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THE ROLES OF BIG DATA AND THICK DATA IN THE DESIGN THINKING PROCESS

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ABSTRACT

This paper studies the role of Big Data and Thick Data in the innovation process of Design Thinking, one of the most commonly used methods for innovation in business. Analyzing the strengths and weaknesses of each of the types of data reveals that Big Data is a great tool for up-to-date and representative quantitative insights, but it does not go deep enough for the purpose of innovation. Thick Data, however, provides in-depth knowledge that enables researchers to understand the consumers' behavior, but the methodology behind it does not allow for large samples to be used in order to make inferences about the population. Therefore, it can be concluded that they are both necessary to achieve the best possible results in the process. By gaining insights about the needs, wants and motivations of the consumer with Thick Data and using Big Data for confirmation and performance tracking purposes, companies can achieve innovation with Design Thinking in the most effective manner.

Key words: innovation, Design Thinking, Big Data, Thick Data, data analysis, consumer behavior, consumer insights

RESUMEN

Este trabajo examina el papel del *Big Data* y el *Thick Data* en el proceso de innovación *Design Thinking*, uno de los métodos más usados para promover la innovación en las empresas. El análisis de las fortalezas y debilidades que presenta cada tipo de datos revela que el *Big Data* es una estupenda herramienta para obtener datos cuantitativos, actualizados y representativos de la población, pero no son lo suficientemente profundos para el proceso de innovación. En cambio, el *Thick Data* proporciona información detallada que permite comprender la conducta de los consumidores. Sin embargo, la metodología para conseguirla no permite trabajar con grandes muestras de población con las que se pudieran hacer inferencias. Por tanto, se puede concluir que ambos métodos son necesarios para conseguir los mejores resultados. Compañías que usen el *Thick Data* para investigar acerca de las necesidades, deseos y motivaciones de los consumidores y empleen el *Big Data* a modo de confirmación y para realizar seguimientos de rendimiento conseguirán innovar de la manera más efectiva usando el *Design Thinking*.

Palabras clave: innovación, Design Thinking, Big Data, Thick Data, análisis de datos, conducta del consumidor, información sobre el consumidor

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EXHIBIT INDEX

1. INTRODUCTION

1.1. Objectives

This report aims to analyze the role of Big Data and Thick Data as tools for innovation in the Design Thinking process. Through a thorough review of the existing literature, I will identify the strengths and weaknesses of each type of data and their distinct role in the process, examining which type of data is the most suitable for each of the stages and how they should be used.

1.2. Methodology

For the purpose stated above, this report was written following a qualitative methodology. The review of the literature entailed research of the secondary sources available on the topic such as reports, articles and interviews. The information used comes mostly from experts on the field of data and or innovation, or professionals with extensive relevant experience in the field. The material was found by searching the databases available through the Northeastern University Library resources. Some of the databases used are Business Source Complete (EBSCOhost), ProQuest, Harvard Business Review and Statista among others. Other sources include The New York Times, TED, and consulting firms like The Boston Consulting Group and McKinsey, for the purpose of accessing real business cases and the insights of professionals on the field. The research was carried out using key terms such as innovation, Design Thinking, data analysis, Big Data and Thick Data.

The information was then examined and synthesized to explain, compare and contrast the different insights of the authors, in order to then make associations between the uses of Big Data and Thick Data and the tasks assigned to each of the stages of the Design Thinking process. In addition, these associations were then illustrated and explained further with real cases of companies such as Airbnb where they used the Design Thinking method.

1.3. State of the Art

1.3.1. Innovation

Innovation has been and still is one of the most talked about topics in the world of business in the last few decades. According to Meyer and Crane (2018), both authors and professors at Northeastern University, throughout the last twenty years, most organizations all around the world have shifted their focus towards innovation. However, research shows that almost every American firm considers innovation as one of their biggest challenges and most of the time the average company is failing at it (Meyer & Crane, 2018).

Innovation in businesses is a term that can translate in many different ways. Therefore, it may be the case that firms do not have a clear goal as to what exactly innovation means for them and what they want to accomplish with it. According to Beth Altringer (2013) the failure rate of projects related to innovations is between 70%-90% and she attributes this very concerning figure to lack of time and resources.

It is worth mentioning that organizations, far from being isolated, affect and are affected greatly by their environment. The outcome and even the entrepreneurial spirit of a company is directly influenced by the business environment, whose forces can be divided into internal, like the status of the area of the organization (growing, mature or in decline) and the availability of resources; and external, that would include suppliers, customers, competitors and the economy. In terms of the status of the area of the organization in question, the mature and declining phases are usually the ones during which most innovations happen, new initiatives are not as appealing in times of growth (Feraru, 2017). However, it is important for companies to anticipate these moments of decline and to be in the constant look for new opportunities. This is probably one of the main challenges that make being an innovative company so difficult, focusing on your activity and main sources of revenue while also keeping an eye out for new opportunities that can come in many different shapes and forms.

1.3.1.1. Innovation as a Source of Competitive Advantage

This drift in organizations' focus towards the challenging phenomenon that is innovation, is supported by numerous studies and authors. Among them, the Austrian political economist Schumpeter, as far back as 1934, already argued that competitiveness and economic dynamics were driven by innovation and that anybody looking for profits must innovate (Feraru, 2017). Almost a century ago economists were already acknowledging the value of innovation in businesses and the fact that to remain profitable and in a favorable position in the market, companies would have to work to ensure they were seeking new opportunities and not remaining stagnant.

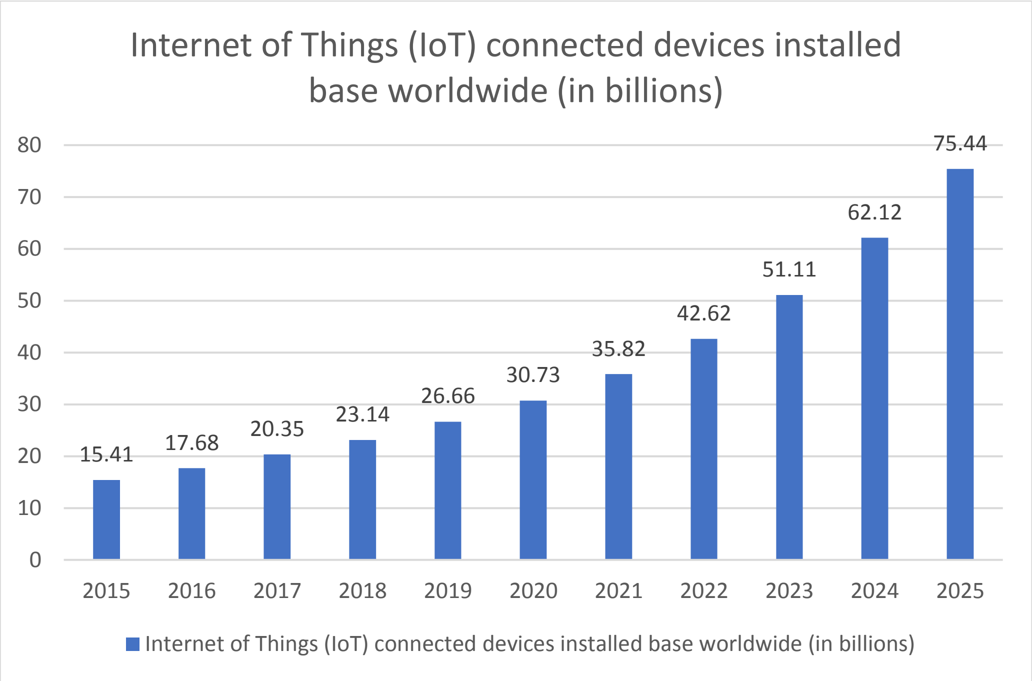
Nowadays that remains true, as innovation is still believed to be of great value for companies. In a survey conducted yearly by The Boston Consulting Group, results showed that innovation was the top-priority or among the top three at their organization for almost 80% of respondents (Ringel, Taylor & Zablit, 2015). This, once again, showcases the relevancy of the topic, especially in the past decades.

According to Feraru (2017), innovation can not only increase organizations' revenues and profits in traditional ways like the creation of new products, but it can also bring other indirect benefits. Companies or divisions that are considered innovative are usually better regarded in the market or within the company. Therefore, it could serve as one favorable point in marketing campaigns. In addition, unsuccessful innovations can also lead to more ideas that can eventually drive to other discoveries. Lastly, companies will be able to gain learnings and knowledge from all attempts and these can help improve the firm or division's effectiveness or efficiency (Feraru, 2017). In conclusion, it is most likely that innovation will only be beneficial for the organization, since even if the initiative turns out to be unsuccessful, it will generate new knowledge and the company will boost their image by being considered innovative and ambitious.

However, some may argue that not only is innovation beneficial for businesses, but that it is necessary. The marketing specialist and contributing writer for Northeastern University, Will Purcell (2019), talks about the need of businesses to continuously adapt in order to succeed nowadays making reference to the phrase “adapt or die”. This is especially true in the present times when new technologies and events now have the power to change the way the whole world works. In fact, one of the main factors Purcell highlights for the importance of innovation is keeping businesses relevant.

Indra Nooyi, CEO of Pepsi, when interviewed by Adi Ignatius (2015) also confirmed that companies do have to reinvent themselves a lot more often nowadays to keep their competitive advantage. This is because, as mentioned, technologies are rapidly changing the environments in which organizations function. There are numerous facts and figures that prove this such as that there are now almost 31 billion devices connected to the internet according to Forbes (2016), and that this number is predicted to keep growing exponentially as shown in the graph below (Exhibit 1). The fact that we are all connected means that what happens in one place can also be disruptive in the other side of the planet, and this is a reality companies have to learn to live with and also use to their advantage when possible.

Exhibit 1: Billions of connected devices worldwide from 2015 to 2025



Source: Forbes, 2016

Another factor discussed by Purcell (2019) is the role of innovation as a promotor of growth in companies, whether that is through incremental growth by improving the current product or business model, by expanding into a completely different line… innovation can lead the scaling of companies in many different ways, which is probably why some of the most successful companies nowadays such as Google, Amazon or Apple are also some of the most innovative according to the Most Innovative Companies 2019 report by The Boston Consulting Group, as presented in the table below (Exhibit 2).

Exhibit 2: Table with most innovative companies of 2019

1	Alphabet/Google	**21**	McDonald's	**41**	Dell
2	Amazon	**22**	Marriott	**42**	Walmart
3	Apple	**23**	Alibaba	**43**	eBay
4	Microsoft	**24**	Bayer	**44**	HP Inc.
5	Samsung [1]	**25**	AT&T	**45**	ING
6	Netflix	**26**	Allianz	**46**	BP
7	IBM	**27**	BMW	**47**	Daimler [2]
8	Facebook	**28**	SAP	**48**	Huawei
9	Tesla	**29**	Philips	**49**	Rio Tinto
10	Adidas	**30**	Royal Dutch Shell	**50**	Hilton
11	Boeing	**31**	AXA		
12	BASF	**32**	Unilever		
13	T-Mobile [3]	**33**	Salesforce		
14	Johnson & Johnson	**34**	Pfizer		
15	DowDuPont	**35**	Stryker		
16	Siemens	**36**	NTT Docomo		
17	Cisco Systems	**37**	Toyota		
18	LG Electronics	**38**	Volkswagen [4]		
19	Vale	**39**	3M		
20	JPMorgan Chase	**40**	General Motors		

Note:

[1] Includes only Samsung Electronics

[2] Includes Mercedes-Benz

[3] Includes only US T-Mobile, not Deutsche Telekom

[4] Includes Audi and Porsche

Source: Ringel, Grassl, Baeza, Kennedy & Manly, 2019

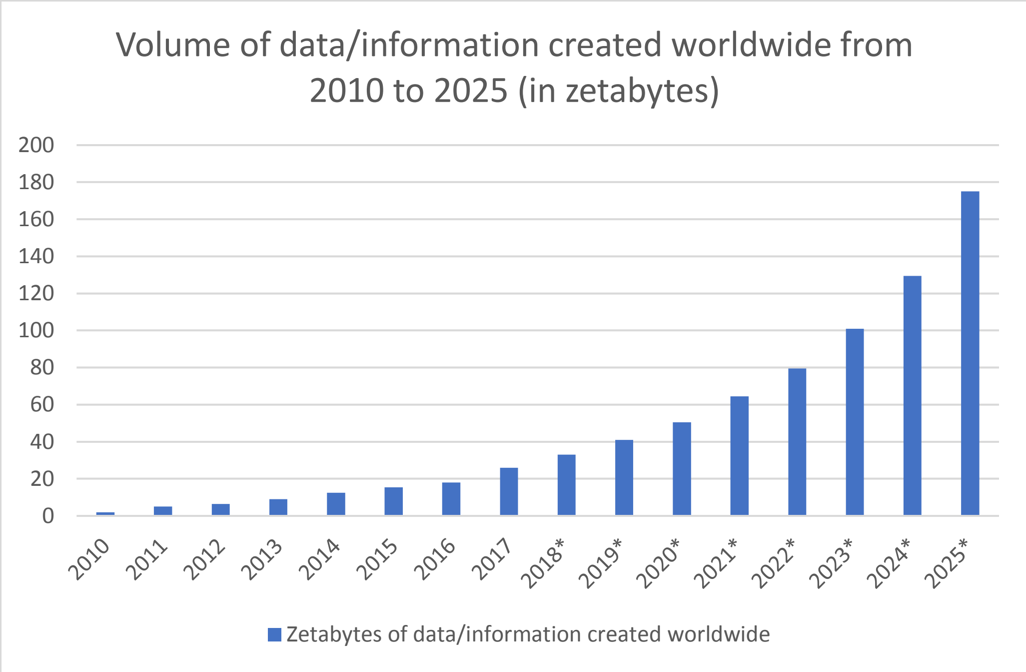
The last factor stated why innovation is so important for businesses is the fact that is a way for companies to differentiate themselves. As Will Purcell (2019) acknowledges, innovation is mainly to find a way to do things in a different way to set the business apart of that of competitors. Differentiation is sometimes undervalued, and companies tend to focus too much on incremental improvements that add little value to their business over that of their competitors. However, Chris Zook and James Allen (2011), partners at Bain & Company leading the strategy practice and authors, defend that the essence of strategy and the primary source of competitive advantage is differentiation. It is not enough to perform an activity that brings value to consumers, companies must make sure they are serving them better and more profitably than their competitors. It is this way that they will give them a reason to choose their product or service over the rest of alternatives.

Having talked about some of the main benefits of innovation, companies wanting to act on them have several ways to implement innovation in their activity. One of the most popular ways of stimulating and encouraging innovation in companies, and the one I will be focusing on in this paper is Design Thinking. As the designer, Claudia Kotcha, who works for Procter and Gamble said "Business people don't need to understand designers better, but to adopt design principles into their problem solving approach" (Kotcha, 2006; cited by Skaggs, Fry, & Howell, 2009). This is exactly what Design Thinking provides, a methodology to implement the best of the Design Thinking principles to their activity.

1.3.2. Data analysis

The other main focal point of this paper is Data analysis. Data nowadays can be found and drawn from everywhere. In the past years, the amount of data created continuously is growing exponentially and is expected to continue growing even more in the following years as seen in the graph below (Exhibit 3) by Statista (2018).

Exhibit 3: Volume of data/information created worldwide from 2010 to 2025



Source: Statista, 2018

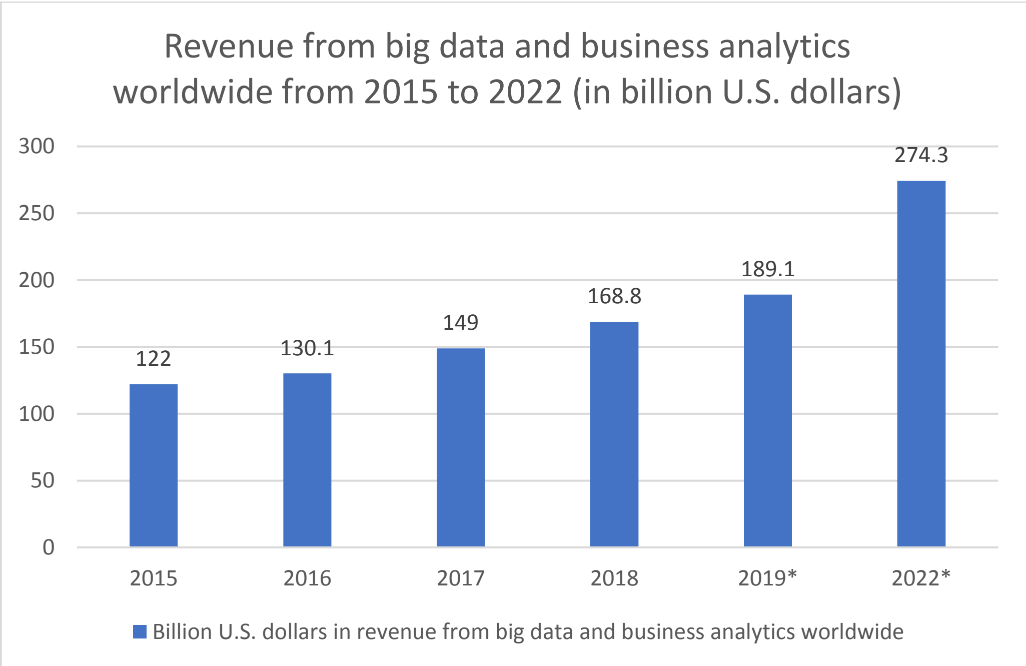
Nowadays, it is not only transactions that generate valuable information, but it can come from any and every interaction with the end user. In fact, services are sometimes offered by companies such as LinkedIn, Twitter, Facebook or Pinterest, free of charge so that they can gain access to more data (Henke et al, 2016).

The companies who are leading in the field of analytics like Apple, Alphabet/Google, Amazon, Facebook, Microsoft, GE, Baidu, Alibaba Group, and Tencent have managed to position themselves among the most valued organizations in the world (Chui & Manyika, 2015; cited by Henke et al, 2016). It was their investments in data infrastructure, unique sources of data, and the best analytics talent that set them apart from the rest (Bughin, 2016; cited by Henke et al, 2016). Therefore, it would not be surprising that if they continue to invest in these technologies, with the increasing amounts of data available, they will continue to grow and be among the top players in their industry. As stated in the McKinsey Global Institute Report “The Age of Analytics: Competing in a Data Driven World” in 2016:

> *The same trend can be seen among the next wave of disruptors: the privately held global "unicorns." These tend to be companies with business models predicated on data and analytics, such as Uber, Lyft, Didi Chuxing, Palantir, Flipkart, Airbnb, DJI, Snapchat, Pinterest, BlaBlaCar, Ola, Snapdeal, and Spotify. This list shows that the next generation of digital leaders is becoming more global* (Henke et al, 2016).

Which means new entrants to the current market are not only investing in analytics but building their business around it. This can be seen in tactics followed by companies such as Quora and Jet who put the same effort on gaining access to valuable data as they do on acquiring profitable clients (Kosoff, 2015; cited by Henke et al, 2016). Furthermore, they seem to be going in the right direction since, as seen in Exhibit 4, revenues from Big Data and business analytics worldwide have been increasing throughout the past years and the International Data Corporation (2019) estimated these revenues to reach a total of $274.3 billion dollars by 2022.

Exhibit 4: Revenue from big data and business analytics worldwide



Source: IDC, 2019

1.4. Main Parts

This report is divided into six parts, the content of which will be detailed below:

The first part is an introduction to the topic. First, the purpose of this report is stated, followed by a description of the methodology used. Then, the state of the art includes information about the relevancy of innovation, Design Thinking and data gathering nowadays.

The second part talks about Design Thinking. Starts by giving an overview of the process and then, goes on to describing three of the most common models: IDEO's three spaces, the Double Diamond and Stanford's Design School model.

The third part reviews the concept of Big Data. Then, three of its applications: performance tracking and optimization, predictive analytics and decision making; are described since they are some of the most relevant for the purpose of Design Thinking; and lastly it presents the possible downsides of this technology.

The fourth part brings the concept of Thick Data forward, going through the description, its disadvantages, and lastly, it compares it to the Big Data method, presenting also the benefits it brings to the table.

In the fifth part, conveying all the information about Big Data and Thick Data presented, the idea of mixed data is introduced. After that, this methodology is applied stage by stage to the Double Diamond method of Design Thinking.

The sixth and last part outlines the main conclusions reached through this research paper, presents the limitations of this report and suggests future lines of research.

2. DESIGN THINKING

As stated above, I will now proceed with the explanation of the Design Thinking process. To understand how the process can aid innovation in the business world, I will present the use of this process and its contributions to innovation in companies, the circumstances when it can be used and three different models to explain the steps to be followed to apply the Design Thinking methodology to a project.

Most people, when faced with a problem, tend to draw upon past experiences and current knowledge to find a solution. Mike Hatrick, Global Head of IP Strategy & Portfolio at Volvo Group Trucks Technology, in an interview with Amanda Ciccatelli (2017) talked about how in his experience, most engineers also tend to look back, think of a similar situation they have faced before and implement the same solution. Although this may work most of the times, it does not lead to innovation. No new things ever emerge from repeating past practices. In addition, people often overestimate their understanding of the issue at hand, meaning that they could mistakenly magnify the similarities of a situation with past experiences causing overconfidence in mediocre solutions for the issue at hand. These are the two main points where Design Thinking can contribute to innovation.

Leigh Thompson is the J. Jay Gerber Professor of Dispute Resolution & Organizations in the Kellogg School of Management at Northwestern University, and the Director of the Kellogg Team and Group Research Center; and David Schonthal is a Clinical Associate Professor of Innovation & Entrepreneurship at the same institution and a Senior Director at IDEO, an award-winning design and innovation consultancy. They defined design thinking as a creative and analytical practice that gives participants the chance to explore, design and prototype, get feedback from users and implement it in new designs (Thompson & Schonthal, 2020).

One of the main attributes that makes Design Thinking such a powerful methodology is the fact that it shines the spotlight in the needs of the consumer. As mentioned in an interview by Dr. Heidi Scott, Chief Learning Officer at HR.com, to Mike Hruska (2020), Innovation Coach and Chief Revenue Officer at Allen Interactions and a former researcher at the National Institute of Standards and Technology, Design Thinking enables people to see their problems from a different perspective, stand in other people's shoes and change the center of attention to your customers' needs and priorities. It is not only a fantastic set of tools and techniques, but also, a frame of thought to use for finding possible ways to solve a problem and testing them in the real world. It can be used to get a better understanding of the environment, the improvement points, see what is possible and ultimately create more value for the customer (Scott & Hruska, 2020). All this can help businesses immensely since, often, is the lack of empathy and understanding of their clients' needs and desires and the environment that prevents them from creating value.

For a while, design and creativity have been regarded as something only relevant to the creation of physical products. Nevertheless, Craig Bedell (2020), head of Bedell Consulting, insurance expert and former Global Insurance Industry Executive at IBM, points out that Design Thinking can serve many more purposes apart from helping create more appealing goods. It can be very beneficial for any product, service, experience or ecosystem surrounding them.

In addition, Mike Hruska (2020) stated that Design Thinking helps to focus the attention in the aspects that will impact and improve the experience of the end user the most. Therefore, not only will they be able to know where they should be looking to improve but they will be able to create the most impact and generate the most benefits out of their actions that will ultimately reduce costs and increase profits.

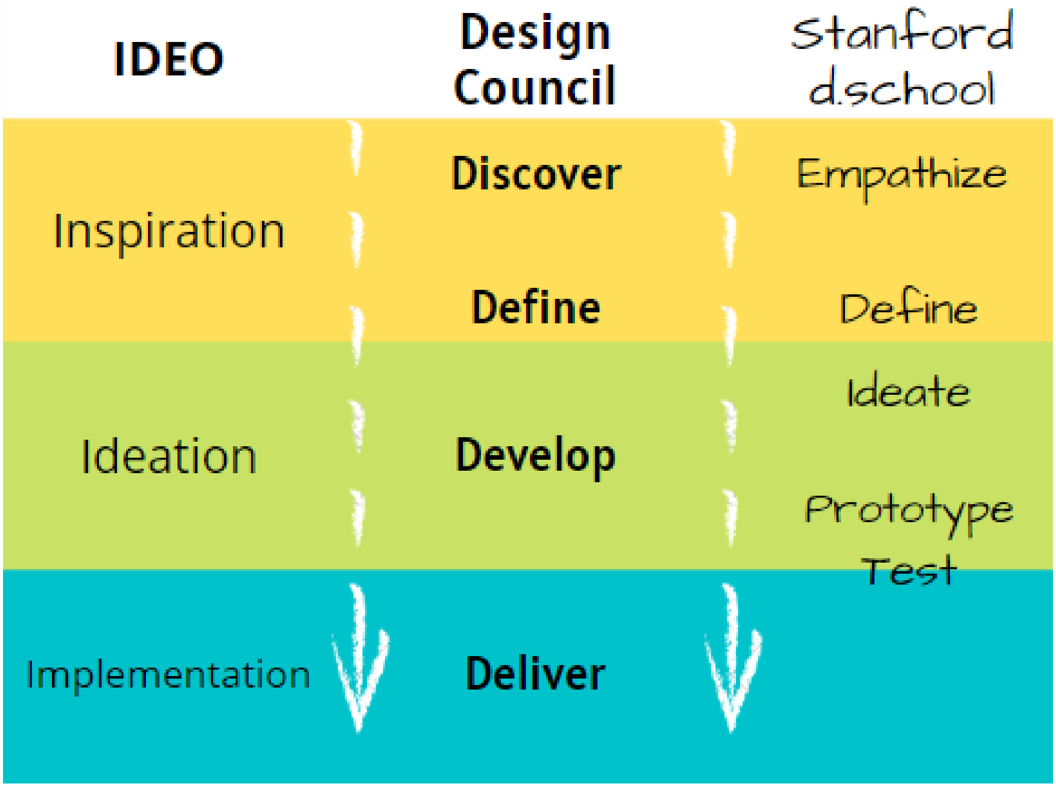
This potential improvement in performance of the companies which implement Design Thinking can be seen in cases in the real business world too. The Partner and Director at Bain & Company and founder of the firm's Global Customer Strategy and Marketing practice, Rob Markey (2020), spotted four main practices looking among hundreds of businesses of different kinds during the over 30 years spent working with them, which have helped the ones with the highest customer loyalty achieve their excellent performance in this aspect. Using Design Thinking to increase their customer loyalty is one of those four practices. Others include constructing the business around consumer needs, having customer value as a metric, having access to the right technologies, and engaging employees and stakeholders in the process. He also stated that when an organization manages to not only meet, but anticipate essential, although sometimes not obvious, customer needs, that is when they gain the loyalty of their customers. And this is achieved by using Design Thinking together with the latest technologies. This illustrates the effects this technique can have, of course, together with the correct implementation and environment.

What most definitions have in common, however, is the customer-focused aspect of the methodology. For Rob Markey (2020), Design Thinking is "about seeing the world through customers' eyes and learning through direct observation." Here, he also adds the way to learn about the customers, because one of the most effective ways to discover how businesses can improve their user experience is watching their behavior and their actions – their whole experience. It is also important to note that the more information on their ways, struggles, tricks… the better, seeing that sometimes the before and after the use of the product or service can provide just as much information as the use of the product or service itself and of course, as mentioned earlier, more often than not, these behaviors are not ones that they can recall or fully express verbally in a survey, but they have to be seen and understood in the situation. That is why Markey (2020) also states that this procedure, together with continuous stream of client feedback, is a great tool that enables teams to design very personalized products. In fact, it also provides information to the sales and marketing departments which enables them to better tailor and target their messages to make sure they are reaching the right individuals, in the right way, at the right time. The objective is no longer to get customers to buy, but to actually better their lives in a way that earns the customers' trust and therefore, loyalty to the company (Markey, 2020). In conclusion, companies need to gather as much information as they possibly can in order to fully understand the people they are serving and create a win-win situation by genuinely helping them, and in return, gaining loyal customers.

However, Design Thinking is a complex process, since it involves many different techniques that, combined, form this very powerful tool. Craig Bedell (2020), mentions some of the techniques often used like empathy maps, the creation of personas, design ideation, as-is scenarios, to-be scenarios, hypothesis-driven design and minimum viable product definition. Therefore, it can be concluded that it is a combination of logic, creativity, inference and systemic reasoning that helps discover new and creative possibilities (Bedell, 2020).

Although the essence of Design Thinking is unique, there are different versions when it comes to explaining the process in detail phase by phase – or space by space. I am now going to describe, analyze and compare three of the most widely used ones: IDEO's three spaces, the Doble Diamond model by the British Design Council, and Stanford d.school's 5-modes (see Exhibit 5 below).

Exhibit 5: Diagram comparing the different Design Thinking models.



Source: Compilation based on Brown, 2008; Stanford d.school, 2018 & Design Council, 2019.

2.1. IDEO's three spaces

Starting with IDEO'S three spaces, Tim Brown (2008), CEO of IDEO, made a point to describe the Design Thinking process as a combination of three spaces instead of a sequence of phases. These still represent the various actions and tasks that will eventually lead to innovation. However, by explaining it as something other than a set of steps to follow in an orderly manner, it alludes to the messy aspect of the innovation process, that may often not be as easy to classify into steps as some may think. He acknowledges that any given project might go through all three seamlessly or reiterate on any one of them (Brown, 2008).

The first one would be "inspiration" and it makes reference to the situation, whether it is a problem, an opportunity or both, that drives the need for action. This space includes activities like observing people and understanding them, knowing the resources available for the project, sharing insights among the team and also, interacting with other departments such as engineering or marketing.

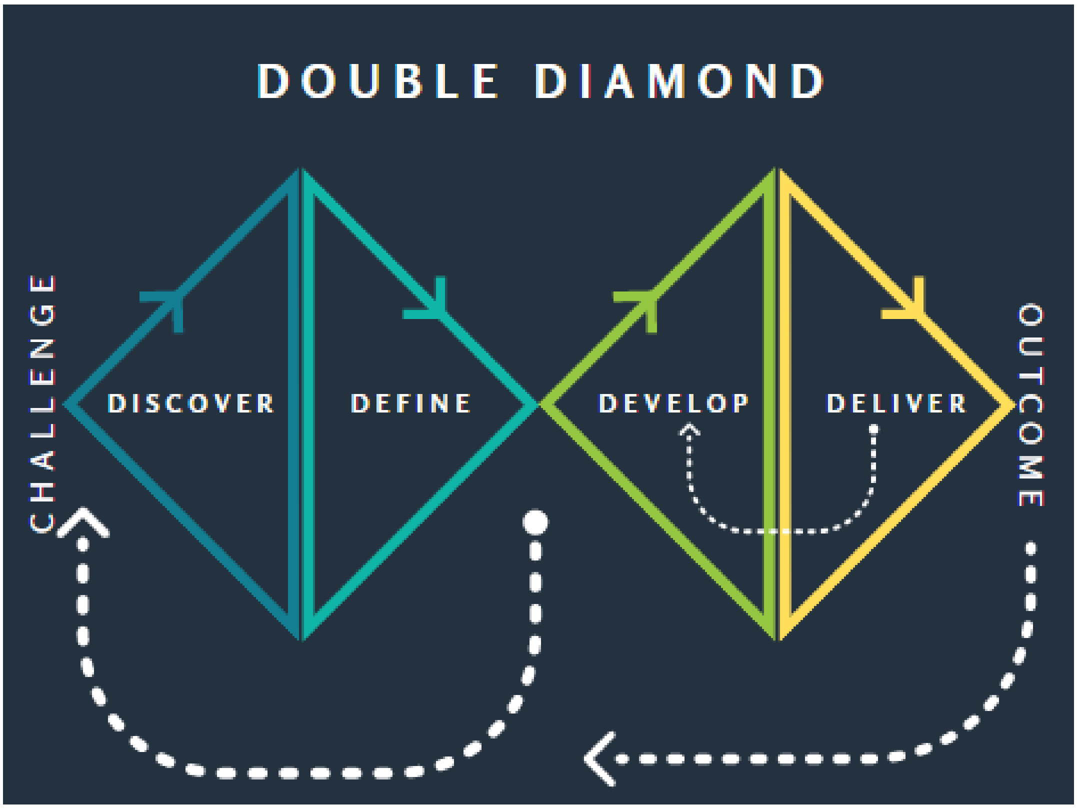
The second one is called "ideation" since it is where ideas are created, materialized and tested. The ideation space is characterized by brainstorming, organizing ideas, prototyping and testing, but it also includes telling more stories and communicating which was also present in the first space.

Lastly, in the "implementation" space, the chosen idea is launched into the market. This entails designing the sales and marketing strategy and communicating with stakeholders (Brown, 2008).

2.2. The Double Diamond

The Double Diamond model, introduced by the British Design Council, is as Jonathan Ball (2019) explains, "a visual representation of the design and innovation process" (see Exhibit 6). The Double Diamond model, as the previous one, also acknowledges that the process may not be a straight line (Design Council, 2015), but that learnings can occur along the way, especially when receiving feedback from users, that might lead the team to start again or revisit one of the earlier stages, represented in this case by the white arrows in the diagram in Exhibit 6.

Exhibit 6: Double Diamond Model for Design Thinking



Source: based on Design Council, 2015

One of the particularities of this model, however, is the deliberate use of the diamond shapes to visually illustrate the use of divergent and convergent thinking throughout the process.

The first stage, “discover”, is about understanding the issue at hand and avoiding assumptions. In order to do this, the team should gather information about the individuals concerned by the issue by talking to them and observing their behavior. It is important to note that is one of the two phases that require divergent thinking, since it is all about listening, observing and being open to new ideas and insights.

The second one is called “define” because using the findings from the previous stage, the aim is to redefine the initial challenge – look at it from a different perspective or go deeper by asking “why” several times like Tina Seelig (2013) suggests for reframing problems. Here, convergent thinking is needed in order to, with all the information available, narrow it down to a single problem that is usually different from the initial one. These two phases, that combined form the first diamond, focus on making sure the scene is set correctly and the right questions are being asked.

Moving on to the second diamond, "develop" would be the third stage and is the one where ideas to solve the previously stated problem flow in, supported by inspiration from any and every source and also, by working in cooperation with people from different walks of life (Design Council, 2015). This allows for more richness and variety of ideas which is what this stage seeks, and why it requires divergent thinking. In this third phase, the team will also experiment and evaluate the different solutions.

The last stage is the "deliver" stage. At this point the findings from the previous phase will allow them to focus on the ones that have shown potential when tested to work on them further and ultimately, choose one that will be the final outcome of the process. Jonathan Ball (2019) cites Anna White, one of the members of the team that came up with this model, who described it in a very simple but meaningful way: “For me the first part of the diamond is about questioning the brief and defining the problem statement. I explain it as ‘designing the right thing’. The second part of the diamond is about exploring possibility, iteration, testing and developing, so ‘designing the thing right’.” It is all about finding the right problem at first, to then be able to come up with the right solution.

2.3. Stanford’s Design School model

Although all three models, explaining the same process are bound to somewhat resemble each other, the third Design Thinking model, brought about by the Design School at Stanford University, and the Double Diamond model explained above are the most similar among them.

Stanford’s five modes model, according to their Design Thinking Bootleg (2018), starts with "empathize", showcasing that it is usually other people's problems the ones to be solved and, as such, it is necessary to focus on their point of view and their values. In order to do this, they advise to observe the users' behavior in the actual context – in their day to day; to engage with them in different ways – formal or informal interviews and encounters; and lastly, to immerse in their experience – "[w]ear your users' shoes. Experience what they experience for a mile or two." This would be the equivalent to the “discover” part of the previous model. However, the names given to the set of actions involved, reveal subtle differences on the approach of the model – implying that “discover” may be more focused on formal research and “empathize” may take a more emotional stand point.

The second mode is "define" and, just like in the Double Diamond model, it is about using the information gathered in the previous stage to draft "an actionable problem statement". In both models the aim is to understand the problem to be able to ask the right questions in order to find the best solution.

Next, what in the previous model is “develop”, Stanford Design School divides it into two phases: “ideate” and “prototype”. “Ideate” also acknowledges the divergent thinking aspect of this stage by using terms such as “going wide” and “flaring” (Design Thinking Bootleg — Stanford d.school, 2018) instead of focusing, to arrive to a large amount and wide array of ideas. "Prototype" is the action of physically representing those ideas in order to explore them further. Prototyping does not necessarily mean spending time and resources in building detailed models of the solutions, in fact, they give some ideas of low-cost alternatives such as role-plays or writing down ideas on post-its. The intent of this set of activities is to learn by interacting with the different ideas and encourage conversations.

Lastly, there is the "testing" mode which is when by using the prototypes created, the team can get feedback from users and improve their solutions. This model also highlights the iteration aspect, therefore any finding in any of the phases might lead them to revisit any of the previous stages. For this one, is it advised to "[p]rototype as if you know you’re right, but test as if you know you’re wrong." (Design Thinking Bootleg — Stanford d.school, 2018). This helps people put effort and energy into trying different things, motivated by the feeling that it is going to be the ultimate solution, but then also remaining humble and open to improvements and suggestions from the users or other team members while testing. Unlike the first one explained, where in the implementation space, it talked about the launch of the final product, this model does not reach the actual launch of the product or service developed. However, it does explain in more detail the actions teams can take to perfect their creation.

In conclusion, the different Design Thinking models present very subtle differences in superficial aspects such as the naming of the different steps or the distribution of the actions in the different phases. Nevertheless, the essence remains in each one of them, since a lot of value and attention is placed in the user and the faster-paced cycle for going from ideas to prototypes to receive feedback and reiterate.

3. BIG DATA

Having looked at the Design Thinking process, I will now explain what Big Data is, making reference to the main uses of this technology that make it applicable and, in fact, a very valuable tool for Design Thinking. However, it is also worth mentioning that Big Data also has some backlashes that should be taken into account.

Big Data is one of those buzz terms we have all heard probably more than once in the last few years. The term big data at its simplest makes reference to the large data sets generated by new forms of technology (Song, Zhang, & Heng, 2020). Or, as Tan and Zhan (2017) define it, the "multimedia-rich and interactive low-cost information resulting from mass communication." There are plenty of definitions of this term, but it can be concluded that most of them make reference to the abundance of data and its origin in the new technologies that have been developed in the last years. The main variation big data presents when compared to the data we knew, is the ecosystem of vast data creation and usage that the previous forms of data were unable to provide (Tan & Zhan, 2017 & George, Haas, Pentland, 2014; cited by Song, Zhang & Heng, 2020)

McAfee and Brynjolfsson came up with the 3V's that describe big data: volume, variety and velocity (Song, Zhang, & Heng, 2020; Tan and Zhan, 2017). Volume, as mentioned, referring to the size of the data sets; variety, probably related to the many types of data available from the different sources – internet traffic, social media, companies' data bases, etc. and velocity, to the speed at which big data is created but it could also refer to the speed at which companies can have it readily available. Veracity and value are two other V's that have been added by other scholars (Akter et al, 2016 & Tan, 2018; cited by Song, Zhang & Heng, 2020). These most likely came later since problems with illicit alterations of the data probably appeared afterwards, just like the realization that maybe not all data provides valuable and useful insights for the issue in question.

3.1. Applications

Big Data has proven to be an amazingly useful tool for a wide variety of purposes. In essence, Big Data is information, and as such, it can be useful in almost anything if used correctly. However, there have been three main applications of this technology that have revolutionized several industries and that will also be useful in the later discussion about the use of Big Data in the Design Thinking process. These are performance tracking and optimization, predictive analytics and decision making.

3.1.1. Performance Tracking and Optimization

Performance tracking and optimization, in this case, refers to the use of the information firms gather in order to evaluate the performance of certain aspect compared to what the company considers to be their quality standard, to then ensure the necessary steps are taken to improve. This is a very broad application since it can be used to evaluate the performance of the company's product or service in the market in terms of sales, customer satisfaction and other similar metrics; the performance of the workforce by using metrics such as number of calls per day or number of deals closed for someone in the sales department; the effectiveness and efficiency of the processes in the business analyzing costs and speed to market or the performance of the company as a whole, looking at profit over the years, growth, brand recognition, customer loyalty, etc. Rob Markey (2020) also suggests "to track how experiments and changes in products, pricing, customer policies, processes, promotions, and services affect each cohort's performance over time. Using time-series analytics, for example, they can monitor customers who have been exposed to specific initiatives—say, a service personalization effort—to determine how that experience will affect lifetime value." Meaning it can also be used at a smaller scale to assess whether specific changes or ideas are worth implementing for good.

For instance, Lockheed Martin, a global security and aerospace company with more than 100,000 employees worldwide, applies performance tracking for their workforce and has been collecting data on employee performance associated to business goals for more than a decade. They built a system that throughout the year collects performance-review data that they can then contrast with their information on employee training to gain insights on how to get the best out of high-potential employees as well as which employees could benefit from additional training (Davenport, Harris, & Shapiro, 2010).

Another example of performance tracking for optimization purposes can be found in Tesco's practices. According to Ryan (2018), Tesco created a way to track their refrigerators' temperature levels by installing sensors that would measure and send the information on the refrigerators' temperature to a data warehouse every three seconds. This allowed them to see what refrigerators were functioning at colder temperatures than the optimal, so that by adjusting them, they could expect to save one fifth of what they were paying for energy. In addition, this also enabled them to check that the refrigerators were working correctly. Before, it was the manager at the store the one in charge of noticing any issues, the problem is that they would only notice when it was already affecting their activity. In addition, fixing the problem would require engineers to go to the store twice: one to figure out the root cause of the problem and a second one to bring the equipment necessary to fix it. However, now if while monitoring their performance they noticed a problem with one of them, they could detect the root cause and come equipped (Ryan, 2018).

3.1.2. Predictive Analytics

Another common use for Big Data is predictive Analytics (Mitchell, 2014), which allows data analysts to forecast using data from previous happenings. This is works on the premise that history is likely to repeat itself, and therefore, algorithms can be designed to predict what will happen next by drawing upon the information already available about past events and comparing it. If they find similarities with previous situations recorded, they will make the prediction according to the previous outcome. The bigger the database and the more exhaustive the information, the more accurate the prediction will be.

Forecasting is also used for a very wide variety of purposes, being some examples turnover predictions in HR, stocks and financial services, demand predictions for supply chain management, weather forecasting…

An example of the use of predictive analytics is being developed by the partnership between Amazon Web Services and Cerner, which is a health IT company. "Using AWS' capabilities, Cerner is developing a new platform called the Cerner Machine Learning Ecosystem to help data scientists build and deploy machine learning models for healthcare applications at scale, the company said.

The goal is to uncover predictive and digital diagnostic insights that will offer earlier health interventions." (Landi, 2019). They plan to use chatbots to whom patients will be able to ask questions or request their personal health records. By leveraging the data, they will determine the possible causes behind re-hospitalizations to prevent them and reduce healthcare waste (Landi, 2019).

Don Peck (2014) talks about another case where predictive analytics were used to save money and resources by automating part of a process. This is the case of one of Shell's business units with the help of Knack. Knack is a small start-up that makes games designed by neuroscientists, psychologists and data scientists to identify high-potential individuals. Candidates only need to spend 20 minutes playing to generate more data than they would with the SAT or a personality test about relevant traits, creating a detailed profile with your personality, intelligence and leadership and innovation skills. Royal Dutch Shell, a huge petroleum company, has a Game Changer unit dedicated to discovering ground-breaking business ideas and assuming the role of a venture capital firm. The problem was that the process of going through all the ideas, deciding, meeting with the owners of the ideas, funding and monitoring was challenging and took a lot of time. So Hans Haringa, member of the Game Changer team, asked previous proponents of ideas to play Knack's games and provided Knack with the information on their performance as idea generators of 75% of them, so that the company could gather the traits of successful participants in comparison to weaker ones. Then Knack was tested to see if they could predict who were the best ones in the 25% left (Peck, 2014). This illustrates a case where Big Data for predictive analytics was used to identify which ideas and innovators would achieve better results without having to rely fully on human power for all the steps in the process. If this worked, they would be able to focus on working with the top participants identified. Knack managed to correctly identify the 10% who performed best and had gotten the furthest in the process. In doing this, Knack found six distinctive traits of successful innovators: "“mind wandering” (or the tendency to follow interesting, unexpected offshoots of the main task at hand, to see where they lead), social intelligence, “goal-orientation fluency,” implicit learning, task-switching ability, and conscientiousness. " (Peck, 2014).

One last example is the case published on The Wall Street Journal and written by Dana Mattioli (2012) of Orbitz Worldwide, a website used to book flights and hotels, who uses data to predict clients' behavior, taste and budget. Looking at their data, this company came to the conclusion that Apple computer users spend almost a third more on hotel bookings, and that they are also 40% more prone to choose a high-end hotel (4 or 5 stars), than PC users. Therefore, they started customizing the display of hotels based on that, showing Mac users the more expensive and high-end ones first. Using the insights gathered, they predicted that searches from a Mac would be more likely to choose one of those hotels than others. So, for instance, someone looking to book a hotel in Miami Beach on a Mac would be shown more expensive hotels on the first page of results than someone searching on a PC (Mattioli, 2012). This is one of the multiple ways companies are using predictive analytics to target customers in order to increase sales.

3.1.3. Decision Making

The third of the main uses of Big Data is one that can often combine the two previous ones mentioned. It is widely known that in order to make better decisions, it is important to have as much relevant information as possible, and to be able to use it properly, which is why making good decisions and informed decisions are often used interchangeably. This is mainly the value Big Data adds to the decision-making process.

Helen Mayhew and Tamim Saleh, associate partner and senior partner respectively in McKinsey’s London office, and Simon Williams (2016), cofounder and director of QuantumBlack, a McKinsey affiliate, in their article “Making data analytics work for you – instead of the other way around” they mention how some of the top companies like Google consistently use data in their decision-making process. But this can not only be found in tech companies, but also in sports. McKinsey data expert, Dorian Pyle, and principal, Cristina San José (2015) wrote:

> *[C]ontenders for the US National Basketball Association championship relied on the analytics of Second Spectrum, a California machine-learning*

> *start-up. By digitizing the past few seasons' games, it has created predictive models that allow a coach to distinguish between, as CEO Rajiv Maheswaran puts it, "a bad shooter who takes good shots and a good shooter who takes bad shots"—and to adjust his decisions accordingly.*

As we can see, in this case, predictive analytics were used among other technologies in order to help make better decisions about what players to recruit. Similar to the famous "Moneyball" case, where the Oakland A's manager started using mathematical models for his decisions about new additions to the team and managed to, with a third of the budget, win as many games as the Yankees (Peck, 2014).

Another case in which Big Data was used for decision making is that of WellPoint in the health insurance industry, written by the Economist Intelligence Unit (2015) and published by the consulting, technology and outsourcing firm Capgemini. Medical knowledge is constantly growing and a lot of it is now shifting towards the use electronic versions. Even though doctors have plenty of information to revise, whenever they see a patient, they usually only get enough time to look at a small fraction of it. The executive vice president of enterprise business services at WellPoint, Lori Beer stated "If you look at the statistics, evidence based medicine is only applied about 50% of the time," and she then added "The issue we often face is that we're not really using the most relevant evidence-based medicine in diagnosis and treatment decisions." (Economist Intelligence Unit, 2015) Therefore, in order to try to fix this, nurses at WellPoint collaborated to help program a supercomputer to decide whether to authorize treatments. They would do this by going through the whole procedure themselves and then rating the performance of the supercomputer. These ratings would be used to improve the system so that eventually it could make the decisions by itself (Economist Intelligence Unit, 2015).

In addition, further developments were made to bring this technology to oncologists at Cedars-Sinai Samuel Oschin Comprehensive Cancer Institute in Los Angeles. For this application, the system will provide suggested treatments but also the evidence to support them so that physicians can also review the relevant documents and make a better-informed decision (Economist Intelligence Unit, 2015).

3.2. Downside of Big Data

It is widely known that Big Data has been one of the greatest advancements in the recent years. However, the downsides of this new technology are less spoken of: Tricia Wang, global tech ethnographer, researcher and co-founder of Sudden Compass; explained in her TED Talk (2016) that, although Big Data has become a $122 billion industry, more than 73% of the Big Data projects are not profitable and attributes these concerning figures to the fact that “investing in this new technology is easy, but using it is hard.” Danah Boyd, Principal Researcher at Microsoft Research, founder of Data & Society and Visiting Professor at New York University's Interactive Telecommunications Program, made reference to some of these downsides in a talk she gave at the WWW 2010 conference. I am going to highlight the three main backlashes of Big Data that I consider the most relevant for this case.

- The importance of quality over quantity. Often, when having thousands of data points, some people may believe insights coming from very large data sets will be truthful and objective. However, as Boyd (2010) remarked, sampling and knowing where your data is coming from is one of the most important factors to consider when analyzing it. This is because data can vary greatly depending on the source from which is gathered. During her talk Boyd (2010) expressed her concern about this misconception: "People from diverse disciplines are analyzing social networks using diverse methodological and analytical approaches. But it kills me when those working with Big Data think that the data they’ve collected from Facebook or through cell phone records are more “accurate” than those collected by sociologists. They’re extremely valuable networks, but they’re different networks. And those differences need to be understood." Especially among the scientific community, Big Data can sometimes be overestimated in reference to the quality of the information and insights it can provide. Particularly in comparison to more qualitative data that is usually harder to quantify and analyze.

  Data scientists must make sure that the data is homogenous in order to be compared, and also, that it is truly representative of the population being analyzed. Kate Crawford (2013), principal researcher at Microsoft Research and a visiting professor at the MIT Center for Civic Media, pointed out that data is often assumed to be representative of the world or large populations. Nevertheless, this is often inaccurate because, especially with data coming from social media or new technological devices, there are parts of society which are not represented. This can be for multiple reasons, one of them being lack of access to these, which may lead to bias towards the more represented parts of society.

- Data as a representation of past practices. To restate, data can come from a wide variety of sources, and nowadays, the data from the previous decades is all available. The issue comes when we let data from decades ago, define what we want the reality to be in the future. If we apply predictive algorithms using the data from years ago, there are many cases where we will probably arrive to very accurate conclusions. However, that will not always be the case because, as Cathy O'Neil (2017) mentioned, algorithms reproduce our previous actions, behaviors and patterns. "They automate the status quo. That would be great if we had a perfect world, but we don't" (O'Neil, 2017). What this implies is that fully relying on Big Data to make decisions about the future, could promote undesirable current practices such as sexism or racism, and there are several examples that illustrate this phenomenon. One of them is explained by Don Peck in his article "They're Watching You at Work" (2014), where he cites Malcom Gladwell when talking about when 40 to 50 years ago orchestras started shifting their recruiting process to blind auditions. This was an initiative put in place to avoid former students getting preferent treatment. Not only did it work for its initial purpose, but it also caused a fivefold increase in the proportion of women getting positions at the most distinguished orchestras, especially when the instrument they played was associated with male musicians. Had they used automation systems and algorithms instead, they would have predicted that the best candidates would be mostly men and former students following the tendency they had had in the past towards hiring musicians with that profile instead of the best performers – reflecting a bias that anyone can have consciously or unconsciously.

- Insights drawn from Big Data are often incomplete. Big Data is very effective to give a snapshot of the current situation and numbers, but when it comes to deeper insights like why that may be the situation or those, the numbers, it is usually up to the researchers to come up with assumptions or hypothesis. Danah Boyd (2010) stated that everyone is awful at acknowledging that any situation can have a different meaning when asking "why", and when people only know the "what" and are left to make assumptions about the "why" it can backlash. They could be attributing the results to completely different reasons and the issue arises because often, when trying to solve a problem, we try to address its root cause – the "why". If the most important part of the issue is only assumed, there is a very high chance that the solution will not be the most effective.

  Crawford (2013) mentioned the tendency towards what she calls "data fundamentalism", which is the misconception that correlation signifies causation and that predictive analytics and enormous data sets will always lead to truthful and objective insights. This misconception can happen very easily, and it can be responsible for findings as crazy as ice-cream causing people to drown. Looking at the data, it may be the case that when ice-cream sales increase, the amount of deaths by drowning also increases, meaning these two variables are directly correlated. However, this does not necessarily mean that one is caused by the other – correlation does not mean causation – we must take into account the fact that there are also external factors that could be affecting both variables such as the climate with the change of season. As summer approaches, temperatures rise and people are more prone to buying ice-cream and to bathe, causing an increase in both ice-cream sales and drownings. This is just an example with a very obvious explanation, but it can happen with other variables with causes which are not as easy to trace back to the origin. Solutions equivalent to taking ice-creams off the market with the purpose of decreasing the amount of people drowning would be implemented just to find that it has no effect and millions of dollars have been lost. That being said, different data sets have different levels of depth, but combining different methods such as data analysis with ethnography or interviews, can help greatly to achieve a clearer picture (Crawford, 2013).

4. THICK DATA

In order to compensate the downsides Big Data can present when applied to Design Thinking, organizations can use what is known as Thick Data. In this part, I will explain the concept of Thick Data, the disadvantages to this form of research, the differences when compared to Big Data, and also the benefits it can bring to a Design Thinking project and how it complements Big Data.

In essence, Thick Data is the more qualitative data gathered from smaller samples of population by using methods such as observation or interviews to explain the "why" of human behavior (Wang, 2016). Therefore, this type of data is part of ethnography. Ken Anderson (2009), anthropologist at Intel Research and cofounder of the Ethnographic Praxis in Industry Conference, explained: "Ethnography is the branch of anthropology that involves trying to understand how people live their lives. Unlike traditional market researchers, who ask specific, highly practical questions, anthropological researchers visit consumers in their homes or offices to observe and listen in a nondirected way." He mentions that the objective of that practice that may seem inefficient, is to get a better understanding of the context and meaning of the product in costumers' day-to-day by observing them "on their terms". It is by observing the whole customer journey, researchers can spot areas of improvement that are of value to the customer and often unthought of before.

4.1. Downsides of Thick Data

However, for some executives, this source of information may seem like a waste of time and resources. The main reasons for this – the downsides of this type of data are three: it requires time and resources, it can be considered less representative and it can also be more subjective.

- Requires time and resources. Research done with this methodology can take months while you can get access to a database in seconds. Gathering information using observation or interviews is a much slower process and this is also why the samples are usually a lot smaller than in quantitative analysis (McLeod, 2019). It usually entails coming up with the correct setting for observing, designing the study, recruiting individuals for the research, scheduling and observing or interviewing. But not only that, analyzing all that qualitative data also takes much longer than writing a formula and letting the computer do the rest (McLeod, 2019). Furthermore, with the need for time, also comes the need for additional resources. Given that it has to be human power dedicating the time and that probably means higher costs in wages and also workforce invested in the matter that could be working in other projects. In addition, equipment and access to customers who agree to participate in the research will also be necessary and for the latter one, companies often have to pay the participants or offer them benefits for them to agree to also dedicate their time.

- Less representative outcomes. Thick Data is about going deeper into a much smaller number of cases. As explained above, this form of research is much more time consuming than Big Data and therefore, the sample used is limited. The issue is that keeping the rest of the variables stable, larger samples leave less room for error and form a more representative image of the population in question (Osborne & Costello, 2004). This can lead to representation issues since, just like with any study, it can happen that the individuals selected for the sample are not the usual cases or what researchers call "extreme users", and therefore, the insights gathered from the study of said individuals are not really applicable or cannot be extrapolated to the rest of the population.
- Subjective outcomes. The fact that it is qualitative data being analyzed by humans can also be argued to give way to more subjective outcomes. In fact, Leigh Thompson and David Schontal (2020) talk about several psychological phenomenon that can take place such as the described by the script theory, according to which people have cause-and-effect schemas which can sometimes prevent them from seeing factors outside of their understanding of the situation based off of previous experience – causing them to miss important information in their observations. Some others would be the fact that, as mentioned, people can often make inferences without even noticing, see patterns where there are none or fall into the trap of inattentional blindness, which happens when people are so focused on one aspect of the reality that they become blind to the rest.

4.2. Differences and Benefits of Thick Data vs. Big Data

It is easy to tell by now that Big Data and Thick Data are almost opposites. Tricia Wang (2013) talks about the differences between the two types of data, and although there are a few, I would like to highlight four main ones: sample size, gathering method, instrument for analysis, and outputs.

As seen in Exhibit 7, Big Data works with massive sample sizes available thanks to the new technologies that have been developed in the last years, and uses computational power to analyze them and provide insights that are usually in the form of numbers. For Thick Data, however, the samples will be much smaller in size, studied using ethnographic methods and analyzed with human brain power to deliver stories that illustrate the social context and connections behind the data points.

Exhibit 7: Table on Differences between Big Data and Thick Data

	Big Data	**Thick Data**
Sample size	Massive data sets, very large sample size (N)	Small sample size (n)
Gathering method	Usually technology-related sources: internet traffic, social media, companies' data bases…	Ethnographic methods: observation, interviews, focus groups…
Instrument for analysis	Computational power	Human brain power
Output	Quantitative findings	Qualitative findings: social context, connections, explanations behind the behaviors…

Source: Compilation based on Song, Zhang, & Heng (2020); Wang (2013); and Wang (2016).

This is incredibly important, in fact, Madsbjerg and Rasmussen (2014), authors of "The Moment of Clarity: Using the Human Sciences to Solve Your Toughest Business

Problems," and co-founders of ReD Associates, defend that firms and executives who make an effort to understand the emotional and ingrained context in which consumers interact with their product or service and manage to adapt to change, are the ones who achieve success. In fact, in their article for the Wall Street Journal they use a great simile to illustrate their point: “By outsourcing our thinking to Big Data, our ability to make sense of the world by careful observation begins to wither, just as you miss the feel and texture of a new city by navigating it only with the help of a GPS.” I believe this way of describing it to be very meaningful since, not only does it make reference to the lack of detail referring to the stories behind the data, but also to the lack of emotion and human touch. In a GPS, historic monuments like cathedrals or other iconic buildings like the Empire State are just blocks in a map, and not only that, if we only look at a map, a neighborhood in New York might look similar to one Barcelona, since both cities have grid-like dispositions. However, they probably look nothing alike in real life, just like two sets of data from two very different samples can look similar.

Wang (2013) also advocates for Thick Data saying that it provides inspiration and also quotes Frans de Waal, biologist and primatologist who proved that the sense of fairness is not only present in humans, in a statement he made saying that people are usually not convinced when shown data and graphs, it is emotions and reactions what makes a difference.

One example of this Madsbjerg and Rasmussen (2014) mention in their article for the Wall Street Journal, “The Power of Thick Data”, is Coloplast, a company that had led their niche market of stoma bags for patients after colon surgery and maintained a considerable growth rate for years, started to have problems reaching their sales targets several times in a row. Studies showed that people who experienced leakages with the product would not buy again, so in order to get back on track and increase their sales, they focused on developing a better adhesive to ensure their customers did not experience leakages. However, these incremental improvements to the stoma bags did not help them reach their goal. This is when Coloplast resolved to gather Thick data, and to do so, they introduced themselves in their customers' world, they engaged with them, observed, and then analyzed their findings. They discovered that the reason customers were switching away from their product was, indeed, leakages.

What they were not expecting to find was that it was not the adhesive causing them, it was the fact that bags did not properly adjust to their customers' different body types and their fluctuations over time.

This illustrates how it is hard even for experts to fully empathize with their end customer and how studies and big data can provide very insightful information, like in this case, the leakages being one of the main causes of customers switching brands or products. But it also shows the lack of depth they can often have and, as mentioned above, what happens when assumptions are made. In this case, researchers assumed the leakages must be caused by their adhesive not being good enough, so they focused on making incremental improvements to it. It was only when they went to discover the whole story and to immerse themselves in their customers' world that they realized they were focusing on the wrong issue – asking the wrong questions. They had to take a step back and reframe the problem from "why is the adhesive not working well?" to "why are customers experiencing leakages?" or even broader "why are customers actually switching brands?". Once they found out, the firm shifted their focus to better tailoring the product by introducing three different lines to use depending on body type so they would fit better, and also gained insights that would help them develop further with a better idea of what is it that their customers care the most about.

5. FINDINGS: IMPLEMENTATION OF BIG DATA AND THICK DATA TO THE DESIGN THINKING PROCESS

5.1. Data in the Design Thinking process: “Mixed Data” approach

As previously explained, Big Data and Thick Data are completely different. However, it is not about arguing which one is better or choosing one over the other. Each one of them adds value in different ways and for different purposes, making both of them necessary to get the whole picture. Therefore, the best results will be achieved by those who use, as Professor Ang (2019) calls it in her report, "mixed analytics (big data and thick data) and mixed research methods (quantitative and qualitative)."

Each methodology has its own downsides, however most of them can be downplayed by the use of the other one. The advantage of Thick Data becomes prominent when it comes to finding the "why" of the population's behavior or coming up with hypothesis to explain it. It helps researchers and designers understand the context and the situations in which the customer uses the product of service. Big Data on the other hand, can only answer "how much", it can quantify it but it cannot explain the reasons behind it. It can inform on the numbers surrounding the product which can speak to the customer’s behavior too, but not to their motivation which can at times be even more important. The strength of this type of data is given by the fact that it draws its information from a much larger sample or "N" as compared to Thick Data, so it can present insights that are much more representative of the population and hence, harder to question (Rasmussen & Hansen, 2015). In addition, it is often difficult for humans to verbalize aspects of their behavior given that a part of it happens unconsciously.

Charles Duhigg (2016), Pulitzer Prize-winning reporter for the New York Times and senior editor of live journalism and author, describes a very interesting example of this practice at Google. Now with all the data that is available, experts are studying all sorts of metrics to find ways to help employees become faster, better and more productive versions of themselves. However, activities requiring teamwork are becoming increasingly frequent and important given the numerous benefits like faster innovation, better quality outcomes, higher job satisfaction and more profitability. That is why, at Google as part of the Aristotle project they looked at data from 180 teams in the company but found nothing that proved that a specific mix of personality types, skills or backgrounds made a difference. Then they started looking at group norms. A few behaviors were identified in successful groups: all group members spoke roughly the same amount by the end of the day, and they had high social sensitivity. These are part of what is known as psychological safety. The results eventually lead a team in Google to have emotional conversations which, they found actually helped the team feel more comfortable expressing their feelings about their worries and concerns at work too. Ultimately, the findings served as an explanation and reassurance that the feelings employees sometimes get at work are normal and should be addressed. This is an example of how Big Data can be used to identify what teams were performing better in order to know what to observe and compare through ethnography and Thick Data. By using both types of data, they were able to spot the best practices that made teams more effective in order to make them known and help other teams adopt them.

Next, I will explain how both of these types of data are relevant and can be used in each of the stages of the Design Thinking Process more specifically. In order to do this, I will go through the stages of the Four Diamonds model by the British Design Council: Discover, Define, Develop and Deliver. I chose this model out of the three explained earlier because the slightly higher number of stages allows for a clearer and more comprehensive outline of the actions in the process. Although following this reasoning the Stanford Design School would have been the better option, the five stages of this model do not reach the final steps of the innovation process of eventually choosing one solution or prototype and launching it on to the market, which the other two models, by IDEO and the British Design Council, do include.

5.1.1. First Diamond: Discover and Define

Discover is one of the most important and data heavy stages of the Design Thinking Process, since as mentioned earlier, the main task is to gather information about the users in order to create value for them. There is no one way of doing this, but in most cases, teams should use both forms of data to form an idea of the situation and the users as accurate and detailed as possible. Big Data in this stage, given the speed at which it can be made available to firms, if they use it, analyze it and act on it efficiently and effectively, it can allow businesses to be the first to develop and market innovative products. In addition, the varied aspect of Big Data can also help researchers to look at it from many points of view (Ji, Yu & Tan, 2020). Having access to current market information can provide very valuable insights on what customers want and what the trends are at that moment so that companies can take them into account to develop new products that are relevant to the user at that specific point in time (Song, Zhang, & Heng, 2020).

The Define stage, however, is about looking at the data collected in the Discover phase and making sense of it until the team is able to define and frame the problem they are trying to solve. Therefore, in this stage researchers are usually not collecting any more data but interacting and working with the one they have. The Stanford Design School (2018) recommends some common practices for this task such as share-and-capture stories gathered, where the team members tell the rest about their experience interacting with the users and about the stories the users shared with them while the rest write down in post-its insights from those, quotes or things that catch their attention; designing journey maps, to come up with a comprehensive timeline of the process to make sense of the information or to help present it to others; powers of ten, which is a technique to reframe the issue by imposing different limits and observing their effect; or creating 2x2 matrix, which allow you to spot relationships between two aspects by plotting them on the X and Y axis polarized (placing the opposite ends of the spectrum in each end of the axis). This last one is the only technique where data analytics could be used in the form of data visualization, although it is not at all necessary since it can be, and more often than not is, performed with insights from Thick Data.

To illustrate how this part of the process may occur, I will use the case Rasmussen and Hansen (2015) talk about in an article for the Harvard Business Review. Starting with the Discover stage: a big supermarket chain in Europe, looking at their Big Data sets on their sales and number of customers, noticed a decrease in both of these metrics. Their clients were ceasing their weekend visits to the supermarket that were usually when they would buy the most. However, the firm did not know what was causing this drop. First, they designed and launched an

80-question survey to upwards of 6,000 shoppers in each area. Lacking any significant insights from the survey responses, they resorted to a study that would provide them with thicker data. Social science researchers would spend hours with customers going through their daily routines with them - going shopping with them, watching them at home while they planned and cooked meals, etc.

Moving on to the Define stage: the study showed that there had been a change in the lives of the consumers. The usual family dinners were becoming rare and so was planning for the next week since it was becoming more and more complicated. One of the biggest changes was that meals were not a shared moment anymore. Family members would eat at different times and often also different things and not necessarily at the dinner table. This caused an increase in the number of trips to the supermarket to more than nine times per week and they chose the supermarket based on convenience and speed. In addition, they also found that the "mood" and experience at the supermarkets played a bigger role in the election of consumers than the price and quality of their products, contrary to popular beliefs. Now, the need they felt before to reduce prices following their assumption that they were losing customers to the discount stores, was substituted by the one to create a compelling user experience that would make their supermarkets feel unique while also being convenient.

To confirm their findings, they went back to the big data and analyzed the effect of the location on the sales figures to look for correlations. They indeed found that the supermarkets with the biggest sales volume were the ones in the locations with the most traffic. Furthermore, Big Data also confirmed that supermarkets offering a distinct experience tailored to the neighboring population would also perform better.

This example shows how both Big Data and Thick Data can be very useful in the first stages of the Design Thinking process. First of all, the issue of the decrease in sales was spotted thanks to Big Data, that with quick calculations is able to provide the figures related to how much each supermarket is earning, how prominent the decrease is, whether it is due to less customers or each customer buying less products, etc. However, as mentioned, Thick Data is needed to obtain an answer as to why that is happening so that the firm can address the issue. In this case, a survey did not suffice, and the team turned to ethnographic methodologies like observation. This is how they found the reasoning behind the decrease in sales: people were shopping in the supermarkets that were the most convenient for them and that offered a distinct experience, due to the change in their lifestyle. The define stage is where the human power is necessary to analyze the information from the data gathered in the Discover stage. Synthesizing techniques are used, but it is mostly about what the team does with the data collected. This, as Rasmussen and Hansen (2015) mention, gave them a sense of direction and a better notion of what their next steps should be if they want to solve the issue. However, they decided to double-check this information with their Big Data again, given that now they had a better understanding of what questions they should be asking and what patterns to look for. The data confirmed their findings from their ethnographic study and their framing of the problem so now they would be able to move on to the next part of the process.

5.1.2. Second Diamond: Develop and Deliver

Develop is the stage where the team comes up with ideas to solve the problem previously stated. The role of data in this part of the process is not as obvious: both types of data usually serve as an inspiration to the team for them to conceive new ideas. Lynn Wu, professor of operations, information and decisions at Wharton University, in an interview in 2019 talked about how analytics can contribute to the use of existing technologies for different purposes or in different domains, as well as the combination of these technologies to achieve innovation. However, Wu (2019) also made the following statement:

> *We didn't have any conclusive evidence that it impedes, but we definitely find that analytics does not help with building or creating de novo innovation that is foundational and can act like a future building block for future combinations. That is something that analysts are not great at. If you think about it, if something's so new, it probably didn't exist in data yet. So, there's not much you can do with data analytics to help you find that pattern.*

This means that Big Data can help in the ideation part when the problem can be solved by using existing products or technologies. Some examples of this approach are outlined by the McKinsey Global Institute in their December 2016 report “The Age of Analytics: Competing in a Data-Driven World” by Henke, Bughin, Chui, Manyika, Saleh, Wiseman & Sethupathy, in which they explained:

> *Alphabet, which used its algorithmic advantage to push Google ahead of older search engine competitors, is now using its formidable talent base to expand into new business lines such as the development of autonomous vehicles. Apple used its unique data, infrastructure edge, and product platform to push into the world of finance with Apple Pay. Similarly, Chinese e-commerce giants Alibaba, Tencent, and JD.com have leveraged their data volumes to offer microloans to the merchants that operate on their platforms. By using real-time data on the merchants’ transactions to build its own credit scoring system, Alibaba’s finance arm was able to achieve better non-performing loan ratios than traditional banks.*

If the team is looking for completely new and disruptive innovations, Big Data will likely only act as a stimulus for new ideas.

It is when it comes to the testing of those ideas, where data becomes very valuable again. The Stanford School of Design (2018) acknowledged that in this phase, given that a lot of the ideas may be completely new, there will be no data to compare them with to prove their value. For this reason, they suggest creating "empathetic data" by creating prototypes and testing them with users. Recording the experiences, reactions, quotes and information of a big enough sample can provide the data necessary to both improve the prototype and convince decision-makers. Furthermore, Joseph L. Bower, Professor Emeritus at Harvard Business School, and Clayton M. Christensen (1995), Professor of Business Administration at the same institution, found that in organizations with very ingrained data-based decision-making processes, Big Data may, in fact, hinder the innovation process in these stages, for this same reason: it will be very hard to prove that it would be beneficial to invest on ideas and customer needs that have not yet been recorded in data-bases as opposed to the existing solutions that have existing recorded evidence of their profitability. Therefore, recording data at this stage, although not necessarily as intuitive as in the first diamond can be very helpful for both improving the prototypes and proving their effectiveness as a possible solution to the problem.

Testing the prototypes and doing it soon can be really helpful and speed up the process. Tim Brown advised to “try early and often”. This is because feedback coming from team members or employees of other departments or actual users can all be really insightful and help reduce costs by getting those insights early in the product development process. Moreover, customer feedback can now be accessible almost in real time, allowing companies to quickly spot trends in users' behavior and act on them (Cooper & Kleinschmidt, 2011 cited by Tan & Zhan, 2017). In conclusion, in the prototyping and testing part of the process, both Big Data and Thick Data can be very useful for feedback purposes.

After several iterations, when the product is ready to launch, the Thick Data collected at the beginning about the problem at hand can be very useful to then design the marketing and sales campaigns. With all the data collected by this point, it will be a lot easier for the firm to communicate what they do, and also why and how they do it (Marr, 2017). "Messaging can be tailored and targeted to put the right offering in front of the right customer in the right way at the right moment. The goal is not simply to induce customers to buy. It is to improve their lives so effectively that the company earns their trust and continued business." (Markey, 2020).

An example that showcases the iteration process and the use of customer data for product improvements is Airbnb. First Round Review (2015) in the article “How Design Thinking Transformed Airbnb from a Failing Startup to a Billion Dollar Business” tells the story of the early days of the company around 2009. By then, Airbnb's top line had become stagnant at $200 a week. They put themselves in their users' shoes and looking at the listings in New York they noticed that the photos of the listings did not really allow potential guests to see properly what they would be booking - where they would be living.

Contrary to their previous learnings about having to build the business with scalable practices, Paul Graham, co-founder of Y Combinator, suggested they go and take quality pictures of the apartments themselves. This would also allow them to interact with the hosts and get feedback from them. So, even though this decision had no data to support it, they did. The next week their revenues doubled after months flatlined (First Round Review, 2015).

After this, "being a patient" became one of the firm's core values and now, as Joe Gebbia, co-founder of Airbnb, explains, “[e]verybody takes a trip in their first or second week in the company and then they document it. We have some structured questions that they answer and then they actually share back to the entire company. It's incredibly important that everyone in the company knows that we believe in this so much, we're going to pay for you to go take a trip on your first week” (First Round Review, 2015). Airbnb has achieved a great balance between being data driven but also experimenting with new ideas. I believe this to be mostly due to their approach of not being afraid to start with just a hypothesis, test it, and then use data to evaluate it and not the other way around – or as First Round Review described it “they don’t let data push them around”.

Gebbia stated "I'm not sure how useful data is if you don't have meaningful scale to test it against. It may be misleading. The way that we do things is that if we have an idea for something, we now kind of build it into the culture of this idea that it is okay to do something that doesn't scale. You go be a pirate, venture into the world and get a little test nugget, and come back and tell us the story that you found" (First Round Review, 2015). By allowing employees to test ideas like new features and analyzing the data on its performance, they can see whether it works, and if it does, develop it further. "This structure encourages employees to take measured, productive risks on behalf of the company that can lead to the development of major new features. It allows Airbnb to move quickly and continually find new opportunities"(First Round Review, 2015).

Airbnb is a great example of the use of prototyping and testing in order to continuously improve their offerings. They implement data analysis but acknowledging that, as mentioned, if it is new, there probably will not be any data available to prove its value. Therefore, their approach to this is to encourage employees to experiment, test it and create their own data – or as the Stanford d.school (2018) would call it – “empathetic data”. The case of Airbnb also showcases how valuable feedback can come from anywhere, employees can also be a great source of feedback for improvement and they make sure they exploit that. Lastly, they differentiate themselves by going back to all the information they have gathered about their users – demographics, what is it that they are looking for, what they care about the most… and using it in their communications. As CEO Brian Chesky stated in an interview at Code 2018 that “the key that makes Airbnb so different is the fact that we’re a community, not just a series of commodities” and this really resonates with the users.

6. CONCLUSIONS, LIMITATIONS AND FUTURE LINES OF RESEARCH

6.1. Conclusions

Design Thinking is a user-centered methodology to achieve innovation. The set of tools and techniques it includes allows the user to immerse themselves in the world of the consumers, understand them and unleash their creativity to really create value for their clients. Therefore, it does not come as a surprise that companies who implement it are able to increase customer loyalty among other metrics for success.

Big Data enables companies to access huge amounts of information, from varied sources and that is continuously created at very high speeds. In the recent years, Big Data has evolved greatly and has been used for many purposes. Among these, it is worth highlighting performance tracking and optimization, predictive analytics and decision making. Nevertheless, just like any tool, it is essential to know how to make an appropriate use of it. Some factors to take into consideration are the importance of quality over quantity and knowing your data and sources, not being over-reliant on algorithms since they can implicitly promote past practices that would be best to avoid, and lastly, that Big Data cannot answer the "why" question.

That is where Thick Data comes in. Thick Data's main purpose is to understand the "why" behind human behavior. It achieves this by using ethnographic methods of research such as observations or interviews which allow researchers to immerse in the users' world to create value for them more effectively. However, it also has its downsides such as being more time-consuming and needing more resources, yielding less representative insights due to the reduced "n", and also being subject to possible bias.

This is why the best results are achieved when combining both, or what it is also known as "mixed analytics". This way, they can complement each other: Big Data can offer reliable and representative quantitative insights and Thick Data, a deeper understanding of the needs, wants and motivations of the consumers.

6.2. Limitations and Future Lines of Research

There are four main limitations to be noted about this study. The first one is that the performance of teams or organizations in their innovation or Design Thinking efforts is very hard to measure. The effectiveness was prominent in the case studies analyzed; however, it might not always be as easily recognizable. The second one is that there is no one-size-fits-all way of implementing the Design Thinking methodology in a company. In the findings section of this paper, a suggestion is presented as to how to best use each type of data throughout the process. However, this may change depending on both the team and the aim of the project. Lastly, the Big Data and data analysis technologies are continuously evolving, so the information presented might soon become obsolete.

Regarding future lines of research, conducting an empirical study might bring value to the information presented, since it could provide further prove to support the benefits of the use of “mixed data” in the Design Thinking process. In addition, more specific studies could be conducted focusing on the Design Thinking of one industry or even an organization to better tailor its needs and availability of resources in this process. Furthermore, another line of research could address the potential applications of “mixed data” to other forms of innovation such as Lean Startup or Agile.

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