal of Consulting and Clinical Psychology, 66, 174–184.

Souder, W.E., Buisson, D., Garrett, T., (1997). Success Through Customer-Driven New Product Development: A Comparison of US and New Zealand Small Entrepreneurial High Technology Firms. Journal of Product Innovation Management 14 (5), 459–472.

Stine, R. A. (1995). The graphical interpretation of variance inflation factors. The American Statistician, 49(1), 53-56

Steiger, J. H., & Lind, J. M. (1980). Statistically based tests for the number of common factors. Paper presented at the annual meeting of the Psychometric Society, Iowa City, USA.

Suhr, D. D. (2006). Exploratory or confirmatory factor analysis? in Statistics and Data Analysis, Paper 200-31, Retrieved from http://www2.sas.com/proceedings/sugi31/200-31.pdf

Tan, K.H. & Zhan, Y., (2017). Improving New Product Development Using Big Data: A Case Study of An Electronics Company. R&D Management, 47(4), pp.570-582.

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic management journal*, *28*(13), 1319-1350.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533.

Tehseen, S., Ramayah, T., & Sajilan, S. (2017). Testing and controlling for common method variance: A review of available methods. *Journal of Management Sciences*, 4(2), 142-168.

Troisi, O. D’Arco, M. Loia, F & Maione, G. (2018). Big data management: The case of Mulino Bianco’s engagement platform for value co-creation, *International Journal of Engineering Business Management* Vol. 10: pp.1–8

Tsai, K. H., (2009). Collaborative Networks and Product Innovation Performance: Toward A Contingency Perspective. Research Policy 38 (5), 765–778.

Turner, D.; Schroeck, M., & Shockley, R. (2012). 'Analytics: The Real-World Use of Big Data in Financial Services.' IBM Global Business Services, 1–12.

Tylka, T. L. (2004). The Relation Between Body Dissatisfaction and Eating Disorder Symptomatology: An Analysis of Moderating Variables. Journal of Counseling Psychology, 51, 178–191.

Valle, S. and Avella, L. (2003). Cross-Functionality and Leadership of New Product Development Teams. European Journal of Innovation Management 6(1):32–47.

Venkatraman, N. (1989). The Concept of Fit in Strategy Research: Toward Verbal and Statistical Correspondence. *Academy of Management Review*, *14*(3), 423-444.

Volle, P. (2001). The Short-Term Effect of Store-Level Promotions on Store Choice, and the Moderating Role of Individual Variables. Journal of Business Research, 53 (2): 63- 73.

von Hippel, E., Thomke, S. & Sonnack, M. (1999) Creating Breakthroughs at 3 m. Harvard Business Review, September–October, 47–57

Wang, Y., & Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research*, *70*, 287-299.

Wang, Y., Kung, L., Wang, W. Y. C., & Cegielski, C. G. (2018). An integrated big data analytics-enabled transformation model: Application to health care. *Information & Management*, *55*(1), 64-79.

Ward, M. J., Marsolo, K. A., & Froehle, C. M. (2014). Applications of Business Analytics in Healthcare. Business Horizons, 57(5), 571–582.

Wedel, M., & Kannan, P. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, *80*(6), 97-121.

Wessel, M. 2016. How Big Data Is Changing Disruptive Innovation. Harvard Business Review. Available at: https://hbr.org/2016/01/howbig-data-is-changing-disruptive-innovation.

Weston, R., & Gore Jr, P. A. (2006). A brief guide to structural equation modeling. *The counseling psychologist*, *34*(5), 719-751.

Wiersema, F. (2013). The B2B agenda: The Current State of B2B Marketing and a Look Ahead. *Industrial Marketing Management*, *4*(42), 470-488.

Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of Big Data Analytics and Traditional Marketing Analytics on New Product Success: A Knowledge Fusion Perspective. Journal of Business Research, 69(5), 1562-1566.

Zhan, Y., Tan, K.H., Li, Y. & Tse, Y.K., (2016). Unlocking the Power of Big Data in New Product Development. Annals of Operations Research, pp.1-19

Zhan, Y, Tan, K.H., Ji, G., Chung, L., Tseng, M. (2017). A Big Data Framework for Facilitating Product Innovation Processes. *Business Process Management Journal*. 23(3), 518536. Retrieved from https://doi.org/10.1108/BPMJ-11-2015-0157

Zhou, S., Qiao, Z., Du, Q., Wang, G. A., Fan, W., and Yan, X. (2018). Measuring Customer Agility from Online Reviews Using Big Data Text Analytics. Journal of Management Information Systems, 35(2), 510–539.

Zolkiewski, J., Story, V., Burton, J., Chan, P., Gomes, A., Hunter-Jones, P., Robinson, W. (2017). Strategic B2B Customer Experience Management: The importance of outcomes-based measures. *Journal of Services Marketing*, 31(2),172–184.

Tables & Figures

Table 1. BDA and its emerging relevance in B2B contexts requiring customer agility for achieving new product success.

Issues in innovating firms reflecting importance of BDA in shaping customer agility in new product success	B2B markets are in a state of flux. There is a growing sense of urgency and pressure on customer-related functions including marketing to rise to the resulting challenges (Wiersema, 2013) BDA has become a potent tool for eliciting solutions to problems on the causal effects of marketing/innovating activities (Wedel & Kannan, 2016). Technology analytics are deployed to drive business innovation rather than mere operations upgrade (Wedel & Kannan, 2016). BDA facilitates value co-creation between innovative firm and corporate customer. It helps innovative firm in finding a 'structural fit' between the customer actions and those of the seller (Heinonen et al., 2010; Marcos-Cuevas et al., 2016). BDA resources vary in importance when considering their performance advantages. Furthermore, the insight generated from BDA will be used in transforming business operations, resulting in improved processes of capturing value. However, there could be limiting forces obstructing unhindered diffusion of BDA potentials within the firm. The firm must therefore design appropriate means to halt and/or overcome the limiting forces (Mikalef et al., 2019). Innovative firms integrate skills, data, technologies and competences to create revenue generating products and services (Braganza et al., 2017). BDA has been implicated in business intelligence and analytics field through which firms attempt to make sense of large gigantic data pool (Hajli et al., 2020).

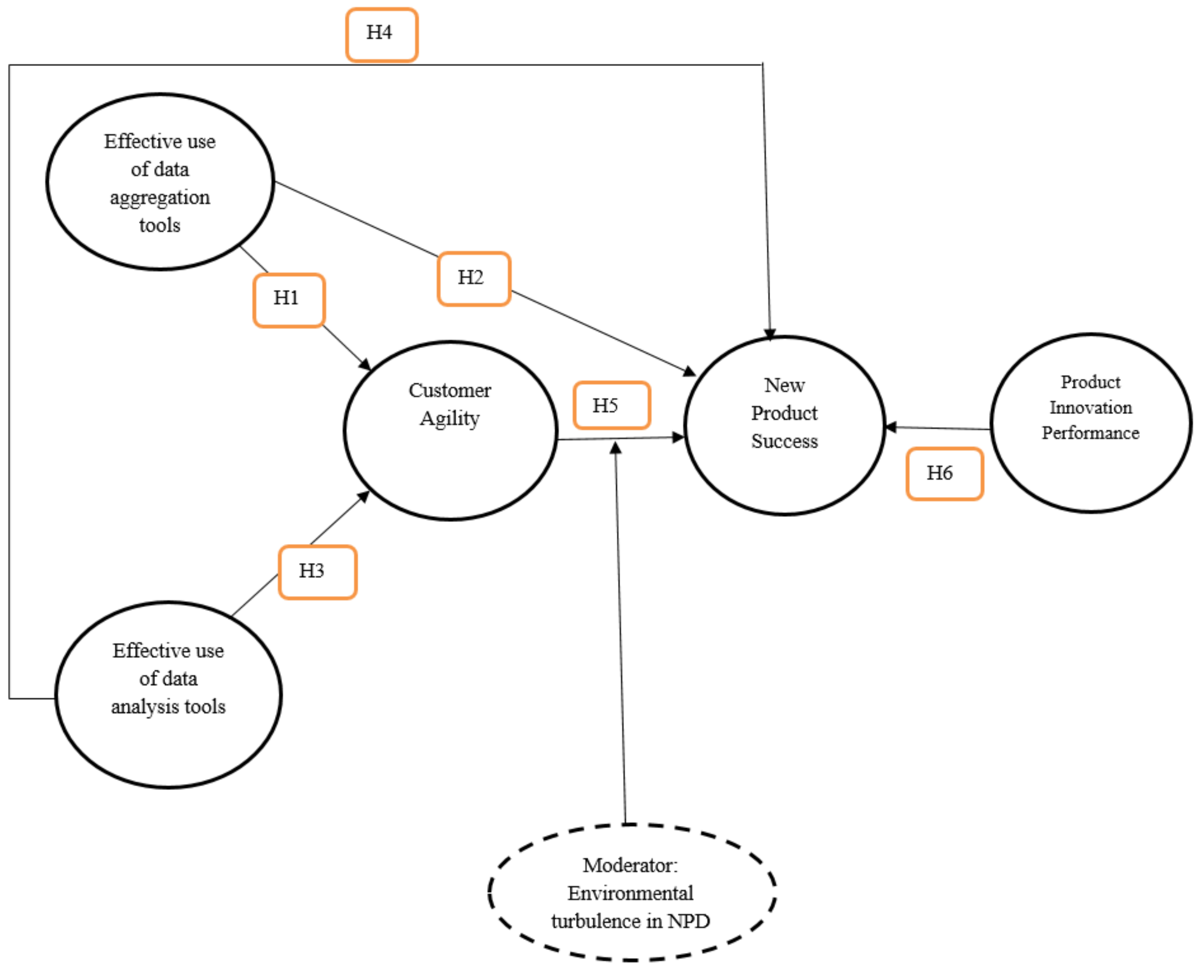

Figure 1: The conceptual model

Table 2. Sample Characteristics

Demographics	Frequency	%
Industry type		
Banking & Insurance	36	30
ICT	32	26.7
HealthCare	8	7.5
Oil & Gas	10	8.3
Training & Consulting	12	10
Service/other	13	10.8
Production & Mining	3	2.5
Transportation	6	5
Number of employees		
Less than 200 employees	30	25
200-500 employees	25	20.7
500-1000 employees	18	15
1000-3000 employees	37	31
3000-5000 employees	10	8.3
Respondents tenure		
Less than one year	4	3.3
Less than 5 years	22	18.3
6-10 years	58	48.3
11-15 years	21	17.5
16-20 years	15	12.5

Table 3: Cronbach's alpha

Constructs	Number of items	Cronbach's Alpha
Effective use of data aggregation	3	0.791
Effective use of data analysis	4	0.950
Customer Agility	10	0.920
New product success	4	0.779
Product innovation performance	4	0.758
Environmental Turbulance in NPD	6	0.766

Table 4: Multicollinerirty VIF Report

Customer Agility (independent variable)
Effective use of data aggregation tools: 1.621
Effective use of data analysis tools: 1.529

New Product Success (independent variable)
Effective use of data aggregation tools: 1.787
Effective use of data analysis tools: 2.168
Customer Agility: 1.572
Product innovation performance: 1.638
Environmental turbulence in NPD: 1.129

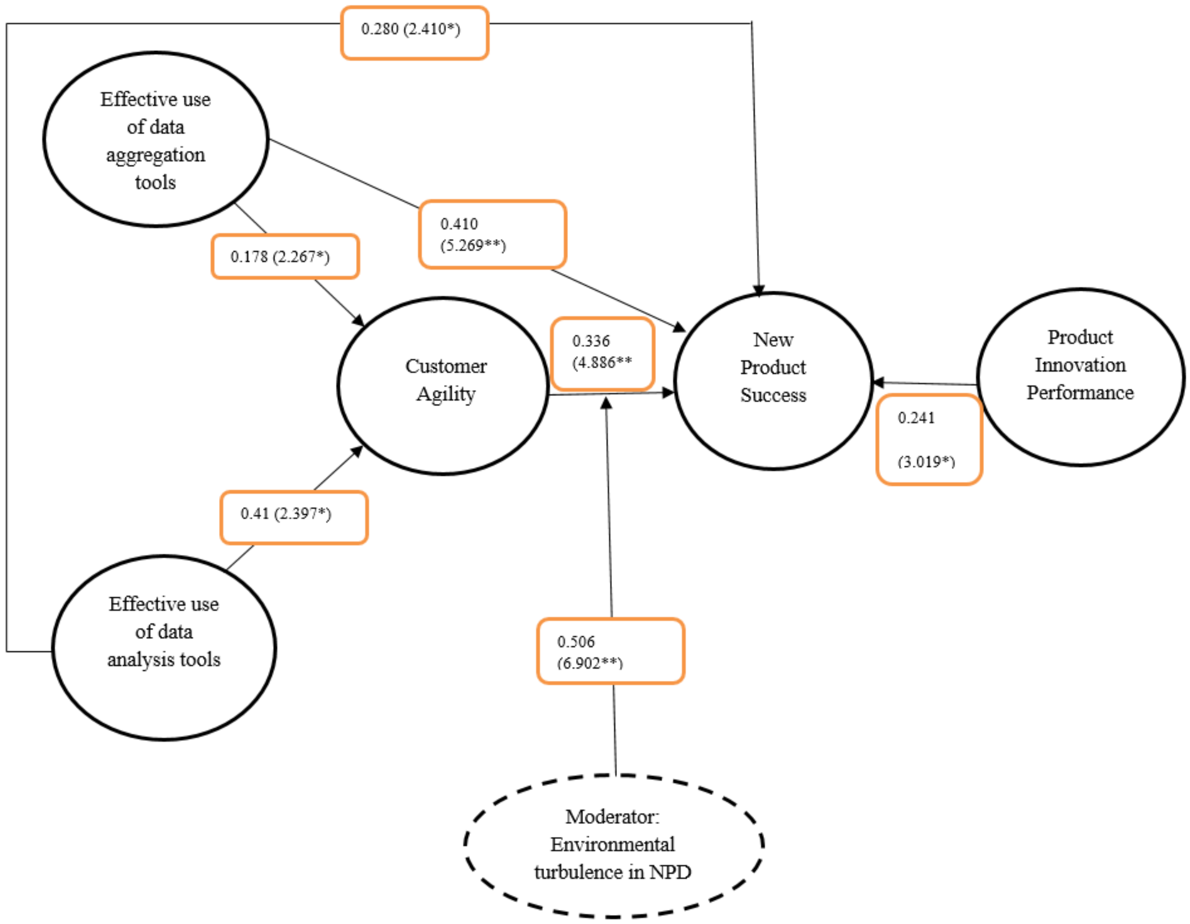

Figure 2: Structural Model

Customer Agility R-square: 0.529, Adjusted R-square: 0.513

New Product Success: R-square: 0.745, Adjusted R-square: 0.732

*. Significant at 0.05 level

Table 5: Fit Statistics

Fit statistic	Value	Description
Likelihood ratio		
chi2_bs(528)	2450.06	baseline vs. saturated
p > chi2	0.000	
Population error		
RMSEA	0.074	Root mean squared error of approximation
pclose	0.000	Probability RMSEA <= 0.05
Baseline comparison		
CFI	0.957	Comparative fit index
TLI	0.900	Tucker-Lewis index

Appendix A: Demographic Tables

Table 1: Age distribution

Age		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	<30	26	21.7	21.7	21.7
	31-40	68	56.7	56.7	78.3
	41-50	20	16.7	16.7	95
	51-60	6	5	5	100
	Total	120	100	100	

Table 2: Gender distribution

Gender		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	31	25.8	25.8	25.8
	Male	89	74.2	74.2	100
	Total	120	100	100	

Table 3: Educational Levels

Education		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Graduate	73	60.8	60.8	60.8
	Ph. D.	47	39.2	39.2	100
	Total	120	100	100	

Table 4: Distribution of Positions

Position		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Executive/Vice	35	29.2	29.2	29.2
	IT Manager	27	22.5	22.5	51.7
	Product Manger	13	10.8	10.8	62.5
	Business Analyst	7	5.8	5.8	68.3
	Project Manager	11	9.2	9.2	77.5

	Sales & Marketing Manager	15	12.5	12.5	90
	Others	12	10	10	100
	Total	120	100	100	

Table 5: Years of experience

Years		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1-5 years	22	18.3	18.3	18.3
	11-15 years	21	17.5	17.5	35.8
	16-20 years	15	12.5	12.5	48.3
	6-10 years	58	48.3	48.3	96.7
	Less than a year	4	3.3	3.3	100
	Total	120	100	100	

Table 6: Company Size

Size		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	< 200	30	25	25	25
	200 - 500	25	20.8	20.8	45.8
	500 - 1000	18	15	15	60.8
	1000 - 3000	37	30.8	30.8	91.7
	3000 - 5000	10	8.3	8.3	100
	Total	120	100	100	

APPENDIX B

Table 1: Construct Reliability and Validity

Constructs	Indicators Description	Indicators	Loading	P Value	CR	AVE
Customer Agility	We continuously try to discover additional needs of our customers of which they are unaware	CAG1	0.857	0.000	0.931	0.767
	We extrapolate key trends to gain insight into what users in a current market will need in the future	CAG2	0.788	0.002		
	We continuously try to anticipate our customers' needs even before they are aware of them	CAG3	0.909	0.000		
	We attempt to develop new ways of looking at customers and their needs	CAG4	0.815	0.000		
	We sense our customers' needs even before they are aware of them	CAG5	0.847	0.000		
	We respond rapidly if something important happens with regard to our customers	CAG6	0.844	0.000		
	We quickly implement our planned activities with regard to customers	CAG7	0.883	0.000		
	We quickly react to fundamental changes with regard to our customers	CAG8	0.926	0.000		
	When we identify a new customer need, we are quick to respond to it	CAG9	0.935	0.000		
	We are fast to respond to changes in our customers' product or service needs	CAG10	0.929	0.000		
Effective use of data aggregation tools	Collect data from external sources and from various CRM systems.	DAA1	0.872	0.000	0.879	0.841
	Make customer records and transactions consistent, visible and easily accessible for further analysis.	DAA2	0.862	0.000		
	We integrate data from multiple internal sources into a data warehouse or mart for easy access	DAA3	0.944	0.000		
Effective use of data analysis tools	Predict product patterns in response to customers' needs	DAT1	0.918	0.000	0.907	0.842
	Analyze data in near-real or real time that allows responses to unexpected market threats.	DAT2	0.896	0.000		
	Support data visualization that enables users to easily interpret results	DAT3	0.920	0.000		
	Provide near-real or real time reporting for the products	DAT4	0.850	0.000		
New Product success	Sales expectations	NPS1	0.875	0.000	0.861	0.780
	Profit expectations	NPS2	0.932	0.000		
	Return on investment (ROI) expectations	NPS3	0.928	0.000		
	Market share expectations	NPS4	0.884	0.000		
	Market share relative to the firm's stated objectives	PIP1	0.902	0.000	0.808	0.708

Product innovation performance	Sales relative to stated objectives	PIP2	0.880	0.000		
	Return on investment related to stated objectives	PIP3	0.910	0.000		
	Return on assets relative to stated objectives	PIP4	0.875	0.000		
Environmental turbulence in NDP	The environment in our product area is continuously changing	ENV1	0.808	0.000	0.863	0.723
	Environmental changes in our industry are difficult to forecast	ENV2	0.792	0.005		
	The technology in this product area is changing rapidly	ENV3	0.658	0.000		
	Technological breakthroughs provide big opportunities in this product area	ENV4	0.826	0.000		
	In our kind of business, customers' product preferences change a lot over time	ENV5	0.859	0.000		
	New product introductions are very frequent	ENV6	0.832	0.001		

Table 2: Fornell-Laker Criterion

Constructs (Fornell-Lacker Criterion)	1	2	3	4	5	6
1 Customer Agility	**0.767**					
2 Effective use of data aggregation	0.201	**0.841**				
3 Effective use of data analysis	0.409	0.293	**0.842**			
4 Environmental Turbulance in NPD	0.223	0.126	0.108	**0.723**		
5 New product success	0.268	0.348	0.108	0.386	**0.780**	
6 Product innovation performance	0.114	0.349	0.291	0.186	0.244	**0.708**

Note:Bold values indicate the AVE and values below indicate square of correleations

Table 3: Cross-Loading

	CGA	**DAA**	**DAT**	**NPS**	**PIP**	**ENV**
CGA1	**0.857**	0.275	0.207	0.342	0.244	0.269
CGA2	**0.788**	0.375	0.361	0.352	0.368	0.214
CGA3	**0.909**	0.301	0.487	0.497	0.364	0.341
CGA4	**0.815**	0.402	0.319	0.235	0.243	0.316
CGA5	**0.847**	0.172	0.287	0.097	0.185	0.327
CGA6	**0.844**	0.358	0.306	0.017	0.322	0.259
CGA7	**0.883**	0.337	0.366	0.243	0.392	0.438
CGA8	**0.926**	0.342	0.253	0.269	0.397	0.479
CGA9	**0.935**	0.105	0.299	-0.108	0.347	0.038
CGA10	**0.929**	0.310	0.231	0.316	0.245	0.366
DAA1	0.467	**0.872**	0.312	0.314	0.319	0.430
DAA2	0.342	**0.862**	0.263	0.208	0.205	0.264
DAA3	0.295	**0.944**	0.252	0.363	0.247	0.240
DAT1	0.340	0.334	**0.918**	0.438	0.358	0.441
DAT2	0.276	0.458	**0.896**	0.306	0.422	0.368

DAT3	0.318	0.324	**0.920**	0.291	0.375	0.234
DAT4	0.346	0.237	**0.850**	0.289	0.324	0.355
NPS1	0.356	0.395	0.418	**0.875**	0.394	0.703
NPS2	0.344	0.480	0.303	**0.932**	0.259	0.278
NPS3	0.316	0.424	0.398	**0.928**	0.255	0.236
NPS4	-0.285	0.054	0.030	**0.884**	0.132	-0.455
PIP1	0.266	0.264	0.221	0.143	**0.902**	0.134
PIP2	0.350	0.418	0.482	0.257	**0.880**	0.220
PIP3	-0.038	0.372	0.230	0.347	**0.910**	-0.151
PIP4	0.339	0.358	0.419	0.567	**0.875**	0.114
ENV1	0.362	0.292	0.218	0.224	0.264	**0.808**
ENV2	0.248	0.068	0.049	0.282	0.055	**0.792**
ENV3	0.220	0.369	0.305	0.337	0.163	**0.658**
ENV4	0.256	0.402	0.187	0.384	0.264	**0.826**
ENV5	0.269	0.225	0.233	0.236	0.244	**0.859**
ENV6	0.280	0.272	0.317	0.308	0.141	**0.832**