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The Internet of Things:
A survey of competitive advantages and hindrances
Do all companies stand even towards this new digital technology?

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Régis Gemoets and Alessandro Tornincasa

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Supervisor(s)
Manuel Kolp and Ramin Sadre

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GEMOETS Régis and TORNINCASA Alessandro

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Chapter 1

Introduction

The world has already undergone several huge industrial revolutions. From the 1st one, which introduced the mechanization with the water and steam power engines, to the current "Industry 4.0", which introduces processes automation, data exchange, Internet of things and cloud computing. Each of these revolutions have had notable impacts on the way people live and interact with their environment, as well as on business processes, strategies and models.

The last decades have been marked by the emergence of tremendously powerful digital technologies, which have dramatically changed the shape of the traditional economy. It is thought that with the advanced robotics and 3D printing, the internet of things is expected to fundamentally transform manufacturing, as well as other activities, over the next couple of decades (Crook, 2017).

Indeed, this "Industry 4.0", marks the start of a new era of large digitization which will bring about the same types of changes to our economy and society as did the steam engine, the spinning jenny, or Henry Ford's assembly line back then (Muhutdinova-Foroughi, 2015). New companies such as Amazon, Google, Apple, Microsoft, and yet many more, have been able already to take advantage of those emerging technologies and to position themselves as leaders in the IT industry by proposing new types of services, and by innovating current business models (Fleisch et al., 2015).

Digital technologies have firstly been used as means to help managers better manage their operations. By enabling them to automate production processes, rely on processors' power to perform complex computations, but also to gain an increased knowledge of their surroundings. In order to achieve those objectives, digitization relies on the generation of diverse data, used by Information technology systems to provide executives with the ability to enhance their decision-making. And in fact, the more a company or an individual makes use of digital technologies, the more data it generates (Fleisch et al., 2015).

As we experienced three industrial revolutions already, academics claim that we are, if not already, on the verge to enter a fourth industrial revolution, namely the "Industry 4.0". Until now, we could distinguish two different types of worlds: the digital world and the physical one. However, the borders between those two states become more and more pervasive, making the distinction between them more and more complicated. This is partly due to the rise of the Internet of Things (IoT), a technology consisting in a collection of connected objects able to sense their environment and to communicate via the Internet in order to leverage useful business insights for companies.

This fourth revolution also triggers another phenomenon, which is the creation of tremendous volumes of data coming from many different data sources. Everyday, about 2.5 quintillion bytes of data are being generated. And according to IBM, about 90% of the data in the world today have been created in the last two years only. Those huge volumes of data promise to deliver many benefits for the firms that would be capable of leveraging their potential. Today, we refer to those as Big Data. And in order to process them effectively, particular Big Data analytic tools and other resources need to be developed.

Information gathering has long existed already (engagement surveys, events participation, customer satisfaction survey, market researches, etc.) and been mostly used to enhance processes and reduce uncertainty for decision-makers. It is easy to see that Big Data constitute a huge improvement in that matter. Indeed, those data originate from multiple data sources, providing decision-makers with enlarged insights on their environment. In fact, each and every action made by a user on the internet generates data: whether it is the visioning of a video on YouTube, the buying of new trousers on online shops, or the posting of a "like" on Facebook, all those information that users generate can be tracked and picked up by connected devices, enabling whoever owns them to make smarter decisions. For example, it helps executives in deciding which components to stock up on, in identifying which components are selling fastest, understanding where customers spend most of their time in supermarkets, or aligning sales data with supply schemes based on real-time information, and so on and so forth. All those better choices make executives save precious time and money, and will possibly allow to generate new revenue streams as well. With the insights provided by advanced analytics comes the power to make processes more efficient. Smart objects and smart systems represent the ability to automate certain tasks, particularly when these are repetitive, mundane, time-consuming or even dangerous.

The rise of IoT will only but favor that data generation and the advantages that are linked to it, as it is estimated by Gartner, Verizon, Cisco and others, that approximately 30 billion connected devices will be spread around the globe by 2020, providing more granular and more accurate data then ever before. According to the Boston Consulting Group, by the same time, companies will be spending about €250 billion a year in the Internet of Things.

While organizations such as the previously stated ones have already heavily invested in such new technologies, firms active in more traditional industries (retail, machinery, automotive, agriculture, etc.), or that do not benefit from the same financial and technical resources, only start considering them. However, many experts agree on the fact that any industrial company wishing to remain competitive in the following decades, should start building up its digital skills and technologies (Chui et al., 2010).

But while these statements emanate from big consulting companies, the reality remains that there is still a long way to go in order to benefit from all what IoT solutions have to offer. Referring to Capgemini Consulting's survey, it appears that while 96% of senior business leaders plan to leverage IoT in some way within the next three years, less than 30% of their organizations have been able to generate new revenues from their IoT solutions (Capgemini, 2014).

Porter and Millar (1985) defines competitive advantages as the capability of any organization to provide a customer value comparable to the one of its competitors in a more efficient manner, or by providing a particular service or product at a comparable cost but in a differentiated manner, leading to an increase in customer's value. We believe that the IoT will help companies achieve at least one of those two types of advantages, however we question the capability of particular firms to efficiently implement IoT solutions leveraging those benefits.

In this thesis, we aim at analyzing the relationships existing between some specific "explanatory" factors and the IoT implementation capabilities of organizations. As such, we want to identify the economic variables impacting the ability of companies to build reliable competitive advantages out of their IoT solutions.

We argue indeed, that the competitive advantages raised from the use of IoT agents, diverge from one firm to another. More specifically, we consider the size of a company and its industry, as the two main explanatory dimensions influencing the types of advantages that will be withdrawn from this new technology.

Furthermore, we wish to investigate the relationships existing between those same descriptive variables and the types of hindrances that companies are facing in their IoT implementation. As this technology remains quite new, and has not yet taken its full take-off, many challenges must still be overcome in order to achieve the tremendous changes that were predicted by academics and professionals. Our thesis therefore has as purpose to provide more insights of the actual reality of companies in the IoT environment, and assess whether they effectively are experimenting all the benefits it is expected to deliver.

The main research question guiding our work is the following: "*Do all companies stand even towards this new technology?*"

1.1 Thesis segmentation

Our thesis will be divided into five main chapters. In chapter 2 we go over the state-of-the-art of IoT and Big Data. This section includes a literature review about concepts such as the "digitization of companies", "business models" and "infonomics". Those concepts being intimately related to the topic of this thesis. In chapter 3, we detail the diverse hypotheses that this thesis aims at answering, and that will help us provide a concrete answer to the above formulated research question. In chapter 4, we explain the methodology applied for achieving the obtained results. Those are than exposed and discussed in chapter 5. Finally, we conclude on our work in chapter 6 and discuss, in section 6.1, all the breaches that were encountered along this research. We explain why the results of this thesis are to be trusted, or if not, what cautions must be taken in order to not misunderstand the findings.

Chapter 2

Literature Review

The literature is filled with articles discussing the state of the art of the Internet of Things, its applications, the opportunities that this new technology has to offer, the hindrances that slow down its global adoption, and all the technologies required for its good development. Therefore we will not spend too much time on those topics but rather provide a short overview.

This section is subdivided into five main parts. The first one discusses the general concept of big data, as it is closely related to the IoT. Then, in the second part, we describe the Internet of things by providing some definitions and give some insights on how companies derive value from that new technology. We will also present some technical challenges facing the wide scale deployment of IoT solutions, and discuss the socio-ethical problems that both the IoT and Big Data seem to raise.

In the third section of this literature review, we quickly go over the topic of digital transformation, as it is a required move towards the adoption of IoT and of prime importance for every company wishing to remain competitive. We then discuss, in the fourth section, the impact that digitization will have on current business models and how companies should adapt them to leverage the benefit that flows from those new digital technologies.

Finally we tackle the concept of the new economy of information, also called the data economy, and the particular type of economics that apply to it. We shall review how enterprises manage to deal with their data, and how they thrive to exploit that new resource. We will show to what extend the Internet of Things is a major factor in the emergence of that new type of economy. Also, we review different ways in which companies can turn the data collected from their smart objects into valuable information, and how to monetize those data to leverage the best competitive advantages.

2.1 Big Data

Manyika et al. (2011), define Big Data as being *"data sets whose size is beyond the ability of typical database software tools to capture, store, manage and analyze"*. As such, they are typically difficult to process through current database and data management softwares (Sagiroglu and Sinanc, 2013). As this is a subjective definition, they argue that, as technology forever improves, data sets that we consider nowadays as Big Data would probably not be considered as such in the future. Also they argue that large data sets vary across industries. Still, it is mainly considered that Big Data today ranges from a dozen of terabytes to thousands of petabytes. Google and Facebook for example process hundreds of data petabytes, and Taobao, a subsidiary of the Alibaba group generates data of tens of Terabytes daily (Chen et al., 2014).

Microsoft provides a more complete and concrete definition, and states that "Big data is the term increasingly used to describe the process of applying serious computing power - the latest in machine learning and artificial intelligence - to seriously massive and often highly complex sets of information".

Some more authors have also provided other definitions for the concept. As a matter of fact, there appear to be no commonly agreed upon definition of Big Data.

Doug Laney, an IT consultant at Gartner, mentioned in 2001 that all data managers were to face the challenges that emerge from the three dimensions of data, which he also calls the 3V's. Besides the *Volume*, he distinguishes the *Velocity*, and the *Variety* of data. Many authors describe and define big data according to those characteristics (Chen et al., 2012; Kwon et al., 2014).

The volume obviously refers to the tremendous amount of data generated. The velocity, refers to the rate of that generation as well as the speed needed to process those data in a timely manner. Finally, the variety can be understood as a measure of the heterogeneity of data. Heterogeneity regarding their format or regarding their structure (Gandomi and Haider, 2015). Typically we distinguish the structured data - found in spreadsheets or database - from unstructured data such as videos, images, texts etc.

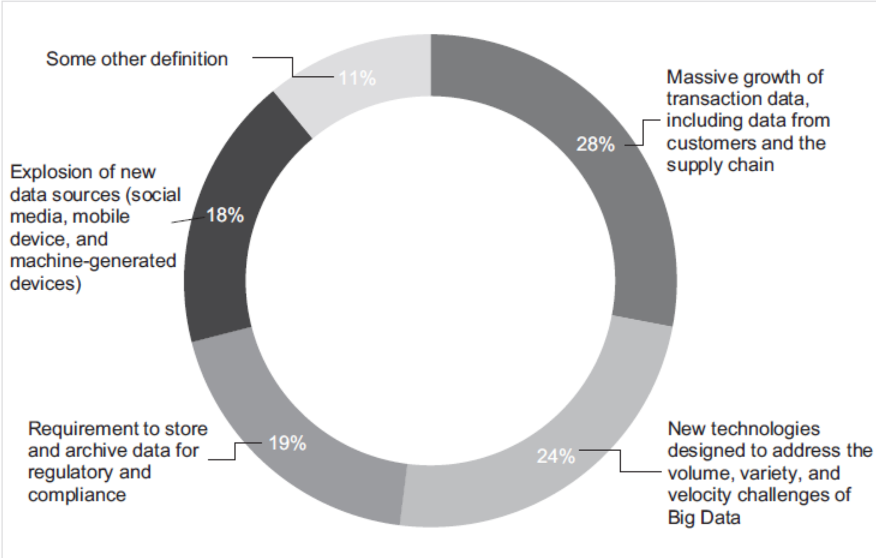

Figure 2.1: Big Data definitions

Big data has gained a lot of attention from both academics and corporations. On one hand because of the many opportunities it provides, on the other, for the various socio-ethico and technical challenges its development poses (Ward and Barker, 2013).

> *"Big data is opening doors, but maybe too many." (Microsoft, Raymond Wash, 2012)*

2.1.1 Big Data value

Big Data are the roots of tremendous value creation for companies, and for the society as a whole. But data are worth nothing when they are not exploitable and analyzed (cfr. 4th law of Information of Moody and Walsh (1999)). Therefore, firms need to get the appropriate processes for data analytics in order to leverage its potential value (Gandomi and Haider, 2015).

> *"The valuable thing is the insight that can be derived from the data" (Evans, 2014)*

Various authors expose the many statistical techniques developed in order to analyze and draw business insights out of structured and unstructured data. As it is not the purpose of our thesis to expose the latter, we recommend the interested reader to refer the article of Gandomi and Haider (2015) for more references.

As data are now considered as one of the most important resource of companies, Big Data and its related analytics techniques will become a huge factor for creating value (Chen et al., 2014). Manyika et al. (2011) argue that it will play a significant part in the enhancement of private commerce, national economies and citizens quality of life. But above all, it will serve companies to enhance their decision-making processes and to achieve tremendous competitive advantages (Ross et al., 2013; Reddy, 2014).

The McKinsey Global Institute (Manyika et al., 2011) identifies multiple ways through which firms could leverage the potential of Big Data. Their survey further explains how this new trend will become the basis for competition in the new data economy era, but remains aware of the many challenges that still need to be overcome in order to reach this point.

2.2 The Internet of Things

Semantic Web, also called Web 3.0, is a new evolution of the Internet that has as goal to mark up web content in order to enable machines to understand it, and to adopt an intelligent behavior on the web. It would allow them to process and share data autonomously, participating in the web content creation (Whitmore et al., 2015). As Web 2.0 only considered human beings as content creators, semantic web also focuses on machines. It is now possible for them to search, organize, process, and interpret information without any human intervention (Breslin et al., 2010). The rapid development of other telecommunication technologies such as the Radio Frequency Identification (RFID) or the Near Field Communication (NFC), the increase of servers' storage capacity, the improvements in data science and cloud computing, as well as the drop in sensors production costs (following the Moore's law[1]) are all factors enabling the takeoff of IoT finally possible (Reddy, 2014).

All those huge technological breakthroughs allow us to dream of a world in which not only humans would be connected to the Internet, but also everyday life objects, participating actively in the content creation and in the exchange of information via the Web (Whitmore et al., 2015).

[1]Moore's law states that the amount of computing power that can be purchased for the same amount of money doubles about every two years.

2.2.1 Definitions

The Internet of Things (IoT) is the term usually used to refer to the connection of usual physical objects equipped with sensors and able to measure divers features of their environment, and to share those measures via a Wireless Sensor Network (WSN). Concretely, such objects, also called "smart objects" or "IoT agents", need to be uniquely identifiable, must be capable of simple to complex computing, should be able to communicate, and of course require features capable of sensing and measuring parameters of their environment (Miorandi et al., 2012; Jadhav, 2014).

The term "IoT" was coined for the first time by Kevin Ashton of Procter & Gamble in 1998. There currently exists no universally accepted definition, but among those we were given to read, we decided to retain the one formulated by Gubbi et al. (2013), stating that "*The IoT is the interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications. This is achieved by seamless ubiquitous sensing, data analytics and information representation with Cloud computing as the unifying framework.*"

The core principle of IoT might not seem that revolutionary, and indeed we have known inter-objects communication for a while. The concept of RFID has been used in supply chain management, and the famous Machine-to-Machine (M2M) is a subject long discussed by academics and companies. Nevertheless, however the IoT relies on such well-known technologies, it goes way beyond that, producing ever more granular information in a much larger quantity and accessibility (Durkin et al., 2017).

> *"The IoT represents an evolution of M2M through the coordination of multiple vendors' machines, devices and appliances connected to the Internet through multiple networks." (Unknown, 2014)*

The IoT represents an evolution in terms of number and nature of objects that will get connected. Indeed, as we currently are familiar with connected devices such as smartphones, laptops, and other tablets, the IoT seeks to integrate all kind of objects previously thought of as non-digital. Soon enough, chairs, toothbrushes, beds and doors will be directly accessible through the Internet and will become data generating hot spots essential for the information economy. Furthermore, as those devices will be gifted with computing capabilities and exhibit ”intelligent” decision making, we no longer are contained into the classical M2M.

Those smart devices promise - if combined with other technologies such as Artificial Intelligence (AI), machine learning, cloud computing and others - to drastically change the world our society has known so far. In particular, they will enable the development of new ”smart services” providing context related and granular offerings (Miorandi et al., 2012). For years now, several studies are being led to enhance the potential of those services (Baldauf et al., 2007; Loke, 2004).

It makes no doubt that, even though IoT is only at its early stage and its adoption is remaining slow, it will provide opportunities for companies to innovate their value proposition and enable the creation of new services.

The IoT provides organisations with a mean to incrementally or disruptively transform their business operations (Bucherer and Uckelmann, 2011). However several authors agree to say that the first uses that will be made out of this new technology will rely on currently implemented business processes, providing firms with an incremental enhancement of their operations (Roussos and Kostakos, 2009).

2.2.2 Applications

The IoT can be used in all kind of domains and offers plenty of different applications. Actually we believe that only human imagination can define its limits. As IoT opens the way for numerous business innovations it could even be the trigger for the creation of completely new industries. Currently, the literature identifies several industries which are considered to be most prone for IoT integration. We distinguish the healthcare industry, the supply chain management, smart homes and smart cities as well as energy monitoring and manufacturing. However, lots of other industries, providing services, such as insurance companies, start implementing IoT solutions too.

There exists a vast literature treating of the diverse applications of IoT solutions in industries and the way they are being used to enhance their performance. As those do not constitute the core of this thesis, we invite the interested reader to consult the works of Miorandi et al. (2012), Gubbi et al. (2013), Bandyopadhyay and Sen (2011), Atzori et al. (2010) and many other for further information.

2.2.3 Ways of Using IoT solutions?

Haller et al. (2008), and other before him, already asserted that the IoT would offer a panel of new opportunities for companies, but for individuals as well, but more generally for the entire society. Since then, many others authors have stated exactly the same.

Lee and Lee (2015) identify three types of corporate use of IoT:

1. Monitoring and control
2. Information sharing and collaboration
3. Big Data and business analytics

The IoT applications belonging to that first category, are for example used in industries in order to collect consistent data in a timely manner in regards of the performances of production machinery, in a purpose to prevent machinery failures, to plan more optimal maintenance schedules, or to develop reliable energy monitoring solutions. This type of use of IoT solutions can also be implemented by individuals to keep track of their home appliances and create a smart home (Kelly et al., 2013). Haller et al. (2008) refer to the term "real world visibility" to designate that first category. Smart things generating consistent and precise information at the right time about their environment, undoubtedly provide companies that benefit from it with competitive advantages in terms of cost reduction and process improvement (Spieb and Karnouskos, 2007).

Organizations have all interests in making good use of the data they collect from their IoT devices. Sharing those data among their network of collaborator (cfr. Section Ecosystems) represents one of those good practices. As we will show in section 2.5.3, the value of information increases when it is combined with other pieces of information coming from different sources. The IoT agents therefore rely on the "high speed network technology" in order to efficiently share the data they gather (Wang et al., 2013). More importantly, in order to facilitate the data exchange,the standardization of the diverse communication protocols and data formats globally must be achieved. Furthermore, WSN must be flexible, reliable and above all scalable in order to host a still growing amount of connected devices (Lee, 2017).

Nevertheless, the gathering and sharing of data will not make much sense if companies do not process them to withdraw valuable knowledge, needed for the enhancement of their decision-making. The development of strong statistical tools is thus an essential point in the IoT actors' agenda.

> *"Big Data and data analytics refers to the process of collecting, organizing and analyzing massive amounts of data to discover useful patterns and knowledge." (Lee, 2017)*

Through machine learning and other advanced statistical techniques, organizations are able to derive trends and more precise business insights from the data in their possession (Haller et al., 2008), enabling them to make better choices from a managerial standpoint.

2.2.4 Deriving value from the IoT

Companies benefit from IoT in two ways. First, they can improve their business processes and therefore reduce their costs. Secondly, they can find new ways to generate revenue streams by developing new services (Reddy, 2014). For those reasons, a still growing proportion of businesses start to implement IoT solutions in their core activities, enhancing their productivity, their customer experience, optimizing their energy monitoring, and providing them with other competitive advantages (Jadhav, 2014).

To date, the IoT seems to be mostly used in conjunction with preexisting technologies, as a mean to improve existing business processes, but not to create new ones. Jadhav (2014) argues that the full benefit of IoT will not be reached until managers change their mindset and start using this new technology for what it is, namely a disruptive technology.

Furthermore, and independently of the industry the IoT agents are used in, Chui et al. (2010) identify 6 types of applications falling into two broad categories: Information and analysis, and automation and control.

The first category would enable companies to make better decisions through "tracking behavior", "enhanced situational awareness", and "sensor-driven decision analytics". Those three types of applications respectively referring to, first, the tracking and monitoring of sensor equipped objects, second, the collection of large amount of data from ubiquitous sensors, providing companies with the ability to react quickly to different sorts of situations and make in time decisions. Finally, the ability to support longer-range decision making processes (Chui et al., 2010).

The second category enables firms to automate processes and thereby increase their productivity. "Process optimization" refers to the ability of IoT devices to send data to an analytic software, which is in turn capable of modifying the specific parameters of operational processes, minimizing waste and avoiding quality problems. "Optimized resource consumption" and "Complex autonomous systems" are the last two applications identified by the authors. In order to achieve those processes' automation, edge computing will be required (Haller et al., 2008). Indeed, performing all the data analysis in the back end is not optimal as systems need to answer quickly to triggers of their environment. IoT agents therefore should be able to perform data analytics on their own, at the edge.

2.2.5 Challenges

As for applications there exist a large number of hindrances, described in various articles, slowing down the adoption rate of IoT. We present here a few of them that we consider as the most important ones. For a more exhaustive discussion, we invite the interested reader to consult the articles of Bandyopadhyay and Sen (2011), Mattern and Floerkemeier (2010) as well as Miorandi et al. (2012).

Generally speaking we could classify the encountered obstacles in two broad categories. We distinguish the technical and technological problems from the societal and ethical ones.

Technical obstacles

Due to the enormous amount of connected devices that will soon be spread all around the world, the number and heterogeneity of data will become problematic. The lack of standards could lessen the competitiveness of IoT products and services (Broll et al., 2009). The standardization of the IoT aims at lowering entry barriers for IoT service providers, but will also improve the interoperability of various devices and softwares hence their competitiveness (Jiang et al., 2012). The standardization of data formats, communication protocols and other technical aspects therefore constitutes an essential point in order to ensure the global success of IoT devices (Bandyopadhyay and Sen, 2011; Reddy, 2014).

Moreover, the WSN must be capable of supporting such a large amount of connections and data streams, traditional servers' potential not being suited for such task (Haller et al., 2008). The scalability of networks is therefore of prime concern. Also, those networks must ensure a large coverage enabling the most granular use of IoT devices as well as make sure that no signaling dead spot exist.

Also, as the amount of generated data is now exceeding the Moore's law, traditional data management will not be able to deal with this in an efficient way (Chen et al., 2014; Gandomi and Haider, 2015). Storage capacity of computers as well as their computing power will have to be improved, and new ways of treating the data must be found.

Ethical obstacles

While for ever growing investments are made in the development of IoT, the adoption rate of that new technology remains relatively low. Based on the TAM model (Technology acceptance model), Gao and Bai (2014) determine the factors influencing the acceptance of IoT by individuals. Their study concludes that the perceived usefulness, the perceived ease of use, the social influence, the perceived enjoyment, and the perceived behavioral control are the variables most susceptible to influence the acceptance of a customer towards IoT solutions.

In addition to those factors, the social acceptance of IoT solutions will rely on the confidence that users will have about the security and privacy of their data (Li et al., 2015). Even though encryption has rendered wireless communication far more secure, some connected devices do not support that solution. Making a more efficient software and improving the energy consumption of IoT devices would favor this type of protection (Bandyopadhyay and Sen, 2011).

It is overriding to protect sensitive information of users, either for companies or individuals, from hacking and cyber attacks. The rise of data availability as spawn a new economy, known as the data economy, into which companies exchange data among each other (Opher et al., 2016). Indeed today, a lot of organizations (i.e. Facebook, Twitter etc.) share or sell the information they collect from their customers, the latter sometimes not even knowing it. However, customers and IoT users must be aware of those actions and their consent should remain the priority (Mashhadi et al., 2014).

Data ownership and GDPR

While Gartner estimates that in 2020 approximately 26 billion connected devices will be spread across the world, it makes no doubt that every player of the data life cycle will try to monopolize its propriety right. Determining the actor who will be able to exploit the data, and harvest all the benefits that goes with it, therefore remains a crucial point.

As IoT devices will gather information about everything, the chances are high that breaches of trust occur between IoT service providers and users. Currently, IoT services lack users' consent regarding how, what for and by who their data are used. Mashhadi et al. (2014) state that the user, which is also the producer of the data, should remain the decider of what is been done with it. As such he should be able to access all the content he generated, decide what he allows the collecting company to do with, and could even ask for a financial compensation when its information are used for different purposes than for the provision of the company's offering itself. The authors describe three different types of ownership models that could serve as references in order to provide a greater control for IoT services users (Mashhadi et al., 2014) .

As this problematic has become serious for the society, governments have decided to tackle the problem and to provide measures helping safeguarding the intimacy of citizens. The EU came up, on the 14th of April 2016, with the European General Data Protection Regulation (GDPR) which will come into effect in May 2018. It is meant to replace the Data Protection Directive 95/46/EC in order to harmonize data privacy laws across European countries, as well as to protect and empower all EU citizens data privacy and to reshape the way organizations across the region approach data privacy [2].

In fact the GDPR will be applicable in all countries across the world, and thus will have to be respected by all corporations processing European data (Kolah and Foss, 2015). Indeed, as the US regulations consider the data privacy as a property right and not as a fundamental one, European citizens were not protected once their data were outsourced for processing by US companies (Ciriani, 2015).

As people see in this new regulation a positive point for the protection of their identity and private life, other authors argue that the data protection reform is flawed and will probably not deliver what it was aimed for (Koops, 2014).

This new regulation will surely have an non-negligible impact on companies, and those will have to adapt their practices as they will face considerable fines in case of non-conformation.

[2] http://www.eugdpr.org/25/06/2017

2.3 Digital Transformation

Since the digital revolution and the emergence of the Internet, the economic environment in which most companies evolve has fundamentally changed (Ng, 2014). The importance of the Internet in companies' operations has kept growing exponentially since 1990 (Fleisch et al., 2015), resulting in shorter products' and services' life cycles (Glova et al., 2014). With the new digital technologies spreading around the globe, the amount of data generated by organisations and individuals is exploding. Eric Schmidt, former CEO of Google, estimates that our society now produces a larger volume of data in two days time than in the period running from the dawn of mankind until 2013.

This hyper connectivity enables firms to access uncountable sources of information and changes completely the relationship they maintain with their market and clients, and the way they achieve their profits (Ng, 2014). As of this shift, a digital imperative appears for companies (Fitzgerald et al., 2014).

> *"The connected world creates a digital imperative for companies." (Fitzgerald et al., 2014)*

2.3.1 Digital technologies do provide competitive advantages!

In the era of IoT and Big Data, information becomes an indispensable asset for organizations. The use of data as an economic resource completely changes the rules of competition and the classical economic models (Ng, 2014).

Many researches lead by big consulting companies show the benefits that digital technologies can have on the economy and on our society. The study of the McKinsey Global Institute (2011) concludes that the use of data as a strategic resource enhances both the productivity and the competitiveness of firms. So that companies see themselves forced to modernize their business models if they wish to maintain chances to rival with their competitors in this new digital era (Fitzgerald et al., 2014). At present, we already notice a shift in the balance of power in certain industries, due to that phenomenon of booming data generation (Veit et al., 2014).

A survey lead by the MIT Sloan Management Review and Capgemini Consulting in 2013 among 1559 executives across different industries, has revealed that companies that succeed in efficiently managing the digital technologies they implement, benefit from notable competitive advantages. More specifically, they experience improvements in the quality of their customer's experience, their productivity, and the development of new business models. In other words, recent advances in digital technologies, including information, computing, communication and connectivity, have led to new opportunities for business model innovation (Bharadwaj et al., 2013).

> *"Potential benefits of digitization are manifold and include increases in sales or productivity, innovations in value creation, as well as novel forms of interaction with customers, among others." (Matt et al., 2015)*

Actually, 78% of Capgemini's survey respondents consider the digital transformation as essential for the future of their organization. However, they also felt frustrated as they discovered how hard it was to achieve great results out of the adoption of new technologies. For example, only 7% of the respondents declared having achieved business model innovation or the creation of new business opportunities through the adoption of new digital technologies (Fitzgerald et al., 2014).

2.3.2 Digital transformation, a must have for companies?

The digitization of business processes, that is what constitutes today one of the most essential point of companies' operational strategies. However, in contrast to larger IT groups such as Facebook, Google, Apple, Amazone and so on, "traditional" firms struggle to implement those new digital technologies into their business processes, for they deviate so much from their current ones (Remane et al., 2017).

Andriole (2017) argues that in order to lead an efficient digital transformation, leaders must not get seduced by the hype, but rather understand its realities. He distinguishes five myths commonly believed by a majority of executives regarding the digital transformation.

First, he argues that not all companies should require digital transformation, as some processes are simply really hard to transform. Then, he states that disruptive business model innovation, most of the time, rely on current strategic technologies and not on new technologies. The third and fourth myths are in our opinion referring to the same thing. Indeed the author exposes that disruption mostly occurs in small or not well-established companies as successful firms are more reluctant to change. Finally, he claims that whatever executives say, there are not so many that are truly willing to perform a digital transformation. While a leading upper management is referred to by many authors as the key to the successful digitization of an organization, the lack of clear vision of some executives constitutes a huge hindrance towards the achievement of effective digitization of certain firms.

As of these assertions, one could ask himself whether the adoption of new digital technologies, such as the IoT and Big Data, is truly needed. To answer that question, we refer to Berman and Bell (2011), from the IBM Institute for Business Value, who state that "*companies with a cohesive strategy for integrating digital and physical elements can successfully transform their business models and set new directions for entire industries*".

> *"The challenge for businesses is how fast and how far to go on the path to digital transformation." (Berman and Bell, 2011)*

2.4 Business models and IoT

Berger (2015) claimed in one of its study that the next industries that were going to perform their digital transformation were the automotive, logistics, health, electronics, machinery and energy. This is driven, by the new opportunities that arise from the ubiquitous connectivity of devices and the ability to exploit the data they generate to automate process and develop new types of services (Remane et al., 2017).

Fleisch et al. (2015) showed in their research that the Internet has had a significant role in companies' business models since the 1990's, and that each new Internet breakthrough has resulted in the development of new digital business models. The emergence of the Internet of Things will not be different.

As of these statements, if those industries want to leverage the full value IoT has to offer, they surely need to develop new business models, more suited to that new technology (Dijkman et al., 2015).

> *"Firms experiment, change, refine and re-invent their business models" (Demil and Lecocq, 2010)*

2.4.1 Business models in general

Some people ask themselves whether the concept of business model really has a meaning and if it is of any importance for managerial science.

> *"Are Business model useful?" (Baden-Fuller and Morgan, 2010)*

The term is often used for and mistaken with the strategy of a company, however they are two well distinguished things (Magretta, 2002). Business models have to be seen for what they are, models. As such they are kinds of recipes for creative management and demonstrate how to do something in order to achieve the intended goal. As recipes, they combine several ingredients, a variety of strategic elements such as the resources, the capabilities, customers, technologies, and so on. But they also provide guidelines to "cook" those elements together. In other words, they provide sets of rules that, if respected, will lead to the aimed objective (Baden-Fuller and Morgan, 2010). Furthermore, they help managers to understand the process of value creation, its delivery, and its capture (Lee, 2017; Osterwalder and Pigneur, 2010).

> *"A business model describes the rationale of how an organization creates, delivers , and captures value." (Osterwalder and Pigneur, 2010)*

The analogy of the recipe introduced by Charles Baden-Fuller and Mary S. Morgan (2010) is strong and very intuitive. One can easily understand that all ingredients are valuable according to the dish we try to cook, and that different recipes, in the end, can deliver the same value to the consumer. As such we understand that there are various ways to achieve the wished outcome and that business models can be modified according to the strategic elements each firm possesses. Other authors also have the same view of business models, splitting them into several components, which they name "building blocks" of the business models (Chesbrough and Rosenbloom, 2002; Morris et al., 2005; Osterwalder et al., 2005).

Definitions

There currently exists no globally accepted definition of what a business model is and how to represent it (Burkhart et al., 2011; El Sawy and Pereira, 2013; Zott et al., 2011). The different definitions that exist often depend of the context in which they are used (Ng, 2014). Searchers usually agree to say that they serve as providers of a generic set of steps, implemented by organizations in order to create, deliver, and capture value (Baden-Fuller and Morgan, 2010). It is an abstract description of the operational activities of the firm it characterizes, hence facilitating its analysis (Glova et al., 2014).

Chesbrough and Rosenbloom (2002) mention that the business model constitutes a relevant starting point for innovation and to align technology and economic goals. The development of a successful business model enables to unite the technological requirements of IoT with its economic perspectives (Glova et al., 2014).

Gassmann et al. (2017) claim that the business model pattern must contain the answers to Peter Drucker's four basic questions: "Who are the customers?, What is being sold? , How is it produced?, How is the revenue earned?". Answering those questions a business model articulates the value proposition of a company, it further identifies the market segment it is aiming for, and specifies the revenue generation mechanism through which they harvest their profits (Hartmann et al., 2014).

> *"A business model is an architecture of products, services and information flows which includes the involved actors and their roles as well as the potential value created for all participants and the sourced revenue." (Timmers, 1998)*

From this definition and the purpose for which they are used in management, business models remain essential to every successful organization, whether it is a new venture or a well-established player (Magretta, 2002).

> *"A good business model remains essential to every successful organizations, whether it's a new venture or an established player." (Magretta, 2002)*

2.4.2 Business models for the IoT

As of the emergence of IoT, new business models must be developed in order to efficiently integrate this new technology into the current business processes of firms. Teece (2010) states that business model innovation is a type of organizational innovation through which companies manage to adopt novel opportunity portfolios. It is a way to achieve competitive advantages and often affects the entire firm (Zott et al., 2011).

> *"Business model innovation is a process of finding innovative ways to create value, delivering value, and capturing value." (Lee and Lee, 2015)*

Since IoT, and digital technology in general, might soon become the norm in most industries, the need for development of new digital business models is becoming urgent. As business model patterns in digital industries were completely different from those in physical industries, those differences tend to disappear with the emergence of the IoT (Fleisch et al., 2015). Veit et al. (2014) state that "*a business model can be categorized as digital if digital technologies trigger fundamental changes in the value dimensions (proposition, delivery, capture)*".

Some attempts to develop IoT suited business models

The literature treating the development of IoT based business models is quite narrow (Dijkman et al., 2015; Whitmore et al., 2015) and data-driven business models need to be developed (Hartmann et al., 2014)].

While some authors have already tried to fill this gap, by developing their own business model for IoT (Bucherer and Uckelmann, 2011; Fan and Zhou, 2011; Li and Xu, 2013), based on the Business Model Canvas developed by Osterwalder and Pigneur (2010), none of those models have empirically been tested . Ideally, business model frameworks should have been tried out in the real world, and their efficiency assessed, so that following firms can reuse them in order to build their own successful business model, suited for the integration of digital technologies (Baden-Fuller and Morgan, 2010).

> *"A business model framework is a tool that helps a company to develop its business models, by providing an overview of its strategic components." (Dijkman et al., 2015)*

Figure 2.2 displays the strategic elements, used by various authors to construct their business model framework.

Even though the above exposed researches on business model framework constitute an improvement for the IoT related managerial literature, we argue that they omit to integrate a very important feature of the Internet of Things. Indeed, they fail to mention the concept of "*ecosystem*", in which every firm active in the IoT field is part of (Turber et al., 2014).

2.4.3 Ecosystems

The Internet of Things and its particularities enable companies to develop numerous types of opportunities. However, due to the complexity of this technology, they most of time

Table 1 Review of different business model frameworks

Author(s) Year	Value proposition/ offering	Key resource	Key activity	Market/ customer segment	Revenue stream	Cost structure	Other elements	Citations (Google Scholar, 19.01.2014)
Chesbrough and Rosenbloom, 2002	✓			✓	✓	✓	Value chain, value network, competitive strategy	1735
Hedman and Kalling, 2003	✓	✓	✓	✓			Competitors, scope of management	456
Osterwalder, 2004	✓	✓	✓	✓	✓	✓	Customer relationship, channels, key partner	1001
Morris et al., 2005	✓	✓		✓	✓	✓	Competitive strategy factors, personal factors	846
Johnson et al., 2008	✓	✓	✓		✓	✓	-	641
Al-Debei and Avison, 2010	✓	✓	✓	✓	✓	✓	Value network	116

Figure 2.2: Review of different business model framework

can only be achieved through collaboration with diverse partners from across different industries (Atzori et al., 2010; El Sawy and Pereira, 2013). Current business models manage to efficiently analyze and comprehend individual firms, but are far less effective when it comes to examine networks of collaborators (Weiller and Neely, 2013).

Companies wishing to integrate IoT solutions cannot consider a firm-centric business model, but should rather consider developing a business model applicable to their entire ecosystem (Yoo et al., 2010a).

A business ecosystem is an economic community supported by a foundation of organizations and individuals interacting in order to leverage value for the whole ecosystem (Moore, 1996). In the more specific case of IoT, we must think of the ecosystem as a gathering of firms active in various types of industries, each bringing specific skills required for its development. As IoT agents are composed of numerous different technologies, expertise across those diverse fields is undoubtedly needed.

The only way to consider a business model for a company active in the IoT sector, or that implement IoT solutions from which it withdraws its value, is to have an overview of its entire ecosystem and to analyze the value creation and capture for all its participants (Westerlund et al., 2014).

> *"An IoT ecosystem is a community of integrating companies and individuals where the companies use a common pool of core assets, based on linkages of*

physical world of things with the virtual world of the Internet." (Tarkoma and Katasonov, 2011)

Turber et al. (2014) developed a business model framework in that context, this time involving the concept of ecosystem. This business model framework recognizes that there are four layers in the IoT device architecture (Yoo et al., 2010b). Each of those layers can be regarded as source of value creation on which multiple partners across the ecosystem can collaborate on (Mejtoft, 2011).

Westerlund et al. (2014), in their research about the construction of business models for the IoT, highlight different problematics. They claim that the lack of standardization among IoT agents and back-end applications, as well as the immaturity of IoT ecosystems are the primary reasons for the weak development of IoT business models. As a mean to overcome those problems, they provide the grounds for new ecosystem business model framework.

2.5 Infonomics and data monetization

As we have made a superficial literature review of the Big Data, the IoT, the digital transformation, and of the business models, we now enter what we consider as the core of our thesis.

2.5.1 Information, the prime resource of tomorrow

Porter and Millar (1985) have expressed in their research to what point information and information technologies constitute a tremendous revolution for the entire economy, and how they deliver huge competitive advantages if properly used. As the IoT will increase the amount of information generated, this trend will only be reinforced in the years to come (Bucherer and Uckelmann, 2011).

"The information revolution is transforming the nature of competition." (Porter and Millar, 1985)

Companies are information consuming entities as they rely on it to process their decision-making (Galbraith, 1977). And indeed, firms evolving in uncertain environments do not adopt the same behavior and results as firms evolving in certain environments.

This desire of reducing risks has created the need to shift from "gut-feel" to fact-based decision making among executives (Friedman and Smith, 2011). This explains why uncertain firms tend to gather a maximum of information. However, they need to possess the required means to process it. Therefore, adapting their capabilities according to the volume of information they treat becomes essential (Tushman and Nadler, 1978).

As O'Reilly (1980) wrote in 1980, executives seems not to have a clear view on that volume. He argues that managers tend to acquire a still larger amount of information, independently of the uncertainty level they face. However, Oskamp (1965) has put into light that past a certain threshold, further pieces of information did not bring any value to its owner. In fact, as for other types of resources, we acknowledge a decreasing marginal use of the information.

Hodge and Reid (1971) even show that, beyond that threshold, the decision maker does not have the clarity of mind anymore to distinguish relevant information from irrelevant ones. As one can imagine, the irrelevance of information and its bad quality can reveal themselves to be very costly in terms of operational mistakes and bad decision making (Wang and Strong, 1996). As Friedman and Smith (2011) showed in their research for Gartner, poor data quality is responsible for the failure of 40% of business initiatives, and affects labor productivity by as much as 20%. In the same line of idea, Chervany and Dickson (1974) experimented that summarized, and relevant information, enabled decision makers to make better choices than when provided with large volumes of poor and unstructured data.

As of these observations, Kaufman and Couzens (1973) suggested that firms favor the use of the information they currently possess, rather than overloading their decision-makers with mountains of messy information, which does not seem to provide any additional benefit. Furthermore, above those managerial issues, an overload of data is more costly to manage, store and process.

2.5.2 The new information economy and the need for adopting a data-driven view

The Internet of Things is with no doubt a factor favoring the emergence of the information economy, also referred to as the data economy. As the amount of connected devices increases, the volume of data naturally follows the same trend. As previous discussions mentioned the advantages that can be drawn from the information management, one can see in how IoT can be of huge help for developing competitive advantages. This should provide firms with another incentive to add this new technology to their business processes.

Not so long ago, the majority of executives treated the information management as a support activity. Still nowadays, as some pretend that we entered the "information era", a period in which the traditional physical assets have made way for digital ones, we notice that the latter are still not broadly considered as an essential resource for many of them. Today, they must see it as the core part of their firm's innovation capabilities (Yoo et al., 2010b) and as a primordial component of their operational processes. The data, the information that flows from it, and the knowledge that corporations build on it, now constitute a good metric to acknowledge the sustainability of firms in their environment (Opher et al., 2016).

2.5.3 The issue of information valuation

As we notice an increase in the global information management investments, information still does not have a proper line in the balance sheets of firms (Moody and Walsh, 1999). This is mainly due to the fact that it is still hard for executives to properly value it.

While the volume of data generated by IoT smart objects and other social networks and so forth, is about to rise exponentially, the valuation of those data seems to remain problematic due to the lack of current quantitative tools that can be applied on it (Bucherer and Uckelmann, 2011). And as states the adage... "*We can't manage what we don't measure.*"

Moody and Walsh even claim that "*of all the corporate assets, information is probably the least well managed.*"

Infonomics

The infonomics is the science studying the economic behavior of information, and aiming at helping executives to better manage it. Gartner provides the following definition:

> *"Infonomics is the emerging discipline of managing and accounting for information with the same or similar rigor and formality as other traditional assets (e.g., financial, physical, intangible, human capital). Infonomics posits that information itself meets all the criteria of formal company assets, and,*

> *although not yet recognized by generally accepted accounting practices, increasingly, it is incumbent on organizations to behave as if it were to optimize information's ability to generate business value."*

Jim Whiterhurst, CEO of Red Hat said in a Ted Ex conference that "*the way businesses are able to differently and better create and leverage information is what will define their competitive advantages and how they create value.*"[3]

In this new type of economy, and with the emergence of IoT in particular, we consider information to be the core asset of value creation in the new coming business models (Bucherer and Uckelmann, 2011). That is why it is essential, for companies willing to maintain a competitive position in that environment, to deal with it as good as possible, as they do with any other type of assets.

Information Laws

Moody and Walsh (1999) define seven laws of information that provide insights on the characteristics and behavior of that new corporate resource.

1. Information is infinitely divisible and can be shared without loss of information.
2. The value of information increases with its use and is null or negative when it is not used.
3. Information is perishable and depreciates over time.
4. The value of information increases with accuracy.
5. The value of information increases when combined with other information.
6. More information is not necessarily better.
7. Information is not depletable.

Through those laws we can see in how IoT can help companies withdrawing value from the information they possess. Indeed, companies can share the data they collect through their entire IoT ecosystem without losing value for their own and favoring the value creation for the ecosystem. Then, IoT agents provide companies with in time and precise

[3] `https://www.youtube.com/watch?v=6ag8DiOWG1I`

data. In turn avoiding the loss of accuracy and limiting the depreciation of information. Moreover, as IoT applications and platforms enable firms to gather information coming from different devices and sources, its value increases according to the fifth law of Moody and Walsh.

Finally, we understand from the second and seventh law of information that the data generated by IoT devices must be used in order to leverage their potential.

2.5.4 Adopting a data-centric strategy

As we mentioned before, there is still a large part of firms that do not consider, or at least treat, information as an essential asset for their success. However, we argue that it is. Still, other points of view exist as several researches have shown that there existed no positive relationships between the investments made in IT departments and the overall performance of organizations (Markus and Robey, 1988; Weill, 1992). Brynjolfsson and Yang (1996) studied this phenomena, while Siegel and Griliches (1992) tried to provide some explanations to it. To that, Glazer (1993) argues that firms succeeding in the achievement of competitive advantages through information technology, simply have adopted a different mindset by placing information itself at the center of their value creation process, rather the technology that supports it.

> *"The successful organizations [...] view the management of information itself as the key variable toward which to direct their attention." (Glazer, 1993)*

However it remains that in order to gain competitive advantages out of data, their value has to be measured (Glazer, 1993).

Due to their specificities, we cannot apply the same valuation tools used for traditional assets, to pieces of data. Indeed it would be useless to value information according to its volume, as we can logically deduce from its sixth law. Instead we would rather value it according to its "meaning", the significance for the one that exploits it (Cherry, 1957).

> *"The formal or quantitative definition and measure of information is that which reduces uncertainty or changes an individual's degree of belief about the world." (Shannon and Weaver, 1998)*

2.5.5 Some models for Information valuation

As we argued that information valuation was essential in order to adopt a data-centric strategy and raise competitive advantages, we also notice any type of usage made by certain companies out of those data. Indeed, several companies happen to trade the information like any other assets on so called "data markets" (cfr. section 2.5.6). For it is necessary to be able to measure the value of information, for those two purposes, several authors have intended to develop models helping managers to approximate the latter.

Doug Laney, research vice president at Gartner Inc, developed six different models spread into two broad categories, namely the financial models and non-financial ones[4]. Repo (1986) tackled the question of information valuation by relying on what he considers as the two features of value. He distinguishes the *value-in-use* and the *market value* of information. The first one is conceptual and is defined as the significance, or "meaning", that information brings to its owner, while the second refers to the price that the market would agree to pay to obtain it. As the market price of assets is determined by the law of demand and offer, the other feature of value seems hard to compute for information assets, due to their non-scarcity (Repo, 1986). However, one can see that the value-in-use obviously differs from one individual to another, as such the market price for those entities should also differ. Shapiro and Varian (1998) therefore suggest that we use the price discrimination technique in order to maximize the value that the market is ready to pay for a company's information assets.

Moody and Walsh, however, claim that it is extremely rare that a firm would resell its information assets. Also, Bonneau (2015) maintains that IoT players dispose of too small and of too raw data sets to position themselves on the information market. Only Big Data aggregators and insight providers such as Google or Facebook, also referred to as OTT's, manage to gain tremendous revenues out of data sales. For Moody and Walsh, in those conditions, it appears that the market value is always null.

Moody and Walsh finally developed their own model. They adapted the classic accounting valuation method of historical costs valuation, so that it could fit to the characteristics of information. Indeed that model had previously been developed to assess the value of physical assets, therefore it is not suited at all for valuing information, as it follows completely different economical laws.

[4] http://searchcio.techtarget.com/feature/Six-ways-to-measure-the-value-of-your-information-assets

Another approach, that is also shared by Moody and Walsh, is the one developed by Glazer (1993) , who got the idea that every transaction, occurring between a firm and its customer or its supplier, or even between departments of a same company, creates a stream of valuable information. That value of that stream is equal to the present value of all the benefits and costs reductions that originate from that information. This model remains theoretical as the author recognizes that it is difficult to forecast such amounts. However, in that context, information valuation requires no different skills but the ones used in other managerial sciences such as financial modelling and budgetisation.

According to all these authors, we can only but acknowledge the fact that is it very difficult to come up with a trustworthy model for information valuation. This having as main reasons the important differences that exist between traditional assets and information. However it seems clear that once executives will finally manage to measure its value, the information management departments will no longer be costs centers, but will turn into important revenue centers (Bucherer and Uckelmann, 2011).

2.5.6 Monetizing IoT data on the IoTM

The literature identifies two main types of benefits withdrawn from data and information. We argue that firms can reduce their costs, by improving their managerial decisions, or create new revenue streams by proposing new types of services (Reddy, 2014).

As the costs reduction seems intuitive, we argue that there exist other ways for firms to generate new revenue streams. Indeed, in opposition to Moody and Walsh thinking, we claim that the spawning of the data economy enables companies to trade information as a common asset on the markets and as such sell and exchange it (Opher et al., 2016).

Bohli et al. (2009) think of a gigantic digital platform on which data providers, consumers and intermediaries would gather exchange information. What they call an Internet of Things Market (IoTM) is in fact a digital marketplace that would enable anyone one to sell or buy its data. Also, other parties offer different types of services such as providing aggregated data and specific insights that can directly be put to work. Today, it is estimated that 70% of big corporations already gather data from external parties, and that the totality of them will in the next ten years (Johannes et al., 2016).

Johannes et al. (2016) provide the following definition of a digital marketplace: "*Digital marketplaces are platforms that connect providers and consumers of data sets and data*

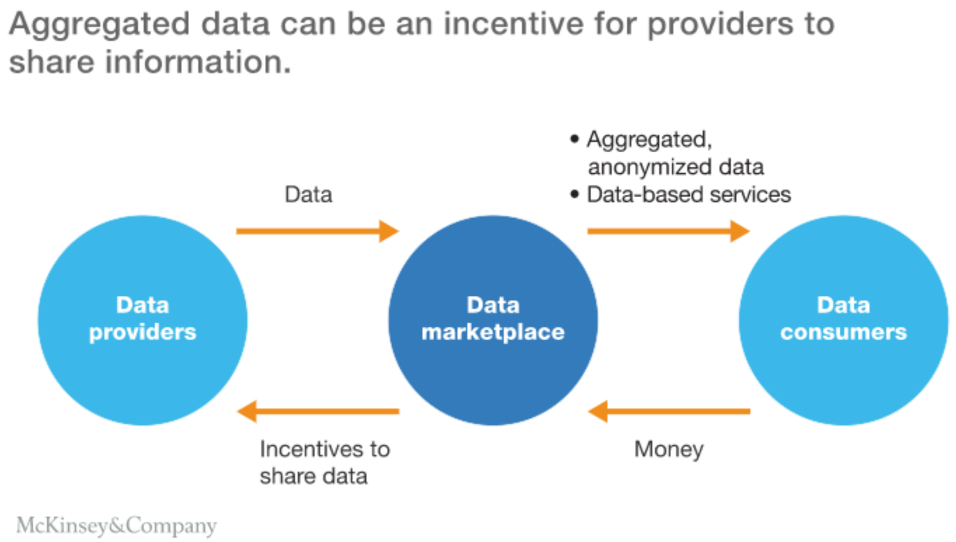

Figure 2.3: Functioning of the data marketplace

streams, ensuring high quality, consistency, and security."

Figure 2.3 shows the illustration that Johannes et al. (2016) use in their report, to represent the data market place.

As connected devices produce large amounts of raw data, only a small portion of those seem to be efficiently processed by firms (Johannes et al., 2016). As we know that data have a null value when they are not used, companies suffer a big renunciation cost. The use of digital marketplaces therefore provides substantial benefits to companies facing those challenges.

But of course, in order to make those marketplaces viable, one must be able to price the data they want to sell or buy. Once again the problematic of valuing data arises. Bohli et al. (2009) consider the pricing schemes of versioning and bundling, described by Shapiro and Varian (1998), as applicable in the context of IoTM. Indeed, they argue that data providers, intermediaries and other parties in the data economy framework must not see the same pricing schemes applied to them. Furthermore, the bundling of information would allow the data providers to grasp a larger portion of the buyers' willingness to pay (Bakos and Brynjolfsson, 2000).

Even though this Internet of Things Market seems to be a very interesting solution for firms as for individuals, it remains an utopia in sight of the many challenges still facing its deployment. Due to technical hindrances, such as the lack of WSN, service providers are facing hard times to enter the market. This in turn does not attract customers and the classic chicken-and-egg dilemma starts, as a market without customers does not provide the incentives for network developers to solution existing technical problems. Therefore, there is a strong need to provide incentives to those players in order to launch the trend. As it goes for every information technology, the utility users withdraw from it increases with global number of its users. This effect is described by the Metcalfe's law[5].

2.6 Further fields of investigation

In our literature review, we have been discussing the themes that we considered as the most relevant to our research topic. Be aware that plenty of other domains of IoT and Big Data have not been tackled here. We think for example of the development of technologies such as the artificial intelligence or the machine learning and robotics.

Lots of researches still need to be done in order to maximize the value that can be derived from IoT. We notice that no globally accepted business model framework exists and that managerial literature in that domain suffers in depth discussions. Also the valuation of information rises lots of questions. And we regret the lack of research in that area as the articles related to that topic are, for the most, already ten years old. Furthermore, important technical challenges still face the wide scale deployment of those new smart objects, as do socio-ethical issues.

As this thesis aims at analyzing the factors enabling companies to efficiently manage the potential of IoT and its data, as well as distinguish which organizations are more suited than others to achieve it, we regret the lack of literature treating the particular case of SMEs. By answering the questions displayed in the next section, we aim at providing some kinds of insights about the reality of firms in the IoT environment.

[5]The total value of a network is proportional to $n(n-1)^2$, with n representing the number of users.

Chapter 3

Problematic

We noticed throughout our researches, that most of the time when authors discuss the topics of IoT and Big data, they tend to consider big corporations such as Facebook, Google, and Amazon as examples for their discussion. Indeed, those companies stand as references when it comes to data management and extracting the value out of personal data. Data constitute the core resource of those firms and are the foundation of their entire business model.

It is no debate anymore that IoT and Big data are means to deliver huge benefits (Santhosh Reddy, 2014). IoT services will become real value-drivers and companies from all sizes will and are already investing in those services, as stated by Verizon (2016) in its state of the market report . Actually, big data analytics will become crucial for corporations willing to innovate and disrupt their market (Marshall et al., 2015).

However, Big data has not yet achieved its promises, and only a few firms, such as the ones cited above, are able to use this technology as a disruptive innovation. Indeed, as we analyzed the business environment in diverse industries, we acknowledged that big data analytics, currently, is being mainly used as a supporting technology for existing business processes, without disrupting them (Huberty, 2015).

Even though, the adoption of IoT has not yet been enlarged to a wide range of companies, it certainly will, thanks to the falling development costs of sensors, improvements in communication means, in data storage capacities, in data analytics solutions, the advances in supporting technologies such as RFID and WSN, the hard work of standardization bodies, and of other IoT ecosystem stakeholder to solution the various technical problems we currently are confronted with (Da Xu et al., 2014).

3.1 What about SMEs?

> *"Companies that were born digital, such as Google and Amazon, are already masters in big data. But the potential to gain competitive advantage from it could even be greater for other companies." (McAfee et al., 2012)*

Lee (2017) conducted a survey among the Fortune 500 companies in order to discover how they used IoT solutions to achieve business model innovation, which we described as an effective starting point for achieving competitive advantages. Also, the IBM's Institute for Business Value, studied 341 business leaders, in order to understand how the most successful organizations manage to innovate using big data and analytics. Finally, The Economist Intelligence Unit carried out a survey, sponsored by ARM, in order to gauge the level of uptake of IoT in the business community (Witchalls and Chambers, 2013).

While already well-established companies like IBM, SAP, Microsoft, Intel and Cisco offer and invest a lot in new technologies, numerous small players are seeking to exploit the new opportunities brought by the IoT and the Big Data. (Financial Times, June 2017)

As the previously mentioned studies rely on the examination of big firms we want to address the same type of questions, this time regarding those small and medium enterprises (SMEs). Indeed, however it results from the study of In Lee that the size of enterprises has no significant impact on the adoption rate of IoT solutions, this study relied on the analysis of Fortune 500 companies and therefore may not be relevant for the case of smaller organizations. Other authors claim that large firms are more likely to adopt new technologies (Zhu et al., 2006). Also, Veen (2004) maintains that the size of a company is an important parameter of a firm's decision to invest in IT technologies. Indeed, while larger groups benefit from technical and financial resources, facilitating their technologies' adoption, smaller firms might suffer from a lack of the latter.

Furthermore, companies providing business intelligence (BI) services seem to target intensively larger companies (Guarda et al., 2013). Gangadharan and Swami (2004) even argue that Business intelligence, can only be applied for the management of large firms. Therefore we ask ourselves the following question: "Do all companies start at the same level when it comes to building competitive advantages out of digital technologies, and IoT in particular?"

When discussing the matter with the Marketing & Operations Manager of Riiot Labs, a

Belgian start-up based in Liège, the idea of unbalanced initial capabilities directly emerged. He explained that it was pretty much impossible for his company to reach the same advantages as bigger groups. The principal reason being that the amount of data its connected objects are able to generate is far from reaching the critical mass needed to build confident knowledge. Indeed, as we learn from the statistical sciences, large samples of data are required if we wish to generalize the analyses outcomes to larger populations.

Also, according to Dimitris Sapikas, Computer System Engineer at Red Hat, most small and medium enterprises use cloud-based solutions provided by big cloud providers (Amazon, Microsoft,..) to store their data. Furthermore, Mr Egan, managing director of cloud and IT solutions for Verizon states that: "*Doing so, SMEs give up the control of their data and make it accessible to almost anyone, or at least their cloud provider.* ". Large companies, on the other hand, have the advantage to be able to keep their most valuable asset internally, as they possess the required infrastructure to maintain them on their own servers. As such, they benefit from a certain competitive advantage, on the contrary of SMEs.

However, according to Eric Wilmot, Commercial Executive at Engie M2M, firms do not need prior capabilities to implement and draw competitive advantages from IoT solutions. Instead, he states that firms must have an objective, a clear vision of what they aim at achieving with the implementation of those solutions into their business activities. As such, IoT devices are to bring an answer to specific questions, helping organizations achieving their goals. Nevertheless, he confirms that large companies, handling Big data, and SMEs, dealing with much smaller sets of data, do not build the same competitive advantages. While SMEs manage to disrupt their market by optimizing the performance of their products and services, or by reducing their costs, they do not have the same capabilities in terms of knowledge creation and development of new business opportunities.

In this data economy context, customers, and the personal data they generate, reveal themselves to be valuable assets as they help firms in creating value. Therefore, benefiting from a greater access to users' information would obviously have a positive impact on a company's bottom line (Sun et al., 2015).

Facebook, the most famous social network, with over 1.4 billion active monthly users, generates the largest amount of social data. Indeed, its users "like" over 4 million posts every minute, 4,166,667 to be exact, which adds up to 250 million posts per hour. In 2008, which is way back in Internet terms, Google handled 20 Petabytes per day. According to Moore's law, and based on those observations, we predict that the social network should be handling at least 160 Petabytes per day by now. No need to say that, according to the previous paragraph, those types of companies start way ahead of the pack in building competitive advantages out of their data. Based on all these discussions, we derived the following hypothesis:

H1: There is a significant relationship between a company's size and the volume of collected data.

Throughout our literature review and interviews, we were able to enlarge our understanding of the SMEs' reality, and distinguished several other factors that may cause the latter to fail leveraging the entire benefits their data offer. We argue that, beyond the volume of data they are able to collect, the following factors vary greatly between small and large companies, and can have an important impact on their capabilities to achieve their aimed competitive advantages. We distinguish:

1. The access to data analysis expertise
2. The portion of annual budget allocated to data management resources
3. The access to a large ecosystem of partners
4. The percentage of collected data effectively used

The access to data analysts expertise is a "must have" in the emergent data driven economy (Jerningan and Ransbotham, 2016). For data have become cheap to obtain, all its complements have become highly demanded (McAfee et al., 2012). Indeed, enjoying the services of data scientists is everything but cheap as the industry acknowledges a shortage of persons trained into those skills. As data are only raw material for companies, the access to data analytics expertise is becoming an highly valued capability. As getting the collected data into the systems only creates a cost for companies, it is not rocket science to understand that leaving those data unused is a clear waste of resources. Indeed, it is only once processed that data can deliver value for the company that owns them (Moody and Walsh, 1999; Watson and Wixom, 2007).

H2: There is a significant difference in the capabilities to access data analytics resources between SMEs and large companies.

In the case of SMEs, and according to the says of Patrick Crasson[1], CEO and founder of Benovate, a consulting company specialized in digital transformation and innovation management, due to their financial reality, SMEs are more focused on the short term and have a very cash flow centered management. Executives of such companies usually do not want to spend large amounts of their monetary resources into data management and BI, as they prefer to invest into their daily operations to ensure a stable flow of revenue. Therefore, smaller companies, that want to drill through their data, often call upon the services of specialized companies in order to obtain direct insights on their data. Therefore, it seems clear that reaching a state of smart data, starting from raw consumer data is a complex process requiring advanced skills, which a lot of SMEs undoubtedly can not afford if they wish to maintain their investment in their core activities.

H3: There is a significant difference in the portion of annual budget invested in data management resources between SMEs and large companies.

We further want to assess whether bigger companies are more likely to have better access to ecosystem information, as we believe that smaller companies maintain a less developed network of partners. According to the CEO of Benovate, it is again easier for larger firms to maintain a broad ecosystem. As the members of the latter expect to build win-win relationships, well-established players may constitute more reliant partners for them. The IoT ecosystem is often used by companies in order to access external data which complement and reinforce their internal ones, to derive valuable insights and knowledge. Firms are also able to sell and buy information blocks on data markets, as explained in the literature review. Data, however, are often expensive and often need to be cleaned to become exploitable for analysis. As those requirements obviously would rep-

[1] The list of questions used for the interview can be found in appendix 2

resent additional costs for small budget companies, they are more likely to seduce larger organizations. Therefore we state the following:

H4: There is a significant difference in the access to broad ecosystem information between SMEs and large companies.

Moreover, we argue that collecting vast amounts of data is of little meaning if the latter remain unused. Indeed, throughout our researches and interviews, we were stroke by the fact that many organizations did not seem to put all their data at work. Often, only a small part of firm's data are being effectively used. Therefore we add the following hypothesis to our research scope.

H5: There is a significant difference in the percentage of data collected effectively used between SMEs and large companies.

As we do recognize that not only the size of companies must be considered as an influencing factor, we also discriminate companies based on their industry. We formulate the exact same hypotheses, this time considering the one organization's industry as influencing variable. Cisco surveyed 1845 IT and business decision-makers in the USA, the UK and in India. This research showed that most successful IoT companies managed to leverage ecosystem partnerships (Johansen et al., 2017). Therefore, we came up with the following hypotheses:

H6: There is a significant difference in the volume of collected data across industries.

H7: There is a significant difference in the access to data analytics resources across industries.

H8: There is a significant difference in the portion of annual budget invested in data management resources across industries.

H9: There is a significant difference in the access a company has to ecosystem information across industries.

H10: There is a significant difference in the percentage of data collected effectively used across industries.

3.2 Thesis's purpose

Previous section has exposed hypotheses that were aimed at highlighting the differences existing between different categories of organizations. As such, the latter have been segmented into diverse groups, based on their size and industry[2].

However, the exposed hypotheses did not provide means to assess whether one group was more likely to build stronger competitive advantages than another.

Next hypotheses are aimed at analyzing the diverse types of competitive advantages those groups are able to build from their IoT solutions, as well as the hindrances preventing their achievement. Through that, our goal is to identify the economic and technical factors that enable, or hinder, companies of each identified group to leverage the maximum benefit from their IoT solutions and the data they deliver.

3.2.1 Competitive advantages and obstacles

Witchalls and Chambers (2013) points out that businesses are currently more prone to use IoT for achieving "*internal*" competitive advantages rather than "*external*" ones. The former type of advantages includes cost reduction achievement via business process improvement (e.g. automation, improved maintenance, etc.), as well as the enhancement of customer experience through product and services improvement as well as through a more tailored customer relationship management (CRM), and enhanced decision-making. We call them *internal* competitive advantages as they focus on the improvement of pre-existing capabilities of a company. The latter type includes advantages such as the development of new products and services, leading to new business opportunities and sometimes the creation of a new market through disruption and business model innovation. This type of competitive advantages is referred to as "external" as it is oriented towards the development of new capabilities.

H11: There is a significant relationship between the volume of collected data and the type of competitive advantages created.

H12: There is a significant relationship between the access to data analytics resources and the type of competitive advantage created.

[2]The "Methodology", section 4, will provide further insights on this segmentation.

H13: There is a significant relationship between the portion of annual budget invested in data management and the type of competitive advantage created.

H14: There is a significant relationship between the access to ecosystem information and the type of competitive advantage created.

H15: There is a significant relationship between the percentage of data collected effectively used and the type of competitive advantage created.

Throughout our researches and interviews we have been able to distinguish diverse types of hindrances. Patrick Crasson mentions in his interview, that the financial aspect is often the first barrier blocking companies in their strategy to achieve a good implementation of IoT solutions. Beyond that obstacle, come the lack of standardization of data types and communication protocols, as well as the limited vision and the reluctance towards innovation of some executives in traditional companies. Furthermore, the low awareness of customers and the immaturity of the market, plus the reluctance of customers to share their data, all are factors hurting the efficiency of strategies relying on data as the roots of competitive advantages.

H16: There is a significant relationship between the volume of collected data and the types of hindrances encountered.

H17: There is a significant relationship between the access to data analytics resources and the types of hindrances encountered.

H18: There is a significant relationship between the portion of annual budget invested in data management and the types of hindrances encountered.

H19: There is a significant relationship between the access to ecosystem information and the types of hindrances encountered.

H20: There is a significant relationship between the percentage of data collected effectively used and the types of hindrances encountered.

Based on the findings derived from those hypotheses, we wish to provide a classification framework for organizations. Relying on the three factors we judged as most relevant, this framework will help classify organizations into heterogeneous groups, each facing different challenges and opportunities. This should provide a model enabling companies to assess what are the economic and technical factors they lack in order to achieve the competitive advantages they were aiming at, when first implementing their IoT solution.

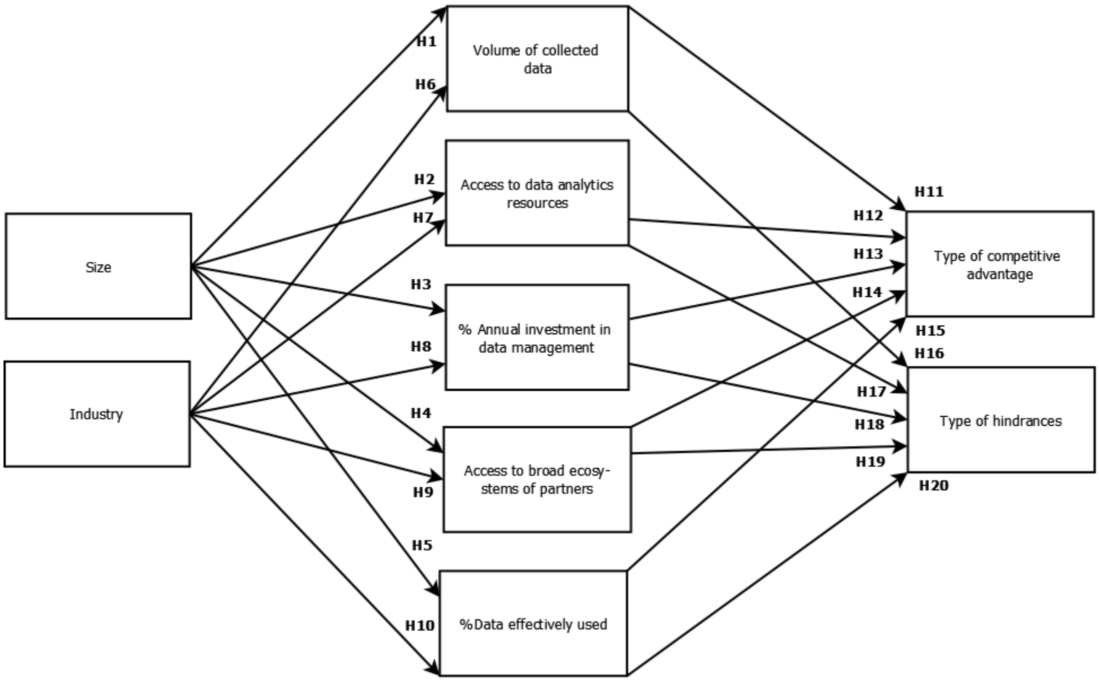

Figure 3.1: Hypothesis Scheme

Chapter 4

Methodology

4.1 Porter's 5 forces model

This new digital era is bringing with the Internet of Things and Big data analytics, tons of new opportunities. Nevertheless, for most companies, the road towards their achievement and the strategy to follow are still pretty obscure. While ahead of the connected journey, the destination must be clear, as current companies do not yet fully understand the impact and effects that this digital and connected world will have on their industry. Organizations must indeed understand their business, their customers,their environment, as well as the essence of the competition they are facing.

But first, let us take a step back. We argue that evaluating the risks and opportunities that offers a company's environment, assessing the potential profitability of an industry, as well as defining clear objectives for the firm are primordial steps towards success. And before installing sensors and communication systems in order to connect devices, to work with the cloud and to analyze data, companies should deeply understand what IoT means to them and how it can perform at its highest potential to favor them. Assessing where IoT-enabled opportunities lay, what customers' needs IoT devices can help better answering, and what impact those smart agents will have on the forces driving competition therefore seem essential.

In the first time, as a mean to assess the competitiveness and attractiveness of the potential applications of IoT technologies in industries, we realized an analysis based on the famous model developed by Michael Porter, namely, the "Porter's 5 forces model". This model will enable us to confirm or infirm what was previously stated in the literature review, regarding the benefits and attractiveness of IoT application in the industry.

Indeed, we aim at providing objective discussions of the features that make of the IoT the new "appealing" technology for small players as well as for already well-established organizations. By understanding the impact of smart devices on the industry competition and profitability, we will be able to get a clearer view on the way of thinking of companies evolving in an IoT-connected environment, their strategies, and how they could adapt those accordingly to thrive in their market.

Also, this model will help pointing out the likely barriers and challenges that both small and big companies must overcome in order to step in and make the most out of IoT solutions.

As a summary, the Porter's 5 forces model highlights the strengths and threats involved in the studied environment, and additionally, it determines the nature of an industry's competition, and its expected profitability for potential entrants.

4.1.1 Theory of the model

Figure 4.1: Porter Model

Figure 4.1 depicts the model that was originally created by Harvard Business School professor Porter (1979). His aim was to analyze an industry's attractiveness and likely profitability. In his research, Porter identified five forces that influence one industry's structure, and can have significant impact on the profitability of its actors. Porter and Heppelmann (2014) claim that the structure of competition within industries changes when new technologies or customer needs appear. It is therefore important to grasp insights on the influence of the IoT technology on the forces that shape that structure.

In this section, we present the five forces of Porter's model, that will be analyzed later on in chapter 5.

Bargaining power of suppliers

This first force analyses the bargaining power that actors taking on the role of suppliers in an industry, have over their clients. That power refers essentially to the ability that these suppliers have to raise the price of their supplied products or services. Obviously, arbitrary price increases decided by the supplier of a firm will end up lowering the profitability of the latter. It is thus important for any company to not suffer the dictatorship of its suppliers, but instead, to be able to bargain properly with them.

The strength of the suppliers' power relies mainly on their number. Obviously, the fewer they are, the more businesses will rely on them, and the more powerful they will be. It is also driven by the uniqueness of the products and services they offer, their relative size and influence on the market, as well as by the costs implied for the buyer when switching from one supplier to another (Mwenemeru and Nzuki, 2015). This last factor refers to the ease that a customer has to chose among different suppliers for a same product or service. On markets where easy comparison can be made between different suppliers, this cost is greatly lowered. However, on markets where comparison proves itself to be more complex, the costs endured by buyers to find and analyze potential suppliers' offers tend to rise.

As of those observations, we argue that the profitability of one's company is clearly impacted when facing suppliers, benefiting of strong bargaining power (Martin, 2017).

Bargaining power of customers

In this case, the force examines the power of the customers relatively to its supplier. Generally speaking, it is the response to the previously discussed force. Again the power of consumers will be dependent on their numbers. Indeed, when dealing with only a few demanding customers, the latter tend to have more bargaining power, as they constitute the sole few sources of the supplier's revenue. The importance of each individual buyer to the organization, as well as the costs to the buyer to switch from one company's product or service to another, are also determining factors of the buyers' power.

In other words, it is more interesting for entrant supplier candidates to position themselves on markets in which they will enjoy a strong supplier bargaining power towards their customers, and a reduced customer bargaining power.

Threat of new entrants

The threat of new entrants is a force analyzing how easy, or difficult, it is for a company to enter a particular marketplace. When new or existing companies enter an industry, the competition naturally increases for its current incumbents. Successful markets, are appealing opportunities to new companies. As those will try to enter it, they inevitably will change the dynamic of the industry and of its competition. In markets protected by few barriers of entry, the risk is high to see such circumstances occur. Therefore, the easier it is to enter an industry, the greater is the risk for established businesses to lose their market shares. Some barriers of entry can include: Patents and knowledge / Access to technology / high initial investments / high switching costs / Access to limited raw materials / Strong customer loyalty.

Threat of substitute products or services

This force analyzes the ease with which a buyer can switch from your service or product to an alternative one. It looks at the likelihood for consumers to be tempted to switch to a competitor's product or service due to diverse factors. Indeed, the threat of substitutes can be affected by brand loyalty, switching costs, relative prices, or trends and hypes. The more substitute there exist to a particular product or service, the more a company's supplier bargaining power will be reduced. Therefore, it will also diminish the attractiveness of the market for a company of which the offering has many substitutes.

Competitive rivalry

"Competitive rivalry" is the last force of the model. It examines the intensity of the competition on a particular market. The intensity is measured by the number of existing competitors, the life cycle of the industry and by how easy and costly it is for a customer to switch to a competitor. Basically, all the previous forces affect this one. Therefore it is also represented as the central force of the model in figure 4.1.

Where rivalry is intense, the main ways for companies to attract customers is by leading an aggressive price war, by leading an effective differentiation strategy, or by spending in high-impact marketing campaigns. No need to say that it is therefore more profitable for companies to enter markets in which there reigns a low competition in their industry.

As a reminder, figure 4.1 puts in image the interaction between the different forces we just discussed.

4.2 Survey

In a second time, a survey, aiming at providing a clearer view of the IoT market and of its players, has been carried out. We hope that it will, in turn, provide the pieces of information required in order to properly confirm or refute the hypotheses expressed in chapter 3.

4.2.1 Survey explanation

Before getting into the discussion of the obtained results, we believe it is necessary to explain in further details some of the concepts involved in the survey's questions. We want to make sure that the reader is confident with the latter, and has fully comprehended their purpose. While some of the concepts used in our survey have already been approached in our literature review, this section will provide further details to the ones that remained unexplained.

The survey was divided into three parts. In the first one - "Company insights" - we ask some descriptive questions in order to picture and frame the respondents' company. As we have been reading more and more recent literature about this topic, we are interested in finding out what sort of companies implement and invest in IoT solutions. In this part of the survey we determine the industry of the respondent, its size, its role in the IoT ecosystem, its maturity stage (according to the business life cycle) and further descriptive factors.

In the second part of the survey, "Data management" ,we interrogated our respondents with regards to their data management habits. As such we wanted to understand the types of usage, companies make of their data.

Finally, in the last section of our survey, we interrogated our interviewees on what we consider as the most important points of our research. Indeed, we asked the survey participants to define the competitive advantages and hindrances they were, respectively, aiming at achieving and at facing as obstacles.

Actors of the IoT ecosystem

By ecosystem, we mean the network of partners surrounding and including all types of IoT actors. In the IBM article (The rise of the data economy, 2016), written by Opher et al. (2016), the role of different players are being described. Opher et al. (2016) distinguish four categories of players :

1. Data presenters
2. Insight providers
3. Data aggregators
4. Data producers

In such digital world, it is no rocket science to spot the new type of valuable asset for companies - data. Organizations are now reporting, collecting, and analyzing vast amounts of them in order to enhance their business processes. In this context, Opher et al. (2016), claim that the above mentioned data producers, generating data from IoT and traditional big data sources, are the players best positioned for long-term success. In fact, they derive their strengths from their ability to collect, to access, and to maintain control over large amounts of exclusive data.

Aside from Data Producers, Data Presenters are also playing an increasingly important role in the data economy. Their role is to make large and complex data sets easily exploitable by the final user. Basically the main role of the Data Presenters is to make all these data consumable for companies transforming texts and information into graphs for example. Data Presenters are in a position of strength due to customer loyalty and dependence. Customer information and content will at the end increase revenue for them.

Those first two types of IoT players are to build trust among ecosystem partners in order to set up an environment allowing data sharing and data monetization (Opher et al., 2016).

The third type of actor in the IoT ecosystem is the Insight Provider. He is the one generating value from advanced analytics such as machine learning algorithms, and statistical models. Once an algorithm is created, it has a defined and limited shelf life because of different reasons. Indeed, it can either:

1. Get copied

2. Be replaced by a better algorithm

3. Abandoned for open source solutions or crowd sourced algorithm becomes available

Finally, the Data Aggregator has the important task of "aggregating" or combining data from multiple sources into one place where it can be easily accessed and shared. Unfortunately automation, as well as robotics, and the data normalization allows data to be combined and aggregated by other participants of the data economy without the need for a Data Aggregator. Therefore the role of the latter is believed to be endangered (Roubaud, 2017).

Business life cycle

As we wanted to have more knowledge on the characteristics of our respondents, we also considered the maturity stage of the company as an important feature for the description of our sample.

Every company goes through a particular cycle, which is called the "business life cycle". This concept was developed by Mason Haire and presents four successive stages which describe the maturity of an organization. Those four phases of the cycle are the following:

1. Start

2. Growth

3. Maturity

4. Decline

Along this cycle, companies will encounter different challenges that will require to adopt different types of financing methods, as well as different operational strategies. For example, organizations will require a different strategy when it comes to market penetration, business development, and retaining market shares, at every different stage of the business life cycle. Also as the business matures, operations and priorities change, requiring business financing to adapt accordingly.

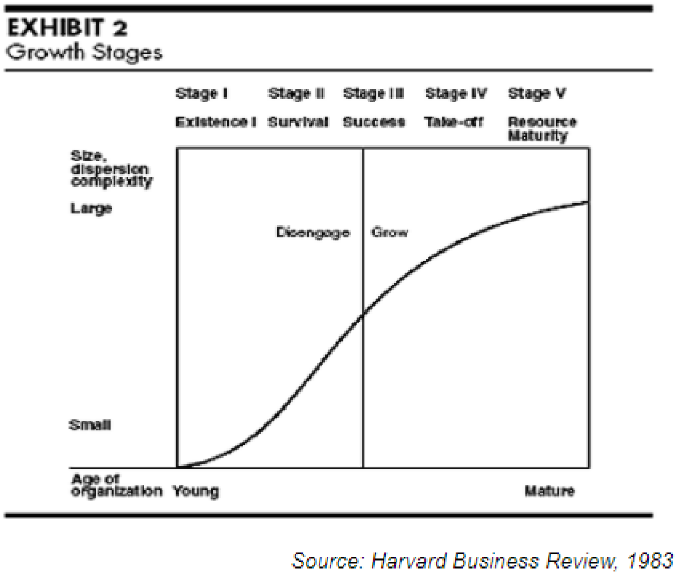

Figure 4.2: Business life cycle curve

The "*Start*" phase marks the real initial stage of a company. The product or service that the business is offering is fully developed and a company will launch its marketing and its distribution. Though, the business remains very vulnerable at this early stage. Both external and internal environmental factors can have significant impacts on the future of the business health (Petch, 2016).

In the "*Growth*" phase, the business is getting continuously new customers and sales should be increasing steadily. This cycle is characterized by a new period of important choices for executives as they try to grasp market shares (Petch, 2016).

"*Maturity*" begins when sales reach their summit and remain at the same level. The business has a good customer base and regular cash flows. In this stage, the risks are minimized as the company has become well-established in its market (Petch, 2016).

In the "*Decline*" stage, sales of the company starts decreasing, the product or service they are offering becomes obsolete or substitutes have been found to replace it. It is usually difficult to reverse the tendency at this stage, this, for some of the following reasons:

- Financial institutions are reluctant to lend money to high risk businesses
- Products may have become obsolete
- Better qualified employees may leave to seek out better opportunities, without a strong workforce, the rate of decline increases.

Regarding the IoT, we can say that the sector is still in the early phases of the technology life cycle. Therefore, it makes sense that the focus of actors in this environment should still be strongly oriented towards the exploration, definition and testing of the feasibility of the devices and services themselves (Ricci, 2015). But as these mature, and become widely adopted, other aspects of the business model - for example optimization of the marketing and monetization - will follow. At this moment of the technology life cycle, monetization is clearly not a top priority for industrial M2M/IoT applications. Right now, the ecosystem players, we believe, are more focused on other attributes:

- Technical feasibility availability
- Keeping low costs
- Reaching competitive advantage
- Utility
- Security management

Yet, we can see that due to uncertainties and unfamiliarities with the potential opportunities, many companies are taking a wait-and-see attitude toward IoT technologies. As shown in a recent survey from MIT and Deloitte of IT executives, most of the interviewed companies intend to leverage IoT-generated data to pursue only small-scope applications aimed at improving business processes. While we understand it is safe to start small and scale applications as they succeed, thinking big is what we believe will make the difference for the future of IoT and data-driven technologies as a whole, but also for organizations aiming at benefiting from their huge impact (Odusote et al., 2016).

Competitive advantages

In the final part of this survey - "Competitive advantages and Challenges"- we were interested in knowing what competitive advantages companies were seeking to achieve with the implementation of IoT devices into their business processes.

A competitive advantage is a leading position gained over competitors by offering customers greater value. In other words, competitive advantages are the reasons why a company is more profitable than its direct competitors. Companies achieving a competitive advantage should try to preserve it in the long run (McGrath, 2013). Integrating the development of "sustainable competitive advantages" within a company's strategy is imperative. According to Porter's Generic Strategies theory of Porter and Millar (1985), there are two traditional strategies that allow a company to achieve competitive advantage:

- Differentiation: which leads customers to have a higher willingness-to-pay for a company's products, than for its competitor's.
- Cost leadership: which leads to a lower cost base than the competition and therefore higher margins or increased customer value.

There are many different ways to achieve differentiation or cost leadership in any industry, but in the end it usually boils down to either access to superior resources (e.g., personnel, patents, data, input materials) or the perfection of better activities (e.g., design, innovation) (Lueth, 2015). In the context of IoT, we argue that both types of competitive advantages are achievable.

4.2.2 Sample Description

This survey was conducted via Google forms and spread to a sample of more than one hundred companies, of which we sadly could only gather twenty-six answers. On top of this survey, we led three interviews with executives from both SMEs as well as bigger companies active in the IoT environment. We also had two informal discussions with other professionals. The interviews' questions as well as the survey's, can be seen in, respectively appendix 1 and appendix 2.

Respondents, all are companies working in the IoT sector or implementing IoT solutions into their business processes. We managed to get in touch with them by spreading our survey by regular mail, on IoT community platforms (IoTBE), on specialized social network groups, as well as by networking at two IoT meetings (The IoT European convention in Mechelen, and The IoT meetup, the latter was organized by IoTBE in Louvain-la-Neuve).

According to the definition of SMEs given by the OECD[1], Small and medium-sized enterprises are non-subsidiary, independent firms which employ fewer than a given number of employees. This number, however, might differ from one country to another. Nevertheless in the European Union, one of the most frequent upper limit designating an SME is 250 employees. The OECD also provides other criteria to determine the category of a firm. Are considered as SMEs, based on the annual turnover, firms whose total annual revenue does not exceed €50 million. In this study, we will consider as SMEs, all companies that do respect this latter rule. On the other hand, all companies that will not conform to that definition will be considered as large companies.

As of that definition, the sample of respondents contains fifteen SMEs and eleven large companies, coming from diverse industries, across the world, and playing diverse roles in their IoT ecosystem.

Figure 4.3, on page 53, depicts descriptive graphs of our sample of respondents.

4.2.3 Analysis

Statistical tests

Having formulated our research hypotheses in the problematic section, we will perform various statistical tests in order to assess their validity or invalidity.

Our hypotheses aim at showing significant relationships that could exist between dependent and explanatory variables - those are economic factors in this case. By stating such hypotheses, we aim at showing that there exist a correlation between diverse types of factors, and that those factors, in turn, influence the capabilities of one organization to effectively implement and leverage competitive advantages from IoT solutions. In those types of hypotheses, we formulate the null hypotheses as follows: H_0 = There is a significant relationship or dependence between the analyzed variables. The statistical test answers the question as to whether any relationship or dependence exists and is sufficiently different from zero that it can be considered as "statistically significant" and due to the

[1]urlhttp://www.oecd.org/about/

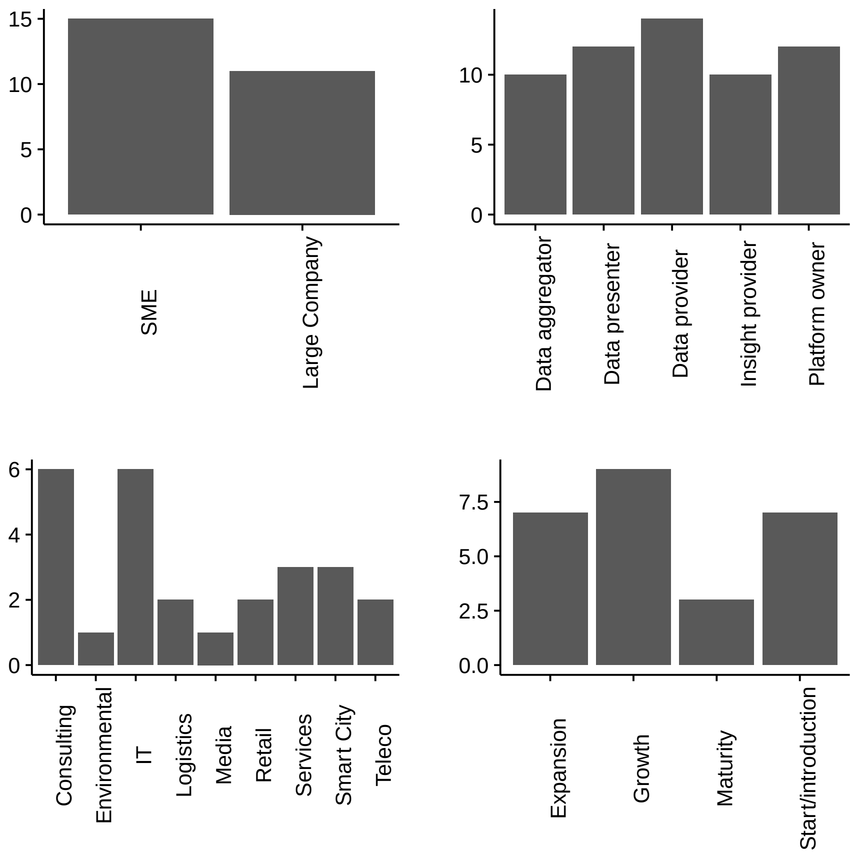

Figure 4.3: Descriptive Graphs of the Sample Distribution

treatment factor.

Also, some of our hypotheses aim at highlighting the potential differences that exist across the diverse identified groups of firms. In those types of hypotheses, we formulate the null hypotheses as follows: $H_0 =$ There is a significant difference between the analyzed groups. The statistical test answers the question as to whether any observed difference is probably due just to random factors, or is large enough to be considered "statistically significant" and due to the treatment factor.

As we got different types of variables, we first need to recognize them in order to be able to choose the most suitable test to apply on particular hypotheses. The statistical science recognizes five types of variables, dispatched in two broad categories, namely the quantitative and qualitative variables. Figure 4.4 displays a classification tree of those types of variables[2].

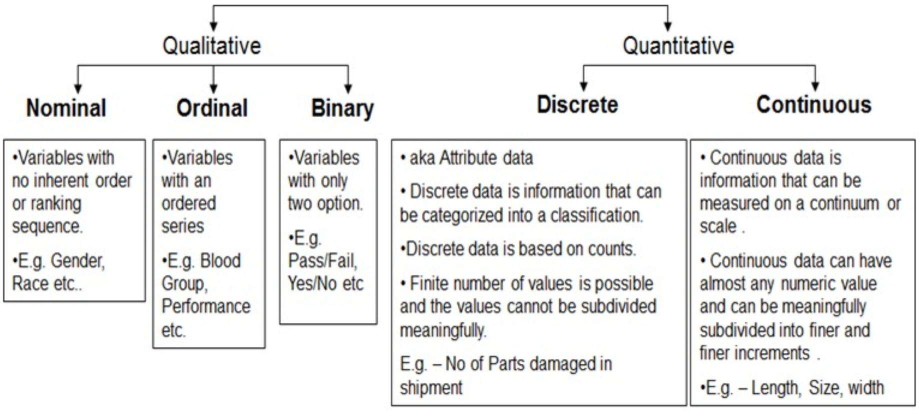

Figure 4.4: Variable classification tree

4.3 Cleaning and transforming the data

The cleaning of the data might probably be "the" most important step in the process of data analysis. Indeed, bad data and unexpected answers by respondents can dramatically hurt the outcomes of the diverse analyses, and deliver disputable results.

Unusable variables

While going through the results of our survey, we could only but realize that a few questions had remained unanswered, or at least, that the answers provided did not correspond to what we had expected. It is for example the case with the variable "volume of annually collected data". Indeed, most of our respondents seemed not to be in possession of such information, or were not able or allowed to share it. Same goes for the "annual investment made in data management".

Another variable with which we encountered some troubles, is the one measuring the access to data analytics. We were in fact not able to determine an effective measurement scale for that variable and therefore could not come up with relevant results.

[2] https://stats.stackexchange.com/questions/159902/is-nominal-ordinal-binary-for-quantitative-data-qualita

Transformed variables

In some cases, variables need to be transformed to better suit analyses. In our research, for example, the "Total annual revenue", being a quantitative-continuous variable, has been transformed into a binary variable, "Size", to introduce the notions of SMEs and large organizations. This transformation has been based on the definition of SMEs provided in section 4.2.2. As such, each organization reaching a turnover of above €50 million has been labelled as "*large*", while others entered the "*SME*" category.

Also, as it appeared to be difficult for respondents to provide exact numbers on some of our questions, and as we could not obtain those answers in any other way, we decided to segment all quantitative variables into classes. As such, the previously continuous variables, "Portion of annual budget invested in data management" and "Percentage of collected data effectively processed", were turned into ordinal variables, composed of different classes.

Figure 4.5 displays the classification table of the variables that will effectively be used in our hypotheses, after reclassification.

Categories		Variables
Qualitative	Nominal	1. Industry 2. Type of competitive advantage 3. Type of hindrances
	Binary	1. Size
	Ordinal	1. Access to broad ecosystem of partner information 3. Portion of annual budget invested in data management 4. Percentage of collected data effectively processed

Figure 4.5: Classification table of variables

Figure 4.6 displays the graphs depicting the counts of the respondents entering in each of these segments after reclassification.

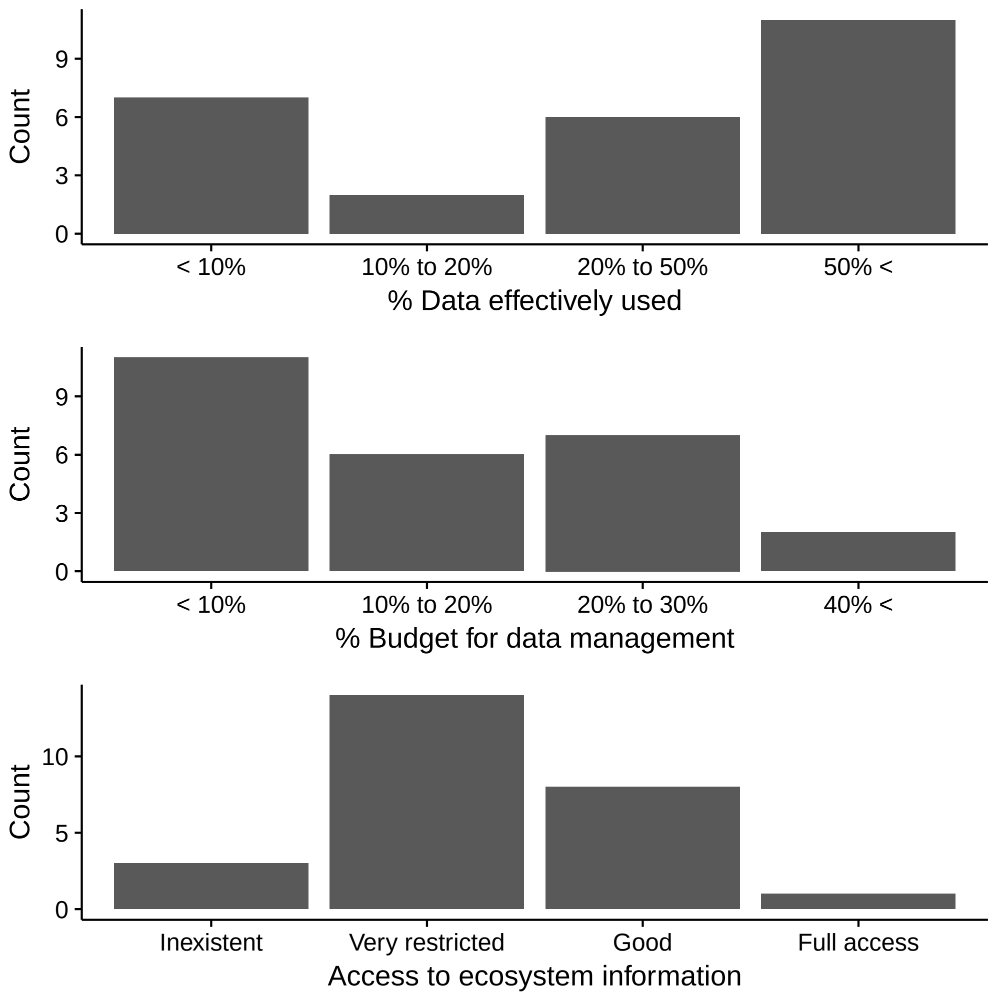

Figure 4.6: Distribution of the Respondents across the Newly Created Variables

4.3.1 New hypotheses

Due to those lacks and transformations, some of the hypotheses, that were formulated in the problematic, had to be left out of the research scope. Table 4.1 displays all the hypotheses that will effectively be investigated in our thesis.

	Hypotheses
H3	There is a significant difference in the portion of annual budget invested in data management resources between SMEs and large companies.
H4	There is a significant difference in the access to broad ecosystem information between SMEs and large companies.
H5	There is a significant difference in the percentage of data collected effectively used between SMEs and large companies.
H8	There is a significant difference in the portion of annual budget invested in data management resources across industries.
H9	There is a significant difference in the access a company has to ecosystem information across industries.
H10	There is a significant difference in the percentage of data collected effectively used across industries.
H13	There is a significant relationship between the portion of annual budget invested in data management and the type of competitive advantage created.
H14	There is a significant relationship between the access to ecosystem information and the type of competitive advantage created.
H15	There is a significant relationship between the percentage of data collected effectively used and the type of competitive advantage created.
H18	There is a significant relationship between the portion of annual budget invested in data management and the types of hindrances encountered.
H19	There is a significant relationship between the Access to ecos. information and the types of hindrances encountered.
H20	There is a significant relationship between the percentage of data collected effectively used and the types of hindrances encountered.

Table 4.1: Hypotheses to be Effectively Tested in this Thesis

As was shown in figure 4.5, we will only be comparing categorical variables. Therefore we will make use of stacked bar charts when presenting our results in the next chapter.

However we have already mentioned several challenges faced along this survey, chapter 6.1 will provide further details about the shortcomings of our research.

4.4 Introduction to Hypothesis tests

In order to clearly understand the following chapter 5, we must explain the diverse principles involved behind the Chi Square hypothesis tests.

The Chi Square test, is a statistical test employed to assess whether the differences between two, or more, studied populations[3] are completely due to randomness or if they are too significant different to be caused by this sole randomness.

There exist other statistical tests measuring the significance of the difference between two populations. We can name the independent sample t-test or the paired sample t-test for example. However those test are not suited for the types of variables at stake in our research.

Indeed, hypothesis tests involve explanatory variables and independent variables. The former ones are considered as the cause of the observed differences between the populations. While the latter one, on the other hand, are the variables from which we observe the distribution in the studied populations. As both our explanatory and independent variables are categorical, the Chi Square test seems to be the most suited for our case.

The way hypothesis test work, is by computing a statistic relying on mathematical computations. Based on that statistic and on the population distribution, we will compute a probability. This probability is referred to as the P-Value of the statistical test. It represents the probability that an observation will take a value greater or equal to the computed statistic.

The P-Value is an essential concept to grasp as it will be the root of our decision to accept or reject the formulated hypotheses. Basically, one must chose a significance level "alpha" which will determine the probability under which we will reject our accept our hypotheses. In our case, hypotheses were formulated in such a way that we will accept them for every P-Value lower than the alpha threshold of 0.05. This means that we consider a difference between two populations, or a relationship between two variables, as being significant, only when the computed Chi Square statistic has a probability of occurrence of less than 5%.

The acceptation of an hypothesis can be translated into the following:

[3] In our research, the studied populations are the classes of the variables Size and Industry.

"The observed differences that exist between the analyzed populations are not due to sole randomness. Therefore a significant relationship must exist between the explanatory and response variables."

One must pay attention to the fact that the rejection of randomness does not imply the existence of any *causal* relationship between the studied variables. This is an important remark which must be remembered. Indeed, it only asserts that a significant relationship exists.

Chapter 5

Results

5.1 Porter's 5 forces analysis

Porter's five forces model presents distinct ways in which IoT is impacting the industry. In the context of the IoT environment, we drew a personalized five forces model representing what we think corresponds the most to the impact of IoT agents on the economic forces at the time of the writing (Spring 2017). The reader will find the model in figure 5.1 below, on page 65.

The connectivity of products significantly expanded the opportunities for product differentiation (Porter and Heppelmann, 2014). Indeed, allowing new features to be integrated to existing devices, the IoT has favored the customization and enhancement of traditional products. In turn bringing the competition to focus on other features than the price alone.

As IoT solutions enable companies to gather information about the customers usage of their products, those are in turn able to identify various customers segments, to adapt their offerings to better meet their needs, to set prices accordingly to better capture value, and to extend their value-added services (Faisal, 2016). These features enable each company to adapt, develop and improve their product and services accordingly, in turn differentiating itself from the rest of the competitors and reducing the competitive rivalry on its market.

But in order to provide more specific insights on those discussions, we will explain the model exposed in figure 5.1. Therefore, let us review each of its forces one by one:

Bargaining power of suppliers

From the point of view of a well-established suppliers in the traditional industry, the rise of IoT technologies and devices does not mark the start of a welfare period. Indeed, as current suppliers of physical components, until now, managed to maintain a good bargaining power, we argue that the introduction of smart objects will reduce the demand for the traditional solutions they propose. The latter appearing to be less effective than new IoT-based solutions.

As those new solutions rely less and less on physical core components, and more and more on softwares and IT components, the importance of the traditional suppliers in the supply chain tends to decrease, as does their bargaining power.

On the other hand, producers of such smart objects will require specific components (sensors, hard drives, etc.) that are only provided by a small set of high skilled actors. Those new suppliers from the IT industry will revolutionize the supplier and redistribution chain. Those firms can indeed expect to enjoy a strong bargaining power, reducing traditional manufacturers power and profits (Perez, 2016).

Furthermore, as IoT solutions will make sure that more and more customer data are collected, suppliers of those solutions will be able to improve and to provide their customers with more specific services, in turn raising the switching costs of the latter and increasing their bargaining power.

Bargaining power of customers

As this force is quite comparable to the response to the previous one, the discussions will seem quite similar. We argue that the bargaining power of customers will be mitigated with the introduction of IoT solutions. Indeed, the capture of historical data on the product usage of the customers will allow their suppliers to improve their products and its related services. Doing so they will improve the relationships they maintain with their users, and by the same time, their loyalty, thereby increasing the switching cost for customers.

In competitive environments, players try strongly to deliver the best experience possible to their customers. In fact, it appears that when companies manage to connect to customer's emotions and needs, the impact on their revenues can be tremendous (Tushman and Nadler, 1986).

Furthermore, connected devices will enable companies to address directly the needs of end users, removing the need for any intermediates. All these factors will decrease the bargaining power of the buyers and reinforce the position of firms offering IoT services in their environment.

On the other hand, the bargaining power of buyers might also increase, as the enlarged access they will get on the functioning of their devices will enable them to better understand its working and performances. Users will thereby be capable of playing manufacturers off each other more easily, and decrease their switching costs (Porter and Heppelmann, 2014).

Which of those observations will have the strongest effect is uncertain, however, we argue that the enhancement of the customer relationship management will win this battle and that IoT actors will end up with a reinforced bargaining power towards their users.

Threat of new entrants

The high entry costs to the IoT sector are due to the large necessary upfront investments, required in all the new IT infrastructure (such as software, storage spaces, analytic tools, etc.). Indeed, those costs constitute actual big barriers for new entrants. Also, as previously mentioned, first-movers should normally have taken advantage of their collection of user data, and have won the loyalty of their clientele, thereby restraining even more the access to customers of new entrants (Lueth, 2015).

Nevertheless, the threat that the latter represent remains very high. In fact, the new popularity and the expansion of possibilities provided by the IoT are enormous, and furnish lots of incentives for motivated firms to enter the competition.

Moreover, as connected things seem to lead to more and more pervasive borders between industries, current incumbents of those markets may face new challenges when big competitors, that did not historically compete with them, start entering their market.

Threat of substitute products or services

Connected objects offer unmatched performances with superior, more useful, more customized and with more customer valued features in comparison to traditional products that might be taken as substitute (Faisal, 2016). This will obviously lead to a reduction of the rivalry coming from conventional products, reducing threats and product substitution and enhancing the industry development and profitability of the company (Porter and

Heppelmann, 2014).

Competitive rivalry

The collection of data and knowledge that will be retrieved from IoT devices will favor a narrow segmentation of the buyers landscape. As such, it will create specified differentiated niches, moving the competition away from price alone, and decrease the overall competition.

The considerably high amount of data collected from customers can also be used to improve the various types of services and offerings. More tailored and customer per customer approach will be easier to implement and will greatly differentiate competitors from each other (Porter and Heppelmann, 2014).

However, the high upfront investment in software, and other necessary IT infrastructures, will increase the fix costs of companies. The latter will seek to spread these costs across a larger number of units sold (Faisal, 2016), making them weaker when facing a price war with competitors.

It is also important to see in that the amount of competitors in particular industries might well rise due to those smart devices. In fact, digital technologies tend to make the borders between industries more and more pervasive. Companies that previously had never considered each other as competitors could, in a near future, become the biggest rival on their market.

As a final note, companies need to be aware that, in such a fast moving environment, new competitors can emerge very quickly and reshape competition and industry boundaries through disruptive innovations.

Conclusion

The structure of an industry changes when new technology, customer needs, or other factors shift these five forces. In this sense, connected products, via the Internet of Things, will substantially affect the structure of many industries (Lueth, 2015). New connected products will definitely transform how value is added and achieved for consumers, how businesses compete with each other, and the definition of products itself (Faisal, 2016). These changes will impact every industry, either directly or indirectly.

The IoT will reduce buyer's power, since competition is no longer based on price, and

Figure 5.1: Porter analysis on the IoT sector

that it is expected to increase their switching costs (Karakaya, 2015). However, we want to mitigate this point. In fact, we claim that consumers will not necessarily be worse off. Indeed, as suppliers gain insights on their needs, they will provide them with better suited services. Clients will therefore enjoy greater customer experience, and withdraw greater value from their products and services.

Smart connected products will certainly shift the focus of companies from achieving a cost differentiation, to a real product differentiation. Threats of new entrants will be decreased with the emergence of IoT as new barriers will be raised (Faisal, 2016). Due to a superior, personalized and high-value products, the threats of new substitutes will be highly mitigated. Such a move will significantly reduce the bargaining power of traditional suppliers, while increasing the one of the new type of actors.

For all those reasons, we state that companies should all consider the potential impact that the introduction of IoT devices, and the rise of the new data economy, will have on their business. Any organization should prepare itself to face new customer needs, or to deal with disruptive new players that might be coming from completely different markets. Furthermore, we argue that those firms should strongly consider the applications of digital technologies that could be applied in their operations, as they will enable them to differentiate themselves from the rest of their competitors.

5.2 Survey results

In this section we present the results obtained from the carried survey. It will be split into two parts. In the first one, we show some descriptive graphics showing the type of usages of data that are made by respondents, as well as the frequency of biggest competitive advantages and hindrances faced by the latter. In the second part, we will display the results of the statistical tests that were performed on our hypotheses.

As companies that agreed to answer our survey wish to remain anonymous, we will not cite any corporation name.

5.2.1 Descriptive analysis

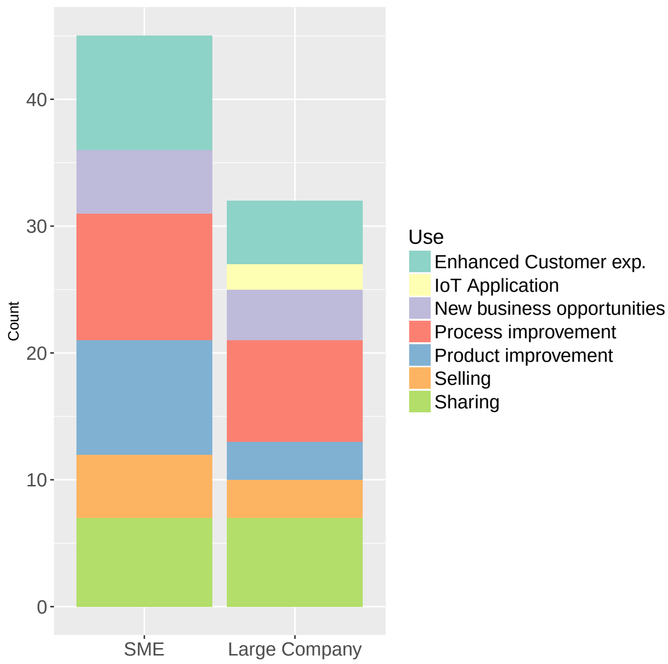

Figure 5.2: Type of usage of data

Figure 5.2 displays the results obtained from the survey regarding the types of uses that company make of their data.

It seems from it that 61.5% of respondents share their data with their collaborators among the IoT ecosystem. While seven respondents do use data markets to sell the data they collect to other companies. It appears that only 26.9% of survey participants do not perform any of those two external uses.

Regarding the internal use, we can see that more than the half of the respondents use their data to improve their business processes. Also, half of the respondents do use those data to improve their customers' experience, as well as their products and services. The detection of new business opportunities seems to account for only a minor part of the internal uses of the respondents. As do the energy monitoring and the environmental alerting.

	Proc. Impr.	Pr. Impr.	New Bus. Op.	Cust.ex.	IoT app.	Sharing	Selling
Co. 1	x						x
Co. 2	x			x			
Co. 3	x		x	x		x	
Co. 4	x		x			x	
Co. 5	x	x	x	x		x	x
Co. 6					x	x	x
Co. 7					x		
Co. 8	x			x		x	
Co. 9		x					
Co. 10	x					x	
Co. 11	x	x	x	x		x	
Co. 12	x					x	x
Co. 13				x		x	
Co. 14	x	x	x	x		x	
Co. 15				x			
Co. 16	x	x					x
Co. 17	x	x	x				x
Co. 18	x	x	x	x		x	x
Co. 19				x			
Co. 20	x	x					
Co. 21	x	x		x		x	
Co. 22	x	x		x			
Co. 23		x					x
Co. 24	x		x			x	
Co. 25	x	x	x	x			
Co. 26				x		x	

Table 5.1: Types of Usage

Table 5.1 provides a clearer representation of the above graphic.

Figure 5.3 and 5.4 display the graphics of the achieved competitive advantages and the, referred to as, biggest hindrances faced by the survey respondents.

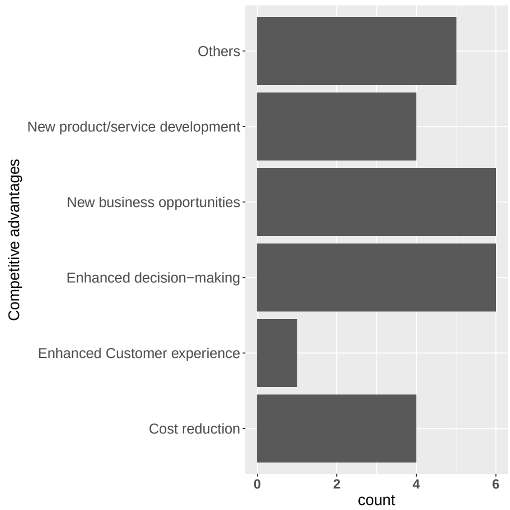

Figure 5.3: Competitive advantages

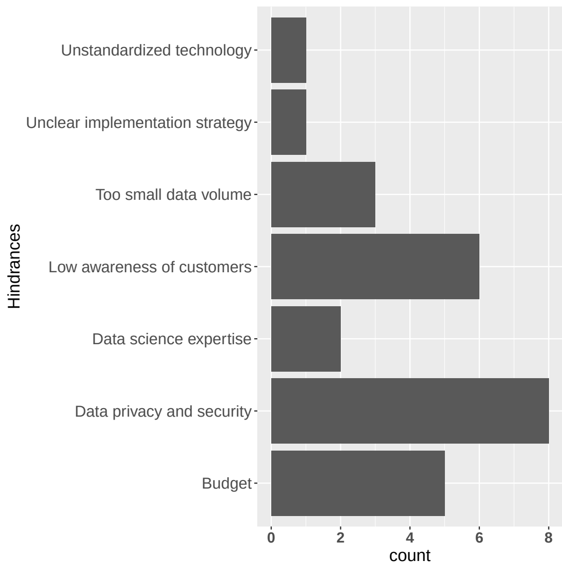

Figure 5.4: Biggest Hindrances

According to figure 5.3, it seems that the most recurring competitive advantages achieved by the respondents are the *enhanced decision-making*, the *discovery of new business opportunities*, and the *automation of business processes*.

Nevertheless, the mostly cited hindrance faced by the respondents appears to be the *data privacy and security* issues. Indeed, figure 5.4 shows that it is considered as the biggest obstacle for achieving an effective implementation of IoT solutions, by approximately 30% of the respondents. It is then followed by the *customer low awareness for IoT applications* and by the *lack of resources and budget*.

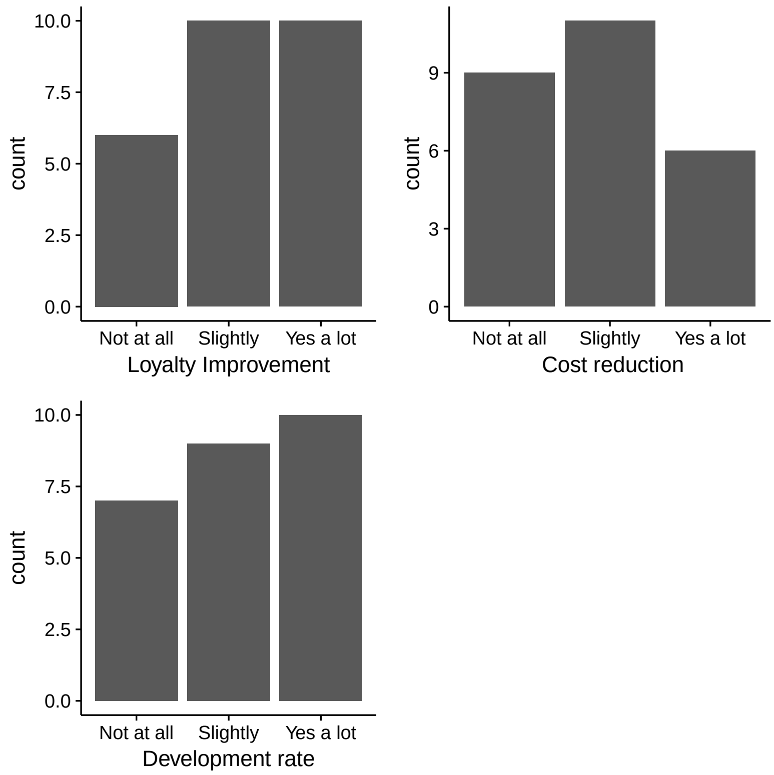

Figure 5.5: Effective impact of IoT on the customer loyalty, the cost reduction, and the development rate of new products and services.

It is also interesting to note that, while asked about the effective impact of IoT devices on their business, respondents tend to agree that they have a positive impact on the loyalty of their customers, and on the development rate of their products and services. And even though the literature pointed out that the use of smart objects was a way to enhance process automation, still an important part of the respondents tends not to notice a big reduction of their costs. All those observations are displayed in Figure 5.5.

5.2.2 Statistical tests results

As we have discussed the way smart connected devices could impact tomorrow's industries, their structure, as well as their overall competitiveness, we now want to understand what companies, active in the IoT field, truly aim at achieving with it. Through statistical tests, we want to show the relationships existing between diverse economic factors, and conclude whether or not they impact organizations' ability to build their aimed competitive advantages and to achieve their objectives.

In this section we present the results of our statistical tests, that will enable us to accept or reject the hypotheses we formulated in section 3. Therefore, we will use bar charts to visualize the impact of one categorical variable on the other.

Before getting into the discussion of those graphs, one must recall that our research has segmented its respondents based on three research variables[1]. As explained previously, the latter are considered as the explanatory factors impacting the ability of companies to build competitive advantages.

This research's first three hypotheses express the relationships existing between the size of a company and those explanatory factors. The following three, however, examine the link between those same factors and the industry the company is part of. Finally, the last hypotheses analyze the connection those variables have with the type of competitive advantages built, and the type of hindrances faced.

As we continuously employ the same analysis variables, the shapes of the bar plots will repeat themselves for every relationship analyzed. Therefore, we must grant more interest to the distribution of the following stacked bar plots rather than on their counts.

Hypotheses tests

H3: There is a significant difference in the portion of annual budget invested in data management resources between SMEs and large companies.

From figure 5.6, we acknowledge that 46.7% of SMEs invest less than ten percent of

[1] Those variables are: The %Budget for data management, the Access to ecos. information, and the %Data effectively used

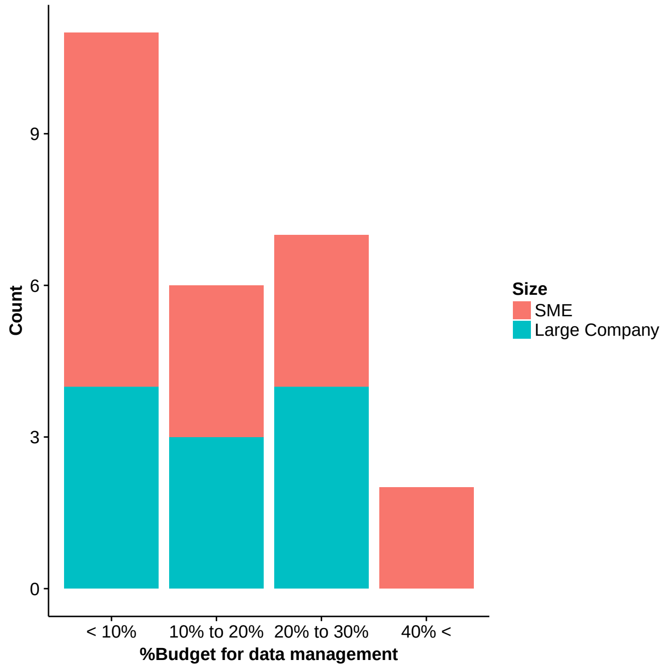

Figure 5.6: Hypothesis 3

their total annual budget into data management resources, for 36.4 % of larger firms. Also the same portion of large companies do invest between 20 and 30% of their annual budget in that resource, for only 20% of SMEs. Nevertheless, the only two companies of our sample that appear to invest more than 40% of their annual budget into data management, are both SMEs.

As SMEs dispose of shallower financial resources than their counterparts, we can argue that the two firms investing more than 40% of their budget in data management resources believe in the potential of data as a strong generator of value and as a mean for the creation of competitive advantages. The lower end of SMEs, on the other hand, might be favoring investments in other departments, more closely related to their core activities.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.2.

	Degree of Freedom	Statistic	P-Value
H3	3	2.403	0.493

Table 5.2: Chi Square test: Hypothesis 3

It is no surprise to witness a computed P-Value of such a high level. Out of that result, it makes no doubt that *Hypothesis* 3 must be rejected.

H4: There is a significant difference in the access to broad ecosystem information between SMEs and large companies.

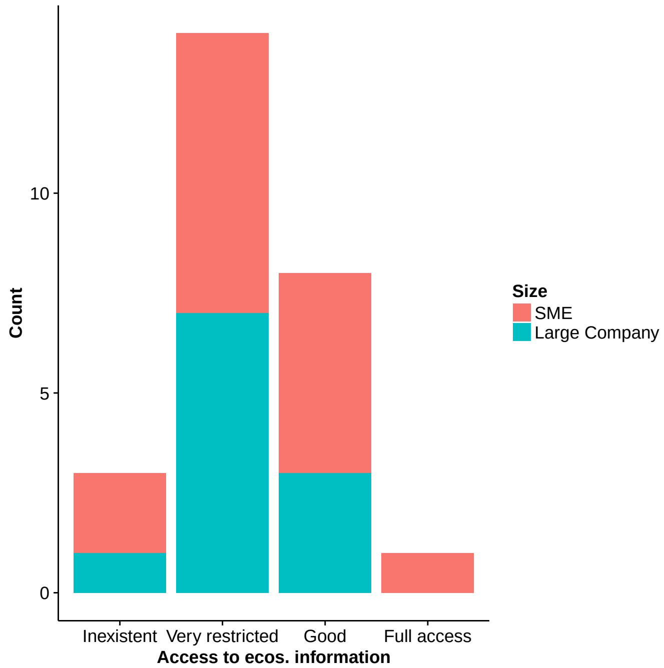

Figure 5.7: Hypothesis 4

In figure 5.7, it is interesting to note that the only company claiming to have a full access to its ecosystem information is, again, an SME.

For the rest, we notice that most of the respondents have a limited, if not a completely nonexistent, access to their collaborators information. Indeed 65.4% claim to have an nonexistent, or at least a very restricted access to external data sources. Relatively speaking, both categories seem to follow the same distribution of their counts across the classes of the independent variable (Access to ecos. information).

Table 5.3 displays this trend. From it we deduce that there exists no real divergence in the access that a company has to its ecosystem information in regards of its size.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.4.

	SME	Large Companies
Inexistent	2	1
Very restricted	7	7
Good	5	3
Full access	1	0

Table 5.3: Distribution of companies according to their access to ecosystem information

	Degree of Freedom	Statistic	P-Value
H4	3	1.247	0.742

Table 5.4: Chi Square test: Hypothesis 4

The results obtained from the test strengthen our previous analysis. Indeed, as almost no divergence between the two distributions has been acknowledged, it is logically that we must reject *Hypothesis 4*.

H5: There is a significant difference in the percentage of data collected effectively used between SMEs and large companies.

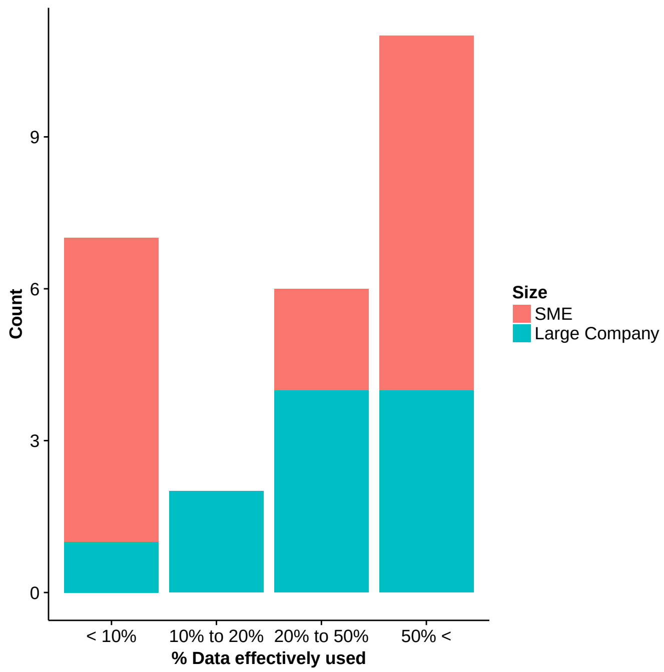

Figure 5.8: Hypothesis 5

According to figure 5.8, we can distinguish a clear cliff delimiting two segments among

SMEs. Indeed while 40% of SMEs do use less than 10% of their collected data, 46.7% of them pretend to use more than fifty percent of the latter.

On the other hand, larger companies tend to be distributed more evenly across the four segments. Still, we notice in that category, a trend towards a lager use of the data. Indeed, 72.7% of our large respondents are spread over the two last segments.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.5.

	Degree of freedom	Statistic	P-Value
H5	3	6.597	0.086

Table 5.5: Chi Square test: Hypothesis 5

The observed fragmentation between the distributions of SMEs and large companies, according to the analysis variable, is well represented by the P-Value resulting from our Chi Square test. Even though we can not accept *Hypothesis 5*, we can still claim that there exist different tendencies towards the percentage of data being processed by small and large organizations.

H8: There is a significant difference in the portion of annual budget invested in data management resources across industries.

From figure 5.9 we manage to detect some tendencies. First of all, we notice that each and every industry is represented in the first segment. It can therefore be deducted that being in a particular industry does not imply any requirements regarding a minimal threshold in the portion of annual budget invested in data management. As we had seen already in figure 5.6, this segment is also the one containing the majority of our interviewees, with eleven companies, accounting for 42.3% of our sample.

Moreover, and surprisingly, the telecommunication firms seem not to invest more than 10% of their budget into the building of data management resources. Same goes for environmental company and the ones active in the retail. On the other hand, industries seeming to attach more importance to that resource are the IT and services companies.

Finally, it appears that in the consulting sector, organizations tend to adopt different

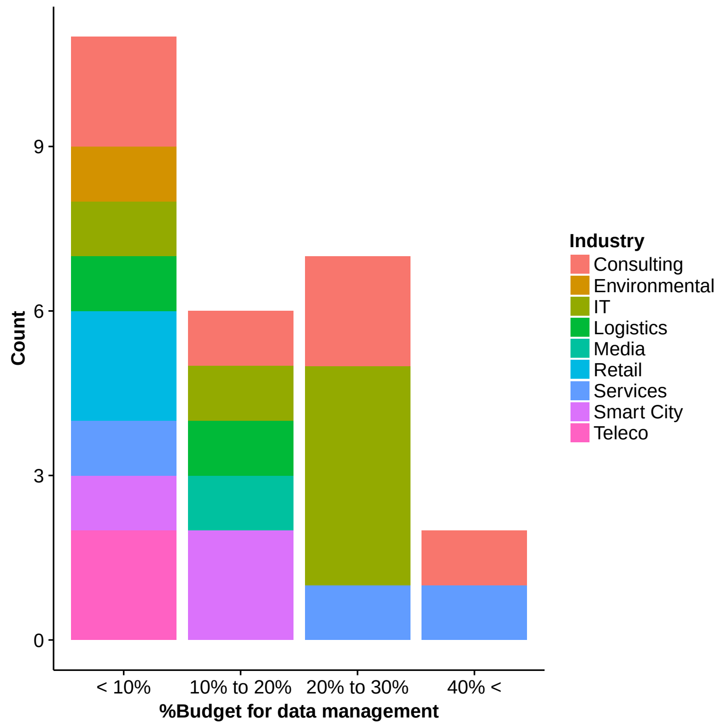

Figure 5.9: Hypothesis 8

approaches regarding this matter. Indeed this sector is fragmented, as 50% of consulting firms claim to invest more than 20% of their annual budget in data management, and the remaining below this level.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.6.

	Degree of Freedom	Statistic	P-Value
H8	24	24.387	0.440

Table 5.6: Chi Square test: Hypothesis 8

From those observations we draw the conclusion that data management resources remain secondary assets for most organizations, as only 7.69% of our sample appears to invest more than 40% of its budget in them. Also, from the outcomes of the Chi Square test, we must reject *Hypothesis 4*. As no clear patterns could be detected from the graph, this result seems consistent.

H9: There is a significant difference in the access a company has to ecosystem information across industries.

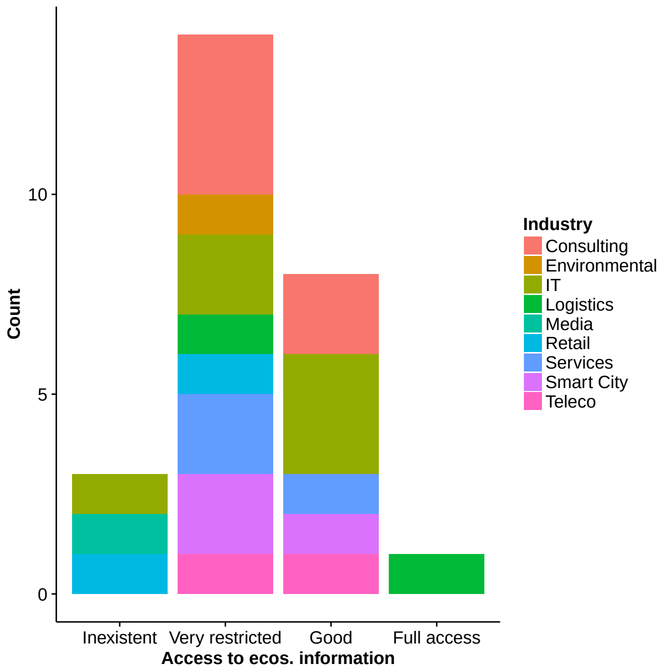

Figure 5.10: Hypothesis 9

Figure 5.10 displays a stacked bar plot presenting the quality of the access that every industry has to its ecosystem information. The first thing to notice is that the only respondent claiming to have a full access the external data of its partner network, is part of the logistics industry. Also, only nine companies, representing 34.6% of our sample, and coming from five different industries consider to have a quite good access to external data. Also worth noticing, is that the three industries pretending to have an nonexistent access to external data are the Retail, the IT sector and the Media.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.7.

	Degree of Freedom	Statistic	P-Value
H9	24	28.063	0.257

Table 5.7: Chi Square test: Hypothesis 9

Here once again, we must reject our hypothesis. According to the P-Value of the Chi

Square test, we acknowledge that there exists no significant difference in the access that a company has to its ecosystem information, according to its industry.

H10: There is a significant difference in the percentage of data collected effectively used across industries.

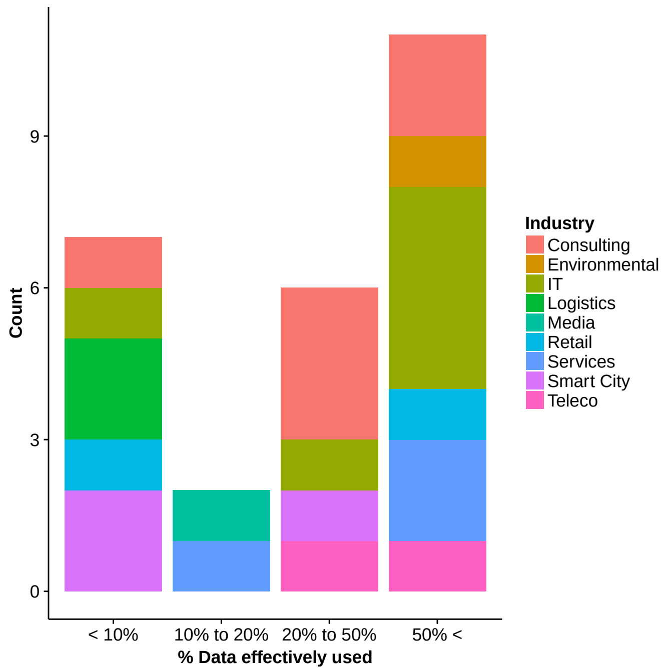

Figure 5.11: Hypothesis 10

We surely can withdraw some learning from this chart. First of all lets note that for once, more companies seem to be part of the last segments. Indeed 42.3% of our respondents claim to use more than 50% of the data they collect. This adds up to the 23.1% of firms that were already using between 20 and 50% of their data. Secondly, we recognize that, of all analyzed industries, "Logistics" is the sole industry having all its members using less than 10% of their data. The telecommunication industry, however, stands among the good students, as do the IT companies and the environmental one.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.8.

	Degree of Freedom	Statistic	P-Value
H10	24	33.400	0.096

Table 5.8: Chi Square test: Hypothesis 10

As we were able to detect certain tendencies in figure 5.11, we are not surprised to obtain such a P-Value from our Chi Square test. Still, once again, those differences among industries are not strong enough to be considered as statistically significant. Therefore we must reject *Hypothesis 10.*

H13: There is a significant relationship between the portion of annual budget invested in data management and the type of competitive advantage created.

We now start to analyze the hypotheses related directly to the type of competitive advantages and hindrances that are respectively achieved and faced by our respondents. One must be aware that we asked our respondents to define the biggest competitive advantage they were most able to reach, as well as the most prevailing hindrance facing its achievement. As such, one must not draw the hasty conclusion that firms are only able to leverage *one* competitive advantage. Indeed, benefiting from cost reductions and of enhanced customer experience are certainly not mutually exclusive phenomena.

As we mentioned in the introduction of this section, we must not be fooled by the look of this graph. Indeed there exists no relationship between the number of competitive advantages, a company is able to leverage, and the studied variable, rather should we focus on the type of competitive advantage. As such one must not believe that investing less than 10% of its annual budget into data management resources will favor the creation of competitive advantages.

Figure 5.12 tells us another interesting story. As we observe the most left-hand sided segment of this graph, it appears indeed, that all competitive advantages can be achieved even without investing much into data management resources. Obviously, if companies investing less than 10% of their annual budget in data management manage to build any type of competitive advantages, we might logically conclude that this variable has a weak

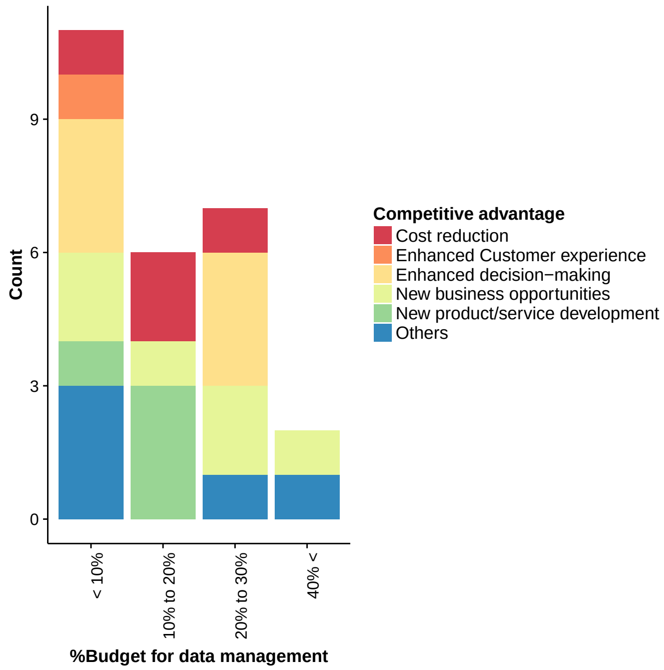

Figure 5.12: Hypothesis 13

impact on the capabilities of any organization to leverage a particular type of competitive advantage.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.9.

	Degree of Freedom	Statistic	P-Value
H13	15	16.212	0.368

Table 5.9: Chi Square test: Hypothesis 13

Once again, the Chi Square test rejects *Hypothesis 13*, and therefore confirms what we stated previously. That no relationship exists between the portion of annual budget invested in data management resources and the type of competitive advantage achieved by companies.

H14: There is a significant relationship between the access to ecosystem information and the type of competitive advantage created.

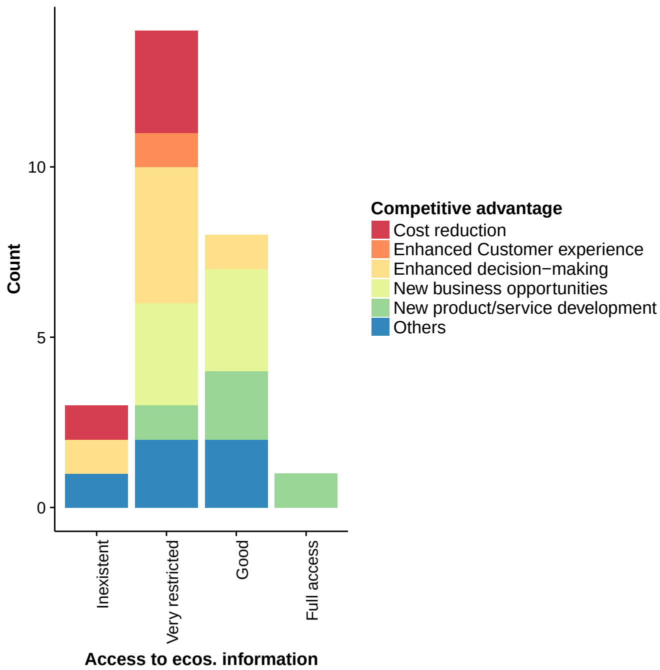

Figure 5.13: Hypothesis 14

In the same way as the previously analyzed explanatory factor, the access to external data, coming from other players of the IoT ecosystem, seems not to favor any particular type of competitive advantage neither. As we cannot detect any particular pattern in the data.

Timidly can we argue, but again in an uncertain manner, that product and services development requires an relatively well developed network of partners, as this type of competitive advantage seem to be mostly achieved in the rightest segments. Nevertheless, the results of the Chi Square test displayed in table 5.10 once again highlight the fragility of those observations.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.10.

As of the displayed P-Value, we reject *Hypothesis 14*.

	Degree of Freedom	Statistic	P-Value
H14	15	12.835	0.615

Table 5.10: Chi Square test: Hypothesis 14

H15: There is a significant relationship between the percentage of data collected effectively used and the type of competitive advantage created.

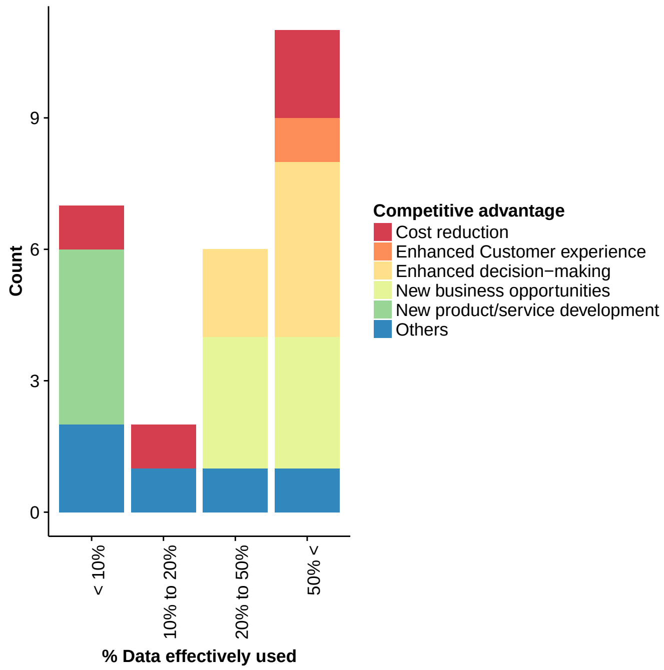

Figure 5.14: Hypothesis 15

This plot, on the other hand is way more interesting than the previous two. Indeed, figure 5.14 displays well distinguished patterns revealing interesting insights. At first, we acknowledge that all respondents achieving the creation of new products and services, tend to use less than 10% of their data. Then, it appears that the creation of new business opportunities, as well as the enhancement of decision making, occur within companies using 20% or more of their data. However once again, benefiting from cost reductions does not seem to be correlated to the analysis' variable.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.11.

	Degree of Freedom	Statistic	P-Value
H15	15	23.911	0.067

Table 5.11: Chi Square test: Hypothesis 15

The Chi Square test provides indeed a P-Value close to our alpha threshold. Nevertheless, it does not permit us to accept *Hypothesis 15*. There is therefore no significant relationship between the percentage of collected data effectively used, and the type of competitive advantage achieved by a company.

H18: There is a significant relationship between the portion of annual budget invested in data management and the types of hindrances encountered.

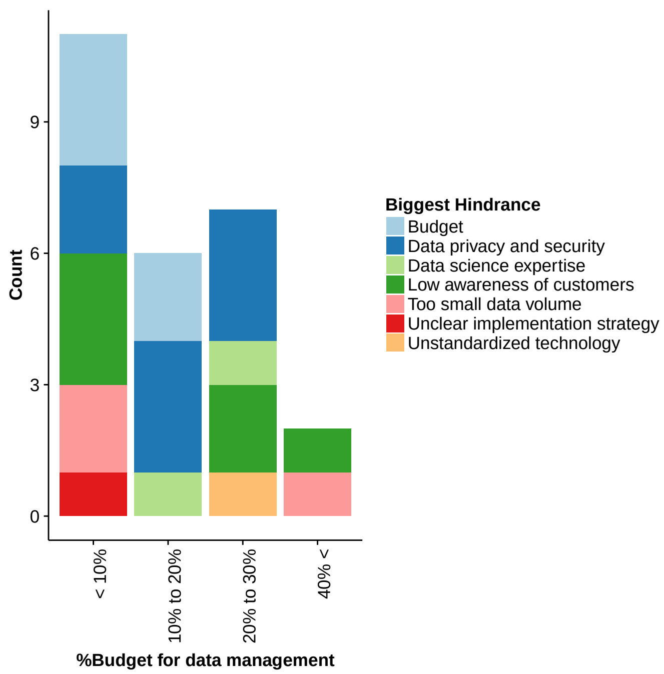

Figure 5.15: Hypothesis 18

We can learn from figure 5.15 that no matter what proportion of their budget our respondents invested in their data management department, the low awareness of customers regarding IoT applications is still hurting them. This confirms what we intuitively could have deduced. Indeed, making people aware of the advantages of services relying on IoT solutions passes through marketing and sensitization campaigns. Furthermore, we acknowledge that issues of data privacy and security are appearing in almost every segments. This hindrance constitutes the one the most encountered overall. Indeed, 30% of interviewees consider it to be their biggest obstacle for leveraging all the benefits of the IoT.

It is also interesting to note that the lack of financial resources is often cited among organizations maintaining a low investment in data management resources. This might signal a causal relationship between those two phenomena. However, affirming such a thing would require more investigations and is beyond the scope of this research.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.12.

	Degree of Freedom	Statistic	P-Value
H18	18	17.731	0.473

Table 5.12: Chi Square test: Hypothesis 18

Those do not enable us to accept *Hypothesis 18*.

H19: There is a significant relationship between the Access to ecos. information and the types of hindrances encountered.

As we could expect, figure 5.16 shows us that firms having a narrow access to external sources of information, consider their too small volume of data as their prime obstacle. We can also note, that the concern of data privacy is evenly present in companies with good connections and in ones with weaker ones. This is surprising as we would have expected organizations involved in large data transactions to be more concerned about the security of their data.

It is hard to detect any other tendency in those data, as other types of hindrances seem to be randomly distributed in the bar plot.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.13.

Again, *Hypothesis 19* must be rejected, and we cannot state that any relationship ex-

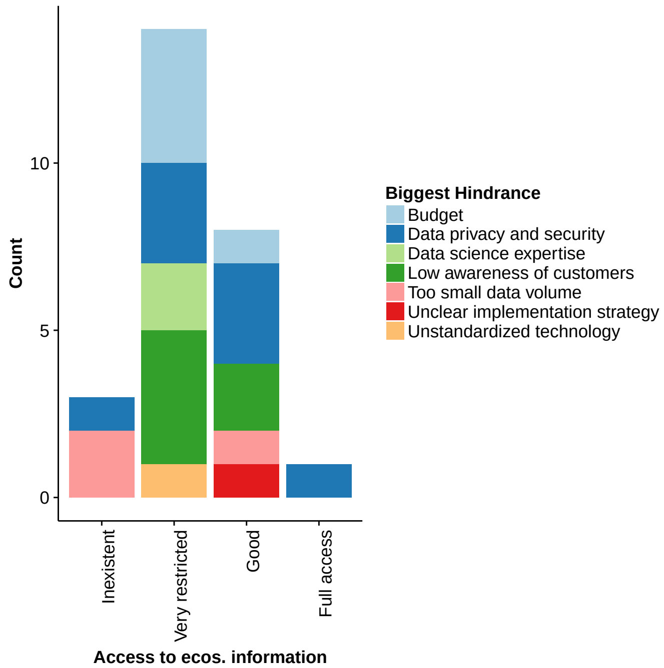

Figure 5.16: Hypothesis 19

	Degree of Freedom	Statistic	P-Value
H19	18.000	19.251	0.377

Table 5.13: Chi Square test: Hypothesis 19

ists between the type of hindrances faced by companies and their access to external data of their ecosystem.

H20: There is a significant relationship between the percentage of data collected effectively used and the types of hindrances encountered.

Finally we have come to our last plot, representing the relationship expressed in our last hypothesis. The first thing on which we can argue, is that, of the companies considering the lack of data as their main concern, two out of three claim to use more than 50% of their data. This is understandable as companies driven by the analysis of data to leverage value, rely on that resource. However, it seems worth mentioning that the opposite is not true. Indeed, the lack of data seems to be the prime concern of only 18.2% of companies belonging to that last segment. The main hindrance facing the latter, according to 36.4% of them, being the low awareness of customers.

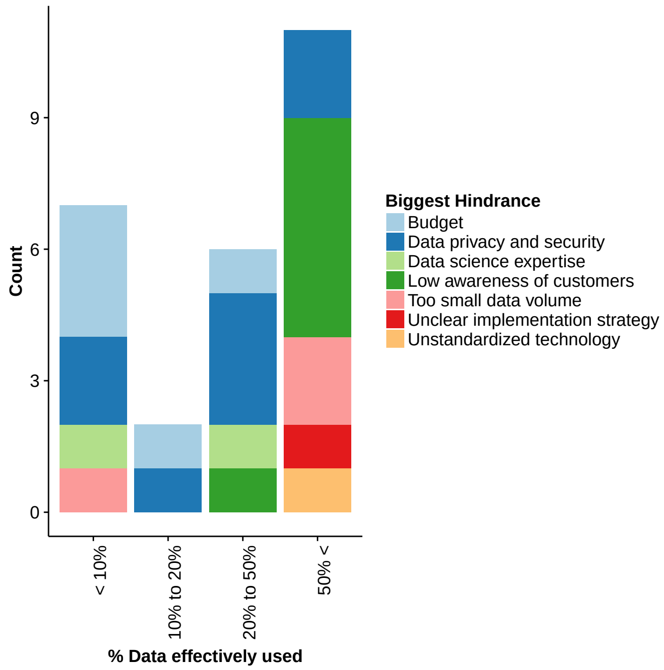

Figure 5.17: Hypothesis 20

Finally, the financial shortcomings tend to mostly concern the firms having a limited use of their data. We might postulate another relationship linking those phenomena. Indeed, financially limited organizations might tend to not use their data properly as they prefer investing their time and money into their core activities.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.14.

	Degree of Freedom	Statistic	P-Value
H20	18.000	17.403	0.496

Table 5.14: Chi Square test: Hypothesis 20

Those results force us once again to reject *Hypothesis 20.*

5.3 Extra Hypotheses

As our initial hypotheses did not provide the expected results, we decided to investigate other ones, this time, directly linking the size, the industry, and the role of the company in its ecosystem to the potential competitive advantages and hindrances. The following hypotheses were not described in the problematic, and add the variable "*Role of the company in the ecosystem*" to the set of explanatory factors.

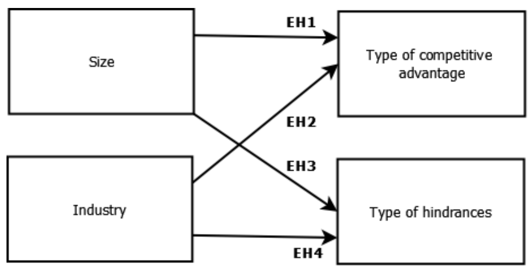

Figure 5.18: Extra Hypotheses Scheme

Extra Hypothesis 1: There is a significant difference in the type of competitive advantages achieved by SMEs and large companies.

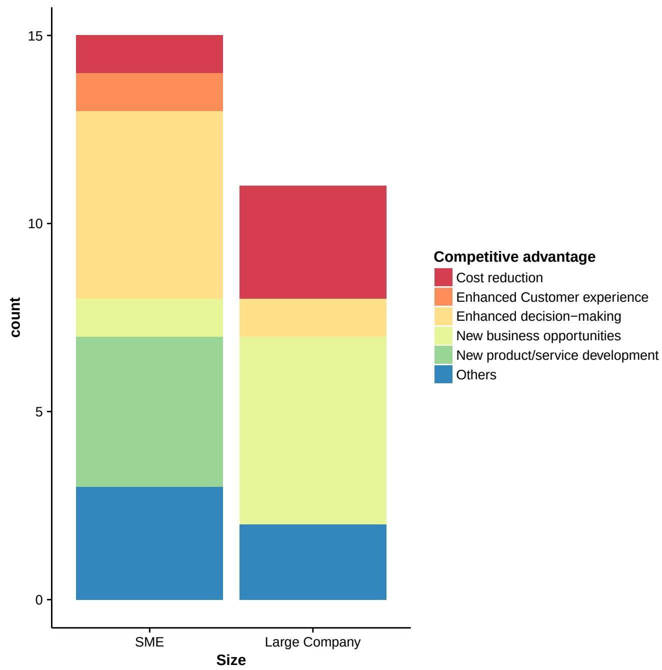

Figure 5.19: Extra Hypothesis 1

Figure 5.19 presents another stacked bar plot. However this time, it directly distinguishes the diverse types of competitive advantages that small and large companies manage to leverage via the use of IoT solutions. This time, we can clearly identify different patterns within the two groups. As 45.5% of large companies define the creation of new business opportunities as their prime competitive advantage, the latter seems not to follow the same trend among SMEs. Indeed, only 3.8% of small companies manage to develop new opportunities through IoT. Instead, smaller organizations claim, at 33.3%, to be able to enhance their decision-makings, and at 26.7%, to be able to develop new products and provide smart innovative services.

Relatively speaking, large companies tend to achieve better cost reduction than SME. However, the enhancement of their customer's experience seem not to be the purpose of their IoT implementations, as this type of competitive advantage was not cited among out large respondents.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.15.

	Degree of Freedom	Statistic	P-Value
Ex.H1	5	11.183	0.048

Table 5.15: Chi Square test: Extra Hypothesis 1

This time, the P-Value computed by the Chi Square test appears to be less than our alpha threshold. We can therefore state that there exists a significant relationship between the *Size* of a company and the competitive advantages it achieves.

Extra Hypothesis 2: There is a significant difference in the type of competitive advantages achieved by industries.

It is quite difficult to detect any particular tendency out of figure 5.20. Somehow we realize that out of the six companies achieving the development of new business opportunities, three of them happen to be consulting firms. We can apply the same analysis regarding the enhancement of decision-making. Indeed 50% of the firms pretending to build their strongest competitive advantage out it, are part of the IT industry. We fur-

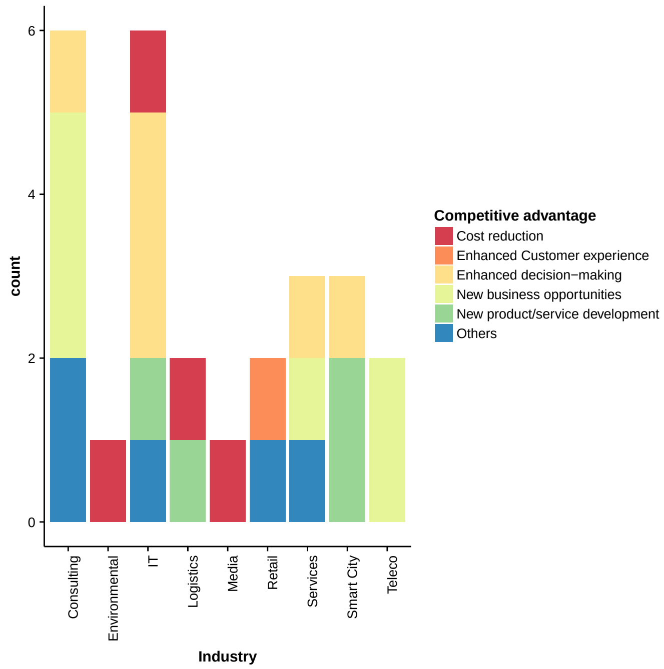

Figure 5.20: Extra Hypothesis 2

ther acknowledge that the other types of competitive advantages seem to be smoothly dispatched among all other activity sectors.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.16.

	Degree of Freedom	Statistic	P-Value
Ex.H2	40	52.722	0.086

Table 5.16: Chi Square test: Extra Hypothesis 2

Those results are quite surprising as we expected a much higher P-Value, according to figure 5.20. Nevertheless it seems that the two analyzed variables are slightly connected. This statement however, must considered cautiously as the Chi Square test still does not enable us to accept *Extra Hypothesis 2*.

Extra Hypothesis 3: There is a significant difference in the type of hindrances faced by SMEs and large companies

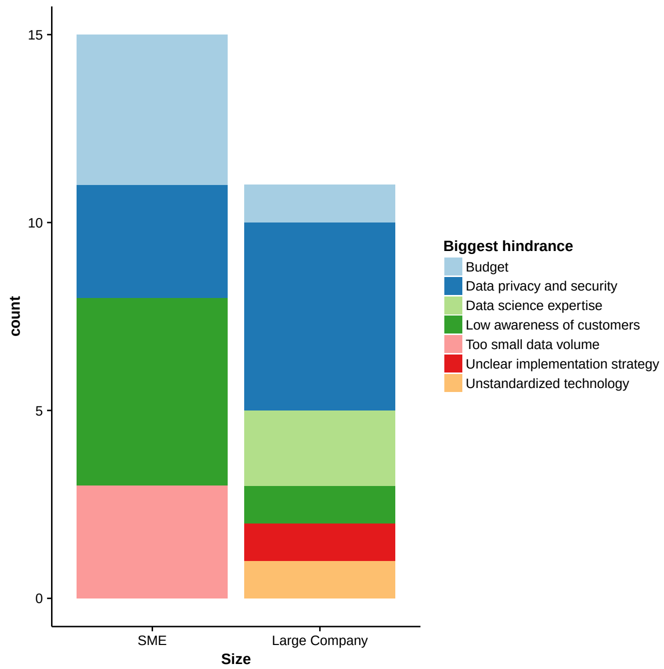

Figure 5.21: Extra Hypothesis 3

Exactly as for the competitive advantages, it seems that two clear different patterns can be identified in the *SME* and *Large company* categories. First of all, notice that the budget appears to be one of the main concerns of smaller companies while it represents only 9.1% of the large's. This observation strongly supports our initial intuition that smaller companies face financial constraints that hinder them in their process towards a greater informational technology development, needed to built long-lasting competitive advantages out of IoT solutions. Also note, that SMEs consider the low awareness of customers for IoT solutions as their prime obstacle, followed by the lack of data and data privacy concerns. Those four problems combined, offer a global view of the hindrances faced by smaller companies. It seems eventually, that they struggle in making their customers aware of the solutions they offer. Furthermore, low awareness may well cause the lack of collected data, as non-aware customers will not tend to use IoT solutions.

Secondly, we note that larger organizations are way less affected by those factors. On the other hand, they seem to be more concerned by data privacy issues, and the access to data science expertise. Furthermore, and however they only represent a small portion of the respondents' biggest hindrances, the lack of standardization of protocols and the unclear implementation strategies complement the set of problems pointed out by this larger organizations.

Concretely, we can say that larger firms tend to focus more on technical and implementation obstacles, while SMEs hardly manage to gather enough data to even allow them to think of those.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.17.

	Degree of Freedom	Statistic	P-Value
Ex.H3	6	11.626	0.071

Table 5.17: Chi Square test: Extra Hypothesis 3

Not surprisingly, the P-Value displayed in table 5.17 is relatively close to our rejection threshold, reinforcing our conviction that the *Size* of companies has an impact on the type of hindrances they face. Still we must reject *Extra Hypothesis 4*.

Extra Hypothesis 4: There is a significant difference in the type of hindrances faced by industries

Figure 5.22, like figure 5.20, seems not to highlight any particular trend. Indeed, at the exception of the lack of financial resources and of the lack of data volume, all types of hindrances seem to be evenly dispatched across the diverse industries. We note however that the problem of non-standardization of IoT-related technologies is mentioned by an IT firm. However this represents only 16.7% of all the concerns of our IT respondents. Indeed, actors evolving in that industry seem to grant more importance to their issues related to the protection of their data.

We also acknowledge that the lack of clear implementation strategy of IoT solution has been identified, with the issues related to data privacy and security, as the most important problems of the telecommunication industry. We discovered that those companies often take a very important function in their IoT ecosystem. Indeed, they act as data aggre-

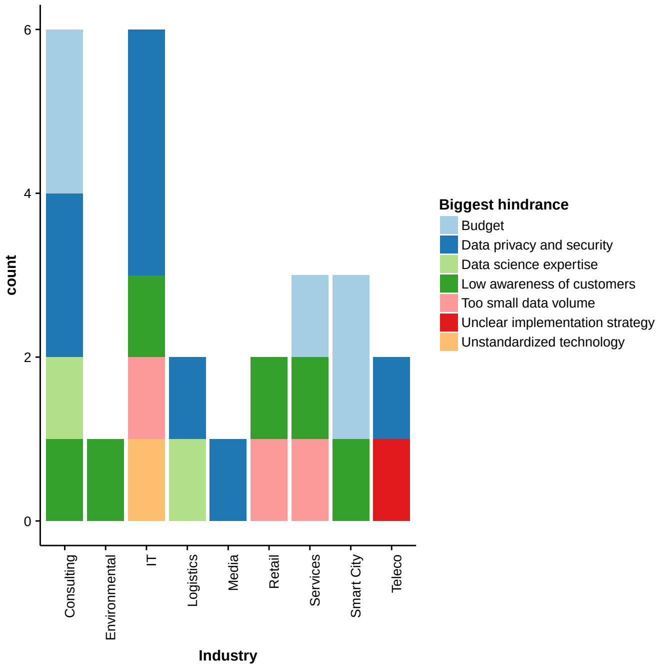

Figure 5.22: Extra Hypothesis 4

gators by using their network to source and transmit data to the right spots. As of this responsibility, it seems very strange that half of those respondents considers to have an unclear vision of its implementation strategy. While on the other hand, it seems obvious that that those types of companies should greatly consider improving the security and privacy of the data they collect and transmit.

As we performed the Chi Square test on those two variables, we obtained the results displayed in table 5.18.

	Degree of Freedom	Statistic	P-Value
Ex.H4	48	45.175	0.589

Table 5.18: Chi Square test: Extra Hypothesis 4

5.4 Results summary

	Degrees of freedom	Statitistic	P-Value	Decision
H3	3	2.403	0.493	Rejection
H4	3	1.247	0.742	Rejection
H5	3	6.597	0.086	Rejection
H8	24	24.387	0.440	Rejection
H9	24	28.063	0.257	Rejection
H10	24	33.400	0.096	Rejection
H13	15	16.212	0.368	Rejection
H14	15	12.835	0.615	Rejection
H15	15	23.911	0.067	Rejection
H18	18	17.731	0.473	Rejection
H19	18	19.251	0.377	Rejection
H20	18	17.403	0.496	Rejection

Table 5.19: Results of Initial Hypotheses

	Degrees of freedom	Statitistic	P-Value	Decision
Ex.H1	5	11.183	0.048	Acceptation
Ex.H2	40	52.722	0.086	Rejection
Ex.H3	6	11.626	0.071	Rejection
Ex.H4	48	45.175	0.589	Rejection

Table 5.20: Results of Extra Hypotheses

5.5 Results Discussion

5.5.1 Initial Hypotheses tests discussion

After having analyzed every graphic and performed all the statistical tests on our hypotheses, we are forced to acknowledge that no clear and indisputable relationships among variables can be derived from those results. Indeed, every, initially formulated hypothesis (*H3-H20*) has been rejected, so that we cannot affirm that any particular explanatory factor has a significant impact on the type of created advantages, or on the faced hindrances.

Furthermore, all hypotheses aiming at showing the impact of the size or the industry of a company on those explanatory factors, have also delivered poor results. As such, we must reject all formulated hypotheses, and conclude that nor does there exist any significant relationships between the size of an organization and its ability to invest in data management resources, to access a broad ecosystem of information, or to process a large portion of the data it collects, nor does there exist any significant relationships between the latter factors and the industry of a company.

Even though our statistical results were not conclusive, we have been able to distinguish a few notable differences among the studied populations. We learn indeed, from *Hypothesis 5* that SMEs tend to be fragmented in two heterogeneous groups according to the percentage of collected data they effectively process. While small and medium enterprises seem to follow an "all or nothing" approach regarding that variable, larger corporations are more smoothly distributed across the four identified segments.

Still according to the percentage of data effectively used, we learn from figure 5.11 that most consulting and IT firms do use more than 20% of their data. As such, those two industries combined represent 58.9% of industries claiming to exploit more then 20% of their data. On the opposite, we note that each respondent active in the *Logistics* industry pretends to use less then 10% of its data.

Because of these teachings, we argue that the size of the company, as well as its industry, still have an impact on the percentage of collected data that a company effectively uses. However, having analyzed the relationship between the size of company and its ability to access external data through their ecosystem, as well as to invest a certain proportion of its budget into data management resources, we recognize that the former variable has no impact on the latter ones. The same statement can be made regarding the company's industry. Indeed, we assess that the type of industry the company is active in has little to no influence on its ability to access external data, nor does it influence its capacities to invest in informational technology resources.

That been told, we were also able to distinguish some differences in the connections linking our three explanatory factors and our competitive advantages and hindrances. Still again, the factor seeming to have the greater influence on the latter, is the *percentage of data effectively used.*

In fact, figure 5.14 highlights the different types of competitive advantages achieved by companies, based on the fact that they effectively process a more or less important portion of their collected data. This graph displays the distribution of achieved competitive advantages of firms, segmented according to the percentage of data they effectively use. It results in a more or less clear scission of the achieved competitive advantages. Indeed, as the achievement of new business opportunities and the enhancement of decision-making seem to belong to organizations processing more than 20% of their data, the creation of new products and services is being claimed by companies processing less than 10% of their data. Regarding the kinds of hindrances faced by companies however, it seems very difficult to distinguish any type of pattern in the data.

Out of all those observations we must retain that the only factor seeming to impact the creation of competitive advantages is the *percentage of data effectively used*. Moreover, one must see in that however there exist no statistical significance between this factor and both the size and industry of a company, some different trends have been highlighted across both groups regarding that factor.

5.5.2 Extra Hypotheses tests discussion

As the indirect link between the size and the industry of a company seem to deliver doubtful results, we counted on our extra hypotheses to provide clearer insights. Those hypotheses were designed by making a direct connection between three descriptive factors (Size, Industry, and Role in the ecosystem) and the competitive advantages and hindrances, respectively achieved and faced.

As a matter of fact, one of those hypotheses was accepted after running all Chi Square tests. *Extra Hypothesis 1*, represented by figure 5.19 clearly shows the fraction that exists between SMEs and larger firms regarding the competitive advantages they succeed in achieving. Figure 5.20 however, shows the impact that the fact of belonging to a particular industry can have on the built competitive advantages. Even though no clear trend can be identified from this graph, the Chi Square test results, displayed in table 5.16, seem to indicate that a quite strong connection exists between the industry and the type of competitive advantages.

Regarding the hypotheses involving the hindrances this time, we again see clear differences in the types of hindrances faced by SME and large organizations. However the statistical test performed on *Extra Hypothesis 4* (figure 5.21) did not determine a significant difference among those two populations. Though, we consider its P-value to be sufficiently close to the alpha threshold, as to claim that the size of the company slightly influences the types of faced hindrances.

All other extra hypotheses however failed to deliver any more help in distinguishing the factors responsible for both the type of competitive advantages created and the hindrances faced.

5.5.3 Overall teaching of this research

As we have discussed and concluded over the many shortcomings and deceptions resulting from the performed hypothesis tests, we now want to provide a global summary of what we have been able to learn from the entire research. As such we want to incorporate the findings of the Porter's five forces model and draw overall conclusions of our work.

We understand from our literature review, the diverse interviews and discussions we have led with professionals active in the IoT environment, and from our Porter's 5 forces analysis, that the IoT and Big Data are about to change tremendously the way industries operate their current business processes, and even business models.

The relationships among participants in diverse industries will be transformed, as many boundaries will fall, enabling several players to be active on diverse markets. In other words, we expect the entire business environment to be reshaped, forcing current and new players to redefine their set of activities and of value creation.

As customers' law awareness of IoT applications seems to be one of the mostly cited hindrances towards the development of effective IoT solutions, it looks obvious that a proper education in this direction is needed as IoT services and products are expected to greatly improve the everyday life of their users.

It appears as an evidence that more and more data will be generated every single day. Companies will have to capitalize on those resources if they wish to remain competitive. As Porter and Heppelmann (2014) mention in their report, smart devices are to transform the structure of competition and to deliver many competitive advantages. Indeed, process automation, product improvement, and the customer's experience enhancement are three of the many more benefits that will be derived from this new technology.

However we could not obtain very generalizable results from our survey, it appears that those competitive advantages can be achieved both by SMEs and large companies, and this no matter the industry in which they operate. Indeed, in most industries, established competitors and new entrants will leverage data in order to innovate, compete, and capture value (McGuire et al., 2012). Nevertheless, according the Moody and Walsh's laws of information, those enterprises will need to use the data they collect in an effective way in order to make better decisions and to hope creating new business opportunities.

To conclude this discussion, we want to put forward one more aspect that might well be the most important in determining the future success of organizations in this IoT and data economy context. The tremendous amount of user data that will daily be collected by companies does not only bring positive aspects. As we mentioned before, the public is not educated towards the use of such technologies and seems to remain slightly defiant towards it. However we currently notice a shift in the global mentality towards a greater acceptation. Still has smart agents will provide organizations with more knowledge on the population's everyday life, customers will pay more attention to the type of use that is made out of them.

As data privacy and security issues turned out to be the mostly cited hindrances, and appeared in every type of companies no matter their size or industries, we argue that an organization succeeding in ensuring high security and privacy for its customers data, will grasp many market shares and build a strong competitive advantage. Privacy and security are "the next green movements" (Conroy et al., 2014).

Chapter 6

Conclusion

Now that we have reached the end of our thesis, we must make the appraisal of our achievement.

As the literature review of IoT and Big Data promises that those technologies are to deliver lots of competitive advantages in the future, it was our purpose to provide a clearer view on what are the explanatory economic factors influencing a company's capability to leverage them. Doing so, we aspired at providing a framework describing the best way of implementing IoT solutions in order to achieve a determined competitive advantage. We intended to reach this objective for both SMEs as well as for large companies across various industries.

Moreover, as the Industry 4.0 is still in its early stages, the Internet of Things, and the other digital breakthroughs that are currently being developed, still face many challenges to achieve their full potential. For that reason, we also wanted to come up with concrete results allowing us to assess the obstacles encountered by companies in this connected world. Those results were meant to provide insights on the types of capabilities required in order to overcome those hindrances.

We must acknowledge that those objectives have not quite been reached. Indeed, in the course of our thesis, we realized that the initially stated research questions were hard to answer, and this for multiple reasons detailed in the following section.

6.1 Breaches

Before concluding on the actual results of our thesis, we need to explain in more details the numerous breaches that have caused our survey to not deliver the insightful results we expected.

First of all, it is clear that the sample of respondents we managed to gather is not representative of the studied population. As we intended to provide conclusions that would be generalizable to a whole set of various industries shaping our economic environment, we could only but gather responses from actors evolving in 9 different industries. Furthermore, the distribution of the interviewees across the latter was quite uneven, as we gathered responses from 6 *Consulting* firms and *IT* companies, while only two from companies active in the *Logistics* or *Telecommunication* industries.

The lack of data, which we mentioned in our own hypotheses as an hindrance in order to leverage insightful knowledge, has proven itself to be true. Indeed, we believe that the approach we used to analyze the research questions was justified and could have achieved its objectives if we had had the opportunity to gather more data. As our small sample size induces lots of variance and doubts in the obtained results, we could not claim that those are the representation of the current reality. Although we hope that the slight tendencies highlighted by our collected responses remain close to the latter. We are however confident, that the discussions held in section 5.5 are to be considered with interest as they were backed up by other sources than this unique survey. Indeed, our various interviews and discussions as well as the literature review have constituted our guide to interpret as good as possible the tendencies depicted by our survey outcomes.

Beyond the lack of respondents, our survey suffers from other biases. We mentioned earlier, in section 4.3, that our data set had to be cleaned before performing our several statistical tests. Indeed, it appeared that some of our questions were answered in an inappropriate manner or even remained unanswered.

We believe that these two phenomena originate from three sources. The first one, is that we could not per se get in touch with respondents possessing all the knowledge required to answer them. That is, we rarely managed to get the CTO of any company to answer our survey. As such, more precise questions seemed to remain vague for our respondents. It was the case for example with our question that treated of the volume of data collected annually. Those type of questions seem indeed hard to answer, and we are actually not even sure that any CTO could have answered them neither. Although it remains that this variable was essential for several of our initial hypotheses. Typically, managing to collect such types of information requires the use of other means then an online questionnaire. We could have used a sensor for example, placed on the internal servers of organizations and providing us with the required details. Obviously, this type of solution was beyond our possibility range.

The second phenomenon we identify as having caused many respondents to not answer some particular questions, may well be that they were simply not allowed to share those type of information. For some reason, certain companies considered particular questions to be too intrusive, or that they could put there competitive advantages at risk if they answered them. In this case, not much could have been done on our side to get respondents to provide clearer data to our research.

The third and last phenomenon we identified, is that we, as surveyors, did not possess the required skills in order to ask the most relevant questions in the most understandable way. We humbly recognize that some of our questions might have been misunderstood or might have seemed completely irrelevant for the research scope. At the time of the survey creation, we did indeed not possess the same knowledge about our topic, as we do at the time of writing these words. Indeed, all questions we included in our questionnaire were issued from our reflection after the review of the literature. Somehow, we might not have chosen the best explanatory variables to analyze the formation of competitive advantages, or the protection against the faced hindrances. However, it appears that even professionals of the IoT sector do not manage to define clear factors that could hurt their achievement.

We would claim that it is not easy to find companies agreeing to answer students' questions, relative to their competitive strategy. Nor is it easier to find those organizations that effectively use IoT solutions into their business processes. As those technologies can be used in everything and everywhere, they serve mostly companies in a supportive way for their current business processes. This makes it even more difficult to obtain clear answers on specific questions regarding its implementation, as no clear function is dedicated to its management in most enterprises.

6.2 Conclusion on the results

As we have exposed the breaches of our survey, one understands why the achieved outcomes of this research might not be representative of the reality experienced by companies participating in the data economy. Though the only definite conclusion that we could possibly make here, would be to state our failure in providing insightful results.

As we have not been able to come up with scientifically proven relationships between our studied explanatory variables and the types of competitive advantages and hindrances, we still could provide some reflections on our collected data.

In fact, it resulted from our sample that the only explanatory factor seeming to have any impact on the type of competitive advantage leveraged by companies is the percentage of data that they effectively use and put to work. Indeed it appears that the types of competitive advantages withdrawn by companies differ according to the percentage of their data they are using. As such we notice that all companies achieving greater decision-making and new business opportunities, are using more than 20 or 50% of their data. Furthermore, it is interesting to note that among SMEs, approximately half of our respondents do belong to that category, while the other half seems to effectively put to work less than 10% of their collected data.

Because our initially stated hypotheses did not provide the expected results, we also investigated the direct link existing between the raised competitive advantages of companies and their size and industry. This time, a significant relationship was derived by our statistical tests. Indeed, the Chi Square test performed highlighted the fact that the *Size* of companies had a impact on the types of achieved competitive advantages.

6.3 Personal conclusion

Even though we could not come up with a proper statistical conclusions, reach the expected results and bring any concrete answer to our research questions, we still managed to gain insights on the state of the IoT market.

Although the literature describes the IoT and the Big Data as being "the" two technologies that each and every company, willing to disrupt their market and innovate their business model, should adopt, the reality we observed throughout our work seems to be quite different. While we intended to describe how organizations implement IoT solutions to achieve greater efficiency and, in turn, derive competitive advantages, we acknowledged that they do not really use that technology in that particular purpose. Instead, firms tend to use IoT solutions to respond to an actual and current problem they are facing in their operations. Thereby, connected objects only bring an incremental enhancement to companies' business processes. This observation matches what Mr. Wilmot stated in his interview; that companies using IoT solutions must have a preexisting objective and a clear vision of what they aim at achieving with this new technology.

In fact, our general feeling is that the market of IoT solutions is far from being mature, and therefore, cannot propose all the described advantages that academics and IT consulting companies tend to mention in their reports. Indeed most companies we have encountered in the course of our work claim that there is still a very low awareness of people for such solutions. Furthermore, lots of concerns still block the way for a global deployment of those new digital appliances. As data privacy and security issues still remain, they vastly endanger companies' businesses.

We are able to provide a recent example of the risks that a lack of data security represents for organizations. Not that long ago two cyber attacks (Petya Cyber Attack) were launched at very large scale, touching companies from all sizes around the world. Firms from which the data were stolen or annihilated suffered terrible losses.

The hard times we have known gathering data from our respondents tends to confirm this lack of maturity of the market. As a matter fact, we understand from our research that most companies do not yet consider their data as a true asset on itself, but rather as an input, something that will help them better manage their actual value creation resources.

As our final words in this paper, we would like to say that we are deeply convinced of the potential that data and the data economy have to become the new sources of value creation. Therefore we also believe that most companies should operate their digital transformation in order to benefit from them. However, we maintain our opinion that the current state of the digital environment is not ready for such large scale deployments. The real takeoff of the IoT and Big Data will require to overcome the many technical challenges they are still facing, as well as the social and ethical issues that these breakthroughs pose.

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