Big data and the innovation process
A systematic review

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Abstract

Researchers have claimed that Big Data has a positive effect on the new product development process. This paper aims to go deeper into this process by systematically reviewing articles that have been written about the new product development process and the big data outputs. This is to find specific links between the new product development process and big data outputs. This has been done in a systematic process by not only reviewing the articles but also to come with a result that can be put into a framework. With this framework, managers can identify which big data sources they should use in a specific new product development process. This framework describes in detail the role of various data inputs and their influence on the various stages of the Innovation/NPD process. The practical implication will be the design of an innovation methodology resulting in better, faster, cheaper, and more successful new products and services. The goal of this research is to tap into the customer-generated data that is relevant for the identification of future customer needs and wants as the primary input in the innovation process is the next future challenge for innovative marketers.

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1. Introduction

1.1 Background to the research

Several studies are published about the innovation/NPD process and many studies identifying the inputs in such processes (Constantinides & Lorenzo, 2015; Yu & Yang, 2017; Tan & Zhan, 2017; Zhan et al., 2018; Jagtap & Duong, 2019; Horvat et al. 2019). Such literature looks at the management issues of the innovation process-specific inputs in various stages of it. However, we have no evidence about which big data inputs relate to certain specific NPD stages. It is essential to establish to what extent existing research has already progressed towards clarifying the relation between Big Data and innovation. As it is believed that a framework that shows the exact relation will improve the speed, efficiency and success rate of the NPD process.

Big Data transforms the new product development process (Yu & Yang, 2016). The ability to use Big data enables companies to achieve outstanding performance over their competitors (Oh et al., 2012). While significant amounts of investment and time are needed to build a big data platform and install the necessary technologies, the long-term benefits of big data are enormous (Terziovski 2010; Song et al. 2016). According to Zhan et al. (2016), many researchers claim that big data plays a crucial role in customer involvement. They also claim that many pieces of research indicate that the company can better understand the preferences and needs of customers by using the data available through customer needs, social media (Bozarth et al. 1998; Tsai et al. 2013; Wamba and Carter 2014) and customization (Franke, 2009). Big data can be generated as a large-scaled cooperative information source that comes from cost-effective mass communication (Urban and Hauser 2004; Dahan and Hauser 2002; Tan et al. 2015).

This study is a systematic literature review that will try to recognise the potential of various sources of content created by users as a source of the Innovation/NPD processes (Constantinides and Romero-Lorenzo, 2015) as Co-creation sources. The study will also identify possible other inputs generated by customer activity (for example Search Data) that can be added to the ones identified in the study below (Figure 1). For this thesis, it is required to do an in-depth theoretical analysis of the connection between the various co-creation inputs and the innovation process according to the literature. Therefore, this thesis will identify such inputs and assess what of these inputs can contribute as information sources the various steps of the innovation process. The study will be the basis of designing a model that will describe in detail the role of various data inputs and their influence on the various stages of the Innovation/NPD process and, in a wider perspective, the role of customer as co-creator in innovation trajectories utilising data generated by various types of customer activities.

The goal of this research is to tap the customer-generated data that is relevant for the identification of future customer needs and wants as the primary input in the innovation process is the next future challenge for innovative marketers. Based on the work of Constantinides & Lorenzo, 2015, the study will create a model identifying the primary sources of such data and its value for the various stages of the innovation process. The model must become the basis of further research, for example, in the area of defining effective ways to capture the customer-generated data, to analyse it and relate it to innovative concepts. The practical implication will be the design of an innovation methodology resulting in better, faster, cheaper, and more successful new products and services. Many studies have concluded that the faster a company completes the product development process, the greater is its likelihood of surpassing its competitors in the marketplace (Day and Wensley, 1988; Ahmad et al., 2013; Dobbs, R., Manyika, J., & Woetzel, J., 2015)

1.2 Research Problem

The research problem that this dissertation will attempt to find an answer to is ‘’How can customer-generated Big Data improve the speed, efficiency and success rate of the NPD processes?’’.

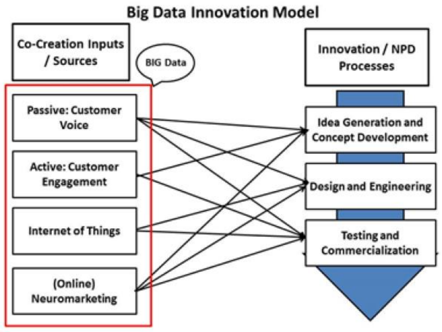


Figure 1 Big Data Innovation Model. Source: (Constantinides & Lorenzo, 2015, p. 5)

The initial big data innovation model is shown in Figure 1. The research question is focused on the identification of the primary sources of the customer-generated inputs (Big Data) and their role as inputs to the NPD process and more specifically, what is the possible role of such inputs in the different stages of the innovation process. By answering these questions, the relationship between Big Data and innovation will be explained and modelled. In other words, the relations between the co-creation inputs and the innovation/NPD process will be described in a comprehensive conceptual framework The first three sub-questions will give the reader a better image on open innovation, big data and the new product development process. It will also give them a clear image of why big data as a co-creation source is the new model for innovation. For the fourth and fifth sub-question, there will be systematic research conducted to look for pieces of literature that will aid in creating the actual crowd-based innovation model. This will be the final framework of this article.

To find an answer to this research problem, a sensible list of research questions will be:

- What is the Innovation/NPD Process?
- How has the innovation process developed over the last decades?
- What are the co-creation input/sources?
- What are the relations between customer-generated Big Data and the various stages of the Innovation/NPD Process?
- How should the crowd-based innovation model be shaped?

1.3 Methodology

According to Tranfield, Denyer & Smart (2003) researchers are less concerned with the effectiveness of certain classes of intervention, and rather more concerned with understanding organizations and management processes. In the case of this thesis, it will be the innovation process as it is imperative to view innovation and product development as a management process (Trott, 2008).

When a stand-alone literature review is conducted using a systematic, rigorous standard, it is called a *systematic literature review* (SLR). There is a clear explanation of Hart (1999) about the necessity of the literature review in pursuit of academic degrees. He explains four purposes for the literature review in a thesis: it synthesizes the understanding a student has on their particular subject matter, it stands as a testament to the research dedication, it justifies future research, and it welcomes the student into scholarly tradition and etiquette (Bruce, 2001). A systematic literature review calls for a degree of consistency that is more than what is typically essential even for the typical dissertation (Okoli & Schabram, 2010).

Purpose of the literature review: The first step in any review entails the reviewer to identify the purpose and envisioned goals of the review. This is necessary for the review to be explicit to its readers. The purpose and the goal of this research are to develop a framework that shows a link between certain new product development processes and the co-creation sources of Big Data.

Searching for the literature: The systematic review should be explicit in describing the details of the literature search and needs to clarify and justify how the comprehensiveness of the search was assured. Scopus and Google Scholar will be used to search for literature. For this research, several different search queries have been used. These search queries consist of combinations of any of the big data sources on the left with any of the new product development process on the right. Afterwards their abstract were checked upon relevancy. Lastly, the articles were thoroughly checked if they could (partly) answer any of the research questions. This resulted in a total of 45 articles, which were checked upon relevancy and used in the entire literature review. 24 articles of the 45 articles where used to build the final framework and to give an answer to the research question.

Practical screen: Also known as screening for inclusion, this step requires that the review is explicit about what studies were considered for review, and which ones were eliminated without further examination (an essential part of any literature review). This article has divided articles that only answer the first three sub-questions and the articles that answer the fourth research question: What are the relations between customer-generated Big Data and the various stages of the Innovation/NPD Process, in a certain way. As articles used for the fourth research question help in shaping the final framework of this research, which is the fifth research question. A systematic review is an objective, reproducible method to find answers to a specific research question. This report will attempt to gather all available research by using clearly defined, systematic methods to obtain answers to a specific question.

Quality appraisal: Also known as screening for exclusion, it is needed to explicitly spell out the criteria for judging which articles are of insufficient quality to be included in the review synthesis. All included articles need to be scored for their quality, depending on the research methodologies employed by the articles. For this research, this will be fairly difficult. As many articles are new and are most likely not cited very often. Many concepts explained in this thesis are still emerging so it is not expected that many articles will come from top journals.

Data extraction: After all the studies that should be included in the review have been identified, the applicable information from each study needs to be systematically extracted. This process is being shown in Figure 2.

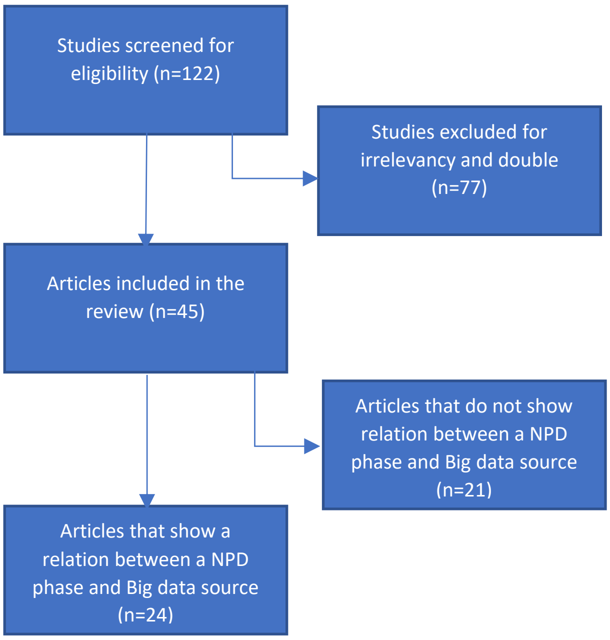


Figure 2 Flowchart of the Record screening process

Writing the review: In addition to the standard principles to be followed in writing research articles, the process of a systematic literature review needs to be reported in sufficient detail that the results of the review can be independently reproduced.

This literature review will consist of 45 peer-reviewed articles. Those 45 articles are a result of screening 122 articles. The articles should partially answer one of the sub-questions. 24 of these articles show a link between the co-creation output and to any new product development process. These 24 articles are segregated from a total of 45 articles because they aid in creating the final framework. In other words, they answered the following critical sub-question: ‘’What are the relations between customer-generated Big Data and the various stages of the Innovation/NPD Process’’. The most recurring journal is the Journal of Product Innovation Management because this journal has many publications about New product development. 77 of the articles were deleted because it had information that was already in other literature, or because it was not focussing enough on the co-creation source as a big data source.

Co-Creation Source	NPD process	Number of articles used
Customer Voice	Idea generation	n=2
Customer Voice	Idea screening	n=1
Customer Voice	Marketing strategy development	n=1
Customer Voice	Product Development	n=4
Customer Engagement	Idea generation	n=2
Customer Engagement	Idea screening	n=1
Customer Engagement	Concept development	n=5
Customer Engagement	Product Development	n=4
Internet of things	Idea generation	n=1
Internet of things	Marketing strategy and development	n=2
Internet of things	Product development	n=4
Neuromarketing	Idea generation	n=2
Neuromarketing	Marketing strategy development	n=5

Neuromarketing	Marketing Testing	n=4
Search Data	Business analysis	n=3
Search Data	Product development	n=1

Table 1 number of articles used per relation

2. Literature Review

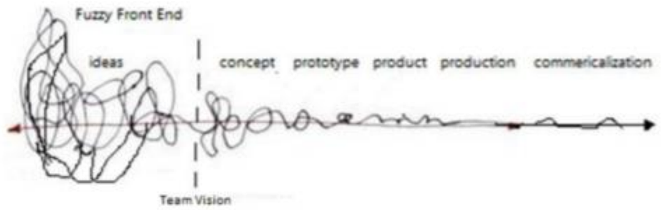
This section will present the results of the literature review to answer the research and the sub-questions.

2.1 NPD/Innovation process

The new product development process is, according to Kotler et al. 2012, described by several successive stages: idea generation, idea screening, concept development, and testing, marketing strategy development, business analysis, product development, marketing testing, and commercialisation. However, because there is no case of product development in the commercialisation stage because the product should be finished by that time, it will be left out of the framework. The goal of this research is to find new Big Data sources that influence the NPD and to discover if these sources, individually, improve speed, efficiency and the success rate of the NPD process. This research will try to give the academic realm a more in-depth insight into the connection between NPD and Big Data.

Philip Kotler (2012), described the NPD process as follows. The NPD process starts with generating ideas. Idea generation commences with the identification and generation of opportunities, new ideas and innovating concepts. This part is crucial for the NPD process as the creation of new opportunities is the starting point and therefore is the most essential stage of the entire new product development (NPD) process. It will be a waste of time and money if it is put into the development of any wrong idea (Abramov, 2015). Idea screening is the step by which the generated ideas are shifted and the ideas which are feasible and practical to develop are chosen. To do this, it is analysed whether the product is compatible with the objectives, strategies, and resources of the company. The essential part of this process is to separate good and bad ideas. If good ideas are separated, they will be considered as concepts. These concepts have to be developed and tested. This is done by checking which ideas are feasible by presenting the ideas to target audiences. After the testing is done, the new product idea will be stated in more meaningful consumer terms. For the product concept, there has to be a marketing strategy made, this is where the managers consider how the product will be launched on the market. The marketing mix will be written. This is where the segmentation, targeting and positioning strategy is clarified. After the marketing mix, a business analysis will be done to review sales, costs and the projected profit for the new product. After the business analysis, it will be checked if the analysis satisfies the objective of the company. The following step is Product Development, this is where the design & engineering is done and the prototype is produced. The prototype will be tested by selecting people who are from the target audience segment to see if any amendments need to be made. The key to the product development phase is that the product will become a physical product in order to certify that the product idea can be turned into a practical market offer. Test marketing means testing the product within a specific geographic area. Here, new product development will be tested in realistic market settings. Commercialisation is the final step where if test marketing is successful, the product is ready for launch.

Another term that is often mentioned is the Fuzzy Frond end of innovation. A model for this was created by Dornberger & Suvelza, (2012), this is shown in Figure 4. Smith and Reinertsen (1991) first noted that more than half the time when a product goes from idea generation to market introduction the product idea "Floats" around, and there is no organised effort to develop it. In the front-end (Figure 2), stakeholders often do not share a clear vision of what they are trying to achieve and why (Dornberger & Suvelza, 2012). Hise et al. (1989), states that ‘’companies that use a full range of up-front activities (e.g. market definition, identifying consumer needs) have a 73% success rate compared to a 29% success rate for companies that use only a few of the up-front activities'' (Hise et al. 1989).



Note: Front-end activities include pre-phase 0 (idea generation), phase 0 (assessment of market, technology and competition) and phase 1 (project justification and action plan) of the phase review or stage-gate system

Figure 3: Fuzzy Front End of Innovation. Source: Dornberger & Suvelza, (2012)

2.2 Development of the innovation process

Many things around us have something where innovation is involved in it. In the field of goods, technology, but also in the written world. Namely, innovation is reviewed in scientific and technical literature, but also social sciences. Since the 2000s, innovation has grown to the extent that it was open to outsourcing as part of the process. When innovation is open to outsourcing it becomes ''open innovation''. Now it does not only rely on its R&D department anymore but they will also make use of multiple external sources, such as customer feedback, to improve their innovation process (Chesbrough & Bogers, 2014). Because of open innovation, scientists and researchers are now urging considerably more for customer participation in the new product development process (NDP) than we see in normal market research (von Hippel and Katz 2002; Chesbrough 2006; Prahalad and Ramaswamy 2004; Sarin and O'Connor 2009; Williamson and Yin 2014). To adopt open innovation, it is necessary to recognise that the performance of NPD is not anymore depending on just internal R&D functions, it also depends now on contributions from a wide range of external influences (Bahemia and Squire, 2010). In the open format model (Figure 5) of Chesbrough (2003, 2006), it is visible that open innovation focuses on the utilisation of external knowledge to optimise the internal innovation process. Rahman and Ramos (2010) explained that ''in terms of process, open innovation covers the management and the accumulation of ideas, knowledge, licenses, intellectual property, patents, and inventions. Open innovation theory corresponds to several innovative approaches whose basic element is made innovation beyond the research and development departments of the organization''.

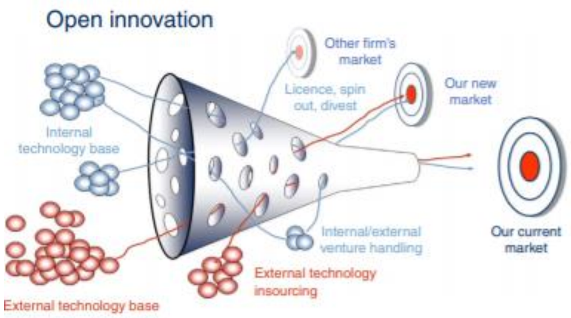


Figure 4: Open Innovation model. Source: Chesbrough (2003)

Date	Model	Characteristics
1950/60s	Technology-push	Sample linear seqential process; emphasis on R&D; the market is a recipient of the fruits of R&D
1970s	Market-pull	Sample linear seqential process; emphasis on marketing; the market is the source for directing R&D; R&D has a reactive role
1970s	Dominant design	Abbernathy and Utterback (1978) illustrate that an innovation system goes through three stages before a dominant design emerges
1980s	Coupling model	Emphasis on integrating R&D and marketing
1980/90s	Interactive mode	Combinations of push and pull
1990	Architectural innovation	Recognition of the role of firm embedded knowledge in influencing innovation
1990s	Network model	Emphasis on knowledge accumulation and external linkages
2000s	Open innovation	Chesbrough's (2003) emphasis on further externalisation of the innovation proces in terms of linkages with knowledge inputs and collaboration to exploit knowledge outputs

Table 2: The chronological development of models of innovation. Source: Trott, 2008

The table above (Table 1), from Trott (2008), shows the chronological development of innovation through the years. Figure 1 shows open innovation as the newest model of innovation. Recent theoretical developments have revealed that big data also has an impact on new product development (Constantinides & Lorenzo, 2015; Yu & Yang, 2017; Tan & Zhan, 2017; Zhan et al., 2018; Jagtap & Duong, 2019; Horvat et al. 2019). Constantinides & Lorenzo (2015), argue that co-creation or crowdsourcing is the new innovation frontier**.** Since the book of Trott (2008) dates back to 2008, we can assume that the table is quite outdated according to the paper mentioned above. We may add crowdsourcing or big data as an innovation input. Many pieces of literature describe Big data analytics as to the “next big thing in innovation” (Gobble 2013).

Many organizations are active in outsourcing their idea generation process making use of various online platforms and sources in order to attract better new ideas for their innovation process. This approach is called crowdsourcing. This is the phase in which data is collected from the internet so that customers are involved in the innovation process. This can happen often without them even noticing. Data collected from the online activity of customers is part of what is known as big data.

Oxford dictionary defines *Big data* as: ‘’extremely large data sets that may be analysed computationally to reveal patterns, trends, and associations, especially relating to human behaviour and interactions.’’ Cambridge dictionary defines *Big data* as: ‘’very large sets of data that are produced by people using the internet, and that can only be stored, understood, and used with the help of special tools and methods’’. To collect Big data, organisations have set up systems to crowdsource ideas for new product ideas. The organisations know that customers are the most appropriate target to evaluate if a new product fills a previously unmet and quite possibly unrecognised need (Franke et al. 2009; Noble et al. 2012; Robert and Candi 2014). This is, therefore, the era of “big data” as input in the innovation process (McKinsey 2011; IBM 2013; Chan et al. 2015).

2.3 Co-creation outputs

Value creation has gone through a change. Because of the emergence of the digital age, it is now possible to call it value co-creation between firms and customers (Bettencourt, Lusch & Vargo, 2014), factors such as the emergence of big data has played a role as the primary driver for this change (Jagadish et al. 2014; Jobs, Aukers & Gilfoil, 2015). In the era of big data, every change in customer behaviour, location, or even psychological data can be recorded and analysed (Efros, 2014). In this part of the research, various outputs where big data is collected from will be explained.

2.3.1 Customer's voice

Constantinides and Lorenzo (2015), claim that companies utilise numerous ways for motoring and processing data from the social media area by “listening” to online customer voice. Properly analysed social intelligence information helps businesses improve productivity and services, reply to complaints and prevent other issues (Constantinides & Fountain, 2007).

The voice of the customer goes deeper into just the demand of customers. It also reveals what customers demand and why they demand it. For marketers to understand the voice of customer better, it is helpful to observe and even take part in the product used for an extended period of their time (Flint, 2002). If a product is developed with some sort of customer input, the likelihood of business success tends to be larger (Ciappei & Simoni, 2005). One way how companies do this is when they start to understand that they first should be proactive in creating long-term relationships with customers. Therefore, it is necessary to pursue them in ongoing interactive and relative activities associated with the NPD (Alam & Perry, 2002; Yakhief, 2005; Judson et al., 2006). Hence, Koufteros et al., (2005), explains that ‘’customers should be incorporated within the NPD process as early as possible to avoid expensive mistakes’’. Finally, Narver et al. (2004), forecasted that organisations have to systematically improve their skill in learning more about the specifics and solutions of the needs and wants of the target customers (Narver et al., 2004).

Many studies have been conducted about customer's voice. Not to mention, Ogawa and Piller (2006), were one of the first to go come with real-world proof indicating that user ideas generated in the course of a crowdsourcing process might also hold commercial potential. Furthermore, the study of Poetz and Schreier (2012), gives a sign that if you conduct crowdsourcing projects among users, it might be possible to outperform internal R&D when generating new product ideas (Poetz & Schreier, 2012). To put it more simply, ideas that are provided by average users are generally more creative than ideas of experts. However, they can be more difficult to implement than the ideas from professionals (Desouza et al., 2008). To optimise this, organisations need to segment the right kind of targets to attain the necessary ideas from the optimal sources (Desouza et al., 2008). Afterwards, the ideas have to be filtered, screened and tested. For this, it is necessary to assemble cross-functional teams where the ideas will go through the new product development process (Desouza et al., 2008).

A firm will profit considerably by optimising and improving the fuzzy front-end of an innovation method (Dahl & Moreau, 2002; Reinertsen, 1999). Customer interaction is incredibly helpful within the front-end stages of an innovation method (Alam, 2002; Gruner & Homburg, 2000) the front-end stages are the most data-intensive (Zahay, Griffin, & Fredricks, 2004).

2.3.2 Customer engagement

The customer's voice is seen as a necessity in the new product development (NPD) (Roman 2010; Nishikawa, Schreier, & Ogawa 2013). It can be that the constant collection and testing of information about customer needs can result in a complex analysis process, as it might be timely and costly (Dahan and Srinivasan 2000; Thomke & Von Hippel 2002; Price, Wringley & Straker, 2015). Normally, firms have to attain customer knowledge from importing the voice of customer via traditional market research approaches (Sawhney, Verona, & Prandelli, 2005). However, in a highly competitive area, this process is more timely and costly as they also have to attain customer knowledge through online methods. More companies are trying to actively involve customers in the new product development process (Fang, 2008; Nambisan, 2002). One is example is that Boeing develops new aircraft models with airline carriers by involving customer representatives in its NPD team (Condit, 1994; Enkel, Perez-Freije, & Gassmann, 2005)

"Customer participation" is stated as the extent to which the customer is involved in the manufacturer's NPD process (Fang, 2008; Kambil, Friesen, & Sundaram, 1999; Prahalad & Ramaswamy, 2000). Constantinides & Lorenzo, (2005) defined Customer engagement, as the ‘’*The Active Way’’*. This means engaging innovative customers by attracting them in social online innovation platforms. This approach targets a new generation of empowered and smart consumers increasingly demanding a greater role in the development of products they buy (Piller, Moeslein and Stotko, 2004). Empowered consumers are often willing to actively participate in the innovation process (Nambisan, 2002; Ogawa and Piller, 2006; Lee, Constantinides, Lorenzo and Gómez-Borja 2008; Olson and Trimi, 2012) in social online interactive environments known as Virtual Customer Environments (Nambisan and Baron, 2009). The active customer online engagement is either incidental or permanent when dialogue and customer engagement happens on a continuous base. Lego, Dell computers, Starbucks, Lays, Boeing, Nokia, P&G and Toyota are some of the examples of firms actively pursuing such permanent online customer engagement in their innovation processes.

Many researchers have shown that companies who empower their customers generate better products at a lower value and risk (e.g., Dahan & Hauser, 2002; Lilien et al., 2002; Sawhney et al., 2005; Ogawa & Piller, 2006). This is when customers are willing and ready to provide NPD input. In other words, customers provide continuous benefits, because a company that empowers their customers will more likely be chosen because of positive word of mouth, contrarily to non-empowering companies (Fuchs & Schreier, 2010). If companies do not empower their customers, they will most of the time not offer new product ideas (Nambisan, 2002).

One of the key success factors for NPD is customer information (von Hippel, 1988; Svendsen et al., 2011). A study by Rindfleisch et al. (2017) pointed out that there is a second digital revolution coming, this is when a customer has more direct contribution in data analytics for NPD. It is also described as ‘’innovation as data’’, this is contrasting to the traditional view of ‘’innovation from data’’. This perception of more active customer involvement in big data analytics is in line with the open innovation theory. The open innovation theory features customers as co-developers in the new product development process (Zhang & Xiao, 2019). It also emphasises empower of customers in the new product development process (Fuchs & Schreier, 2010), whereby there is more intensive cooperation between firms and customers in process of product development (Nijssen, Hillebrand, Jong & Kemp, 2012)

2.3.3 Internet of things

The Internet of Things (IoT), is a fast-growing network of internet-connected embedded devices like sensors, actuators, machines and wearables allowing ubiquitous connectivity of machines, systems, factories, vehicles, homes, cities and people (Gubbi, Buyya, Marusic & Palaniswami, 2013; Miorandi, Sicari, De Pellegrini, & Chlamta, 2012).

The rapid development of the internet, internet of things, mobile applications and cloud computing has led to an immense increase in data in almost all business and industrial sectors (Yu & Yang, 2016). It is possible that devices connected with the internet of things can autonomously respond to internal and external stimuli (Yan and Huang, 2008). Therefore, they produce an immense flow of data (McAfee and Brynjolfsson, 2012), which can constantly exchange data with each other (Lee et al., 2013). With the arrival of the Internet of Things combined with the extraordinary amount of data generation, the potential to improve the new product development process can be utilised by companies. It can subsequently reduce the failure rate of new products launching to the market (Mahmud, 2018). In recent years, a great amount of new product development models or processes have been invented by there is little attention to the role of IoT and the success it provides to the NPD process (Mahmud, 2018). Perhaps because the internet of things is a recent invention, as the term was first mentioned in 1999 (Ashton, 2009). Therefore, it is possible that a gap could be identified in the academic and scientific literature, where not many researchers have examined the effect of IoT and the success factors on the NPD process.

2.3.4 Neuromarketing

Constantinides & Lorenzo (2015) describe neuromarketing as an input for new product development. They also described that applying neuroscience technologies and processes for marketing purposes is an approach that allows marketers to better understand human behaviour in new ways (Lee, Broderick, & Chamberlain, 2007) and understand the mechanisms of decision making in the subconscious of the human brain (Ariely & Berns, 2010). Neuromarketing emerges as a study of consumer behaviour that links with neuroscience. To introduce, neuromarketing was controversial when it first emerged in 2002, nevertheless, it gained rapid credibility and adoption among advertising and marketing professionals (Morin, 2011). Neuromarketing can be lightly described as a measurement of psychological and neural signals to collect insight into the motivation, preferences and decisions of customers. This can help inform creative advertising, product development, pricing, and marketing areas (Eben, 2019). The method of brain scanning measures neural activity and physiological tracking. This is done by measuring eye movement and other proxies for the activity, these are one of the most common methods of measurement (Eben, 2019).

There are many techniques of neuromarketing to collect data with. fMRI, EEG, Eye tracking: gaze, Pupilometry, Biometry and facial coding. The EEG is described by Sebastian, (2014) as ‘’by means of the electrodes placed on the scalp, measures the brainwaves and records the changes of the brain bio currents’’ (Sebastian, 2014). This instrument can track changes in activity over fractions of a second and it helps improving advertisement and branding (Harrell, 2019). With the fMRI, it is possible to measure the increase of the oxygen level in the brain’s blood flow. Pradeep, (2010) describes the usage of the fMRI as: ‘’this instrument is capable of accurately identifying increased activity in a certain brain area while a stimulus/stimulus situation is being presented’’ (Pradeep, 2010).

Therefore, fMRI can help with set pricing and improve branding (Harrell, 2019). However, because it is performed in a lab, it is not possible to get massive amounts of data because the fMRI is performed in a lab and it is expensive. Thus, the data collected from fMRI will not be considered as big data. Loewenfield (1993), refers to pupillometry as ‘’the modification of the pupil size and also to the mobility of the pupil over time’’ (Loewenfield, 1993). This is were the iris muscles react to the parasympathetic and sympathetic stimulus to determine the pupil size and movement (Loewenfield, 1993; Nowak et al., 2014). Eye-tracking is a way to measure the attention of customers (Harrell, 2019), it further provides data about communication processing and effectiveness. This cannot normally be obtained by traditional measures because of what Wedel & Pieters, (2008) describe as: ‘’the speed and lack of conscious access to the rapid attentional processes taking place during communication exposure’’

Biometrics sees the skin conductance, heart rate, and respiration to measure the level of engagement, and whether their response is positive or negative this can be used for advertisements (Harrell, 2019). Finally, facial coding looks at facial expressions to measure general emotional response to having data on feedback on advertisements to improve the content (Harrell, 2019). It will be more likely that facial coding and eye tracking will be more compatible with big data as it is less costly.

2.3.5 Search Data

Since the introduction of the internet and search engines, customers are now capable to search for information about almost anything. Besides, the cost of searching for information has also been lowered (Bardhan et al., 2010). This means that search engines are the main sites for customers to know more about a product, concept or a term of interest (Kulkarni, Kannan & Moe, 2012). According to Madden (2006): ‘’of Internet users, 91% report using a search engine to find information’’ (Madden, 2006). Thus, it is clear that both Internet use and search engine data have many big data offered that can be collected to predict consumer preference.

2.4 The relation between Big Data inputs and NPD processes

Davenport, 2014 cited that the creation of value in Big Data-based organizations as the generation of improvements in products and services based on insights taken from analysed data. Mcafee (2012) characterizes the creation of value related to Big Data concepts as the improvement or development of new products. Constantinides & Lorenzo, 2015 addressed that the emerging Big Data Innovation model (Figure 1) identifies the main sources of such data and its value for the various stages of the innovation process. The co-creation sources are gaining more attention from academics and practitioners. The Big Data Innovation Model (Figure 1) is emerging as the new innovation frontier (Constantinides & Lorenzo, 2015). In this part of the research, the link between specific co-creation outputs and the phases of new product development will be explained to go deeper and further expand the Big Data Innovation Model.

2.4.1 Customer Voice

Already many businesses are trying to benefit from using the voice of customers to generate new product ideas for the new product development process (Cooper & Dreher, 2010). Noticeable brands like Adidas, BMW, Ducati, Procter & Gamble, 3M and many others have created online platforms collect ideas from their customers. These companies are trying to use these platforms to integrate the new product ideas into the new product development process more actively, directly and systematically (Ogawa and Piller, 2006; Pitt et al., 2006; Sawhney et al., 2005).

For the early stages of the NPD process, it is useful to create suggestion boxes where customers can come up with their ideas. There is, for example, Ben & Jerry with their ‘’Suggest-a-Flavour’’ where they allow customers to contribute ideas for their new ice creams flavours. However, it is crucial to have clear rules concerning intellectual property rights. If this is done correctly than companies can use the ideas that are suggested by customers, while customers can also get financial or non-monetary rewards. Some ideas have been found to improve the joint idea generation (Toubia, 2006; Shawhney et al., 2005). Another example is from Ducati who uses its virtual communities to improve their ideation in the new product development process and utilise the abilities of lead users. Afterwards, they screen the ideas by utilising specific polls to check if the ideas are well-designed by involving a large number of customers. The sense of belonging of the community is linked to the high response rates because of the individual commitment and brand loyalty (Shawhney et al., 2005).

Chen, Khoo & Yan (2003), suggested that it has been recognised that the voice of customers is an important source of input to attain design metrics and specification in the early stage of product concept design. Thus, having customers involved in the new product development process improves product concept effectiveness. This can be done within the Quality Function Deployment (QFD). Deatz (1989), described QFD as ‘’an approach developed by the Japanese for guaranteeing that the voice of the customer is acquired and transmitted through all the phases of creating and marketing a new product: product definition, product design, prototype construction, production, and sales/service’’. Customer data is the start of adaptable product design. Both academics and industries make use of the QFD. Industries use it to collect customer voice, benchmark and customers’ preferences through the leaders of their industry, and then they transfer the data into functional requirements (Afshari & Peng, 2015) Mazur (2014) claimed that big data can work in QFD for gathering the voice of the customer, and not just the response of the customer. A possible area of integration is market segmentation. Statistical analysis that can delve out hidden differences in demographics and use modes. It can also discover preferences based on purchases of unrelated items.

In the realm of market-driven product design, customer surveys help to predict customer requirements. However, because of the emergence of online reviews and the huge amount that can be collected, useful recommendations from customers can also be found there. Largely because of their free text and quantity, unfortunately, these reviews are often neglected and rarely used directly by designers (Jin, Ji & Liu, 2014). With numerous amounts of online reviews, the useful voice of the customer, are beneficial for consumers and product designers. Identifying and analysing useful assessments that efficiently and accurately meet the needs of both current and potential customers has become a critical challenge for market-driven product design. The use of assessment data collected from Amazon.com and real assessments are given by design staff indicates that useful product assessments can be identified from a designer's perspective by automatically analysing the assessment content (Liu et al., 2014).

According to a study of Tucker & Kim (2011), by designing predictive models to predict trends in product properties, the design engineer can observe which product design features are outdated or popular over time and include these findings in future product design decisions. With large-scale trend data from customer preferences, designers can better assess the emerging problems of a current product or favourable characteristics of past products and integrate these findings into the next-generation product concept phase. Design engineers can also compare their product with that of competitors by comparing the product characteristics of time series with those of competitors (Tucker & Kim 2011).

The Preference Trend Mining algorithm was presented by Tucker and Kim (2010), this algorithm was made to address several important tasks of current demand modelling techniques that are used in the product design community. This can deliver to the multi-stage predictive modelling approach that measures the changes that the customer preferences have over time. This allows design engineers to foresee next-generation product characteristics before they become mainstream (Tucker & Kim, 2010)

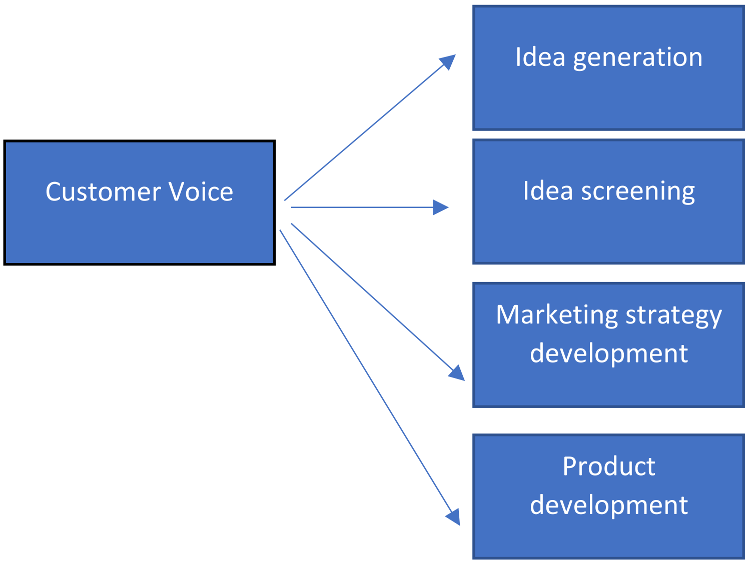


Figure 5

Author(s)	Article quote	Topic	Journal
Fuchs & Schreier, 2011	Adidas, BMW, Ducati, Procter & Gamble, 3M, and many others have created online platforms that aim to integrate their customers' innovative new product ideas into NPD processes more actively, more directly, and more systematically	Customer Voice optimises idea generation	Journal of product innovation management
Shawhney et al., 2005	Mechanisms that are useful at the early stages of the NPD process include suggestion boxes where customers can contribute their own innovative ideas. Well-designed incentives have been found to remarkably improve collaborative idea generation	Customer Voice optimises idea generation	Journal of interactive marketing
Shawhney et al., 2005	Ducati uses its virtual communities to enhance idea generation and tap into the competencies of lead users, but then relies on specific polls to verify the soundness of these ideas by involving larger numbers of customers to generate successful "next bikes." These polls achieve extraordinary response rates, because the sense of belonging to the community increases individual commitment and brand loyalty.	Customer Voice optimises idea screening	Journal of interactive marketing
Mazur 2014	Big data can work in QFD for gathering the voice of the customer, and not just the response of the customer. A possible area of integration is market segmentation. Statistical analysis that can delve out hidden differences in demographics and use modes. It can also discover preferences based on purchases of unrelated items.	Customer Voice optimises marketing strategy development	International Council for QFD

Jin, Ji & Liu, 2014	With market-driven product design, customer requirements are usually obtained from consumer surveys. However, valuable recommendations from customers can also be found in a large number of online reviews. Largely because of their free text and quantity, unfortunately, these reviews are often neglected and rarely used directly by designers	Customer Voice optimises product development	Journal of Engineering Design
Liu et al., 2014	Large amounts of online reviews, the valuable voice of the customer, are beneficial for consumers and product designers. Identifying and analysing useful assessments that efficiently and accurately meet the needs of both current and potential customers has become a critical challenge for market-driven product design	Customer Voice optimises product development	Computer-Aided Design
Tucker & Kim, 2011	By designing predictive models to predict trends in product properties, the design engineer can observe which product design features are outdated or popular over time and include these findings in future product design decisions.	Customer Voice optimises product development	Proceedings of the 18th International Conference on Engineering Design
Tucker & Kim, 2010	The preference trend mining algorithm contributes to the multi-stage predictive modelling approach that records changes in consumer preferences (as they relate to product design) over time, allowing design engineers to anticipate next-generation product characteristics before becoming mainstream	Customer Voice optimises product development	International Design Engineering Technical Conferences and Computers and Information in Engineering Conference

Table 3

2.4.2 Customer engagement

Having enough knowledge about the sources of ideas is essential for innovation. Today, many companies are trying to find new methods to have customers involved in the idea generation process. Having environments where customers feel contented and inspired to give feedback on products is an essential factor in collecting customer-generated ideas. This can be done with online co-innovation communities (OCCs) to have interaction with customers through social networks (Bugshan, 2014). Having customers involved in innovation also has advantages for companies. For instance, when Starbucks created its OCC platform which was called MyStarbucksIdea.com, it persuaded their tech-savvy community to join by offering them various incentives if they shared, voted, discussed and review ideas in themed categories (Lee and Suh, 2013). This resulted in more than 200,000 ideas from customers that were engaged in MyStarbucksIdea.com. More than 1,000 of those ideas were used by Starbuck's to improve their products and services, while at the same time improving their customer experiences and involvement (Zhang, Kandampully & Bilgihan, 2015). In short, with the data collected from online customization tools known as configurators, companies will have a better insight into customer preferences. This might be helpful when a company is looking to generate and screen new ideas.

Within the Product development stage, the role of the customer is described more correctly as co-creator (Lengnick-Hall, 1996; Nambisan, 2002). Franke (2009) found out that products customized based on customer preferences deliver clear benefits to the customer. To explain, the demand for customised products have increased, additionally, customer preferences have become more heterogeneous in many markets (Gilmore & Pine 1997; Smith, 1956). Being a co-creator of products, it is possible to provide to a variety of product design, this includes the validation of product architectural choices, the design and prioritisation of products (Nambisan, 2002). Some companies depend on customers to contribute to design choices as actual members of product development teams.

For example, in some companies, customers have played the role product co-creators by participating in researching for consumer idealized design (Ciccantelli & Magidson, 1993), and component selection (Kambil et al., 1999; Nambisan, 2002). In other words, customers can be involved in creating new ideas for new products, co-creating the products with firms, testing finished products, and in supporting the product as end-users (Sawhney & Prandelli, 2000). Finally, the tools in the back-end stages and broad customer engagement like toolkits for users innovation, open-source mechanisms, web-based patent markets are fit to improve the product development phase (Shawney et al. 2005).

Customer input is also used for developing the concept of new products by drawing on user prototypes developed by lead users (Von Hippel, 1980). Lead users gain from having their needs met, by frequently finding a solution by themselves. This solution for the product concept can be picked up in the concept development process. Besides, having users participate in evaluating alternative concepts is also beneficial for the concept development process (Dahan & Srinivasan, 2000). It is more useful to use tools in the front-end stages and broad customer engagement like online surveys, market intelligence services, web-based conjoint analysis and listening-in techniques in the concept-testing phase (Shawney et al. 2005). In some companies, customers have played the role of product cocreator by, for example, participating in concept testing (Page & Rosenbaum, 1992).

The role of end-users or buyers can be taken by the members of virtual communities. For instance when Vodafone conducted together with Game creator a user-friendly test of an Internet platform that allows customers to develop and download their mobile java games from the Internet without them having any knowledge in programming. This was either totally from scratch, or by just adjusting a preconfigured template game (Fuller & Matzler, 2007). Basically, in this way, customers share opinions or ideas in such virtual communities, these interactions generate data (Broniatowski, Paul & Dredze, 2014; Archer-Brown, Piercy & Joinson, 2013; Efros, 2014; Xie, Wu, Xiao & Hu, 2016). This is how concepts for a new product can be developed and tested.

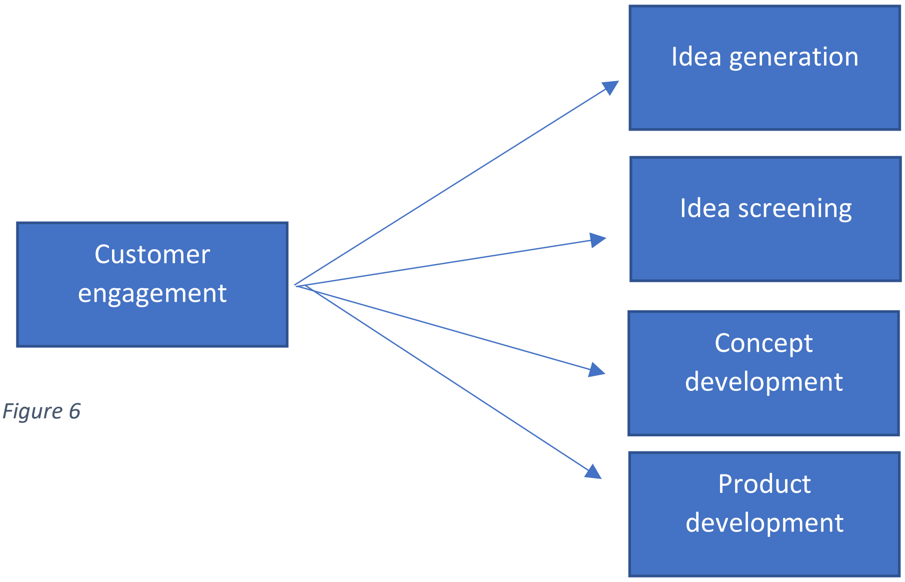


Figure 6

Author(s)	Article quote	Topic	Journal
Bugshan, 2014	Creating arenas where customers feel comfortable and encouraged to provide feedback is a key component of collecting customer-generated ideas. For example, firms use online co-innovation communities (OCCs) to connect with customers through social networks	Customer engagement optimises idea generation	Journal of Strategic Marketing
Zhang & Kandampully & Bilgihan, 2015	Engaging customers in innovation also has advantages for companies. When Starbucks invested and built its OCC platform MyStarbucksIdea.com, it enticed tech-savvy community members to join by offering various incentives if they shared, voted, discussed and reviewed ideas in themed categories. More than 200,000 ideas, to date, have emerged from MyStarbucksIdea.com, and more than 1,000 of those ideas have been put into action to improve Starbucks' products and services, while also enhancing customer experiences and involvement	Customer engagement optimises idea generation & screening	Journal of Hospitality and Tourism Technology
Dahan & Srinivasan, 2000	Concept development uses customer input by drawing on user prototypes developed by lead users. This is a product concept or a development solution that can be picked up in this stage of development. Concept development is also supported by participation of users in evaluating alternative concepts.	Customer engagement optimises concept development	Journal of Product Innovation Management

Fuller & Matzler, 2007	Mobile gaming enthusiasts playfully familiarised with the new service tested the platform and downloaded their self-created games to their mobile phones. When customers exchange opinions or ideas in a virtual community, these interactions generate data	Customer engagement optimises concept development	Technovation
Shawney et al. 2005	Tools for front-end stages and deep customer engagement (suggestion boxes, advisory panels, virtual communities, Web-based idea markets) are more relevant to the ideation and concept development stages.	Customer engagement optimises concept development	Journal of interactive marketing
Nambisan (2002)	Customers have played the role of product cocreator for example, by participating in concept testing (Page & Rosenbaum, 1992)	Customer engagement optimises concept development	Academy of management review
Xie, Wu, Xiao & Hu, 2016	When customers participate in value co-creation process, for example, designing a customized product on a digital platform, their actions are recorded as data and collected by firms for analysis (Efros, 2014)	Customer engagement optimises concept development	Information & Management
Kambil et al., 1999	As cocreators of products, customers can contribute to a variety of product design and development activities, including the validation of product architectural choices, the design and prioritization of product. In the consumer sector also, customers have played the role of product cocreator for example, by participating in concept testing consumer idealized design, and component selection	Customer engagement optimises product development	Outlook Magazine
Sawhney & Prandelli, 2000	Customers can be involved in cocreating ideas with firms, in testing finished products, and in providing end user product support.	Customer engagement optimises product development	Journal of interactive marketing
Nambisan (2002)	Customers have played the role product co-creators by participating in researching for consumer idealized design (Ciccantelli & Magidson, 1993), and component selection (Kambil et al., 1999; Nambisan, 2002).	Customer engagement optimises product development	Academy of management review

(Shawney et al. 2005)	Tools in the back-end stages and broad customer engagement like toolkits for users innovation, open source mechanisms, web-based patent markets are more fit to improve the product development phase	Customer engagement optimises product development	Journal of interactive marketing

Table 4

2.4.3 Internet of things

Today, the number of devices that are connected to the internet has increased immensely. Devices that are connected to the internet collect intelligent information with sensor technology, therefore they can be used as industrial design tools. Oliana (2016), argue that it is expected that there will be many businesses that use data from smart products. They will be able to use these data in the feedback loop between product launch and ideation to optimise the new product development process. Additionally, it is also expected that businesses will use the same data to identify market segments in detail which is useful to create a fitting marketing strategy (Oliana, 2016). In research of Jara et al. (2014), a participative marketing model is introduced that gives feedback from product to the business, which is something that can be done with the internet of things. It works with the identification technologies of the Internet of things with sensory devices like RFID or Barcode. First, the business received feedback from proactive customers through social media, internet and mobile platforms. Afterwards, this data can be analysed to conduct analytics from the business side to reach a positive influence on the customers (Jara et al., 2014), which can also be advantageous to build an appropriate marketing strategy. Data flows from sensors can be processed quickly in most organisations (Lv, 2019).

With the emerge of the internet of things environment, the interaction between humans and machines can now realise the remote-controlled computer-aided industrial design, this can make designing more convenient to designers (Tian et al., 2018). Data received from the product can give ideas to product designers about how the design can be better. To elaborate, Mischo, 2016 explains that data that is received from IoT devices contain information about the product design, usage, operating environment, maintenance history, customer preferences and resource consumption. So basically, the fuzzy front end of the NPD can be optimised greatly with data from sensors. Sensor data can give deeper levels of insight about customers, such as customer demand. The way that it is different than customer voice research is that data will be sent to companies that give information about how customers use the products in their daily routines. This is the main advantage of the Internet of things. This data can also be of great value for testing of prototypes and new product features (Mischo, 2016). As a result of the Internet of things, companies can discover various requirements from various customers. These requirements have to be filtered as some of them can be meaningless, the designers need to filter and translate these requirements into products (Tian et al., 2018).

With all these data that is collected from smart products, it is now possible to conduct continuous engineering. IBM claims that product development can be changed by the internet of things as products are no longer isolated. ‘’They become a combination of product and network-derived service. And product designs must continuously adapt to the ever-evolving Internet of Things, of which they are a part’’. Product development has to go from the old model of design, manufacture sell to closed-loop development where ‘’operational insights continuously informing product creation, update and improvement.’’ This is where continuous engineering comes in. IBM defines continuous engineering as ‘’an integrated approach to product development that: verifies work continuously to keep projects on track, reuses assets and information to save time and effort and makes effective use of analytics-driven insight throughout development’’ (IBM, 2015). Also, according to Caputo, Marzi and Pellegrini (2016), products with RFID tag directly embedded in the product, which are also constantly connected product constant flow of data. These produced data is useful for product tracking, production planning and strategic decision making. This is also called ''smart manufacturing'' (Caputo, Marzi & Pellegrini, 2016).

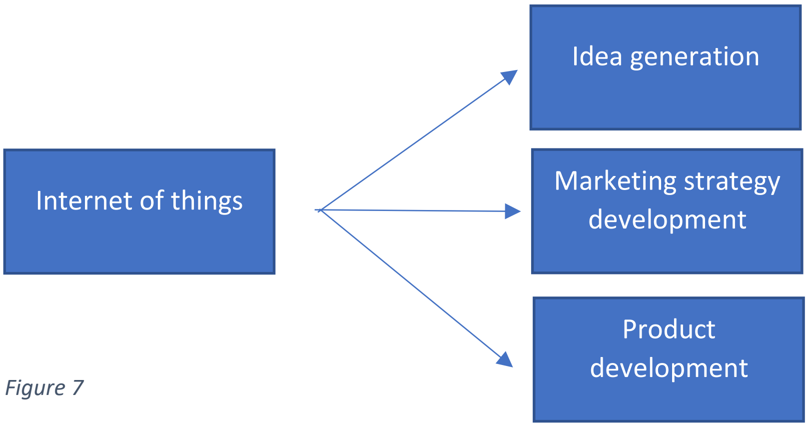


Figure 7

Author(s)	Article quote	Topic	Journal
Oliana, 2016	It is expected that businesses that use smart product data will be able to Use smart product data in the feedback loop between product launch and ideation to improve future New Product Development processes.	Internet of things optimises idea generation	Bachelor's thesis, University of Twente
Oliana, 2016	It is expected that businesses that use smart product data will be able to identify market segments in detail, down to the individual level	Internet of things optimises marketing strategy and development	Bachelor's thesis, University of Twente
Jara, A. J., Parra, M. C., & Skarmeta, A. F. (2014).	Through the identification technologies of Internet of things (RFID or Barcode) the business receives feedback from the proactive consumers, through social media and the capabilities offered by the new generation of internet and mobile platforms. This can be analyzed with the objective to carry out the required actions from the business side to reach a positive influence on the consumers.	Internet of things optimises marketing strategy and development	Personal and Ubiquitous Computing
Mischo, 2016	Sensor data can provide deeper levels of insight about customers such as information about latent customer needs. The main advantage with regards to customer voice research is the ability to get insights into how customers use products in their daily routines, which was previously not possible. Insights into how customers use products and devices can be of great value for the testing of prototypes and new product features.	Internet of things optimises product development	Bachelor's thesis, University of Twente

Tian, B., Yu, S., Chu, J., & Li, W. 2018	Intelligent tools with intelligent information collection technology, sensor technology, sensing technology, can be used as industrial designers design tools. With the development of IoT technology, various people will have a variety of requirements. Some of these requirements are meaningful to designers and users, some are meaningless, how to filter, and how to translate these requirements into products need the wisdom of designers	Customer engagement optimises product development	MATEC Web of Conferences
Caputo, Marzi & Pellegrini, 2016).	Produced data is useful for product tracking, production planning and strategic decision making: smart manufacturing.	Customer engagement optimises product development	Business Process Management Journal
IBM, 2015	Product development has to go from the old model of design, manufacture sell to closed-loop development where ‘’operational insights continuously informing product creation, update and improvement.’’ This is where continuous engineering comes in. IBM defines continuous engineering as ‘’an integrated approach to product development that: verifies work continuously to keep projects on track, reuses assets and information to save time and effort and makes effective use of analytics-driven insight throughout development’’	Customer engagement optimises product development	N/A

Table 5

2.4.4 Neuromarketing

With Neuromarketing it is possible to identify the needs of customers, and therefore product developers will be able to develop more useful and pleasant products (Eser, Isin & Tolon, 2011). Neuroscience provides the potential to predict the differences in the thought process of customers when they look at a product, which might not be observable with their behaviour (Venkatraman et al., 2012). Generally, people do not want to explain or cannot tell why they went for a certain product, because 95% of the decision-making process is tacit for many customers in case of consumer goods (Zamani, Abas & Amin, 2017). Although the applications of neuroscience for the fuzzy front-end are still rare, evidence that designers, engineers and neuroscientist can work collectively to create products and services that match the preference of customers is increasing. However, the evidence is increasing that neuroimaging can make tacit knowledge of customer’s preference more implicitly without them explaining it, this is normally not possible through traditional methods (Suomala, 2018; Glimcher and Fehr 2013; Falk et al. 2016; Boksem and Smidts 2015; Venkatraman et al. 2012).

The contribution of neuromarketing helps to improve branding or brand positioning strategies. Goto et al (2019) suggest that ERPs related to some consumer articles may be relatively accurate predictors of behavioural preferences before a product is purchased. Branding Research examines how brand information influences decision-making (Hubert & Kenning, 2008). The question about how brand information influences decision-making can be answered with neuromarketing. This is done with a study to decide which neural processes are engaged in the brain during the processing of brand information (Hubert & Kenning, 2008). Most of the applications of neuromarketing are related to advertisement optimisation (Bridger, 2015). There is an upcoming trend to apply brain scans both electroencephalography (EEG) and fMRI to advertising optimisations. All in all, there is information about the human brain about customer preferences which can only be attained via neuroscientific evidence (Glimcher & Fehr 2013; Falk et al. 2016; Boksem & Smidts 2015). This has encouraged many managers to apply these results for solving real marketing problems (Suomala, 2018).

Cherubino et al., (2019), claimed that neuromarketing has evolved because, through neurometric instruments, scientists can provide new research methods, which can provide new insights to understand how and why consumers respond to marketing stimuli and interact in the marketplace (Cherubinho et al., 2019). As neuroimaging's ability to predict or influence purchasing decisions after design seems to be limited, neuroimaging is more appropriate for calculating reactions before the products are marketed. As neuroimaging can obtain information into the product experience itself (Ariely & Berns, 2010).

Understanding the neural mechanisms of decisions will improve the ability of product marketers to enhance the marketing of their products. As neuroscience can model potential influences on the decision process. This includes pricing, choice strategy, context, experience, and memory, in addition, it can give new information into individual differences in consumer behaviour and brand preferences (Venkatraman, 2012)

Experienced people in behavioural economics found that decisions on purchasing behaviour are not fully rational nor predictable. In most of the cases, they are influenced by subjective emotions. Regarding long term product strategy, customer neuroscience can be applied to decide which customer segments are targeted through advertising strategies, or if there is a chance that there will be any future purchases of the brand (Hubert & Kenning, 2008). It can also be applied in the determination of the market potential for a new product or discontinued products. The new techniques that are offered by an upcoming field can address the questions that can relate to the potential profitability of the revitalisation of a discontinued brand (Kenning et al., 2002; Braeutigam, 2005). In every human there is a different cognitive constrain, this means that every different marketing techniques that appeal to specific emotional states is differently effective and is also limited because the marketing message will not be received, interpreted and understood by everybody in the same way for the intended manner (Wrona, 2014).

Author(s)	**Article quote**	**Topic**	**Journal**
Eser, Isin & Tolon (2011)	Neuromarketing can identify consumers’ needs and, therefore, to develop more useful and pleasant products	Neuromarketing optimises Idea generation	Journal of Marketing Management
Suomala, (2018).	There is growing evidence that neuroimaging will reveal information about consumer preferences that are unobtainable through conventional methods	Neuromarketing optimises Idea generation	Innovative Research Methodologies in Management
Goto, Lim, Shee, Hatano, Buratto, Schaefer (2019)	The contribution of neuromarketing helps enhancing branding or brand positioning strategies.	Neuromarketing optimises Marketing Strategy Development	Frontiers in integrative neuroscience

Venkatraman, V., Clithero, J. A., Fitzsimons, G. J., & Huettel, S. A. (2012)	Just as neuroscience can model potential influences on the decision process—including pricing, choice strategy, context, experience, and memory—it can also provide new insights into individual differences in consumption behaviour and brand preferences	Neuromarketing optimises Marketing Strategy Development	Journal of consumer psychology
Venkatraman, V., Clithero, J. A., Fitzsimons, G. J., & Huettel, S. A. (2012)	Neuromarketing can potentially predict differences in thought processes being deployed by consumers that might not necessarily be observable with behaviour	Neuromarketing optimises Marketing Strategy Development	Journal of consumer psychology
Hubert & Kenning (2008)	Branding research is engaged in examining how brand information affects decision-making	Neuromarketing optimises Marketing Strategy Development	Journal of Consumer Behaviour
Hubert & Kenning, (2008)	Neuromarketing can answer this question with a study to determine which neural processes are involved in the brain during the processing of brand information	Neuromarketing optimises Marketing Strategy Development	Journal of Consumer Behaviour
Cherubino et al., (2019)	Neuromarketing has emerged because, through neurometric tools, scientists can offer new research methods, that can provide new insights to understand how and why consumers respond to marketing stimuli and interact in the marketplace	Neuromarketing optimises Marketing Testing	Computational intelligence and neuroscience
Wrona (2014)	People have different cognitive constraints, meaning that the effectiveness of various marketing techniques appealing to specific emotional states is also limited as the marketing message sent is not necessarily received, interpreted and understood in the intended way	Neuromarketing optimises Marketing Testing	Marketing Instytucji Naukowych i Badawczych

Hubert & Kenning (2008)	With regard to long-term product strategy, consumer neuroscience could be used to determine which consumer segments are reached by advertisement strategies, or whether a future purchase of the brand is probable	Neuromarketing optimises Marketing Testing	Journal of Consumer Behaviour
Hubert & Kenning, (2008)	Another possible field of application is the determination of the market potential for a new product or for discontinued products. The new techniques offered by the emerging field could address the questions associated with the potential profitability of revitalization of a discontinued brand	Neuromarketing optimises Marketing Testing	Journal of Consumer Behaviour

Table 6

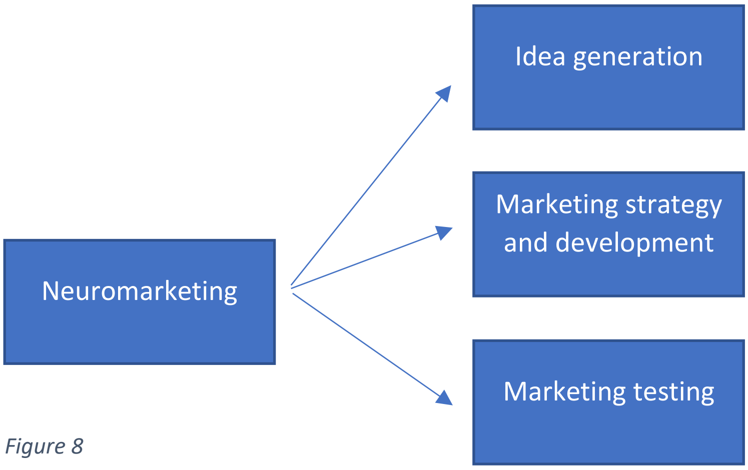


Figure 8

2.4.5 Search data

Kulkarni, Kannan and Moe, 2011 argue that data on search terms used by consumers can provide interesting measures and signs of consumer interest in a product, concept or a term. To explain, the indication of consumer interest can be used to forecast sales. They find that the use of search terms follows fairly obvious patterns periods before and after the launch and that the model gives a powerful force in predicting the release of release week sales as a function of search activity prior to release (Kulkarni, Kannan & Moe, 2011). Wu and Brynjolfsson, 2015, state that conventional economic and business forecasts are based on statistics collected by government agencies, annual reports, and financial statements. These are always published with a published delay and collected in a relatively small number of pre-specified categories. This limits their usability for predictions, especially for dealing with time-sensitive issues of a new question. Always when any customer who is a business decision-maker searches for a product via the Internet, there will be interesting information revealed about the customer's intention to make a future purchase (Wu, & Brynjolfsson, 2015). Customer search data, with name data collected from Google Trends, can be useful to reduce sample forecasting errors, adding customer search data to time series models collected from sample forecasting errors. source of input that can inform future forecasts. Knowledge of these intentions can be used to predict future demand (Boone et al., 2018)

Afshari and Peng, 2015 used Google Trend to generate data sets, with that they proposed a method to minimize uncertainty effects on product design objectives in the design phase. Big Data analytics can be used in different stages of the product design phase (Afshari & Peng, 2015).

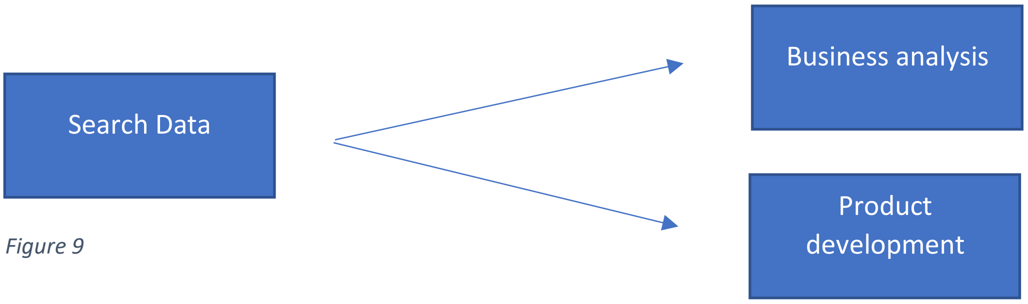


Figure 9

Author(s)	**Article quote**	**Topic**	**Journal**
Kulkarni, Kannan and Moe, 2011	Data on the search terms used by consumers can provide valuable measures and indicators of consumer interest in a product, concept or a term. The use of search terms follows fairly predictable patterns in pre-launch and post-launch periods and that the model provides a powerful force in predicting the release of release week sales as a function of search activity prior to release	Search data optimises Business analysis	Decision Support Systems
Wu, & Brynjolfsson, 2015	Every time a consumer of a business decision maker searches for a product via the Internet, valuable information is revealed about the person's intentions to make a future economic transaction	Search data optimises Business analysis	Economic analysis of the digital economy
Boone et al., 2018	Customer search data, with name data obtained from Google Trends, can be used to reduce sample forecasting errors, adding customer search data to time series models obtained from sample forecasting errors. source of input that can inform future forecasts.	Search data optimises Business analysis	Production and Operations Management

Afshari & Peng 2015	Afshari and Peng, 2015 used Google Trend to generate data sets, with that they proposed a method to minimize uncertainty effects on product design objectives in design phase. Big Data analytics can be used in different stages of product design phase	Search data optimises product development	International Design Engineering Technical Conferences and Computers and Information in Engineering Conference

Table 7

Discussion

The goal of this research was to identify the primary sources of the customer-generated inputs (Big Data) and their role as inputs to the NPD process. To identify this, the following research question was developed: 'How can customer-generated Big Data improve the speed, efficiency and success rate of the NPD processes? In answering the research question, this research presented literature regarding the connection between the specific inputs of big data and the phases of the new product development process. Afterwards, a new framework has been created according to a systematic literature review which can be used by managers to choose which co-creation sources they should utilise in a specific phase when developing a new product. To answer the research question, this article first split the new product development process and the big data sources into its concepts to be able to create a more in-depth overview with each other. This is to have a deeper understanding of the relation between big data and new product development. At the beginning of the literature review, development and the innovation process and the co-creation inputs were explained so the reader will have a clear image on how the innovation process has developed through the years and to show that there is a new model in progress, namely crowdsourcing/big data. Afterwards, the co-creation inputs were explained and how these inputs are affiliated to big data. Finally after an intensive search in the literature and summarising them, all new product development processes where assigned to the affiliated co-creation inputs. Together with this, it has also been found out that big data collected from search data can affect the new product development process. At the stage of customer engagement, many examples about communities are being used in case of large firms, like Starbucks, as these companies are more attractive for customers to engage with, I believe that it is less likely that there will be a huge amount of people engaging in communities of small firms. Furthermore, some predictions about successful products are made by top managers of large companies who were aware of the voice of customers collected within their companies. The voice of customers, upon which their forecasts were made, apparently was incorrect. Examples of these are: "There's no chance that the iPhone is going to get any significant market share." (Steve Ballmer, former CEO of Microsoft, 2007.) "There is no reason anyone would want a computer in their home." (Ken Olsen, co-founder and president of Digital Equipment Corporation (DEC), 1977. Moreover, unfortunately, there are not many articles found in journals about how the internet of things can be used in new product development, many research about this has only been done in conferences and bachelor theses. This might be because it is a fairly new technology and it might take time to properly research the effect it has on certain new product development phases. Lastly, this thesis was written in 2019/2020, there is always new research published about this topic because it is a fairly new concept. Therefore there is still room for changes in the framework in the future.

Limitations

Naturally, a systematic review is prone to several limitations. This part of the dissertation will discuss the limitations of the study. First, the selection procedure was done only by the author of this research. Therefore it misses a process of revision by a second researcher. Thus, there is a chance that some studies are not included. Tranfield et al. (2003) explained that only studies that meet all inclusion criteria specified in the assessment protocol and that do not show any of the exclusion criteria should be included in the assessment. The strict criteria used in the systematic review are linked to the desire to base assessments on the evidence of the best quality. Because decisions regarding inclusion and exclusion remain relatively subjective, this phase of the systematic review can be performed by more than one reviewer. Which is not the case in this research, because only the author has reviewed the articles. In addition, the criteria were not strict either as the articles that were selected are not all from highly regarded journals, many of them even come from conferences or bachelor theses. This can be crucial, as even one review proving a certain relation between the co-creation sources and phases of the new product development process can change the framework. As this research is written in 2019/2020, and the fact that the concept is fairly new, there is always room for technological improvements which can extend the framework. Another limitation entails that many articles used in the articles to describe the relation between co-creation sources and specific phases of the new product development processes are tested within specific products/cases. Therefore, it might be that some relations are not applicable in all cases, thus it has less generalisability. This systematic review has research from different kinds of industries, this can give a broad view, however it might give a heads up to companies at the same time since they have to implement the framework in a way that is beneficial for their products. Furthermore, some of the relations tested are not published in journals, but in conferences or student dissertations, and therefore it might question the strength of the framework.

Conclusion

Big data has often been found to have a positive effect on the New Product Development process (Constantinides & Lorenzo, 2015; Yu & Yang, 2017; Tan & Zhan, 2017; Zhan et al., 2018; Jagtap & Duong, 2019; Horvat et al. 2019). This systematic review has reviewed more in-depth on how the parts of these processes and concepts identify each other. For the customer's voice, creating online platforms to collect suggestions from customers to collect more ideas, these ideas can also be screened by the customers itself by having them choose the best ideas. Furthermore, data from the voice of customers can be collected to segment the demographics of a product because with big data they can detect from which demographic the voice comes from, this will help the market segmentation for their marketing strategy. Lastly, the voice of customer collected from internet reviews to predict future popular product designs. Preference trend algorithms can be created from collected useful assessments from online reviews that the design engineers can use to predict future design trend. For customer engagement, big data can optimise idea generation by using online co-innovation communities (OCCs) to connect with customers through social networks, moreover, concept development and testing can be improved by having customers participate in evaluating alternative concepts or by drawing on user prototypes developed by lead users. Product development can be optimised by involving customers in product design and development activities with for example by engaging them in testing idealised design and component selection. Customers can also be usefully engaged with conducting experiments for evaluation. Here they test finished products and provide end-user product support. For the internet of things, idea generation is improved by data retrieved from smart, connected objects. Smart product data can help to identify market segments and offer participative marketing to enhance marketing strategy and development. Furthermore, sensor data can provide information about latent needs, this is possible due to collecting data on how customers use their products. This is of great value for testing of prototypes and new product features. Moreover, IoT can help new product development with continuous engineering or smart manufacturing, products with RFID chips sent data about the product, for example when they need an update and what the product is doing wrong. This can help engineers to better address the challenges of developing the products.

Neuromarketing has an impact on the process of the generation of the initial idea for a product by revealing with neuroscience information about customers that is otherwise unobtainable. Development of the marketing strategy by contributing to the brand position strategy to see what is involved in the brain during the processing of brand information. Marketing testing by predicting how the customer will react to the product. Lastly, search data collected from google trends can decrease forecasting errors in the business analysis stage by adding search data to time series models. It can also minimize uncertainty effects on product design objectives in the design stage. By conducting this systematic review the big data sources that were effective on the specific New product development process where identified. Figure 10 shows the framework that is finally created according to the literature review. This framework tries to show which Big Data sources can optimise, according to the systematic literature review, a specific innovation/NPD processes. So it is not only explicit that Big Data has a positive effect on New Product Development, but it should also be clear now which of the sources have a positive effect on which processes.

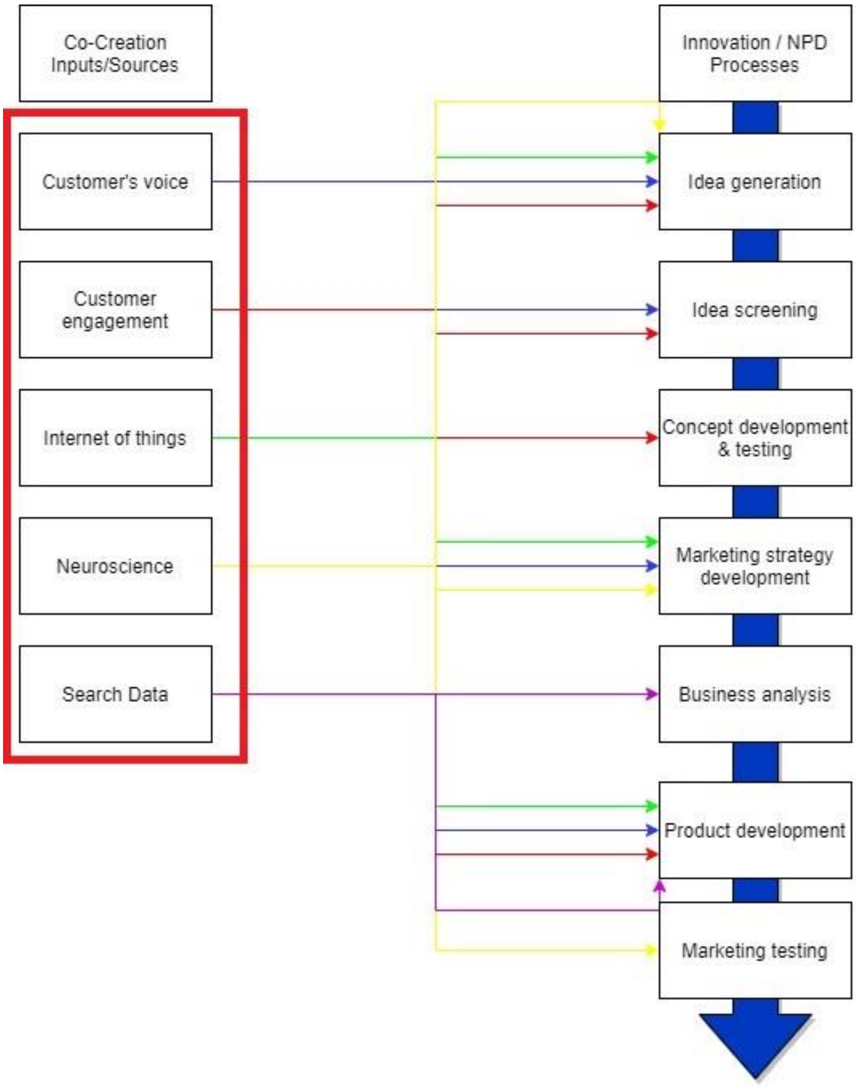


Figure 10: Big data innovation framework

Practical implications and future research

This research contributed to the academic realm by going in deeper to the relation between the new product development and Big Data co-creation sources. It might be new for managers to try this framework for the new product development process. The identified co-creation sources to each phase of the new product development process can be combined in many different ways. By following this framework, it will be possible to see in every process of developing a new product, where to get the data from. By combing these big data sources and implementing them on the right NPD process, it can influence the whole process. Small companies should take note that they might have more difficulties in collecting data and using this whole framework might be difficult for them. Though, they might adjust the framework and use it differently by opting for cheaper ways of Big data like customer's voice and search data to collect Big data. They can leave out some NPD phases and conduct some phases without using Big data. In the scientific world, this research can also be relevant for other scientists to create algorithms to predict the strength of the relationship between each co-sources to the specific new product development phase. Mathematicians can also build algorithms to predict the success of a new product with the help of this framework as they can leave out specific NPD processes for every co-creation sources. This research can also be extended with text mining. This can be applied to aid in systematic reviewing. A third-party implementation of LDA in python, Gensim, can be used to predict the topic distribution for each document. This implementation uses a different method to estimate topics, an online algorithm. Topic modelling is a text mining technique that discovers patterns of word co-occurrence across a corpus of documents; these patterns of word co-occurrence are then conceived of as hidden “topics” which are present in the corpus.

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