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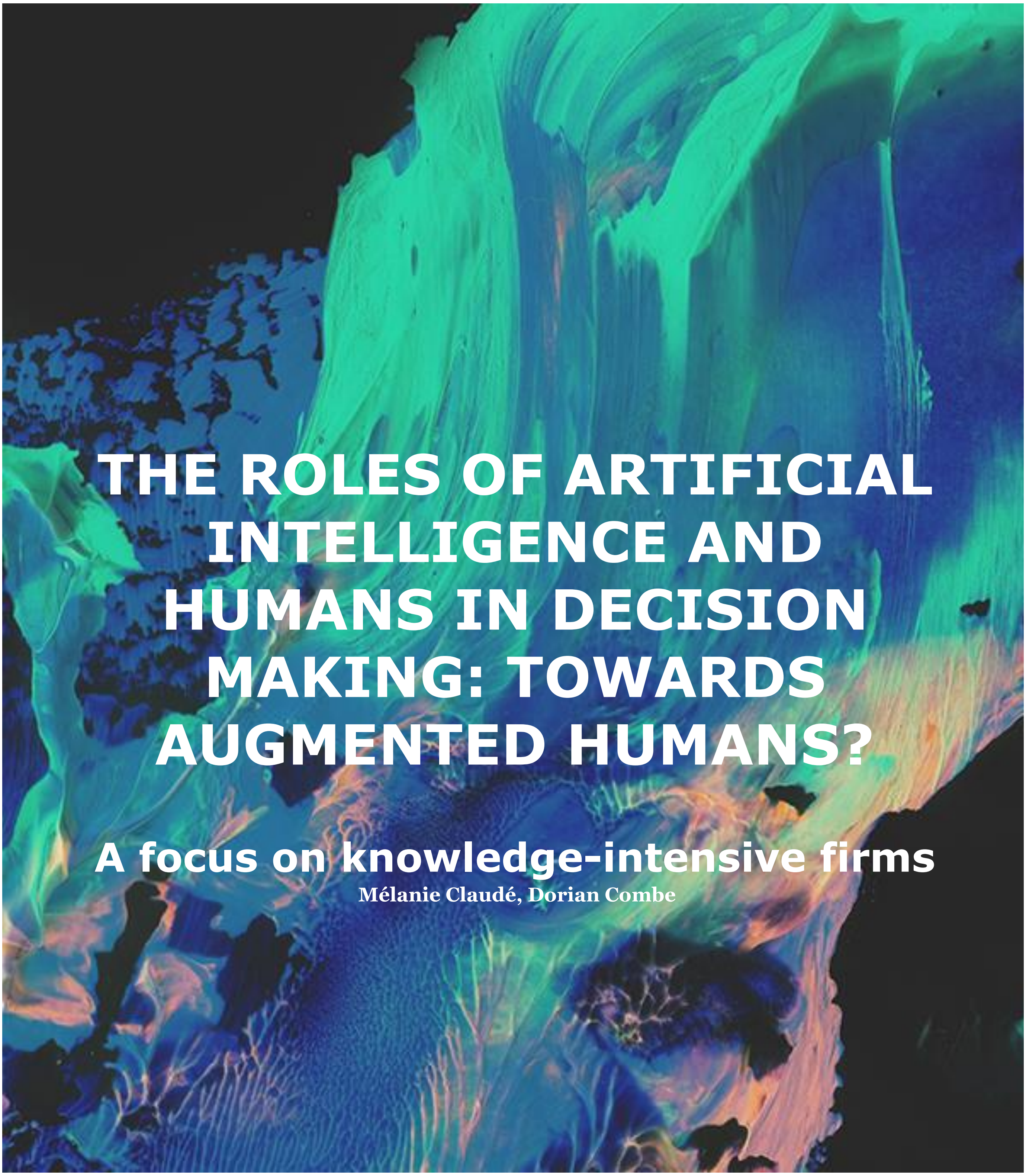

THE ROLES OF ARTIFICIAL INTELLIGENCE AND HUMANS IN DECISION MAKING: TOWARDS AUGMENTED HUMANS?

A focus on knowledge-intensive firms

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Abstract

With the recent boom in big data and the continuous need for innovation, Artificial Intelligence is carving out a bigger place in our society. Through its computer-based capabilities, it brings new possibilities to tackle many issues within organizations. It also raises new challenges about its use and limits. This thesis aims to provide a better understanding of the role of humans and Artificial Intelligence in the organizational decision making process. The research focuses on knowledge-intensive firms. The main research question that guides our study is the following one:

How can Artificial Intelligence re-design and develop the process of organizational decision making within knowledge-intensive firms?

We formulated three more detailed questions to guide us: (1) What are the roles of humans and Artificial Intelligence in the decision making process? (2) How can organizational design support the decision making process through the use of Artificial Intelligence? (3) How can Artificial Intelligence help to overcome the challenges experienced by decision makers within knowledge-intensive firms and what are the new challenges that arise from the use of Artificial Intelligence in the decision making process?

We adopted an interpretivist paradigm together with a qualitative study, as presented in section 3. We investigated our research topic within two big IT firms and two real estate startups that are using AI. We conducted six semi-structured interviews to enable us to gain better knowledge and in-depth understanding about the roles of humans and Artificial Intelligence in the decision making process within knowledge-intensive firms. Our review led us to the theoretical framework explained in section 2, on which we based our interviews.

The results and findings that emerged from the interviews follow the same structure than the theoretical review and provide insightful information in order to answer the research question. To analyze and discuss our empirical findings that are summarized in the chapter 5 and in a chart in the appendix 4, we used the general analytical procedure for qualitative studies. The structure of chapter 5 follows the same order than the three sub questions.

The thesis highlights how a deep understanding of Artificial Intelligence and its integration in the process of organizational decision making of knowledge-intensive firms enable humans to be augmented and to make smarter decisions. It appears that Artificial Intelligence is used as a decision making support rather than an autonomous decision maker, and that organizations adopt smoother and more collaborative designs in order to make the best of it within their decision making process. Artificial Intelligence is an efficient tool to deal with complex situations, whereas human capabilities seem to be more relevant in situations of uncertainty and ambiguity. Artificial Intelligence also raises new issues for organizations regarding its responsibility and acceptation by society as there is a grey area surrounding machines in front of ethics and laws.

Keywords: Artificial Intelligence, Augmented humans, Decision maker, Decision making, Decision making process, Ethics, Knowledge, Knowledge-intensive firms, Organizational design, Organizational challenge, Smart decisions.

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We would like to thank our supervisor Nils Wåhlin for his support, his availability and his insights. He was always critical of our work in a relevant and constructive way. Artificial Intelligence is a field of research that is still widely unexplored and Nils Wåhlin helped us to go through this leap in the dark and to keep us motivated.

We are grateful to all the participants of our study and to all the people that contributed to help us grasp this complex yet exciting field of study.

Finally, we also would like to thank our families and friends, who made the accomplishment of this study possible through their continual encouragements and support.

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Abbreviation list

AI	Artificial Intelligence
ES	Expert System
ML	Machine Learning
NLP	Natural Language Processing
KIFs	Knowledge-Intensive Firms
PPI	Processes, Protocols and Infrastructures
GAFAM's	Google, Amazon, Facebook, Apple and Microsoft
BATX's	Baidu, Alibaba, Tencent and Xiaomi
ANN	Artificial Neural Network
DSS	Decision Support System
GSS	Group Support System
GDSS	Group Decision Support System
IoT	Internet of Things

1. Introduction

In this chapter, the purpose is to present to the reader our research topic, to give a short overview of our theoretical framework and to identify a research gap in the current literature. Moreover, we provide a concise explanation of the key terms and theories related to our research topic and the relations between the different concepts under study. We have decided to develop the introduction more than usual because we thought that the topic of AI needs to be more developed regarding its fame in the media and the news and also regarding its technical aspects that tend to retract people. Also, the introduction is longer as we have just presented theories about AI in the introduction in the sections 1.4.1 and 1.4.2. and we do not develop AI further in the theoretical review mainly because our field of study is not computing science. AI is a buzz topic, it is one of the reasons we decided to choose this topic. Beyond the lure that AI casts to companies, we also think that AI is of importance, and we wanted to illustrate with the part 1.3 how much AI is booming and to what extent AI will change the entire economy. Then, we decided to develop the techniques related to AI, plus we decided to elaborate on the difference between a strong AI and a weak AI. Most of the time, people are afraid of the strong AI, an AI with a conscious, and they tend to confuse it with the weak AI that exists now. We wanted to make this distinction to ease people about their future with AI. Nowadays, AI is just a smarter algorithm. For instance, Siri's Apple, thanks to a technique of AI that we will explain in the part 1.4.2, can talk with us but in a very limited way. Sometimes Siri encounters bug or does not know what to answer as the question is not clear, ambiguous or complex. According to AI experts, there is still a long path to go to have a powerful and strong AI (Dejoux & Léon, 2018, p.191).

1.1 Subject Choice

We are two management students in the second year of master studying in Umeå School of Business, Economics and Statistics (USBE). We are enrolled in a double degree between France and Sweden. We are currently following the Strategic Business Development and Internationalization program. We are both interested in new technologies, especially about artificial intelligence (AI). That is why we chose to write our master thesis about the use of AI in business, together with our belief that AI will play a major role in the upcoming changes of organizations and the whole economy.

AI is considered to be the most important evolution our current industrial age has witnessed since the digital transformation brought by Internet and the digital technologies, AI is even seen as the next revolution (Brynjolfsson & McAfee, 2014, p. 90; Dejoux & Léon, 2018, p. 187). In the Second Machine Age, Brynjolfsson & McAfee explained how a useful and powerful AI has emerged nowadays - for real - and how AI will change the economy, the workplace and the everyday life of people in the years to come (Brynjolfsson & McAfee, 2014, p. 90, 91, 92, 93). In March 2016, with the victory of the computer program AlphaGo by Google over the human world champion player of the Korean game Go, the world realized that the society has entered a new civilization: the era of AI (Jarrahi, 2018, p. 1; Dejoux & Léon, 2018, XIV; Deepmind, 2016). Indeed, Go game has always been considered as the most difficult game ever invented in the history and to be out of reach for computer programs as it lies on intuition and on a significant experience in Go playing, in other words what a human brain is capable of. AI potentialities in business are exponential, AI has applications in broad economic sectors such as Finance, Health, Law, Education, Tourism, Journalism and so on (Brynjolfsson & McAfee, 2014, p. 90, 91, 92, 93; Dejoux & Léon, 2018, p. 189, 190). The International Data Corporation has estimated that by 2020, the revenue generated by AI will have reached $47 billion, and that in 2016 big tech companies spent up to $30 billion on AI worldwide (McKinsey & Company, 2017, p. 6). That is why, along with the vision of the company IBM, we believe that the 4th industrial revolution will be leveraged by AI.

Having studied Strategy as our first module in Umeå, we decided to focus on the design of organization and decision making in the era of AI. We think that AI will represent a competitive resource for the enterprise in the future. Therefore, we wanted to study how the configuration of an enterprise can adapt to this change and how managers can leverage AI in their decision making. AI is another wave in the digital era and it will bring thorny challenges for enterprises and managers to tackle, especially about their devoted tasks and how they make decisions (Dejoux & Léon, 2018, p. 187, 188). Indeed, in 2017, McKinsey compared AI as the next frontier as they compared Big Data as the next frontier in 2011 (McKinsey & Company, 2017; McKinsey & Company, 2011). As Galbraith studied the influence of Big Data upon the design of the organization, we think that AI can have an influence on the design of the organization (Galbraith, 2014, p. 2).

1.2 Problem Background

In the Second Machine Age, authors exposed how impressing progress is with digital technologies in our modern society (Brynjolfsson & McAfee, 2014, p. 9). The changes generated by digital technologies will be positive ones, but digitalization will entail tricky challenges (Brynjolfsson & McAfee, 2014, p. 9). AI will represent a thorny challenge to handle quickly as it will accelerate the second machine age (Brynjolfsson & McAfee, 2014, p. 92). Companies have understood the strategic advantage that AI represents in their organizational processes; indeed, AI can suggest, can predict and can decide (Dejoux & Léon, 2018, p. 196). However, AI is questioning the role of humans in the process of decision making (Dejoux & Léon; 2018, p. 218). Some scholars have considered the complementary relationship between machines and humans in decision making (Jarrahi, 2018, p. 1; Dejoux & Léon, 2018, p. 218; Pomerol, 1997, p. 3). While other scholars considered the superiority of AI upon humans in the decision making (Parry et al., 2016, p. 571).

In an ever-changing environment full of uncertainty, equivocality and complexity, digital technologies are reshaping the economic landscape, the way organizations function and the way we view organizing (Snow et al., 2017, p.1, 5). Such companies in “biotechnology, computers, healthcare, professional services, and national defense” experience these changes and are considered to be KIFs (Snow et al., 2017, p. 5). This type of companies relies on the arrangement of their employees within the organization with a flat hierarchy and a strong sense of collaboration (Snow et al., 2017, p. 5). The workplace integrates new digital tools and new digital actors (Snow et al., 2017, p. 5). There is a “new division of labor” where AI demonstrates excellent skills in analytical and repetitive tasks, yet AI cannot recognize perfectly patterns since some tasks cannot be decomposed as a set of rules and put into codes and algorithms. Some tasks will remain in the human field as the human brain excels in gathering information from senses and perception and analyzes it for pattern recognition (Brynjolfsson & McAfee, 2014, p. 16, 17).

To cope with this change, companies have to leverage digital technologies, especially AI and redesign their organization according to it (Snow et al., 2017, p. 1). Snow et al., have studied how an actor-oriented architecture is suitable for digital organizations in the context of KIFs.

1.3. News and facts supporting our observation

We made the choice to investigate a buzzing topic that we believe will reach new heights in the coming decades. Indeed, there is evidence that AI is considered as a disruptive technology by many stakeholders. This part presents AI trends that validate our decision to study this field and make us think it is a fertile ground for research.

1.3.1 The economy of AI

Forbes depicted AI as one of the "9 Technology Mega Trends That Will Change the World in 2018" (Marr, 2017). Nevertheless, AI dates back from the 1950's. Indeed, the basis of AI had been developed by the scientist Alan Turing when he succeeded to decrypt the Enigma Code during the second world war (Clark & Steadman, 2017). However, AI as a field of study truly emerged in 1956 with the scientists Claude Shannon, John McCarthy, Marvin Minsky, and Nathan Rochester. Consequently, one can say that our society is witnessing another wave of AI, but unlike in the 1950's, companies now have the capacity to collect and storage data like never before. Thus, KIFs in the tech industry such as the American Google, Amazon, Facebook, Apple, and Microsoft (GAFAM's), or the Chinese Baidu, Alibaba, Tencent, and Xiaomi (BATX's), agree that it is not a craze and we will not live another "winter AI". Indeed, according to a report made by IBM, "90% of the world's data was created in the past two years" (Markiewicz & Zheng, 2018, p. 9). The change is now, and it will occur fast. As Nils J. Nilsson, the founding researcher of Artificial Intelligence & Computer Science at Stanford University said, "In the future AI will be diffused into every aspect of the economy." (Markiewicz & Zheng, 2018, p. 1).

1.3.2. The 4th industrial revolution: the reasons why AI is booming now

Although AI is not new, its development has taken a new dimension for the last 15 years (Pan, 2016). While AI had been constrained for years, major changes in the information environment have allowed AI research and development to take a second breath (Pan, 2016). Until the 2000's, the work on AI had been slowed down by the limited amount of available data and the lack of perceptible practical applications. However, today, the rise of internet and the increase in the power of machines, together with the emergence of new needs within society, have allowed a renewed interest in AI, that is called AI 2.0 or the 4th revolution (Pan, 2016).

The 3rd industrial revolution with the Internet described by Dirican (2015) changed considerably the way of working and gave way to a new society to emerge, the digital world. Holtel (2016) thinks that AI will trigger tremendous changes in the workplace and especially for the manager. One of the future challenges of management will rely on the adaptability of the organization to handle change and transform themselves. The report made in collaboration with the MIT Sloan management and BCG stated that this organizational challenge will be handled by managers using soft skills and new ways of human-human interaction and collaboration, but also thanks to human-machine interaction and collaboration. The French Government, recommended in a report about the development of AI that "As a technical innovation, it constitutes an input regarding both firm's internal processes (management, logistics, client service, assistant, etc.) and firm's outputs, be it consumer goods (intelligent objects, self-driving cars etc.) or services (bank, insurance, law, health care, etc.). It will be a major risk for competitiveness not to integrate those technologies.". Indeed, the famous French mathematician Cédric Villani suggested in a report on AI to "create a public Lab for the work transformation in order to think, anticipate and above all test what artificial intelligence can bring and change in our way of working."

1.4 Theoretical background

Although such recent surge of interest for AI, its concept and its technology are not new. AI comprises various types of technologies that offer interesting possibilities. Among the wide range of possible applications of AI, decision making support is one of the most promising and studied, especially within KIFs.

1.4.1 A presentation of AI

The father of AI, McCarthy, defined the AI problem as "that of making a machine behave in ways that could be called intelligent like if a human were so behaving" (McCarthy, 1955, p. 11). In other words, AI is a machine able to learn and to think like a human being; AI is able to emulate cognitive humans tasks (Jarrahi, 2018, p. 1; Brynjolfsson & McAfee, 2014, p. 91). Nevertheless, AI is a wide field of study that has evolved over time.

1.4.2 Main characteristics and techniques of AI

A powerful and useful AI has emerged those past few years thanks to technological progress in computing, the explosion of generated data and recombinant innovation - the combination of existing ideas - and also thanks to enterprises such as GAFAM's, BATX's and IBM that have invested a lot of resources in research (Brynjolfsson & McAfee, 2014, p. 90; Dejoux & Léon,2018,189). AI can perform cognitive tasks and AI abilities now cover many fields that used to be humans' attributes such as complex communication and image recognition (Brynjolfsson & McAfee, 2014, p. 91). AI is able to reproduce human reasoning in a faster and flawless way (Dejoux & Léon, 2018, p. 188,189,190). AI applications cover wide domains such as health, finance, law, journalism, art, transport, language, etc. (Dejoux & Léon, 2018, p. 190). For example; famous banks such as Orange Bank or the alternative banking app Revolut use chatbots, AI wrote articles for the Washington Post, the Google car is autonomous, Sony created a song with AI in 2016 (Dejoux & Léon, 2018, p. 190).

There are two types of AI, the 'weak' one and the 'strong' one (Susskind & Susskind, 2015, p. 272). This typology of AI, weak and strong, has been established by the society, scientists and philosophers. The weak one is present in the everyday life of people and it includes Expert Systems (ES), Machine Learning (ML), Natural Language Processing (NLP), Machine Vision and Speech recognition (Dejoux & Léon, 2018, p. 190). One of the first fields of application of AI in enterprises is ES, and Denning (1986, p. 1) defined ES as "a computer system designed to simulate the problem-solving behavior of a human who is expert in a narrow domain". ML is "the ability of a computer to automatically refine its methods and improve its results as it gets more data" (Brynjolfsson & McAfee, 2014, p. 91). NLP is defined as "the process through which machines can understand and analyze language as used by humans" (Jarrahi, 2018, p. 2). Speech recognition technique is based by definition on NLP techniques. Machine vision is "algorithmic inspection and analysis of image" (Jarrahi, 2018, p. 2).

Taking the example of IBM's Watson, AI can combine NLP, ML and machine vision techniques (Jarrahi, 2018, p. 2). Watson is an AI platform which has been developed by IBM since 2006. It is able to analyze huge amounts of data and communicate in natural language. NLP enabled IBM's Watson to play and win the TV game show Jeopardy! in 2011. During this game, not only Watson developed an understanding of a wide range of the human culture, but also an understanding of "nuanced human-composed sentences and assign multiple meaning to terms and concepts" (Brynjolfsson & McAfee, 2014, p. 20, 24; Jarrahi, 2018, p. 2). Moreover, in the medical field ML has allowed Watson to make decisions regarding diagnosis of cancer thanks to its ability to learn and develop smart solutions based on the analysis of data and previous research articles and electronic medical records (Jarrahi, 2018, p. 2). Machine Vision has empowered Watson to scan MRI images of the human brain and to detect really tiny hemorrhages in the image for doctors (Jarrahi, 2018, p. 2). The figure below summarizes the broad range of capacities AI can perform.

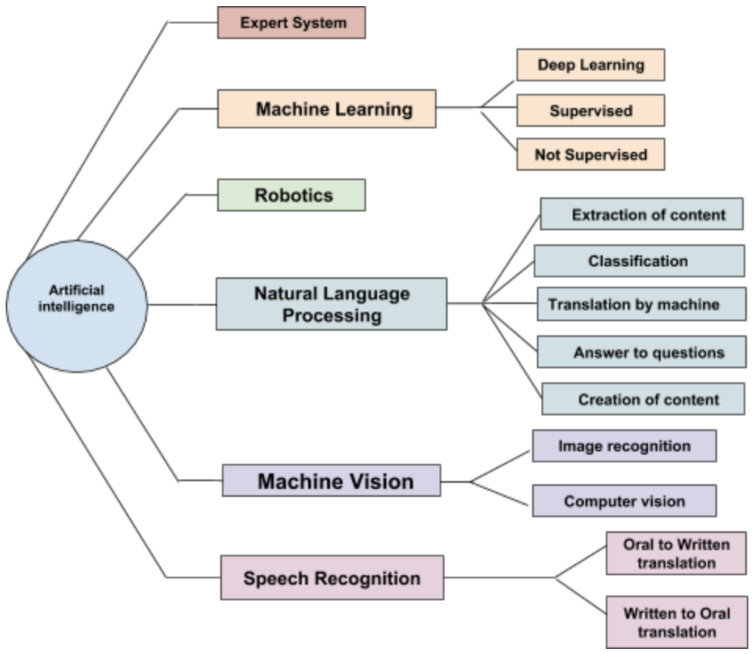

Figure 1: AI applications and techniques (Dejoux & Léon, 2018, p. 188)

The weak AI is able to emulate the human logic through analysis of huge amounts of data (Jarrahi, 2018, p. 3). The weak AI, thanks to ML and algorithms, can be the decision maker when the process of decision making is totally rational and can be automated, as it already exists in the sector of high frequency trading (Dejoux & Léon, 2018, p. 198, 199). The weak AI can be a support to the rational decision making since AI analysis can be predictive and propose different scenarios to the decision maker (Jarrahi, 2018, p. 3).

The second type of AI, the strong AI, is defined as being able to have a conscience and to emulate the main function of the human brain (Dejoux & Léon, 2018, p. 191). Strong AI is very polemical and divides public opinion into three main school of thoughts. Although strong AI does not exist yet, we have chosen to elaborate on this topic to clarify that the AI that exists today is far from being the AI that people tend to fear. The first group of thoughts sees strong AI as a non-dangerous technology that could make human beings augmented in their decision making (Dejoux & Léon, 2018, p. 191). Thus, firms such as GAFAM's have integrated AI in their structure and praise a partnership between human beings and machines (Dejoux & Léon, 2018, p. 191). The second school of thoughts considers a merge, an hybridization of humans and a strong AI in order to save humanity; including the transhumanism philosophy (Dejoux & Léon, 2018, p. 191). The third school of thoughts, that includes Stephen Hawking, is against the raise of a strong AI as it will take over humans' jobs, or automated humans tasks (Jarrahi, 2018, p. 2; Dejoux & Léon, 2018, p. 191). This school of thought tackles ethical and societal debates that a strong AI will bring about: AI developers have to bear in mind the ethical issues when creating an AI. Thus, developing an AI in order to correct humans' flaws should not make us eradicate the essence of humanity (Dejoux & Léon, 2018, p. 191). The strong AI is seen as a threat of an unprecedented wave of automation, threat for the humanity and to ethics, but the weak AI embodies a lot of potential for the future of work as AI can support humans in their tasks and replace humans in routine tasks (Jarrahi, 2018, p. 2; Dejoux & Léon, 2018, p. 191).

The distinction between weak AI and strong AI is also concerned with rule adherence, i.e. the way machines interact with rules. Wolfe (1991, p. 1091) distinguishes rule-based decisioning in which machines strictly respect the rules set by developers from rule-following decisioning in which machines follow rules that have not been strictly specified to them. Rule-based decisioning matches weak AI, while rule-following decisioning is an attempt that tends towards strong AI. An example of rule-following decisioning is neural networks (NN), that allow algorithms to learn from themselves. Strong AI would be machines making their own rules and then follow them, which is not possible at the stage of right now (Wolfe, 1991, p. 1091). Since AI draws its strength from huge amounts of data from which it is able to give meaning, it seems logical to think that businesses that deal with such environments are fertile grounds for AI applications. Thus, most of the business literature on AI focuses on this type of firms.

1.4.3 Knowledge-intensive firms

There are many who argue that we are shifting from the 'Industrial Society' to the era of the 'Knowledge Society' that is commonly called 'knowledge-based economy'. In that new economy, knowledge is supposed to play a more fundamental role than in the past. Nevertheless, although numerous uses and attempts to define it across the literature, it is hard to find a clear definition of the concept of the knowledge-based economy (Smith, 2002, p. 6). It is often used as a metaphor rather than a meaningful concept (Smith, 2002, p. 6). The origins of that concept are not clear either. While the use of the term knowledge-based economy has become popularized in the 1990's, this concept already existed in the 1960's (Gaudin, 2006, p. 17). However, it is during the 1990's that scholars attempted to define it. This change in the worldwide economy is traditionally attributed to globalization and new technologies (Nurmi, 1998) such as internet, and, more recently, big data, which have had a strong impact on the spread of knowledge.

The first definition of 'knowledge-based economy' from the OECD is about ''economies which are directly based on the production, distribution and use of knowledge and information'' (1996, p. 3, cited in Godin, 2006, p. 20-21). Smith (2002, p. 8) considers that four characteristics are often retained by scholars to qualify the knowledge-based economy: 1) knowledge is becoming more important as an input, 2) knowledge is increasingly more important as a product (consulting, education, etc.), 3) a rise in the importance of codified knowledge compared to tacit knowledge, 4) innovations in information and communication technologies led to the knowledge economy.

KIFs are those firms which are fully part of that 'new' economy. Scholars studied how they differ from traditional firms through the prism of the knowledge-based theory of the firm (Starbuck, 1992; Davis and Botkin, 1994, Nurmi, 1998). Much attention has also been paid to the unique features of those firms regarding their organization (Boland & Tenkasi, 1995; Grant, 1996) and decision making (Grant, 1996; Jarrahi, 2018). We chose to focus our study on KIFs since we believe that AI is more likely to be developed in these firms; indeed, most of previous research on AI and organizations was about KIFs. Due to their specific features, KIFs' organizational design has been widely studied in the literature. It is of course of interest for the purpose of our research.

1.4.4 Organization Design

The organization configuration is defined as the set of organizational design elements that fit together in order to support the intended strategy (Johnson et al., 2017, p. 459). To design an organization, key elements have to be taken into account (Johnson et al., 2017). Snow et al. (2017), have explored the design of digital organizations and they have concluded that new organizational designs base their principles on those used in designing digital technologies such as object-oriented design or the architecture of Internet (Snow et al., 2017, p. 3). Such architecture is called actor-oriented organizational architecture and it is a suitable and optimal organization for KIFs (Snow et al., 2017, p. 5,6). This organizational architecture should include three elements from the actor-oriented architecture: the actors, the commons and protocols, processes and infrastructures (Snow et al., 2017, p. 6). We defined those terms further in the chapter 2, in the section 2.2. We have established a framework summarizing the three elements composing the organizational design of KIFs (Figure 2). Building on these three elements, the organization should have a flat hierarchy in which actors share a strong sense of self-organizing and collaboration with a decentralized decision making (Snow et al., 2017, p. 6). Decision making processes within KIFs adopting an actor-oriented organizational design is of interest as they present a different type of decision making. Focusing on the actors, KIFs empower the decision maker.

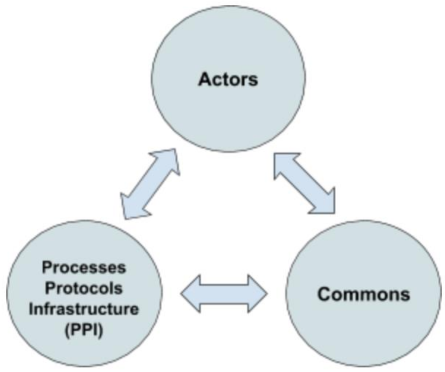

Figure 2: Organizational design in KIFs: an actor-oriented architecture

1.4.5 Decision making

According to Edwards (1954, p. 380), the economic theory of decision making is a theory about how an individual can predict the choice between two states in which he may put himself. Decision making theories have become increasingly elaborated and often use complex mathematical reasonings (Edwards, 1954, p. 380). Decision making is also related to time, effectiveness, uncertainty, equivocality, complexity and human biases (Dane et al., 2012, p. 187; Jarrahi, 2018, p. 1; Johnson et al., 2017 p. 512). AI and decision making theory are intertwined: “diagnosis representation and handling of the recorded states for AI; look-ahead, uncertainty and (multi-attribute) preferences for decision theory.” (Pomerol, 1997, p. 22). AI arises change and challenges regarding decision making within an organization, AI can replace, support and complement the human decision making process (Jarrahi, 2018, p. 1; Pomerol, 1997, p. 22; Parry et al., 2016; Dejoux & Léon, 2018 p. 198,199). In fact, AI has three roles when it comes to decision making within an enterprise, AI can be an assistant to the manager, AI can be a decision maker instead of the manager, and AI can be a forecaster for the manager (Dejoux & Léon, 2018, p. 199).

In this thesis, we will focus on the weak AI - defined in the part 1.4.2 - and its role towards decision making within KIFs’ organizational design. According to scholars, the weak AI could be the decision maker or could be just a support to the human decision maker or could even empower the human decision maker (Jarrahi, 2018, p. 1; Pomerol, 1997, p. 22; Parry et al., 2016; Dejoux & Léon, 2018 p. 198,199). Jarrahi thinks that a partnership between the rationality of machines and the intuition of humans is the best combination to make a decision; moreover, taking into account just one resource humans or machines' capability is not relevant especially when it comes to make collective decision making and rally support and approval to the decision (Jarrahi, 2018, p. 6). This relationship is supported by Dejoux & Léon who think that AI can augment human decision making (Dejoux & Léon, 2018, p. 219).

1.5 Research gap and delimitations

AI as a field of research has emerged recently. Few researchers have focused on AI and organizations, AI and decision making, AI within KIFs and let alone AI with designing organization and decision making within KIFs. During the 1980's and 1990's, many scholars have explored the field of ES, a technique of AI, but the actual trend seems to be to study AI applications as a whole (Wagner, 2017). That is why, while exploring the literature related to AI, we have observed a craze in the 1980's and 1990's of published articles talking about ES and AI, but this craze faded until this last decade. Presented in the Second Machine Age, AI has experienced a winter in the 1990's and the first decade of 2000 due to the limited power and storage of computer as well as a lack of data (Brynjolfsson & McAfee, 2014, p.37). However, since 2011, with the victory of Watson's IBM in Jeopardy! and the victory of AlphaGo's Google, our society has been witnessing the emergence of a powerful and useful AI (Jarrahi, 2018, p.1). Duchessi et al., (1993) had identified back at the time the changes AI could constitute for organization and management. Duchessi et al., (1993) built a simple framework linking artificial intelligence to management and organization as a two-way relationship shown in Figure 3. They made a focus on the consequences that such interactions can trigger notably in the fields of organizational structure, organizational support and workforce.

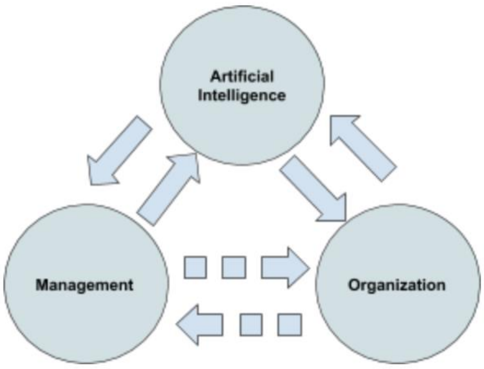

Figure 3: Framework depicting interactions between AI, organizations and management (Duchessi et al., 1993, p. 152)

With our best knowledge, until now the literature has mainly focused on the application of AI in particular industries or functions of the enterprise. Some scholars have conducted general research about the use of AI within a specific function of the enterprise, such as Martínez-López & Casillas (2013) who carried out an overview of AI-based applications within industrial marketing, or Syam & Sharma (2018) who studied the impact of AI and machine learning on sales (Martínez-López & Casillas, 2013, p.489; Syam & Sharma, 2018, p. 135). Other scholars have focused on a particular application of AI within the enterprise: Kobbacy (2012) studied the contribution of AI within maintenance modelling and management, Wauters & Vanhoucke (2016) compared the different AI methods for project duration forecasting (Kobbacy, 2012, p. 54; Wauters & Vanhoucke, 2015, p. 249). The use of AI in decision making has also been studied, but through the prism of a particular industry, and focusing on practical applications. Thus Stalidis et al. (2015) investigated AI marketing decision support within the tourist industry, while Klashanov (2016) studied AI decision support within the construction industry. Jarrahi has explored how the partnership between AI and humans in decision making contributes to overcome the challenges of uncertainty, complexity and ambiguity resulting from the organization environment (Jarrahi, 2018, p. 1). Pomerol (1997), before Jarrahi, has studied how AI can contribute in the decision making (Pomerol, 1998, p. 3). Dejoux & Léon have explored how managers can be augmented by AI and digital technologies (Dejoux & Léon, 2018, p. 219). Parry et al., (2016) have considered how AI can replace humans in decision making (Parry et al., 2016, p. 572).

However, little interest has been granted to the way AI applications and techniques change the design and the decision making process of knowledge-intensive companies. Galbraith (2014) has explored how Big Data changes the design of companies and Snow et al., (2017) have considered how digital technologies are reshaping the configuration of the enterprises in the knowledge-intensive sector using the actor-oriented architecture (Galbraith; 2014; p. 2; Snow et al., 2017, p. 1).

Our study aims to contribute to this lack of research within the field of AI and decision making within organizations. We decided to focus our research on KIFs that are using AI especially in IT-firms and professional service firms. We will explore how AI change the design of KIFs through actor-oriented architecture and the process of decision making. Our aim is to develop a better understanding of the role of AI and humans in the organizational decision making process. Also, by conducting this study we want to contribute to the demystification of AI to show what AI is capable of or not and by extension that AI is not a threat for the society neither for the future of job or the humanity. We believe that AI will change our life and the economy but for the better. AI will enable people to save time, to focus on what truly matters at work or in life. For instance, according to Galily (2018), while AI replaces human tasks that are merely factual, it also enables humans to focus on other activities such as creativity.

1.6. Main research question and underlying sub questions

To ensure that our purpose is fulfilled, we have formulated the following research question:

- **How can AI re-design and develop the process of organizational decision making within knowledge-intensive firms?**

The research question is followed-up with underlying questions in order to make it more precise:

- What are the roles of humans and Artificial Intelligence in the decision making process?
- How can organizational design support the decision making process through the use of Artificial Intelligence?
- How can Artificial Intelligence help to overcome the challenges experienced by decision makers within knowledge-intensive firms and what are the new challenges that arise from the use of Artificial Intelligence in the decision making process?

2. Theoretical review

In this chapter, the purpose is to present the previous literature related to our topic and the relation between the different concepts. First, we will present KIFs to set the context for the study. Secondly, we describe what is the suitable organizational design for KIFSs, the actor-oriented architecture. Then, we define the type of decision making approaches - intuitive or rational-, the organizational challenges related to decision making - uncertainty, complexity and ambiguity-, the decision maker -humans and AI- in the process of decision making and the way the decision making process can overcome the three organizational challenges. We conclude with presenting the new challenges related to the development of AI within decision making.

2.1 Knowledge-based economy and Knowledge-intensive firms

The aim of the following part is to define the scope of our research subject, namely knowledge-intensive firms. There are many definitions of what a KIF is across the literature. Consequently, our review does not aim to be exhaustive. We will simply explain what the main characteristics of KIFs are, how they differ from traditional firms, and later focus on the specific aspects of decision making within that type of firms.

2.1.1 The knowledge-based theory of the firm

The knowledge-based theory of the firm was born in the 1990's, with authors such as Prahalad & Hamel (1990), Nonaka & Takeuchi (1995), and Grant (1996). It originates from the assumption that companies should build a comprehensive strategy regarding their core competencies in order to succeed: they should organize themselves so that they become able to build core competencies and make them grow (Prahalad & Hamel, 1990). According to Nonaka & Takeuchi (1995), knowledge is that core competency that can provide firms with competitive advantage in an uncertain world. It is an "outgrowth of the resource-based view" (Grant, 1996, p. 110), knowledge being the most important component among the firm's unique bundle of resources and capabilities. Thus, "knowledge and the capability to create and utilise such knowledge are the most important sources of competitive advantage" (Ditillo, 2004, p. 401). It is important to notice that the knowledge-based theory of the firm does not specifically apply to one type of business. This theory claims to be relevant for any industry. That so, KIFs are enterprises that make profit thanks to its employees' knowledge.

2.1.2 Knowledge-based economy and knowledge-intensive firms

As the Industrial Society was characterized by industrial manufacturing companies, the Information Era will be led by KIFs (Nurmi, 1998). What is that type of firms? A problem of definition arises there: "the difference between KIFs and other companies is not self-evident because all organizations involve knowledge" (Ditillo, 2004, p. 405). The term 'knowledge-intensive firms' is built on the same model than 'capital-intensive' and 'labor-intensive' firms. Following the same logic, it refers to businesses in which "knowledge has more importance than other inputs" (Starbuck, 1992, p. 715). However, some scholars distinguish KIFs from traditional firms through the nature of their offering. Thus, KIFs are companies that "process what they know into knowledge products and services for their customers" according to Nurmi (1998, p. 26). Other scholars add a focus on the location of the resources of the firms. It is the case of Ditillo (2004, p. 401), who argues that "knowledge-intensive firms refer to those firms that provide intangible solutions to customer problems by using mainly the knowledge of their individuals". Davis and Botkin

(1994, p. 168) argue that as awareness of the value of knowledge is increasing, many companies try to implement a better use of it within their organization. Thus knowledge-based business are companies that manage to do it through putting information to productive use in their offering; it means that they try to make the best possible use of the information they access, at every level of their organization.

2.1.3 Erroneous preconceptions

At this point, it seems necessary for us to clarify some common preconceptions about KIFs. First, there is the idea that the more knowledge is embodied in an organization's products or services, the more the organization is considered knowledge-intensive. Thus, companies whose products are fully made of knowledge, such as consulting firms or advertising agencies, would be the most knowledge-intensive companies. This is a dangerous assumption according to Zack (2003, p. 67). It is not about the amount of knowledge embodied in products and services. "The degree to which knowledge is an integral part of a company is defined not by what the company sells but by what it does and how it is organized" (Zack, 2003, p.67). Secondly, the distinction between KIFs and high-technology firms must be highlighted. While the common meaning may have evolved over years, high-tech firms are according to the OECD companies that spend more than 4% of their turnover in R&D (Smith, 2002, p. 13). Thus, although the terms 'KIFs' and 'high-tech firms' are often combined, the former refers to a specific approach vis-a-vis knowledge, while the latter focuses on high investment in order to seek innovation. Consequently, these concepts may be often intertwined but they are not similar. For the purpose of our research, we chose to focus on KIFs that are professional service firms since they are more visible.

2.2 Organizational design within KIFs: Actor-oriented architecture

KIFs' environment is characterized by uncertainty, ambiguity and complexity (Snow et al., 2012; Fjeldstad et al., 2017). According to Fjeldstad et al., and Snow et al., (2012, 2017), actor oriented organizational design is an adequate organizational design for KIFs that need to leverage knowledge and adapt to change continuously in a complex and uncertain environment (Fjeldstad et al., 2012, p. 734; Snow et al., 2017, p. 6). Actor-oriented organizational design is also appropriate for digital organizations, and so for organizations using AI (Snow et al., 2017, p. 1). Indeed, in the second machine age, Brynjolfsson & McAfee (2014) introduced the innovation-as-building-block view of the world, i.e. "each development becomes a building block for future innovation" and "building block don't ever get eaten or otherwise used up. In fact, they increase the opportunity for future recombination" to explain that digitalization enables the combination of previous blocks existing in the environment (Brynjolfsson & McAfee, 2014, p. 81). Considered the fact that AI is a main element in the second machine age as it will accelerate this phenomenon, AI is another step and another building block into the digitization of enterprises (Brynjolfsson & McAfee, 2014, p. 81,89). That is why actor-oriented architecture is also suitable for organizations that want to implement AI.

Actor oriented organizations are characterized by collaboration and self-organization with a minimal usage of hierarchy to reduce uncertainty and risk, speed the development of a new product and reduce the cost of process development, and access to new knowledge and digital technologies (Fjeldstad et al., 2012, p. 739). Decision making within this organizational design is decentralized, which means that the decision belongs to the team in charge of the project and not the top management (Fjeldstad et al., 2012, p. 739). The design of actor-oriented organization boils down to three components summarized in the Figure 2 present in the theoretical background in section 1.4.4 (Fjeldstad et al., 2012, p. 739). The first element is the actors "who have the capabilities and values to self-organize", the second element is the commons "where the actors accumulate and share resources"; and finally, the third element is described as "protocols, processes, and infrastructures that enable multi-actor collaboration" (Fjeldstad et al., 2012, p. 739).

2.2.1 Actors in the organizational design of KIFs

Actors refer to individuals, teams and also firms that have the ability to self-organize and collaborate (Snow et al., 2017, p. 6). Actors in an actor-oriented architecture possess suitable knowledge, skills and values for digital organizations where they can work with digital co-workers (Snow et al., 2017, p. 8). They have accumulated hard and soft skills as well as a specific knowledge from their internet activities (Snow et al., 2017, p. 8). Hard skills are considered to be "about a person's skills set and ability to perform a certain type of task or activity" (Hendarmana & Tjakraatmadjab, 2012). Hard skills in KIFs involve computational thinking or information and communication technologies (ICT) literacy and knowledge management (Snow et al., 2017, p. 8; Hendarmana & Tjakraatmadjab, 2012). Knowledge management can be defined as "how best to share knowledge to create value-added benefits to the organization." (Liebowitz, 2001). To collaborate with the digital co-worker, humans should understand basic knowledge about coding and data to better understand the basic function of AI and systems in order to educate and to learn from AI (Snow et al., 2017, p. 8; Dejoux & Léon, 2018, p. 209, 219). Soft skills are defined as "personal attributes that enhance an individual's interactions and his/her job performance (...) soft skills are interpersonal and broadly applicable" (Hendarmana & Tjakraatmadjab, 2012). Soft skills in the digital environment include social intelligence - like complex communication when to teach or manage - and collaboration capabilities, trans-disciplinarity, sense-making, critical thinking, systemic thinking i.e. contextualization and design mindset (Brynjolfsson & McAfee, 2014, p. 16-20; Snow et al., 2017, p. 9; Dejoux & Léon, 2018, p. 211). Design thinking enables actors to develop their creative and empathetic mind (Dejoux & Léon, 2018, p. 55, 210). Design mindset is related to design thinking, and according to Dejoux & Léon, design thinking skills boil down to the following four skills: trans-disciplinarity, empathy, creativity and test & learn (Dejoux & Léon, 2018, p. 219). Soft skills are by definition attributes that machines do not have or cannot imitate and constitute a competitive advantage for humans (Brynjolfsson & McAfee, 2014, p. 16-20). As digital technologies have evolved and are now integrated into tools and equipment used in the workplace, actors collaborate with digital co-workers (Snow et al., 2017, p. 10).

2.2.2 Commons in the organizational design of KIFs

Commons overall purpose is to provide the actors of the organization with resources to learn and adapt to the ever-changing environment. (Snow et al., 2017, p.10). There are two types of commons, situation awareness and knowledge commons (Snow et al., 2017, p.7). The first common is to share situation awareness that consists of knowing what is happening in the organization (Snow et al., 2017, p. 7, 10). This common helps to reach an efficient collaboration and decision making between humans and machines (Snow et al., 2017, p. 7, 10). Digitally shared situation awareness - possible through digital platform and software - creates current, accessible and valuable information for all the members of the organization enabling them to make decisions in accordance with the situation of the organization (Snow et al., 2017, p. 7, 10).

Knowledge commons, the second type of commons, refer to knowledge and data used and created by the members of an organization for collective purposes and it can be represented by software platforms (Snow et al., 2017, p. 7, 10). We distinguish two main types of knowledge, the explicit and tacit knowledge. According to Alyoubi, (2015, p. 280), explicit knowledge is a "formal knowledge that can be expressed through language, symbols or rules." Then, tacit knowledge refers to "a collection of person's beliefs, perspectives, and mental modes that are often taken for granted" and "Insights, intuition, and subjective knowledge of an individual that the individual develops while being in an activity or profession" (Alyoubi, 2015, p. 280). Knowledge commons are paramount for KIFs as this set of shared resources contributes to the process of learning and adapting within an organization (Snow et al., 2017, p. 10). Knowledge commons can develop the collective intelligence within a firm thanks to an online open ecosystem to enable and enhance the sharing and the combining of knowledge throughout different departments (Dejoux & Léon, 2018; Galbraith, 2014; Snow et al., 2017, p. 7). This integration of data and information coming from different sources within an enterprise is paramount for the enterprise in order to create, transfer, and share knowledge (Fjeldstad et al., 2012, p. 741; Galbraith, 2014). According to Dejoux & Léon (2018), this open ecosystem can consist of communities animated by managers where they share the best practices through case studies as it exists for example in Accenture (Dejoux & Léon, 2018; Fjeldstad et al.,2012, p. 741; Snow et al., 2017, p. 10). Thanks to this broad knowledge base, Accenture employees can make decisions locally and in an autonomous way (Fjeldstad et al., 2012, p. 741).

2.2.3 Processes, protocols and infrastructures (PPI) in the organizational design of KIFs

Infrastructures are the links between actors and it is also the system that gives access to the same information and knowledge (Fjeldstad et al., 2012, p. 739). In digital organizations, infrastructures are represented by communication networks and computer servers (Snow et al., 2017, p. 11). Protocols are utilized by actors as codes of conduct to pilot them in their interaction and collaboration within an enterprise (Fjeldstad et al., 2012, p. 739). Protocols - embedded in software applications and in the communication systems - reduce ambiguity as they coordinate actor's interactions and the access to commons (Fjeldstad et al., 2012, p. 741; Snow et al., 2017, p. 11). The division of labor is one of the most important protocols (Fjeldstad et al., 2012, p. 739). With the emergence of AI, tasks attributed to humans in the decision making process can vary. A new division of labor can emerge where AI takes care of analytical, repetitive tasks while humans use intuition, imagination and senses in the decision making process (Brynjolfsson & McAfee, 2014, p. 16, 17). Processes are utilized to foster an agile organization - agile principles are based on experimentations, short cycles of iteration with continuous learning- that is the most prevalent type of processes within KIFs (Snow et al., 2017, p. 6; Dejoux & Léon, 2018, p. 42). Agility is a process created in computer firms that enables the creation of autonomous groups in order to make decision making more local and decentralized (Dejoux & Léon, 2018, p. 42). Agile management is suitable to handle firms' environments that are uncertain, ambiguous and complex (Dejoux & Léon, 2018, p. 42). Furthermore, Staub et al., (2015, p. 1484) linked agility with AI saying that when considering both the features of agility and AI, they "are structures offering creative and talented employees, coordination skill for concurrent activities, proactive approaches, existence of technological information, a rapid adaptation skill to the information obtained by the enterprise, diversification and personalization approach, a structure with a developing authorization and cooperation feature, an approach to realize opportunities and constant learning."

In the management of knowledge, infrastructures, processes and protocols are important supports for the creation and the sharing of explicit knowledge. Taking the example of Accenture, Fjeldstad et al. (2012), showed that new knowledge stemming from projects is codified into explicit knowledge and shared for all the consultants via knowledge commons

(Fjeldstad et al., 2012, p. 744). This consistent base of shared knowledge and information about available resources coupled with a decentralized and autonomous decision making, enables the empowerment of actors - individuals or teams - in decision making (Fjeldstad et al., 2012, p. 741). Alyoubi (2015, p. 281) described the process of knowledge management within four dimensions (Figure 4): externalization, combination, internalization and socialization. Externalization refers to the transfer from tacit knowledge to explicit knowledge, it happens through infrastructures that give access to knowledge commons (Fjeldstad et al., 2012, p. 739; Alyoubi, 2015, p. 281). Combination happens when explicit knowledge is converted into new knowledge thanks to the storage of information, i.e. the knowledge commons accessible via digital platform (Fjeldstad et al., 2012, p. 739; Alyoubi, 2015, p. 281). The third dimension, internationalization, occurs when explicit knowledge is converted to implicit knowledge thanks to knowledge commons "to modify the internal mental model of the knowledge worker" (Alyoubi, 2015, p. 281). The fourth dimension, socialization, happens when people share their tacit knowledge; in the workplace it occurs between actors sharing their experiences, their feelings, ... it happens thanks to collective intelligence and communities of interests (Alyoubi, 2015, p. 281).

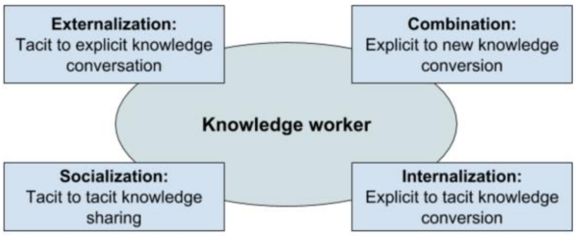

Figure 4: The process of knowledge management (Alyoubi, 2015, p. 281)

2.3 Decision making within KIFs

2.3.1 Type of decision making approaches

Having studied the organizational design of KIFs, we are going to focus in the part 2.3 on the decision making approach within KIFs. We have seen that in the actor-oriented architecture used within KIFs, decision making is decentralized. The decision making is made by self-organized and autonomous actors that collaborate thanks to PPI through commons. We are going to focus on individuals, i.e. the actors and their approach to decision making. Scholars distinguish between two main types of decision making approaches, the decisions that are intuitive and the ones that are rational (Dane et al., 2012 p. 188; Johnson et al., 2017 p. 512; Jarrahi, 2018, p. 3).

2.3.1.1 Intuitive decision making approach

The first type of decision making approach is intuitive. According to Dane et al., intuitive decision making is "affectively-charged judgments that arise through rapid, nonconscious, and holistic associations" and it is "a form of knowing that manifests itself as an awareness of thoughts, feelings, or bodily sense connected to a deeper perception, understanding, and way of making sense of the world that may not be achieved easily or at all by other means." (Dane et al., 2012 p. 188; Sadler-Smith & Shefy, 2004, p. 81). Intuition is a cognitive approach that is opposed to rational, analytical and logical thoughts (Dane et al., 2012 p. 188; Sadler-Smith & Shefy, 2004, p. 77, 78). Intuition is a phenomenon that humans experience every day and use naturally (Sadler-Smith & Shefy, 2004, p. 78, 79). Intuition includes also expertise, implicit learning, sensitivity, creativity, imagination (Sadler-Smith

& Shefy, 2004, p. 81; Jarrahi, 2018, p. 3). Intuition is also related to a gut feeling sensation or to instinct in understanding key problematics (Sadler-Smith & Shefy, 2004, p. 78). Therefore, executives experiencing a gut feeling can identify quickly whether an innovative product is likely to make it or not, whether a financial investment has potentiality to turn into profit (Sadler-Smith & Shefy, 2004, p. 78), etc. This type of intuition is called superior intuition or even intuitive intelligence: "the human capacity to analyze alternatives with a deeper perception, transcending ordinary-level functioning based on simple rational thinking" (Jarrahi, 2018, p. 3).

Besides, intuition relies also on expertise (Sadler-Smith & Shefy, 2004, p. 81). Indeed, according to Sadler-Smith & Shefy (2004, p. 76), domain experts are the individuals that can exploit at best intuition for decision making. The concept of domain expert - the most likely person to effectively benefit from intuition - is an individual who has accumulated knowledge and expertise in a precise field thanks to experiences (Kahneman & Klein, 2009; Klein, 1998; Salas et al., 2010). As intuition relies on subjectivity, this process cannot be decomposed in tasks like a rational process, it is rather similar to tacit knowledge obtained through experiences and familiarity (Dane et al., 2012, p. 187, 188; Jarrahi, 2018, p. 5; Klein, 2015, p. 167). Indeed, it is hard to decompose the judgment made by an artist about an artwork or to judge if a behavior is moral or even to explain why a decision feels right (Dane et al., 2012 p. 188; Jarrahi, 2018, p. 4). In other words, intuitive decision making is linked to emotions, sense-making and gut feeling. Moreover, intuition is connected to perception and subjectivity and intuition is built upon experience and familiarity (Klein, 2015, p. 167). Finally, intuition depends on both expertise and feelings (Sadler-Smith & Shefy, 2004, p. 81).

2.3.1.2 Rational decision making approach

The second type of decision making approach is rationality. Rationality is based on "analyzing knowledge through conscious reasoning and logical deliberation" and "develop alternative solutions" thanks to a methodical information gathering and acquisition (Jarrahi, 2018, p. 3; Sadler-Smith & Shefy, 2004, p. 77). Being rational involves looking into costs and benefits and examine which alternative solution is appropriate (Dane et al., 2012 p. 188). Analytical reasoning is heavily based on depth of information, indeed "the more information, the better" (Jarrahi, 2018, p. 3; Sadler-Smith & Shefy, 2004, p. 77). Moreover, rational thinking is not based on feelings, but it is rather based on logical reasoning to conceal emotions from the decision making (Sadler-Smith & Shefy, 2004, p. 77). Rational decision making can be easily decomposed into rational axioms and prefered conditions to set up frameworks of alternatives to deliberate on the best option (Fishburn, 1979, p. vii). As a result, rational decision making is objective and impersonal, i.e. there is no personal judgement. That so, machines can easily emulate humans' rationality process in decision making (Jarrahi, 2018, p. 6).

2.3.2 Challenges in decision making

The context plays an important role in decision making processes, one of the key factor that can influence the decision making process is the environment (Papadakis,1998, p. 117, 118). Decision making process comprises three challenges related to the environment and organization of KIFs: uncertainty, complexity, and ambiguity (Snow et al., 2017, p. 5; Jarrahi, 2018, p. 1).

According to Pomerol, one experiences uncertainty in decision making when "the future states are obviously not known with certainty" and uncertainty arises from a lack of information about the environment (Pomerol, 1997, p. 5; Jarrahi, 2018, p. 4). Making a decision in an uncertain situation necessitates to interpret the situation where information is missing about the future outcomes and alternatives or the consequence of outcomes and alternatives. Complexity is concerned with "situations [that] are characterized by an abundance of elements or variables." (Jarrahi, 2018, p. 5). Making a decision in complex situations requires to analyze a lot of information in a short period of time, it can be overwhelming for human brains (Jarrahi, 2018, p. 5). Ambiguity is context dependent as it relates to "the presence of several simultaneous but divergent interpretations of a decision domain" and ambiguous situations are occurring "due to the conflicting interests of stakeholders, customers, and policy makers." (Jarrahi, 2018, p. 5). The decision maker confronted to ambiguity cannot adopt a rational and impartial decision making approach but a subjective and intuitive one as he has to find a common ground to rally the divergent parties at stake in the decision making (Jarrahi, 2018, p. 5).

As a conclusion, we have established the framework summarizing the decision making approaches and the organizational challenges within KIFs (Figure 5). As we presented, the decision making can be divided into two main approaches, intuition and rationality. The decision making within KIFs comprises three challenges - uncertainty, complexity and ambiguity - that are related to organizational challenges.

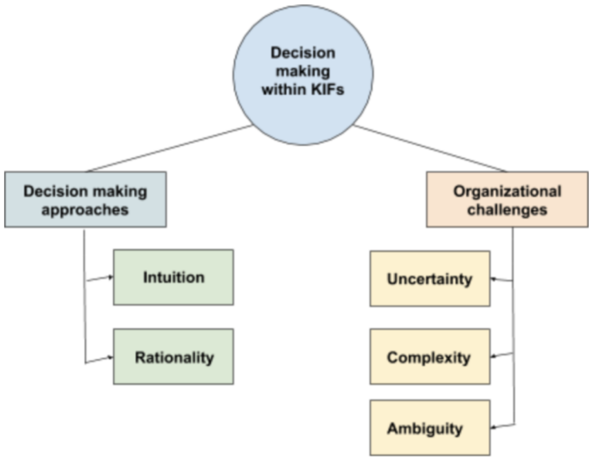

Figure 5: Decision making approaches and organizational challenges within KIFs

Following the structure of our framework in the figure 5, we have chosen to develop first in section 2.4 the decision making process on the basis of what we have developed about the decision making approaches. Then, in section 2.5, we study the organizational challenges - uncertainty, complexity and ambiguity- and link it to the decision making process and the decision maker - humans and AI.

2.4 Decision maker: humans and AI in the process of decision making

After presenting the two main approaches implicated into the decision making and the three organizational challenges stemming from decision making within KIFs, we are going to present in the part 2.4 the different processes involved in the decision making related to the type of decision maker present in KIFs - humans and AI -. We have introduced intuition and rationality as the two main approaches in decision making. We are going to make a link between these two approaches and the decision making process used according to the two types of decision makers. We will consider three situations depicting three decision making processes. First, human decision making processes related to both approaches, then AI decision making processes related mainly to rationality, and finally the relationship between AI and human decision making processes considering both approaches.

2.4.1 Human processes in decision making

We have described in section 2.3 the two main types of decision making approaches and we are going to dwell on the decision making process specifically applied to humans. Within KIFs, actors are decision makers and we are going to present their processes when making a decision according to intuition and rationality. When it comes to decision making, humans are not always rational, they can also be intuitive. Intuition and rationality in decision making are seen as dual processes because they are "*parallel systems of knowing"* (Sadler-Smith & Shefy, 2004, p. 88). Nobel prize-winner Daniel Kahneman presented the two processes of human decision making, intuition and reasoning, as we show in Figure 6 (Kahneman, 2003, p. 698; Johnson, 2017, p. 512). On the scheme, we can distinguish two systems, intuition and reasoning that are the two different processes in the decision making. We can see on the scheme that intuition is coupled with perception as perception helps to build intuition. Kahneman has described both of the systems by assigning them adjectives related to their processes.

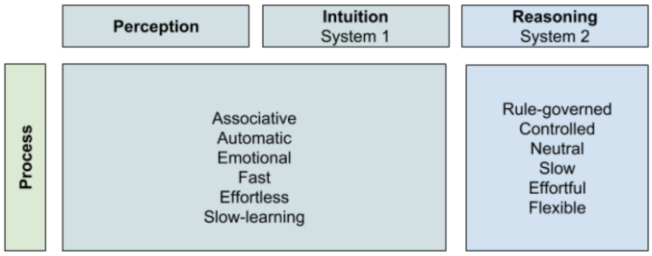

Figure 6: Process in Two Cognitive Systems: Intuition vs Rationality (Kahneman, 2003, p. 512)

First, we are going to describe the process of the first system, intuition. According to Kahneman, intuition is linked to emotions and automatisms learned through experiences; it is a slow learning process as this process is function of experiences lived and prolonged practices; it is also an effortless and fast process as humans naturally have intuition (Kahneman, 2003, p. 698). Kahneman linked the concept of intuition along with the notion of perception and according to him, intuition is a process stemmed from automatic operations of perception (Kahneman, 2003, p. 697) Those two concepts are considered to be natural assessments and they are useful in the judgement about what is good or bad according to the context (Kahneman, 2003, p. 701). In a nutshell, we can summarize the first system as "automatic, holistic, primarily non-verbal, and associated with emotion and feeling" (Sadler-Smith & Shefy, 2004, p. 88). Second, we are going to describe the process of the second system, reasoning also called rationality. Rationality is connected to intelligence, based on the need for cognition and correlated to statistical reasoning (Kahneman, 2003, p. 711). To sum up, the second system can be described as "intentional, analytic, primarily verbal, and relatively emotion-free" (Sadler-Smith & Shefy, 2004, p. 88). If the system 2 - rationality - comes after system 1 - intuition - in the Figure 6 it is because system 2 has a monitoring role in decision making process; yet it can also constitute a process by itself without intuition (Kahneman, 2003, p. 699). For example, when people make a quick decision on the spot, they can start their process with intuition and it is then endorsed by rationality or they can directly rely on rationality if no intuitive impulse occured (Kahneman, 2003, p. 717).

We are developing rational processes used by humans in order to make parallel further in the literature with AI rational process. Utility theory has emerged from economics, statistics, mathematics, psychology and the management science (Fishburn, Utility theory for decision making, 1979). It relies on the axiomatic approach: the decision-maker "puts forth a set of axioms or conditions for preferences (Fishburn, Utility theory for decision making, 1979, p. vii), which are assumptions that will help him to set up a frame in order to analyze and take a decision. This structure, together with a specific numerical model connected to the latter that is chosen according to the context, aims to help the decision-maker to examine the problem and hopefully take the best decision according to his current knowledge of the situation (Fishburn, 1979, p. vii). According to Fishburn (1979, p. 2), "the fundamental theorem of utility [...] has to do with axioms for preferences which guarantee, in a formal mathematical sense, the ability to assign a number (utility) to each alternative so that, for any two alternatives, one is preferred to the other if and only if the utility of the first is greater than the utility of the second". Therefore, the utility of an alternative refers to its value for the decision-maker. Utility theory proposes a framework in order to compare alternatives and take a rational decision. As an example of utility theory and to illustrate the process of decision making for a traveler, Pomerol used the example of a decision tree to build a probabilistic network of scenarios to make the best choice (Pomerol, 1997, p.8, 9).

The scheme in the Figure 6 is representing the human decision making process. It helps to understand to what extent AI can be a support to rational decision making, the system 2. Indeed, the process of rational decision making (system 2) can be reproduced by AI through algorithms as rationality is a rule-governed, controlled and neutral process (Kahneman, 2003, p. 698). Moreover, rationality is a slow and effortful process for humans that can be handled in a fast and easy way by AI (Kahneman, 2003, p. 698; Jarrahi, 2018, p. 5). Thus, AI can easily become expert in a very specific field thanks to ML, but AI cannot think out of this specific field and adopt an intuitive, creative way of thinking neither integrate a transverse view of the situation as rationality cannot accomplish what intuition enables (Dejoux & Léon, 2018, p. 206; Sadler-Smith & Shefy, 2004, p. 78). The intuition process is something that cannot be handled by the weak AI since intuition is a process linked to emotion and past experiences through a prolonged practice that are human characteristics (Kahneman, 2003, p. 698; Dejoux & Léon, 2018, p. 206). Besides, when rational processes, i.e. AI, are not appropriate to the conditions of the decision making notably because of ambiguity and uncertainty; intuition enables to cope with these challenges; indeed "a carefully crafted intuitive knowledge, understanding, and skill may endow executives with the capacity for insight, speed of response, and the capability to solve problems and make decisions in more satisfying and creative ways." (Sadler-Smith & Shefy, 2004, p. 78).

2.4.2 AI decision making processes

Along with the development of AI techniques and applications, organizations are questioning the influence of AI on human jobs (Jarrahi, 2018, p. 2). Elon Musk considered AI as a disruptive technology that will replace human in a broad range of jobs. Thus, AI may be seen as the principal cause of an *unprecedented wave of automation* (Jarrahi, 2018, p. 2). Some scholars praise the rise of machines as a substitution of human decision making since humans are too biased and irrational (Parry et al. 2016, p. 571, 572). The power of computers to analyze huge amounts of data - Big Data -, their objectivity and their processes based on rules enable them to make decisions based on grounded facts and models (Parry et al. 2016, p. 577, 580). AI-based decision making systems are free of human preconceptions and present a better representation of the reality (Parry et al. 2016, p. 577). AI can decide in an autonomous, unbiased and rational way thanks to ML and algorithms (Dejoux & Léon, 2018, p. 198, 199). Decisions are already made by machines when to consider high frequency trading (Dejoux & Léon, 2018, p.198). In an investment fund called Bridgewater, a CEO decided to put an AI at his position to run the enterprise (Dejoux & Léon, 2018, p. 199).

Within KIFs, commons (especially knowledge commons) and PPI - platforms with processes and computer servers - can potentially assist and replace the human decision maker especially when they adopt a rational process. A crystallization of commons and PPI for the decision making is represented by Decision Support Systems, DSS. Alyoubi (2015, p. 278) defined DDS as “popular tools that assist decision making in an organization” and according to Courtney (2001, p. 20), DSS are used as knowledge source or ways to connect decision-makers with several sources. That is why Alyoubi (2015, p. 278) links DSS to knowledge management as knowledge management helps the decision making process in organizations. Figure 7 represents the decision making process of DSS. DSS start the process with the problem recognition and definition. Then, following a human rational decision making process described in section 2.4.1, DSS generate alternatives with a model development in order to choose the best option and implement it.

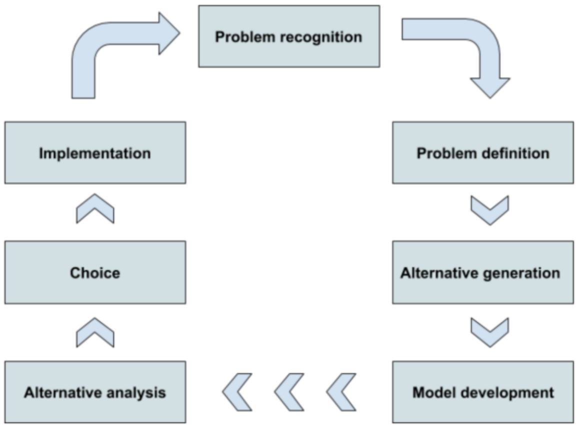

Figure 7: Example of DSS decision making process (Courtney, 2001, p. 280)

The most common application in organizations for system supporting decision making is Group Support System (GSS) or Group Decision Support System (GDSS) which is the convergence of DSS and knowledge management (Alyoubi, 2015, p. 278; Courtney, 2001, p. 20). Indeed, over the past two decades, with the development of AI and ES, GDSS have emerged to “provide brain-storming, idea evaluation and communications facilities to support team problem solving”, i.e. GDSS deliver to the decision maker a smart support (Courtney, 2001, p. 20). Indeed, Parry et al., (2016, p. 573) qualify GDSS as decision making processes that attempt to imitate human intelligence. GDSS are described as systems that “[combine] communication, computing, and decision support technologies to facilitate formulation and solution of unstructured problems by a group” like IBM’s Watson (Parry et al. 2016, p. 573). GDSS adopt a rather rational decision making process based on knowledge and unstructured information. According to Parry, AI is used in enterprises to deal with “routine operational decision processes that are fairly well structured” but also “Recently, however, there have been indications that automated decision making is starting to be used in non-routine decision processes that are quite unstructured” thanks to Big Data, pattern recognition and the objectivity of the machine (Parry et al. 2016, p. 572). In fact, AI can aggregate and analyze more data than humans do. As AI is based on rules and codes, AI can identify alternatives like humans do in utility theory or in with decision trees but in a more precise way (Jarrahi, 2018, p. 3). In practice, as we have seen it in the introduction part 1.4.2, platforms like IBM’s Watson can make decision in very specific fields, for instance better than doctors do in the medical field. We have developed one particular example to illustrate how AI can adopt a rational decision making process within KIFs via the utilization of a group decision support system, we present it in Figure 8 (GDSS) (Parry et al. 2016, p. 573).

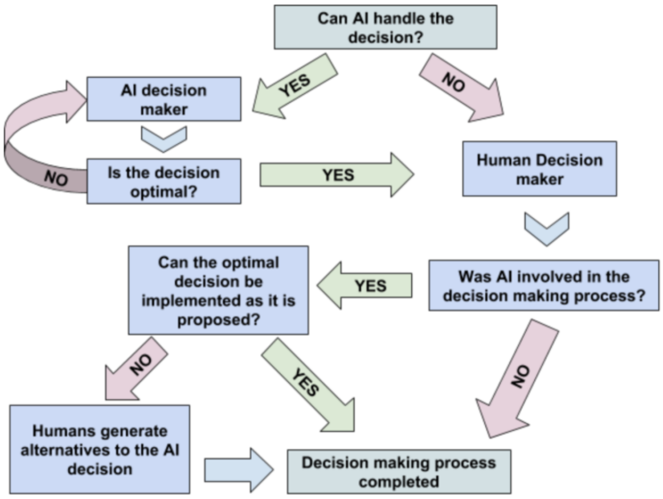

Figure 8: Flow diagram of leadership decision making delegation to AI systems with veto (Parry et al., 2016, p. 575)

Figure 8 presents an AI-based decision system and defines the role of AI in the decision making process in order to tackle the issue of a delegation to AI. The figure 8 starts with asking if the decision can be handed to a machine. Then, there are two possible paths: it is whether yes or no. In the case that it is a yes, the machine will generate a solution and assess if it is an optimal solution or not. If it is not an optimal decision, the machine will search for the optimal decision. When the solution is optimal, the decision will be proposed to humans. Then, humans will assess if the AI-system is involved in the decision. If it is not involved, the process of decision making is completed. If the AI-system is involved in the suggested decision, humans will evaluate if the decision can be implemented as it is. If the solution can be implemented directly, the process of decision making is completed. Otherwise, humans will exercise a veto to find and implement another alternative to the AI-system decision and the process of decision making will be completed.

2.4.3 AI and ethical considerations

When Brynjolfsson & McAfee, (2014, p. 140) said in The Second machine age "Technology is not destiny. We shape our destiny." they wanted to express that technology will bring about a lot of changes and great opportunities for individuals and the society, but we should be aware that we are still master of our time and we should think further about the challenges brought by new technologies. Taking the path of an AI-based system can be dangerous as AI does not incorporate moral and ethics values (Parry et al. 2016, p. 574). That is why, in the field of AI, a movement comprising transhumanists like Stephen Hawking, and researchers, think about AI applications that are more altruistic and praise the decisive role of humans in decision making (Parry et al. 2016, p. 574; Dejoux & Léon, 2018, p. 202). When considering the partnership between Humans and AI, several challenges arise. Dejoux & Léon, (2018, p. 182) have synthesized those new challenges, in four categories: the first one is concerned with ethics, the second one is about laws and regulations, the third one refers to trust and acceptance from society and the last one is related to the location of responsibility and power. For each category, Dejoux & Léon, (2018, p. 182) have formulated unanswered questions to bear in mind.

Regarding ethics, one should question the power that we can give to machines in regard to the concept of what is right or wrong: to what extent have machines been coded to integrate ethics and moral values (Dejoux & Léon, 2018, p. 182)? Humans build their values upon experience, a process that AI cannot do since they do not have a conscious. However, one can create AI to specifically follow some values, 'good and evil' for instance (Gurkaynak et al., 2016, p. 756). It has to be stressed that affective computing- "systems that can detect and express emotions" - is making progress as Big data and AI soar (Susskind & Susskind, 2015, p. 170, 171). According to Olsher, (2015, p. 284) AI gathers and displays complex and socially-nuanced data in order to help humans resolve conflicts, for instance with the cogSolv project: "In summary, cogSolv's Artificial Intelligence capabilities provide decision-makers with critical tools for making socially-nuanced life-or-death decisions." However, Susskind & Susskind (2015, p. 171, 172) believe that as capable as machines may become, "affective computing is not reaching any kind of plateau.". Moreover, each culture has its own judgement over what is commonly right, wrong and what are the accepted social standards in a society, that is why teaching a machine ethics is hard to accomplish if we, human beings, do not agree on ethics. That so, in the process of decision making, humans should be the final decision maker as humans can apply their grid of values to assess if the alternatives given by machines are right (Parry et al. 2016, p. 574; Dejoux & Léon, 2018, p. 202).

Towards power and responsibility, one should be aware that "The technologies we are creating provide vastly more power to change the world, but with that power comes greater responsibility" (Brynjolfsson & McAfee, 2014, p. 140). In fact, Dejoux & Léon, (2018, p. 182) question who should be responsible to unplug and stop the actions of the machine? How can humans share the power with machine? Which type of management should be adopted to manage a team of humans and machine? The ability of AI to learn from its personal experience, through ML for instance, leads to independent and autonomous decision making that are characteristics of legal personality (Cerka et al., 2017, p. 686). Consequently, AI cannot be treated as an object anymore. Thus, although this subject is not a big issue for weak AI, it is becoming a major issue with the premises of strong AI.

In regard to law, "we may be living in the dawn of the age of artificial intelligence today. Consequently, the legal landscape surrounding our lives will require rethinking, as the case was with every big leap in technology" (Gurkaynak et al., 2016, p. 753). Thus, one should question the juridical status of the machine interacting with humans in the workplace and in the society and also question the rights and duties of a machine especially if the machine makes a wrong decision (Dejoux & Léon, 2018, p. 182). The only global regulation for now is the general principle in article 12 of the United Nations Convention on the Use of Electronic Communications in International Contracts that states that messages generated by machines should be the responsibility of people on whose behalf it was programmed (Cerka et al., 2015, p. 387). Zeng (2015, p. 4) underlined that "AI-enabled hardware and software systems, as they're embedded in the modern-day societal fabric, are starting to challenge today's legal and ethical systems." To fill the void, we tend to refer to the work of Isaac Asimov, the Three Laws of Robotics: "(1) A robot may not injure a human being or, through inaction, allow a human being to come to harm; (2) a robot must obey the orders given to it by human beings, except where such orders would conflict with the First Law; (3) a robot must protect its own existence as long as such protection does not conflict with the First or Second Laws." (Brynjolfsson & McAfee, 2014, p. 19). Besides, with the rise of interest in AI in the past few years, several researches have been conducted throughout Europe to extend Asimov's set of rules, and five laws have been put forward: "(1) robots should not be designed solely or primarily to kill or harm humans; (2) humans, not robots, are responsible agents. Robots are tools designed to achieve human goals; (3) robots should be designed in ways that assure their safety and security; (4) robots are artifacts; they should not be designed to exploit vulnerable users by evoking an emotional response or dependency; (5) it should always be possible to find out who is legally responsible for a robot." (Zeng, 2015, p. 5). With these sets of laws, society starts to build a legal frame over the action of machines, however, there is no law to strictly assess the responsibility of a machine in case machines make a wrong decision.

Regarding the society acceptance and trust, Dejoux & Léon, (2018, p. 182) question to what extent machines should undertake human's tasks, what should be the role of humans collaborating with machine, and also "are there tasks that only human beings should be permitted to undertake?" (Susskind & Susskind, 2015, p. 281). The acceptance of AI within society is deeply rooted in the concept of trust (Hengstleret al., 2016). In fact, Hengstleret al., (2016) linked the willingness to use the technology with the concept of trust, since trust is a paramount condition in human interactions. Hengstleret al., (2016, p. 112, 113) explained in his article that the usage of AI "sounds scary because there is a lack of understanding, pretty much like any new technology that is introduced into society. When a technology is not well understood, it is open to misunderstanding and misinterpretation". Furthermore, the society fears a wave of automation of jobs "in response to the question 'What will be left for human professionals to do?' it is also hard to resist the conclusion that the answer must be 'less and less'" (Susskind & Susskind, 2015, p. 281, 283). Moore's law (Brynjolfsson & McAfee, 2014, p. 26; Laurent, 2017, p. 65)- stated that the power of computer will increase over the years. With IoT and smartphones the amounts of data had exploded, enabling AI to emerge and credibilising transhumanism projects about the future of humans. This rise of AI feeds apocalyptic prophecies of Elon Musk and Stephen Hawking. GAFAM and IBM created a Partnership on Artificial Intelligence in order to sensitize the society to the use of AI and to get society's acceptance (Laurent, 2017, p. 61). Hengstler et al., (2016, p.113) explained how a clear, transparent and democratic communication towards AI could facilitate the society acceptance by showing how AI can be beneficial for the society, claiming that "many people would reconsider their resistance if the benefit of this application can be successfully proven to them".

2.4.4 Partnership between humans and AI in the decision making process

According to Kahneman (2003, p. 712), when it comes to making a decision, the dual-task method can be useful; this method consists in validating assumptions of an underlying intuitive decision - system 1 of the Figure 6 - thanks to the support and correction of a rational thinking - system 2 of the Figure 6 - (Kahneman, 2003, p. 712). If we draw a parallel of this process of decision making with the symbiosis in decision making between AI and humans described by Jarrahi (2018, p. 1), we can assign the system 1 to humans and the system 2 to AI. It appears that a partnership between humans and AI can foster the decision making process.

Indeed, other scholars see AI as a support for human decision making, as machines cannot make a decision on themselves since they lack intuition, common sense, and contextualization (Jarrahi, 2018, p. 7). AI can help to formulate rational choices (Parry et al. 2016, p. 577). In their decision making, humans have comparative advantages regarding intuition, creativity, imagination, social interaction and empathy (Brynjolfsson & McAfee, 2014, p. 191,192; Dejoux & Léon, 2018, p. 206). When Kasparov played against Deep Blue he gave some insights about what computers cannot do: machines have hard time creating new ideas - it is the concept of ideation that can be illustrated when a chef creates a new dish for the menu - (Brynjolfsson & McAfee, 2014, p. 191). Machines are also constrained by their codes and algorithms so that they cannot think outside of the box and be creative and innovative (Brynjolfsson & McAfee, 2014, p. 191; Dejoux & Léon, 2018, p. 206, 211).

Even if some scholars have considered a partnership between AI and humans, Epstein (2015, p. 44) addresses some limits when considering this partnership on a theoretical level since “Although tales of human–computer collaboration are rampant in science fiction, few artifacts seek to combine the best talents of a person and a computer” (Epstein, 2015, p. 44). Consequently, according to Epstein (2015, p.44), the gap existing in the literature can be explained with the following two main issues: (1) it is complex to include humans in empirical studies “Because people are non-uniform, costly, slow, error-prone, and sometimes irrational, properly designed empirical investigations with them are considerably more complex.”; (2) “the original vision for AI foresaw an autonomous machine. We have argued here, however, that a machine that shares a task with a person requires all the behaviors the Dartmouth proposal targeted, plus one more — the ability to collaborate on a common goal.”

However, other scholars have considered that a partnership between AI and humans could help to overcome the limits and weaknesses of each other in decision making (Brynjolfsson & McAfee, 2014; Jarrahi, 2018; Dejoux & Léon, 2018). That is why, based on the framework of Dejoux & Léon (2018, p. 203), we have presented the interaction between AI and humans in decision making. In the process of decision making between humans and AI, Dejoux & Léon explained that the first step consists of explaining the problem to AI (Dejoux & Léon, 2018, p. 202, 203). Then, AI analyzes a consistent amount of data present in the system thanks to algorithms (Dejoux & Léon, 2018, p. 198, 199, 202, 203). Stemming from this analysis, AI proposes different patterns to humans and two options emerge: either AI chooses the pattern and automates the solution by itself or humans choose one pattern according to their values and objectives (Dejoux & Léon, 2018, p. 202, 203). In a nutshell, we can say that AI can be a decision maker or AI can be an assistant in decision making. We have summarized this process of decision making between AI and human beings in the Figure 9, a framework that we translated from Dejoux & Léon, (2018, p. 203).

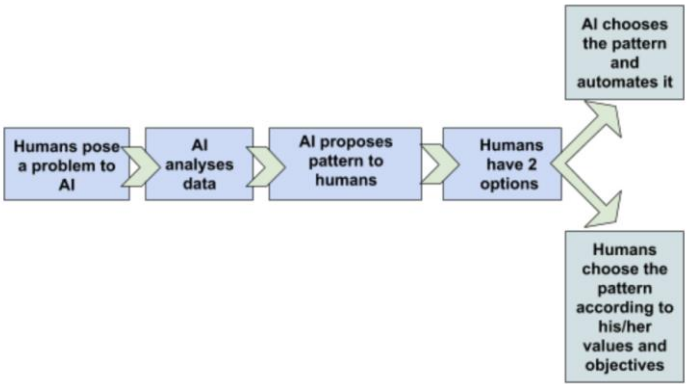

Figure 9: Process of decision making between AI and humans: AI can be a decision maker or AI can be an assistant in decision making (framework translated from Dejoux & Léon, 2018, p. 203)

To sum up our part about the role of AI and humans in decision making processes, we have established a continuum describing the decision making process and the related decision maker in the figure 10. Intuition and rationality are the extreme parts of the continuum. We have coupled those two indicators with the three types of combinations of decision makers that we have described, humans only, the relationship between humans and AI, and autonomous AI.

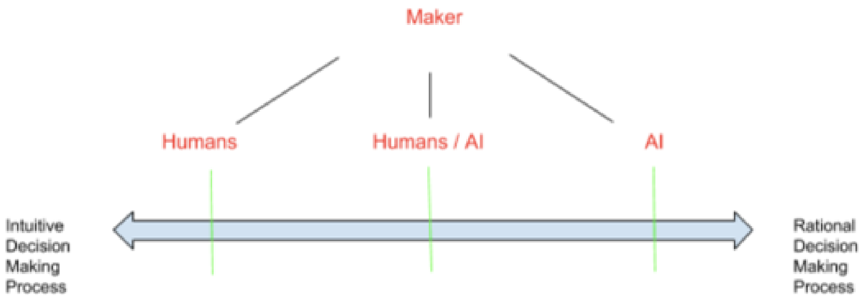

Figure 10: Decision maker within the continuum of decision making processes

2.5 Decisions making challenges within KIFs

In the previous sections, we have seen that decision making comprises two approaches, intuition and rationality, and that on this basis decision makers - AI and humans- have different ways to process a decision. In this section, we are going to present how to overcome the three challenges stemming from KIFs in the decision making process - uncertainty, complexity, ambiguity - according to the decision maker process and the approach within KIFs.

2.5.1 Overcoming uncertainty

To overcome the challenge of uncertainty in KIFs, humans, denominated by actors - individuals or teams - in organizational design of KIFs, gifted by soft skills and especially intuitive decision making, appear to be the most competent decision makers. Nevertheless, AI support through its analysis and rational reasoning can be complementary in the process of decision making. Within KIFs organizational design, AI support is represented by the commons. For instance, smart tools that allow a firm to monitor and sense its external environment have already been developed within consulting firms Deloitte and McKinsey, so that these organizations were able to implement semi-automated strategies (Jarrahi, 2018, p. 4).

According to Kahneman, there is no uncertainty in intuitive reasoning: the decision maker has only one alternative coming to his/her mind (Kahneman, 2003, p. 698). This approach is consistent with Natural decision making (NDM). NDM is the process through which individuals that are experts in a field make intuitive decisions while recognizing a pattern that they have stocked in their memories (Kahneman & Klein, 2009, p. 516, 517). NDM was developed to understand how commanders of firefighting companies that are highly exposed to a context of uncertainty were able to make good decisions without comparing options (Kahneman & Klein, 2009, p. 517). Commanders of firefighting companies first mentally identified a pattern from their past experiences in order to recognize a potential option and then they mentally assessed this option to see if this option was likely to solve the situation (Kahneman & Klein, 2009, p. 517). This process is called recognition-primed decision (RPD), and it is a good strategy when the decision maker has consistent tacit knowledge about the situation (Kahneman & Klein, 2009, p. 517). Indeed, according to Jarrahi, in their decision making, humans use their intuition and their ability to recognize patterns that machines do not have or sense especially in situations of uncertainty (Jarrahi, 2018, p. 4). However, when it comes to making a decision in uncertain contexts, the support of machines that provide accurate information is complementary with the human understanding of the situation (Jarrahi, 2018, p. 4). AI can provide humans with real-time information in situations of uncertainty to support the decision maker thanks to statistics and pattern recognition (Jarrahi, 2018, p. 4; Dejoux & Léon, 2018, p. 218). Uncertainty is present in the KIFs' environment; this challenge has been tackled by Network Centric Operation thanks to shared situation awareness - the commons in the actor-oriented architecture of KIFs- and collaboration notably i.e. clear and exact information and an understanding of the situation (Fjeldstad et al., 2012, p. 743). The challenge of uncertainty in decision making within KIFs can be overcome thanks to essential elements of the actor-oriented architecture: commons and collaboration between actors. Commons are a support in the decision making process and provide information to the actor. The actor makes a decision thanks to his/her awareness of the situation and his/her intuition; as Kahneman said, there are rarely moments of uncertainty in intuitive decision (Kahneman, 2003, p. 703).

Intuition enables experienced decision maker under pressure to act fast, they seldom choose between alternatives as most of time they only think about one option; for example, Steve Jobs was famous for his ability to make fast and intuitive decisions (Kahneman, 2003, p. 701; Jarrahi, 2018, p. 4). At the light of the literature, it appears that human intuition in decision making is decisive and that humans still have a competitive advantage in uncertain situations (Jarrahi, 2018, p. 5). In fact, humans outperform AI in situations of uncertainty thanks to their intuition because it is a fast, natural and unconscious cognitive process (Kahneman, 2003, p. 698; Jarrahi, 2018, p. 4; Dejoux & Léon, 2018, p. 206). Intuition does not make room for doubt or a second alternative when to make a decision in an uncertain situation (Kahneman, 2003, p. 701).

2.5.2 Overcoming complexity

In KIFs, overcoming the challenge of complexity is mostly undertaken by AI represented by commons and PPI. However, the actors -the individuals and teams- can still have a role in the loop of decision making. AI has a competitive advantage over humans in complex situation when it comes to analytical skills and rigor (Jarrahi, 2018, p. 5). AI is based on rational decision making processes and algorithms that work on the analysis of information and data; the Big Data has created new possibilities for AI to deal with complexity and make precise analysis for decision making (Jarrahi, 2018, p. 5). An AI which is autonomous in the decision making can analyze different layers of complex information and a consistent amount of data coming from various sources in order to recognize patterns and weak signals (Parry et al., 2016). AI, thanks to causal loops - 'if this happen, then do that' - can also simplify the complexity of a situation by identifying causal relationships and put forward the right cause of action (Jarrahi, 2018, p. 5). AI within KIFs can be represented through commons. Indeed Fjeldstad et al., (2012) have taken the example of the case of Network Centric Operation; this firm has overcome the complexity challenge with shared situation awareness, in other words, precise information and a comprehension of the situation (Fjeldstad et al., 2012, p. 743).

However, actors have a role to perform in decision making processes as they understand protocols, division of labor and codes of conduct so that they are able to share situation awareness and gather the right information coming from the commons of the firm. Actors can control AI thanks to their sense-making, their critical thinking, their systemic thinking (contextualization) and their hard skills. AI algorithms are coded by humans, so they can be biased too. Indeed, according to O'Neil, (2016) "algorithms are formalized opinion that have been put into code" so that critical thinking is paramount (Dejoux & Léon, 2018, p. 205, 218). Actors should critically review and control AI decisions since AI is human made algorithm and can contain human biases in the patterns it proposes (Dejoux & Léon, 2018, p. 205, 209, 210). Moreover, Voltaire (Brynjolfsson & McAfee, 2014, p. 191) once said that a man should be judged not by his answers but by his questions; indeed, being critical and being able to raise new questions and identify problems is paramount for decision making (Dejoux & Léon, 2018, p. 218).

Complex situations are sometimes resolved by humans who experience "gut feel" (Sadler-Smith & Shefy, 2004, p. 78), i.e. that they immediately understand all the components of the problem, as if they were making use of their instinct (Sadler-Smith & Shefy, 2004, p. 78). Thus, some people may instantaneously understand very accurately whether the launch of a new product will be a success or not, whether hiring one person is a good idea, etc. (Sadler-Smith & Shefy, 2004, p. 78). However, this kind of choice will be hard to explain for the decision maker: most of the time he/she will be unable to describe his/her reasoning in other words than just doing what "[feels] right" (Sadler-Smith & Shefy, 2004, p. 78). Sadler-Smith & Shefy (2004, p. 78) argue that when rational reasoning cannot lead to satisfactory predictions, managers should acknowledge the uncertain character of the situation. They could also accept ambiguities and be able to bring a pragmatic, smart and fast answer in that context of uncertainty: there is a need to recognize the capabilities of their intuitive thinking (Sadler-Smith & Shefy, 2004, p. 78). Moreover, due to the usually fast pace of decision making and the increasing amount of data, "executives may have no choice but to rely upon intelligent intuitive judgments rather than on non-existent or not-yet-invented routines" (Sadler-Smith & Shefy, 2004, p. 78).

2.5.3 Overcoming ambiguity

In situations where rational reasoning is not suitable, i.e. the data available does not allow the decision maker to make an unambiguous choice, intuition is an interesting solution to overcome uncertainty and complexity and make unique decisions (Sadler-Smith & Shefy, 2004, p. 78). "As an outcome of an unconscious process in which there is little or no apparent intrusion of deliberative rational thought, intuitions can be considered 'soft data' that may be treated as testable hypotheses or used to check out a rationally derived choice" (Sadler-Smith & Shefy, 2004, p. 78). In such context, intuition can provide decision makers with speed of response and looking to the problem through a different lens, so that they can solve problems and make choices more effectively and using more resources (Sadler-Smith & Shefy, 2004, p. 78). The challenge of ambiguity is overcome in KIFs thanks to the collaboration between actors - individuals or teams - and AI supported by commons. Humans have a competitive advantage over AI in ambiguous situation thanks to their soft skills and their perception (Jarrahi, 2018, p. 4; Kahneman, 2003, p. 701). AI is an excellent analytical tool, but it is not able to analyze the subtlety of human interactions and communications; AI does not have a common sense and cannot contextualize information (Jarrahi, 2018, p. 7). AI can analyze sentiments and predict reactions that are likely to occur about organizational decisions (Jarrahi, 2018, p. 6). However, AI does not know how to interact with humans, neither how to motivate them or how to convince them that decisions taken under situations of ambiguity will rally the different stakeholders (Jarrahi, 2018, p. 6). That is why humans have a competitive advantage: they can use their social intelligence in situations of ambiguity to negotiate, convince others and understand the context in which the decision is taken - regarding social and political dynamics - (Jarrahi, 2018, p. 6). According to Kahneman, *the ambiguity is suppressed in perception*, there is no apparent need for an AI support in such context as AI decision making relies on rationality - a process working without the use of perception- (Kahneman, 2003, p. 701).

We summarize our arguments in the framework of Figure 11. This framework is composed of our three main themes: KIF organizational design, decision making process and decision maker - humans and AI. Those three themes are intertwined. Indeed, we have started the literature review by the presentation of KIFs. In such firms, knowledge is a paramount concept. We have linked KIFs with a particular organizational design - actor-oriented architecture. This organizational design fits KIFs as this design enables KIFs to change and adapt to their environment characterized by three challenges: uncertainty, complexity and ambiguity. Then, as we have seen in actor-oriented architecture, the decision making is decentralized, we have focused on the whole process of decision making and the two mains processes involved, intuition or rationality. We have presented what are the challenges related to organizational decision making. In order to tackle those challenges, we have presented two types of decision makers, human beings and AI. We have presented their advantages and disadvantages and their role in decision making. We have then considered how human beings and AI can compensate each other's limits if they were to make a decision together.

At the junction between organizational design and humans and AI, there is knowledge. Knowledge is a paramount concept in KIFs and their organizational design. Knowledge is also related to human beings and machines in the concept of tacit and explicit knowledge, knowledge management, and knowledge commons. At the junction between organizational design and decision making, there are challenges - uncertainty, complexity, ambiguity- that are related to both the environment of KIFs and to the organizational decision making. At the junction between decision making and humans and AI, there are roles. Roles are related to the decision maker, whether humans or AI are the most suitable decision maker.

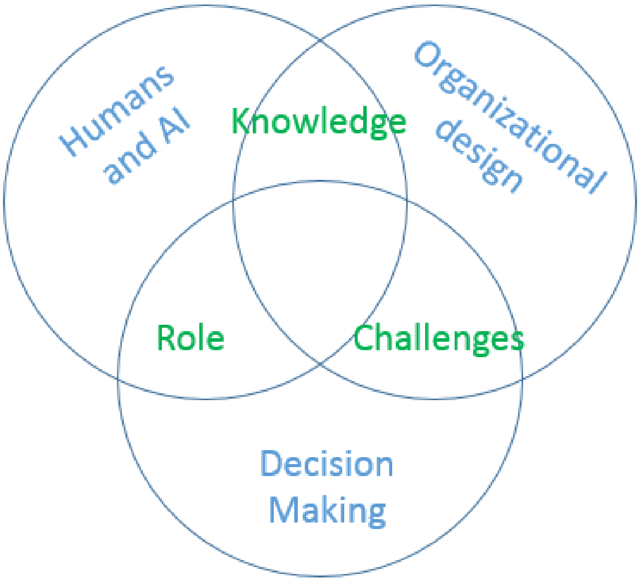

Figure 11: Framework depicting interactions between decision makers (humans and AI), organizational design and decision making

3. Methodology

In this chapter, the purpose is to present our philosophical point of view for the research and the related assumptions regarding ontology, epistemology, axiology and rhetoric. Further, we will explain our research approach, our research design as well as our sample choice, interview design and ethical considerations.

3.1 Research philosophy

3.1.1 The paradigm

A research paradigm represents a philosophical framework used as a guide to conduct scientific research (Collis & Hussey, 2014, p. 43). This philosophical framework relies on people's philosophy and their suppositions about the reality that surround them and the nature of knowledge (Collis & Hussey, 2014, p. 43). The two main paradigms are positivism and interpretivism.

Positivism is a paradigm that has been developed by theorists like *Comte (1798-1857), Mill (1806-1873) and Durkheim (1859-1917)* (Collis & Hussey, 2014, p. 43). Positivism has emerged with the development of science and especially physics; for a long time, positivism constituted the only paradigm ever considered (Collis & Hussey, 2014, p. 42). Indeed, scientists that study physics only focus on inanimate objects subjected to properties of matter and energy and interactions between them (Collis & Hussey, 2014, p. 42). Positivism has been used in natural science and scientific approach, and it still represents the preferred philosophy for this field of study.

Positivism is based on the fact that reality does not depend on people perception, i.e. the reality is singular, and the social reality is external to the researchers (Bryman et al., 2011, p. 15). In other terms, the researchers will not have any influence on the reality when investigating it. The aim of positivism is to discover theories where knowledge can be verified thanks to logical or mathematical evidence (Bryman et al., 2011, p. 15). Positivism uses causation principles where relationships between variables are established thanks to deductivism in order to build theories (Collis & Hussey, 2014, p. 44). Theories in positivism explain, and forecast, the occurrence of a phenomenon in order to understand how the phenomenon can be controlled (Collis & Hussey, 2014, p. 44). In a nutshell, positivism relies on the concept of objectivism and deductivism.

The development of interpretivism, the other main paradigm, is linked to a criticism of the positivism paradigm (Collis & Hussey, 2014, p. 44; Bryman et al., 2011, p. 17). This criticism has emerged with the development of industrialization and capitalism, and the paradigm is based on the principles of the philosophy of idealism developed notably by Kant (1724-1804) (Collis & Hussey, 2014, p. 44). Positivism is criticized on the fact that it is hard to consider the researchers as external from the phenomena under study as the researchers exist and are part of the reality they want to study (Collis & Hussey, 2014, p. 45). As part of the reality under study and in order to understand the phenomena, researchers have to understand their perceptions first of *their own activities* (Collis & Hussey, 2014, p. 45). Therefore, the researchers are not objective, and they are influenced by their values and interests.

Interpretivism is based on the belief that the social reality is multiple, subjective and socially constructed (Collis & Hussey, 2014, p. 45). The social reality is extremely subjective as the researchers perceive it and understand it through their perceptions (Bryman et al., 2011, p. 19, 20). The social reality in interpretivism is consequently affected by the researcher's investigation ((Bryman et al., 2011, p. 20). Hence, it is not possible to acknowledge that just one reality exists, there are as many realities as researchers. The goal of interpretivism is to explore the complexity of the social phenomena under study in order to gain deeper understanding (Collis & Hussey, 2014, p. 45). Interpretivism is based on the principles of inductivism where data stemming from interpretations are converted into theories. Interpretivism "[seeks] to describe, translate and otherwise come to terms with the meaning, not the frequency of certain more or less naturally occurring phenomena in the social world" (Collis & Hussey, 2014, p. 45). In a nutshell, interpretivism is subjective and inductive.

Our thesis aims at exploring the complex social phenomena of AI research field within the field of decision making and organizational design. We think that positivist principles are too limited to collect knowledge about this topic as we want to gather deeper understanding with rich and subjective data about the phenomena under study. The interpretivism paradigm will guide our research. Interpretivism is more suitable to our research question and purpose and our field of study can be further explored. Nowadays, the interest in AI research field is increasing but AI still constitutes a field of research to explore and especially within the field of management and organizations.

3.1.2 Ontological assumptions

Ontology refers to the nature of reality (Bryman et al., 2011, p. 20). There are two main assumptions about it: the objectivist one and the constructivist one (Bryman et al., 2011, p. 20). On the one hand, the objectivist assumption, associated with positivism, is to judge that "social reality is objective and external to the researcher" (Collis & Hussey, 2014, p. 46), and that reality is unique and inseparable. Thus, everyone perceives the same reality, and the researcher is supposed to be outside of it (Collis & Hussey, 2014, p. 47). On the other hand, the constructivist assumption, associated with interpretivism, is to consider that social reality is a social construct so that it is subjective and that there are several social realities (Collis & Hussey, 2014, p. 46). In that case, each person may have its own sense of reality: the term 'reality' refers to a projection of the very own characteristics of that person, that is, by definition, unique (Collis & Hussey, 2014, p. 47).

We adopt constructivism, as we want to get a deeper understanding of social actors in relation with decision making and AI. Indeed, our study is partly exploratory since the relationships between AI and decision making within organizations have not been studied in depth so far. Moreover, AI is a complex technology which may have numerous applications. Therefore, in order to gain a satisfactory understanding of it, we think it was mandatory for us to interview experts of the subject in order to gain in depth insights. Consequently, an important part of our study relies on the knowledge of the interviewees, which makes this thesis part of a particular social reality. It is also of interest to notice that the scope of our study, KIFs, does not refer to the same stakeholders for everyone. All these reasons incorporate our study within a socially constructed and multiple reality.

3.1.3 Epistemological assumptions

Epistemology refers to the nature of knowledge (Bryman et al., 2011, p. 15). What valid knowledge is made of varies according to the two paradigms. Within the positivist paradigm, knowledge is justified only by objective evidence in relation to phenomena which are observable and measurable (Bryman et al., 2011, p. 15). Positivists think that facts and information must be proven following the scientific stance in order to constitute valid knowledge. Thus, the researcher must be independent from the phenomena under study in order to keep an objective stance. Within the interpretivist paradigm, "knowledge comes from subjective evidence from participants" (Collis & Hussey, 2014, p. 46). Interpretivists are concerned with building a stronger link between the researcher and the participants: the researcher should interact with phenomena in order to get a deeper understanding of them (Collis & Hussey, 2014, p. 46-47). Positivism aims to study social sciences using the same evidence principles that apply within natural sciences, whereas interpretivism grants more importance to the perception of the participants (Bryman & Bell, 2011, p. 15; Collis & Hussey, 2014, p. 46).

We embrace the interpretivism point of view about knowledge. Indeed, we believe that decision making is inherently related to the perception of decision makers and knowledge providers, so that it was necessary for us to attempt to understand by what processes people come to make a decision. We therefore interacted with the phenomena under study. Moreover, AI and KIFs are fields of study that are broad, complex, and rather new. Consequently, it seems relevant to us to appeal to the perception of their stakeholders to understand as much perspectives as possible.

3.1.4 Axiological assumptions

In the process of research, axiological assumptions are connected to the role of values (Collis & Hussey, 2014, p. 48). On the one hand, positivism view of axiological assumptions considers the researcher as independent and external to the phenomena under study, for this reason, the results stemming from the study are unbiased and value-free (Collis & Hussey, 2014, p. 48). Indeed, researchers adopting positivism view of axiological assumptions have the belief that the objects under study already exist before they started to have interest in them and those objects will still exist after the study (Collis & Hussey, 2014, p. 48). The researchers are studying the interrelation between inanimate objects, for this reason they do not consider influencing the phenomena under study with their values (Collis & Hussey, 2014, p. 48). Moreover, the researchers consider that they do not interfere with the phenomena as being external and objective (Collis & Hussey, 2014, p. 48).

On the other hand, interpretivism view of axiological assumptions considers social reality as subjective and socially constructed and for this reason, the results of the research are biased (Collis & Hussey, 2014, p. 48). The researchers have values; those values determine what are considered as facts and the interpretations that are derived from them (Collis & Hussey, 2014, p. 48). The researchers have to acknowledge that the findings of the study are biased and subjective (Collis & Hussey, 2014, p. 48).

Our thesis will be guided by interpretivism view regarding axiological assumptions. We consider that the positivist view is not suitable to our study as we have chosen for the philosophical assumptions the interpretivist paradigm. Moreover, positivism view regarding axiological assumptions focuses on the fact that results are value-free. We think that we have preconceptions about the topic and we acknowledge the study to be subjective and biased. We have preconceptions about AI, organizational design, decision making and KIFs that are crystallized through our experiences, our studies, our interests, our background and the widespread preconceptions that society has upon AI.

3.1.4.1 Authors' preconceptions

One of the author (Mélanie Claudé) had preconceptions stemming from her family, her own interest about AI and her professional experience. Her family influenced her in her interest for new technology and especially her dad. In the nineties, her dad participated to the development of software in Thomas J. Watson Research Center that is considered to be an epicenter of the most disruptive technologies regarding the future of AI. She worked in KIFs during her gap year and she has experienced herself how much important it is to leverage knowledge in such firms. Her interest about organizational design is resulting from a professional experience. She worked in an enterprise going through a major digital transformation. This enterprise understood that to be successful it would have to change and adapt to the major change of the society described in the Second Machine Age (Brynjolfsson & McAfee, 2014). She realized how much an optimal combination of the components of an organization is important for the long-term strategy. Moreover, during her studies at Kedge, reading the book of the French philosopher Joël de Rosnay, *Je cherche à comprendre: Les codes cachés de la nature et de l'univers* made her realize that our society has moved to a new civilization where robots - a new type of species - and AI will change deeply the society. Then, the book of Dr Laurent Alexandre *La guerre des intelligences* made her understand to what extent it was important for her to question the future role of human beings at work when to consider that it takes on average 23 years to train a human to become an engineer and 30 years to become a doctor whereas a machine can become an expert in a few days (Laurent, 2017).

One of the author (Dorian Combe) had preconceptions stemming from his studies, his working experience and his own interests. He worked in various firms using different data collection systems and data analysis systems, most of them being KIFs (Safran Aircraft Engines, Panasonic, HanesBrands Inc.) It made him realize that companies may have totally different levels of digitization and data integration, and that it implies very unaligned degrees of support for decision making. It made him understand the importance of knowledge management, and especially knowledge sharing within an organization. His working experience made him come to the idea that digitization and knowledge integration are fundamental transformations for a firm to gain decision making efficiency, since it enables employees to make decisions relying on a bigger amount of data and to act faster. He also came to the idea that companies which are late on these issues and do not attempt to bridge the gap are taking a dangerous path. Other preconceptions of that author come from his personal interest in new technologies, as he worked within this type of firms and was part of projects relating to new technologies, such as the creation of a strategy contest for the launch of customized Microsoft Xbox One's joysticks.

3.1.5 Rhetorical assumptions

The rhetorical assumptions are concerned with the language used in the research and in the dissertation (Collis & Hussey, 2014, p. 48). The positivist stance is to be formal and use the passive voice, in order to match with the core goal of the researcher which is to remain objective within the study (Collis & Hussey, 2014, p. 48). On the contrary, there is no such entrenched writing rules in an interpretivist study. The style should reflect the direct involvement of the researcher in the phenomena under study and be appropriate to the field of research and the other components of the research design (Collis & Hussey, 2014, p. 48). Moreover, interpretivists usually use more qualitative terms and do not rely on many a priori, while positivists prefer quantification and the use of established definitions.

We adopted the interpretivist rhetorical assumption. To our best knowledge, the existing literature about decision making, artificial intelligence within management, and KIFs, does not favor any style of language. Since we recognize that our study may be biased by our experience, our interests, and those of the participants, we chose to write in a personal style to transcribe it in the dissertation itself. Indeed, we believe that language is leaning, and that it is an indicator of the ideologies and preconceptions of the researcher. From that point on, if we wanted to stay honest with the reader we had no choice but to write in a personal style, using words such as 'we think' or 'we chose'.

3.2 Research approach and methodological assumption

The research approach can adopt one of the two main approaches: deductive or inductive. On the one hand, the deductive approach is based on the development of a conceptual framework built upon theories (Collis & Hussey, 2014, p. 7; Bryman et al., 2011, p. 11). The conceptual framework representing the relationships between variables is then tested with empirical observations via assumptions (Collis & Hussey, 2014, p. 7; Bryman et al., 2011, p. 11). Those assumptions must be confirmed or rejected at the end of the study (Collis & Hussey, 2014, p. 7). Deductivism collects specific data of the variables (Bryman et al., 2011, p. 11). Deductivism is a method that moves from *the general to the particular* (Collis & Hussey, 2014, p. 7). On the other hand, inductivism is the opposite of deductivism, that is to say inductivism is a method going from the particular to the general (Collis & Hussey, 2014, p. 7). Therefore, inductivism is based on empirical reality as a starting point that leads to generalization (Collis & Hussey, 2014, p. 7).

We have decided to adopt an inductivist view as our starting point was an observation that AI is a strategic technique to leverage decision making since AI can analyze a lot of data and in a fast and flawless way. AI in decision making has been used to support the decision with suggestions. The perception we have about AI is stained both by the society's fear of AI involved in the destruction of jobs and the potentiality enterprises see in AI. We identified GAFAM and BATX as KIFs that have understood how they can benefit from AI in decision making. We also linked KIFs with a specific organizational architecture as they are known for their agile management and knowledge management. We have privileged trustworthy sources for the thesis as recommended by Collis & Hussey (2014, p. 76) such as books, scientific articles, databases, reports, professional journals, found thanks to Umeå library search, Google Scholar and Elsevier notably. Most of the literature was found on the internet and in two cornerstone books, the first one by Dejoux & Léon (2018) and the other one by Brynjolfsson & McAfee, (2014). However, when to make our empirical observations we have used corporate websites of KIFs, mainly IBM and Atos. We used mostly the keywords presented in the abstract of our thesis to find relevant sources.

3.3 Research design

3.3.1 Qualitative method

There are two main methods to collect data, the quantitative method and the qualitative method. On the one hand, the qualitative method is concerned with the context in which the phenomena under study takes place (Collis & Hussey, 2014, p. 130). The qualitative method is related to the interpretivist paradigm and the result in findings are highly valid (Collis & Hussey, 2014, p. 130; Bryman et al., 2011, p. 27). Validity refers to the extent to which the research findings are representing accurately the phenomena under study (Collis & Hussey, 2014, p. 130; Bryman et al., 2011, p. 42). On the other hand, quantitative study is a precise method that can take place at anytime and anywhere (Collis & Hussey, 2014, p. 130). The quantitative method is associated with the positivist paradigm and the results in findings are highly reliable (Collis & Hussey, 2014, p. 130; Bryman et al., 2011, p. 27). Reliability is about the lack of difference if the study were to be replicated (Collis & Hussey, 2014, p. 130; Bryman et al., 2011, p. 41).

We have chosen the interpretivist paradigm, so the qualitative method is the most suitable choice for our study. Moreover, we want to get better and deeper understandings about AI, the process of decision making within KIFs and how it is combined with the particular organizational design of KIFs. We want to collect rich and in-depth data with a high degree of validity.

3.3.2 Data collection in qualitative method

The data collection process in an interpretivist paradigm is to first select a sample and select a data collection method (Collis & Hussey, 2014, p. 131). A sample can be described as “a subset of the population” (Collis & Hussey, 2014, p. 131). Then, the study must identify what data will be collected to design the questions. It is then of importance to test the questions with a pilot study and make modifications accordingly (Collis & Hussey, 2014, p. 131). Finally, the study can collect the data in an efficient way (Collis & Hussey, 2014, p. 131).

3.3.2.1 Sample selection

To answer our research question and assess the accuracy of our theoretical framework, we chose to collect data through interviews. In order to do so, we first needed to determine the population relevant to our study, and if we had to select a sample. According to Saunders et al. (1997, p. 125), it is necessary to select a sample as soon as it is impractical to question the whole population relevant to the research question. Since the population of our study refers to all the people who have knowledge about KIFs, decision making, and AI, it seemed quickly necessary to select a sample. There are two types of sampling techniques: probability and non-probability (Saunders et al., 1997, p. 126). Since there has been few previous research about AI and decision making, and because it is sometimes difficult to define what are AI and KIFs, making our scope of research and its population hard to precisely determine, we chose non-probability sampling techniques (Saunders et al., 1997, p. 126). We then decided to choose purposive sampling - also called judgmental sampling - because it allows us to select participants according to our judgement; i.e. participants that will be best able to answer our research question according to us (Saunders et al., 1997, p. 145). This is of interest for our study since we were looking for in-depth insights about the current use of AI in decision making and about trends for the future, so that we wanted to interview people who are experts about the subject. This sample technique is also very common when working with small samples (Saunders et al., 1997, p. 145). It was important for us that our sample comprised people working in different companies, also both in startup and big companies, and in different countries, in order to get various findings. We selected: two people from Atos, a multinational French leading IT consulting firm, one working in France and the other one in the Netherlands; two people from IBM, a multinational American leading IT consulting firm, both working in France; two people from Loogup, a Swedish startup proposing solutions through a digital platform for the real estate industry, and one person from KNOCK, a French startup also offering solution on a digital platform in the real estate industry. The size of the company has nothing to do with being or not a KIF. Being a KIF include making a focus on knowledge and be a professional service firm. Furthermore, both IT real estate startups and IT consulting big firms have to cope with an environment characterized by uncertainty, complexity and ambiguity. All the aforementioned companies have incorporated AI in their organization and/or sell AI-embedded products. We provided details of the interviews we conducted in appendix 3, informing about the company name, the number of employee, the language spoken during the interview, the interview position, the date of the interview, the duration of the interview and how we conducted the interview.

3.3.2.2 Data collection method

An interview is defined as "a method for collecting primary data which a sample of interviewees are asked questions to find out what they think, do or feel." (Collis & Hussey, 2014, p. 133). Using interviews to collect data is a good way to "gather valid and reliable data which are relevant to your research question(s) and objectives" (Saunders et al., 1997, p. 210). There are many different types of interviews, including for instance structured interviews, semi-structured interviews, and unstructured interviews, and the choice of the type of interview should be done according to the research questions and objectives, and the purpose and the strategy of the research (Saunders et al., 1997, p. 210). Indeed, the choice of the nature of the interview can lead to different data collection results. We will explain our interview choice in the next section.

3.3.2.3 Interview design

We chose a semi-structured interview approach to give to the researcher more freedom and flexibility in the discussion (Collis & Hussey, 2014, p. 133; Bryman et al., 2011, p. 467). Indeed, during the interview, all the prepared questions do not have to be asked. Prepared questions guide the interview in order to tackle every theme of the literature review (Collis & Hussey, 2014, p. 133; Bryman et al., 2011, p. 467). Semi-structured interview is needed when the researchers focus on a deeper understanding of the interview's opinions and beliefs (Collis & Hussey, 2014, p. 133). Unstructured interview allows more freedom than in semi-structured interview to the interviewee and the risk is to not control what the interviewee says and to not tackle the main themes (Bryman et al., 2011, p. 467). Besides, researchers can waste time when conducting unstructured interviews as they do not have pre- prepared questions and control over the interviewee (Collis & Hussey, 2014, p. 135). That is why we have decided to follow a semi-structured interview approach in order to get deeper understandings of people working with AI and making decisions within KIFs. Moreover, semi-structured interview approach allows us to be more flexible and free during the interview and helps to create a smooth discussion. We were not rigid in our data collection as we did not follow a strict procedure, and we did not let the interviewee discuss about things out of our scope of research as we had prepared questions to encourage the interviewee to discuss about our main themes.

There are two main types of questions, whether close or open. A close question is a question to which someone can answer in a binary way, yes or no, or answer via a predetermined list of answers (Collis & Hussey, 2014, p. 133). On the contrary, an open question cannot be answered with a "yes" or "no"; the interviewee can answer in a more developed way. We have opted for open questions that allow the interviewee to express his/her opinion and explain it. We have designed our interview in six parts.

We present the interview guide and interview questions in the appendix 1 and 2. The first part deals with general information about the background of the interviewees, their current positions and their daily missions. We also asked how they defined AI. Then, in our second part we asked questions about our first theme regarding KIFs and organizational design. The second part is about how the three components of the organizations - actors, commons and PPI- are designed. We mentioned the concept of knowledge as well, that is paramount for KIFs, and how knowledge management is dealt within the enterprise. In a third part, we talked about the decision making approach, processes and the influence of the context over the decision. Then, we asked the interviewee questions about the roles of humans and AI in the decision making process: if AI can be autonomous in the decision, if decision making remains a human task, or the possibility of a partnership between AI and humans. Next, we asked questions about decision making in relation to organizational challenges - uncertainty, ambiguity and complexity. We wanted to know who was the more able between AI and humans to make decisions in uncertain, complex, or ambiguous situations. Finally, we ended the questionnaire with a conclusion part in which we let the interviewee talking about future perspectives and challenges regarding AI and the roles of AI and humans in the decision making process. We let the interviewee time to ask further questions about our study.

3.3.2.4 Pilot study

Specialists when to check interview questions should ensure the quality of the language and the clarity of questions before conducting interviews (Saunders et al., 1997, p. 394). We prepared one template for the interview in English. We conducted the interviews both in English and in French. Before the pilot study, we reviewed our questionnaire with our supervisor to make sure our study were respected the ethical principles and the clarity of the questions. Then, we tested our questionnaire with the brother of one of the researcher to get an idea of the length. We decided after this first interview to shorten our questionnaire and to modify some questions. We had to modify the formulation of some question since they seemed unclear to the respondent. By shortening the questionnaire, we wanted to ensure accuracy, clarity and synthesis, besides, respondents do not have much time to dedicate to the study. Thanks to this feedback, we could modify accordingly our questionnaire and be operational for conducting the study.

3.3.3 Data analysis method for qualitative study - general analytical procedure

The variety and the profundity of qualitative data make it challenging to analyze, especially because "there is no standardized approach to the analysis of qualitative data" (Saunders et al., 1997, p. 340). Unlike in quantitative research, data analysis in qualitative research is not a fixed step of the research. Data collection, data analysis, and the emergence of a set of theories are intertwined steps that nurture one another, so that new hypothesis can be built as the process progresses (Saunders et al., 1997, p. 345). We chose to make the use of existing theories in order to define our research questions and objectives. Then we should also analyze the data using the framework that we built from these theories. Nevertheless, given the extent of our field of research and its limited amount of literature, we also chose to analyze data in an inductive way, because we have assumed that our theoretical framework may be not up to date given the fast change in the technology and progress. Commencing the project with a framework identifying the main themes of the research, and the relationships among them, was a good starting point to guide the analysis (Saunders et al., 1997, p. 349). We therefore tried to follow this initial analytical framework while connecting it to other theories as they emerged through inductive approach.

We made the choice to follow the general analytical procedure as described by Miles and Huberman (1994). This procedure comprises three steps: data reduction, data display, and conclusions. We made summaries of the interviews and then selected the data relevant to our study and simplified it; then we grouped the data within various themes, using tables to gather the parts of the interviews that discuss similar subjects in the same theme. Our theoretical framework helped us to do it, as it also helped us to build connections between the themes in order to organize our findings and give more meaning to them. We attempted to lead these three activities simultaneously, as advised by Miles and Huberman (1994). The last part of the general analytical procedure is also concerned with verifying the validity of our conclusions.

3.3.4 Ethical Considerations

Ethics are related to the moral values that guide people behavior (Collis & Hussey, 2014, p. 30). Research ethics refers to the way the researcher carry the study and how the findings are collected and published (Collis & Hussey, 2014, p. 30). According to Saunders et al. (1997, p. 109), ethics within academical research refers to the appropriateness of the researcher's behavior towards all the people being affected by his/her research, especially regarding the respect of their rights. Scholars have established ethical guidelines for the researchers to follow while conducting the study; we have listed the eleven principles regarding ethical considerations: harm to participants, dignity, informed consent, privacy, confidentiality, anonymity, deception, affiliation, honesty, reciprocity, misrepresentation (Collis & Hussey, 2014, p. 31).

According to Saunders et al. (1997), ethical issues as stated above can be divided into three categories according to the stage of the research. The first type of ethical issues is connected to the design of the research and the way to gain access to data (Saunders et al., 1997, p. 110). To respect the privacy and the informed consent of participants, and to avoid any kind of pressure on them, while seeking interviewees, we explained to each of them, either by email or phone call, that they could withdraw from the process at any time, that their privacy would be strictly respected, and that no information about the use of the data collected would be hidden to them. Moreover, once they had accepted, before any interview, we presented to the participants a piece of paper summarizing all these ethical considerations (Appendix 1), and we asked for their agreement to allow us to use the data collected as stated in our information paper. The second category of ethical issues is concerned with the collection of data (Saunders et al., 1997, p. 110). To maintain objectivity during data collection, i.e. "collect data accurately and fully" (Saunders et al., 1997, p. 112), we recorded all the interviews and then transcribed them so that we were then able to analyze all the data collected on an equal basis, being unaltered by our memory or unconscious choices. We also informed the participants about the use of the data collected during interviews and their right to decline to answer any question, while we avoided putting any pressure on the participants during the interviews due to asking stressful or inconvenient questions. All of these issues are particularly relevant in the case of qualitative research, especially if they include interviews (Saunders et al., 1997, p. 113). The third type of ethical considerations refers to issues arising from the analysis and reporting of data (Saunders et al., 1997, p. 110). We tried to organize our findings and conclusions in the most clear and objective way in order to avoid any misrepresentation (Saunders et al., 1997, p. 114), as well as we maintained the confidentiality and anonymity of the participants in this part of our study. According to Saunders et al. (1997, p. 115), the researchers should take in consideration the "impact of research on the collective interests of those who participate", i.e. that if the researchers are aware that readers could use their conclusions to disadvantage the participants, then they should either inform the participants, or construct their study so that future decisions drawn on their conclusions would not be able to be detrimental to the interests of the participants. In our case, this issue could arise from interviewees fueling widespread fears about the development of AI, such as the replacement of human jobs by machines or ethical considerations regarding AI decisions. To avoid such problems, we built a balanced interview guide so that participants would be able to qualify their answers.

4. Results and findings

In this chapter, the purpose is to present the empirical findings from our qualitative study. We present the data that we collected during the interviews and we organize the findings by firms, starting with the IT consulting firms and moving on with the real estate tech firms. The first IT consulting company we interviewed is Atos, then IBM. The first real estate firm we interviewed is KNOCK and then Loogup. For each company, we synthesize the findings according to the interview guide themes. To transcribe the feelings of the interviewees as honestly as possible, and because they provided us with insightful knowledge, this part may be unusually long. We are aware of this, yet we think it is relevant given the nature of our research and our paradigm. We summarized the findings in the appendix 4.

4.1 Atos

4.1.1 Presentation of Atos

Atos is an IT company founded in 1997. It is the result of the merger between two French IT services companies, Axime and Sligos. Since 2002, Atos has had a consulting division. Atos has offices all around the world as Atos counts around 100 000 employees spread within 73 different countries. Atos has become a worldwide leader in digital transformation, and its approximate annual revenue is €13 billion.

4.1.2 General background of the interviewees

Atos employee 1 is working at Atos as a Big Data integrator. Atos employee 1 is in the cybersecurity and Big Data department, in the branch that is responsible for the collection and gathering of information coming from various sources. Atos employee 1's day-to-day mission is to collect; gather and make sense from the huge amounts of data he receives from Atos. Atos employee 1 is graduated from a famous French engineering school. He specialized in networks, security and system administration and did various research works. AI within Atos is present through ML notably as ML is often linked to Big Data. That is why, a part of the division of Atos employee 1 is working with AI, however his day-to-day missions are more linked to Big Data itself. Atos employee 1 has a strong technical background in engineering and that is why we have decided to orientate the interview towards the technical aspect of AI in order to grasp more accurately what AI can do or not and understand the limitations of AI in decision making.

Atos employee 2 is a business information analyst based in the Netherlands. He is also a trainer specialized in decision making and business solutions. He is expert about this subject, in the sense that he gives courses to other Atos employees. He has a rule-based technology educational background and has been working in business analysis for 25 years. He did not studied AI, so he is not an expert in the techniques, but he looks at it from the perspective of the applications. He teaches about enterprise decision management, aiming to "*make it into real applications and solutions for customers*" as it builds a bridge between traditional business processes and AI and analytics.

4.1.3 A definition of AI and its classification

According to Atos employee 1, AI "includes *a set of techniques that enable a machine to cope with a problem that is not clearly stated by humans, so the machine can adopt its behaviour according to the stated problem.".* AI is not a simple algorithm. AI classification boils down to two main domains. The first one is expert system (ES) (rules, decision trees) and the second one is ML with NLP, image recognition. An ES is "a *set of rules established by humans. ES follow the principle that if there is this type of input there, there will be this type of output.*" In other words, ES is similar to a decision tree. Also, ES is often called a "*white box*" since we can comprehend the links made by the algorithm and the rules of ES are set beforehand by humans.

ML is an algorithm that is learning continuously through training. The model of algorithm used in ML is based on the human neurons and human brain, that is why we call this model of algorithm Artificial Neural Network (ANN). This model functions as the human brain, the neurons in the algorithm are gathered in layers: input layer, hidden layers and output layer. The input layer receives the raw data from humans. Humans get the results of the algorithm from the output layer. Between the first and the last layers, there are hidden layers that connect the neurons with one another. We call them 'hidden' because humans do not understand the connections the algorithm made between neurons. We illustrate the ANN algorithm in Figure 12. ANN is a technique increasingly used in the branch of ML.

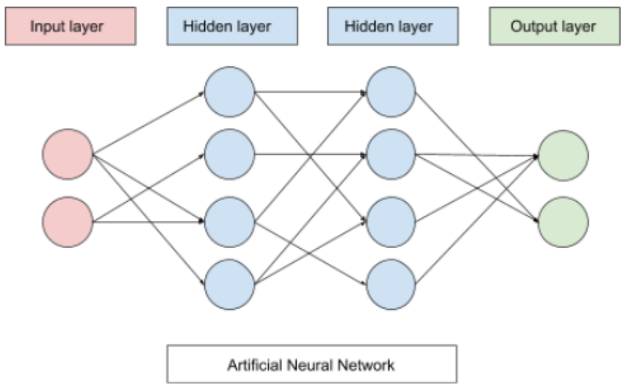

Figure 12: Representation of an Artificial Neural Network, a model of algorithm used in ML

The algorithm's training can be supervised or unsupervised. In supervised training, human's role is determinant as humans will orientate the algorithm and if humans are wrong the algorithm will be wrong too. In supervised training, as input to the ANN, humans will show images and will calculate the expected image outcome for each neuron. Then, humans will make a comparison between the expected outcome and the outcome given by the ANN. Next, if the model did not give the expected outcome humans will, with a retroaction function, change the weight of the inputs to orientate the results.

In supervised training, ML is using labels in order to classify data during the input stage of the algorithm - the input phase is when humans give data to an algorithm and the output phase is the result given by the algorithm - and control the expected outcome. For example, in a binary classification like recognizing a face or not on a picture, we are going to give to the algorithm images that contain a face or not. Then, the algorithm will give us as output two classifications of images, one with faces and the other one without faces. In ML, we can also use features instead of labels in order to get complex data from the output.

However, in unsupervised training, the human role is not determinant as the algorithm learns on its own. The algorithm will be autonomous in the tasks. If we take the example of image classification, we can ask the algorithm to classify the image in clusters, i.e. in a determined number of categories. Also, humans can let the algorithm choose the criteria for each category, or humans can ask the algorithm to classify without precising the number of categories. When the algorithm will classify the images, the choice of classification will not make sense for humans. In that case we talk about "*black box*" among the ANN. Atos employee 2 explains that, at the stage of right now, "*[AI] is just to mimic the cognitive aspects of what a human can do, or several humans.*" Yet, he clarified that this definition narrows down to neural AI, so that AI comprises in fact many other capabilities.

4.1.4 KIFs and organizational design

Regarding the organization, Atos employee 1 is part of a project team that functions in an autonomous way. The team of Atos employee 1 is in direct contact with the project direction department. Atos employee 2 is part of a very self-stirring and dynamic team, which can make its own decisions. The team comprises various expertise holders, who are those supposed to make decisions in a particular field.

Regarding actors, one relevant skill when working on AI projects is, according to Atos employee 1, to know "*what is AI and what is not AI"* in order to be aware of the limits of AI. Otherwise, "*AI fantasies*" can easily lead to a feeling of disenchantment since AI is not able to accomplish everything. AI is a useful technique to tackle a very precise problem using the type of data it was trained on. Atos employee 2 explained that important skills at Atos are those that computers cannot really possess, or at least not yet. He referred to 1) critical thinking, i.e. the ability to discuss information, to assess whether it is valid or not, which is a valuable skill at the time of digital; 2) systemic thinking, i.e. "*always [keeping] the whole in consideration and not only your own task or perspective*"; 3) and empathy, the "*human measure*", which allows humans to think about things that machines cannot between the decision and its implementation.

Concerning the commons, shared situation awareness is used at Atos. For example, on a global level it is represented through committees to keep a global strategy among all branches in order to be on the same page regarding the global strategy. Then, on an individual level, Atos employees communicate digitally shared awareness thanks to internal tools, notably via an internal social network. Atos employees can connect and gather in communities of interests with people from other teams or departments. Besides, knowledge commons are used by Atos employees. Thanks to internal tools like platforms, employees can leverage knowledge from previous projects and experiences coming from other people within the same department. Even though, the sharing of knowledge is delicate when it comes to deal with confidential information. According to Atos employee 2, e-learning and tools that aim to build common interest groups are developed within Atos. Trainings and workshops are also common, in order to "*train [people] to go beyond what is common, what is mainstream*". Thus, he gives courses about enterprise decision management.

In terms of PPI, Atos has adopted an agile management as Atos employees have regular feedbacks and they do a lot of iterations in project development. When we addressed agility, Atos employee 2 pointed out that "*There are a lot of things that are called agile and are not.*" He explained that agility is not about picking out one or two agile tricks in order to follow the trend, but rather than "*Agile, it's a trip, it's in your character. It goes much deeper than just doing some rituals*."

4.1.5 Decision making approach, process and organizational challenges

Atos employee 1 has a rational decision making approach and process. "*First, you have to quantify both your targets and the different levers upon which you can act. Then, you try to reach an optimal match between the targets and the levers. Knowing that in reality there is* *not only one optimal solution. Between all these alternatives, you will have to choose and apply other criteria, related to ethics for example.*" According to Atos employee 1, context in decision making is of importance because it can change its decision making process. Atos employee 2 describes himself as a "*visual thinker*". He first appeals to his intuition, then attempts to figure out the cause of what he intuited, in order to transform intuition into an idea. He tries to find out the rational roots of his intuition, thinking backwards; then he decides to follow or not this intuition. Intuition "*comes from [his]feeling, and this feeling is often based on experience*".

4.1.6 Decision maker: humans and AI in the process of decision making

4.1.6.1 Human processes in decision making

According to Atos employee 1, the advantages of human over machine in decision making are intuition, instinct, moral and ethics. Employee 1 emphasizes the concept of legitimacy in decision making, by saying that humans have a competitive advantage regarding legitimacy over machine. Even if the decision is optimal, the very fact that a machine made this decision will invalidate the choice made. In other words, humans are not ready to accept a decision coming from a machine. The interviewee explained his point of view saying that regarding a human beings' point of view, the decision taken by machines will have effect on humans and not machines. Consequently, humans are not ready to follow machines' decisions that are not considered as members of our society. Atos employee 1 elaborated by saying that if machines are lacking legitimacy, it has something to do with the black box case. In fact, people do not understand how the algorithms function. That is why, people question the legitimacy of an algorithm to make a decision. The challenge of acceptance of AI has been tackled partly in the Cambridge Analytica case when people figured out that algorithms could have influenced their choice during the American elections. In that sense, Atos employee said that our life is already influenced in some way by algorithms.

According to Atos employee 2, in decision making *"humans still have a very important role, because humans are still the owner, they are still responsible*." Atos employee 2 distinguishes between the owner and the executor of the decision. The owner of the decision defines the rules of decisioning and mandates a decision maker – humans or machines - to execute decisions according to these rules; this is called rule-based decisioning. It is the role of the business information analyst to elicit the knowledge in order to define the rules. Thus, the human is in charge and let the machine do autonomous decision making within the boundaries of his rules.

4.1.6.2 AI decision making processes: autonomous AI in decision making

Atos employee 1 thinks that currently we cannot fully give the whole decision making process to machines, and Atos employee 2 thinks that it is possible to a certain extent. Atos employee 1 motivated his argument explaining that machines do not have a global view. Indeed, machines are just trained to solve a very precise problem, they do not integrate a synthesis function. In a decision making process human beings must evaluate several factors that compose the overall picture. Some of those factors cannot be evaluated by a machine today, for instance ethics or feelings. Such things as ethics and feelings cannot be coded and transcribed into rules or algorithms. However, Atos employee 1 thinks that AI has a consistent advantage through ML: the capacity to analyze huge amounts of data. In fact, machines can consider and analyze a lot of cases, especially particular cases, when humans are limited to their memories, their experiences and their peers' experiences. It is what IBM's Watson performs in medical and law fields. Watson's IBM looks into huge databases and finds the particular case adapted to the situation. The more data the human beings can give to the machine to analyze, the more precise the model will be and so the precision of the decision making. Atos employee 1 thinks that "*in the future, we can imagine an almost strong AI that will combine a lot of algorithm sub models, each of the models being specialized to give a decision for a specific task, and they will all give their decisions to a single model of algorithm which will be the synthesis between all these outputs, and this model will take the final decision*".

According to Atos employee 2, machines have no biases, and they are scalable, which are two big advantages compared to humans. He states that "*if you can define decision making with business rules, then you can make a full automated decisioning service based on these rules". He explained that in Atos "[they] elicit the knowledge [necessary] to make the decisions, and [they] can automate decisions and then integrate these automated decisions in business processes*". He believes that many operational decisions can be automated, up to 90% in a company.

4.1.6.3 Partnership between humans and AI in the decision making process

Atos employee 1 thinks that "*as a first step, the optimal decision making is a combination of both humans and AI*" and because "*Nowadays, nobody has seen a machine make a clear-cut decision.*" But then, "*will come a time in which machines will gain legitimacy and we may change our opinion about AI independence in the decision making*." Also, it eases humans to think that they still have a role to play in decision making process. Besides, having humans in the process of decision making enables us to know who is responsible of the decision. Regarding the process of decision making, Atos employee 1 visualized it as follows: "*first humans have to state the problem. Then, humans will use different tools in order to get their algorithms to suggest solutions. Finally, humans will choose among the solutions proposed even if there is only one solution proposed. It is of importance that humans choose because humans can put their subjectivity on the rational decision taken by machines.*" That is why Atos employee 1 thinks that machines are a support and help to the human decision maker more than being autonomous in the decision making: machines analysis of huge amounts of data enable humans to save time.

Atos employee 2's view of humans/machines collaboration is that the responsible -a human being- mandates the machine only when all its rules have been evaluated and validated. In a way he has to know what the machine will decide. Then, he has to ask the right question to the machine, and data scientists have to find the right data and right patterns, following specific methodologies. According to him, "*the decision always keeps explainable to the last detail*": they are no black boxes since data scientists have been recently able to understand all the patterns. Finding the right question to ask to machines is the key element in this process of collaboration. Atos employee 2 outlined that AI needs continual tweaks in its rules in order to be adjusted to changing circumstances, such as rules and regulations, the market, etc… Atos employee 2 believes that AI will replace humans in non-rewarding and repetitive tasks.

4.1.7 Decision making within KIFs

4.1.7.1 Overcoming uncertainty

To overcome the challenge of uncertainty, Atos employee 1 adopts a rather rational decision making process based on opportunity and cost. According to Atos employee 1 rationality is the key to overcome uncertainty; that is why machines are the most suitable in this situation.

According to Atos employee 2, AI can cut out uncertainty. Indeed "*the machine is quite strict on its decision making, but it always depends on the question you ask*", in that way the human beings must ask the right question otherwise humans will not get the appropriate answer.

4.1.7.2 Overcoming complexity

Atos employee 1 considers that ML combined with Big Data like Watson's IBM platform is useful to overcome the challenge of complexity. Atos employee 1 thinks that ES – decision trees that automatically generate an idea - are also useful in the context of complexity, and he said that "*the more data, the more precise the decision making will be*". Indeed, Atos employee 2 believes that AI can manage really huge amounts of complex data, but once again only if the question humanshu ask to AI is the right question. In fact, despite its calculation capabilities, AI is still narrow in its decisioning.

4.1.7.3 Overcoming ambiguity

If the context is ambiguous, Atos employee 1 thinks it will be harder to evaluate and estimate the costs. According to Atos employee 1, ambiguity exerts a lot of pressure and it can influence the way the decision is taken. The situation will require a decision that is related to intuition, instinct and the personality of the decision maker. Atos employee 1 took the case of self-driving cars to illustrate his thoughts. If an accident occurs, the driver of a normal car has less than one second to react. In this case, it is the driver instinct that calls for a decision, so that it can be totally hazardous according to the person that is driving the car. But if we program a car in advance to make a certain decision in each accident situation, there will not be any doubt and hazard about who might die in the accident because we would have made this choice in the programming. In the first situation, with a normal car, humans die and there was not any possibility to forecast who would die. In the second situation, with a self-driving car, we can make a choice. Then, who is responsible for this decision? According to Atos employee 2, asking the right question to AI allows to reduce ambiguity. The process used within Atos to find this right question is to model out the decision and to adjust the questions as humans see the results of the machine. It means that "*if you get the results and the machine gives you ambiguous answers, then you have to think back, and figure out how I could ask questions in that way to remove ambiguity?*"

4.2 IBM

4.2.1 Presentation of IBM

The acronym of IBM means International Business Machines Corporation. IBM - also nicknamed Big Blue - is an American company which headquarters are based in New York, in the United States, with offices spread worldwide. Global Business Services (GBS) is a division of IBM oriented towards IT consulting activity notably. IBM Interactive is a branch that is 100% affiliated to GBS. IBM counts approximately 380,000 employees and that makes IBM among the world's largest employers. In 2017, IBM reached $79.1 billion in revenues.

4.2.2 General background of the interviewees

IBM employee 1 is a subject matter expert, in the service department of GBS. His mission is to find innovative solutions regarding human resources - change management, HR advices, training - for his clients that are mainly CEOs looking to transform their organizations into digital organizations. IBM employee 1's educational background includes both AI and education science. IBM employee 2 is a junior business analyst within the practice of Watson - Watson is IBM's AI program-, in the cognitive branch of IBM Interactive. As a junior business analyst at Watson, IBM employee 2 is designing a chatbot for a client, i.e. IBM employee 2 is training a chatbot. Also, IBM employee 2 has to carry the feasibility study. IBM employee 2 has a master's in international strategy and business intelligence, so everything that is linked to the management of a firm, and she has also done a master thesis within the field of AI.

4.2.3 A definition of AI

To define AI, IBM employee 1 likes to refer to the Turing Test. Though, within IBM employees do not talk about AI but they rather refer to cognitive systems. "*Cognitive systems are based on algorithms that can learn and they are rather oriented on neural networks*." AI is a solution that IBM sells and uses. According to IBM employee 2, "*Nowadays, AI is to put the intelligence of a robot to fulfil human off-putting tasks. AI won't replace humans, AI will assist humans in their basic tasks. Also, currently AI exists in every sector of the economy but in a rather limited way*."

4.2.4 KIFs and organizational design

4.2.4.1 KIF design and PPI

According to IBM employee 1, IBM's organizational design is somewhere between Taylorism and Holacracy. IBM employee 1 defined Holacracy as "*a system of organizational governance based on collective intelligence, that is to say, there is no hierarchical pyramid, no manager…*" According to IBM employee 2, the concepts of collaboration, flat hierarchy and decentralized decision making with self-organizing employees are concepts that IBM is willing to implement. IBM employee 1 said that currently IBM France has a "*matrix organization: the entire organization works in a project mode*," that is to say that each employee has a project leader with a manager and there is one organization per country, per team, per business unit, while IBM employee 2 said that IBM Interactive is considered as a startup and the organization is transforming itself digitally. However, IBM employee 2 explained that within IBM "*we say that everybody is at the same level*" but that in reality, IBM resorts to a hierarchy "*we have junior and senior consultants monitored by managers, so the hierarchy is not so flat*". Also, according to IBM employee 2, employees are quite autonomous in their decision making, but they need the final approval from a senior or manager. IBM employee 2 is totally autonomous and takes initiatives when working with a client. Regarding the collaboration, IBM employees communicate thanks to digital platforms like Slack. Employees of IBM Interactive share their previous experiences and projects to leverage the common knowledge and create a lot of assets in order to use them in future projects.

4.2.4.2 Actors

IBM employee 2 thinks that actors should be as follow "*one should be proactive, be curious, be aware of the technological trends, be different*" since IBM employee 2 explained that this very difference in terms of abilities contributes to the wealth of IBM Interactive. Then, it is paramount to know what AI is capable of doing or not; indeed, IBM employee 2 explained that regarding AI "*in the media, it is not exactly the reality, there is an emphasized feeling*" and "*you cannot accomplish everything, it is not magical*" and this can lead to a misunderstanding between customers and consultants. IBM employee 1 has a different approach regarding skills. IBM employee 1 considers soft skills as an "*outdated*" term for businesses in transition or transformation in a fast-changing environment like IBM, mainly because soft skills are defined and attached to a specific job and the jobs do not exist yet for those businesses, so do the related soft skills, "*Transversal skills are not enough anymore*". Traditionally, IBM's employees are "*mathematicians, data scientists*" according to employee 1; besides*, "in IBM we consider that after two years within the company the employee's skills are obsolete.*" That means that employees must perpetually evolve, think differently and adapt. That is why, IBM employee 1 said that "*in IBM they tend to give more interest to the attitude to continuously learn and having the intellectual agility to learn things*" rather than hard skills. IBM is looking for "*agile brains*" i.e. people that are "*open-minded and can go outside of their comfort zone*".

4.2.4.3 Commons in KIFs

According to IBM employee 1, IBM deals well with knowledge, especially the explicit knowledge. In fact, according to IBM employee 2, the strength of IBM Interactive is how they manage and leverage the creation and sharing of knowledge within the firm. Indeed, IBM invented a "*Netflix for the employee training based on AI*". IBM employee 1 described this Netflix of training: "*This Netflix of training is an algorithm which learns from employees' cognition, the way the employees think, in order to make the most relevant suggestions of training for them.*" and, "*This platform is a hub that will search unstructured information coming from communities of practices, documents shared between employees, in the database, and in the training catalogue*." Moreover, consultants use platforms like Slack to share previous customer projects. Consultants within IBM Interactive create a lot of assets thanks to their wide range of experiences.

However, according to IBM employee 1, part of the knowledge within IBM is lost: the tacit knowledge that exists in the mind of its employee. Indeed, IBM employee 1 explained that "*tacit knowledge is impossible to code, it exists in the mind of experts and experts understand each other and we cannot explain why we don't understand them.*" In order to access to this tacit knowledge, IBM employee 1 said that "*IBM has algorithms that look into abilities and behaviors rather than skills and knowledge, in order to find the person with whom I have to be in contact with to access to his/her tacit knowledge, this is a good demonstration of collective intelligence."* Besides, IBM employee 2 explained how IBM Interactive consultants are relying on collective intelligence "*I had a training about the blockchain by IBM consultants*", and IBM employee 2 concludes by saying "*we self-train between us*". Regarding collective intelligence, IBM employee 2 also mentions the use of communities. For instance, IBM employee 2 explained: "*let us consider the theme of agility, you can enrol to the group related to agility and you will have access to their resources and assets*."

4.2.4.4 PPI

At IBM Interactive they try to do every project in an agile mode. Their processes and protocols are using the agile method; for instance, IBM employee 2 explained to us that "*it is done step by step like the agile method requested. We have all the processes that are related to agile management like the sprint meeting, and the like*". All in all, IBM employee 1 indicated that "*IBM heads towards a more agile organization, more flexible, more design-thinking... all of these approaches head towards Holacracy."* Holacracy is the ultimate organization to aim for according to IBM employee 1.

4.2.5 Decision making approach, process and organizational challenges

According to IBM employee 1 and IBM employee 2 decision making approach and process will depend on the context. IBM employee 1 said that it can be either rational or irrational when choosing for non-important things like an ice cream. Regarding the same type of decisions, IBM employee 2's decision making approach is irrational as she tends to rely on experiences and feelings. She said "*clearly, a decision is based on experiences and feelings. As a human being you have your stories, your knowledge that will enable you to make a decision according to this frame of reference*". Then, IBM employee 2 does not really have a decision making process strictly speaking, she relies on intuition and she tries to rapidly determine what she needs, what she can gain in terms of opportunities. Instead, at work, she will have a rather rational approach and process in which "*I will look, I will observe, I will do a thorough research about the topic, then I will analyze it and next I will decide*", and if the decision concerns a group work, "*we will discuss, brainstorm, benchmark on the topic and then make a decision".*

4.2.6 Decision maker: humans and AI in the process of decision making

4.2.6.1 Human processes in decision making

According to IBM employee 1 and 2, decision making remains a human task. However, IBM employee 2 added a nuance saying that "*Nowadays, I will say yes, but in 10 years I will say no.*" Indeed, it should remain a human task due to the limit of the AI technology but also because humans are gifted with creativity, common sense, critical thinking (IBM employee 1). That is why, they can solve a dilemma, putting this dilemma in perspective in a context, innovating in the solutions proposed. Humans can push the boundaries of our world. All of those characteristics are specific to humans and "*it is not possible to put those specificities into code.*" According to IBM employee 1, humans are gifted with intuition and for this reason "*humans can make an intuitive decision thanks to their own implicit knowledge and experience. Humans cannot explain explicitly why they made this decision but they embrace the decision made and they can visualize it.*" IBM employee 1's motto is "*they did not know it was possible, until they realized it*". According to IBM employee 1, humans always strive towards progress and "*push the boundaries of what is possible, this is something that is subjected to human intelligence*" because if humans program a set of rules, the machine will always abide by the rules the humans put in its code no matter what. Moreover, IBM employee 1 said that "*If you say to the machine that this is impossible to accomplish, the machine won't ever try*" in other words, the machine cannot think outside of the box or contradict the rules. Instead, IBM employee 1 explained that "*humans are proved in History by their desire to push the boundaries and to do the impossible, for example when the first man landed on the Moon or when we first discovered the vaccine*." Also, on an ethical level, humans will still have a role to play and the society is not ready to accept a decision coming from a machine, IBM employee 2 stressed "*one of the most complex challenge towards AI is the society acceptance, it will come a day, but it is like a fourth revolution, so as Internet we have trouble to adopt it, AI has to be accepted, be democratized, and be adopted by the jurisdiction.*" She emphasized then by saying "*acceptability rate of AI is really low, especially among the young.*"

IBM employee 1 thinks that humans have limits regarding "*their brain plasticity in the sense that a person is accustomed to make a decision in a certain way due to his cognitive system and what he learnt during his life.*" In other words, the decision making approach and process is deeply rooted in the people's mind and brain. Considering this limit, IBM employee 1 reckons that humans tend to make a decision by applying the same approach and process; and it is hard to adapt to a new way of decision making. However, IBM employee 1 explained that humans brain can evolve and adapt from one generation to the next using the reference of Michel Serres. Indeed, even if people tend to oppose human intelligence to AI, Michel Serres demonstrates that from one technologic revolution to the next - writing, internet…-, human's brain has evolved from one generation to the next. That is why, humans can change the way they make decisions from one generation to another one. According to IBM employee 1, "*the digital native generation have a different brain plasticity when comparing with Einstein brain plasticity*", so digital native generation makes decisions in a different way. IBM employee 1 extend the topic by saying "*If we consider a generation that will be accustomed to the usage of AI, internet and the like right at the beginning of the primary school, they will consider the approach and process of decision making in a different way and they might make better decisions than the generation of today.*"

4.2.6.2 AI decision making processes: autonomous AI in decision making

IBM employee 1 told us that AI is already autonomous in some processes. On the contrary, for the IBM employee 2, is not possible at all to give the decision making to the robot, she justified it with "*AI is a learning machine, so humans make the decision, that is to say that humans choose what raw data they will give to the machine in order to have suggestions.*" In other words, even if there are algorithms to make a decision, it is humans that will make the decision. Though, IBM employee 1 gave us the example of trading "*AI is completely autonomous is the decision making in the sector of trading for some years because operations in trading are about microsecond*." IBM employee 1 said that there is an example within the financial sector that prevent people from implementing it: "*In the subprime crisis in 2008, machines overreact to the machines witnessing the fall of the market. To stop this domino effect, a human being had to unplug the machine.*"

AI has advantages over humans when it comes to speed of analysis and data storage. However, AI has the following three limits technical, legal and societal. First, for the technical limit, according to IBM employee 1 "*AI is not capable of create something new, solve a new problem, to have common sense or being innovative. Those characteristics are peculiar to humans. That is why, people doubt to what extent an algorithm can drive a car.*" Besides, IBM employee 1 added that AI is based on rules, but when making a decision we have to go beyond the rule because of creativity and innovation, so AI is not able to go beyond the rules as humans do. Second, regarding the legal limit, IBM employee 1 explained that if AI make a bad decision, it is hard to determine who is responsible for the decision and how the legal system can assert the responsibility of AI. To illustrate, IBM employee 1 took the example of the problem of responsibility raised by self-driving car. "*The machine is not able to forecast human behaviours, so accident can occur. In this case, with a self-driving car who is responsible for the accident? The car maker? The owner? or the person who develops the algorithm?*" Third, in regard to societal limits, IBM employee 1 said that AI is not accepted fully by the society and the society does not trust AI. Then, IBM employee 1 illustrated this trust issue within the society: "*when considering AI and means of transport, even if people are not willing to have self-driving car yet, in Lille there is subway without driver.*" and then, he emphasized by saying "*If we consider aeronautics, we are able to take off and land without a driver, but will you go into this plane? It is matter of trust and societal approval.*" IBM employee 1 expressed to what extent he does not think an AI will take over humans in the process of decision making "*In IBM, with cognitive systems it is important to stress that it is never the machine that make a decision*." IBM employee 1 explained his thoughts with the following example "*so for example in the medical field, Watson will suggest protocols, but Watson will never choose the final protocol. Because Watson can read a lot of previous cases, databases; Watson will* *associate reliability percentage to each protocol with explanations; but at the end, it will be the doctor that will make the decision to choose a protocol.*"

4.2.6.3 Partnership between humans and AI in the decision making process

IBM employee 2 described the collaboration between humans and machines as follows: "*machines will replace humans in off-putting tasks to enable humans to focus on what truly matters in their job, on the core business, on the added value, while nowadays we have lost this added value.*" Machines will make the analysis and humans will make a decision thanks to their larger spectrum of knowledge. On one side, the advantages of humans over machines are their humanity, their emotions and how they can be empathetic towards one another while machines stay impartial. On the other side, the advantages of machines are their ability to analyze a huge amount of data in order to be more accurate and have a thorough analysis. The idea that humans and machines are completing each other has been expressed by IBM employee 1: "*the combination of the machine and the man is superior if we consider just the man or just the machine. We can hypothesize that in the decision making process, the human decision making and the machine decision making are less effective than the decisions made by humans augmented thanks to the machine*"; in other words they believe that a partnership between humans and AI in decision making processes are more effective than only machines or humans on their own. That is why, IBM employee 1 said that at IBM they prefer to talk about "*augmented intelligence rather than artificial intelligence*". IBM employee 1 demonstrated his thought with the following example: "*IBM has identified that when asking a human being and a machine to diagnose on their own cancer cells, the human being was able to identify up to 90% of cancer cells, the machine up to 95% but the partnership between the human being and the machine was able to identify up to 97%.*"

4.2.7 Decision making within KIFs

4.2.7.1 Overcoming uncertainty

To overcome the challenge of uncertainty, according to IBM employee 1, AI can be a support in the decision making process or can replace humans in the process while IBM employee 2 thinks that the most qualified decision maker is human being. Indeed, IBM employee 2 explained that "*humans can decide because humans can embrace and visualize the decision and humans will understand the current trends*". On the contrary, IBM employee 1 thinks that AI can help the decision making in uncertain context by reducing the risk. IBM employee 1 took the following example: "*banks when granting a loan to a client, will evaluate the risk related to the client's loan. Thanks to AI, banks will use data mining and classical systems to assert the risk completed by non-structured information found on internet, social networks and the like in order to profile the client. Then, AI will be able to suggest a level of risk to the banker.*" Second, IBM employee 1 explained to us how AI can be a support or a substitute to the human decision maker in uncertain situations by being objective and reducing human biases when they make decisions. IBM employee 1 illustrated his argument with the following example. When considering the aeronautics, there are two schools of thoughts regarding the role of AI in the decision making process: Airbus and Boeing ones. Boeing follows the principle that the final decision should always be granted to humans while Airbus operates with the opposite principle, i.e. when there is inconsistency in human decision making, the machine can take over the decision from humans. To do so, at the beginning, a firm can decide the level of involvement of machines in the decision making process and then, the firm will integrate this parameter in its information systems, mechanics and computerization. IBM employee 1 elaborated his argument with this case in point: when the Airbus A320 landed miraculously on the Hudson river in New York, the pilot made the decision to land but it was the machine that took over the landing because it was impossible for humans to deal with such situation; then according to IBM employee 1" *If it were a Boeing, the plane might have crashed*."

4.2.7.2 Overcoming complexity

To overcome complexity, IBM employee 1 thinks that AI makes decisions that are faster and more relevant, and so IBM employee 2, because "machines can manage better the variability and several factors in order to make more accurate and reliable decisions". In fact, she explained that machines can handle better several factors at a time compared to humans, and IBM employee 1 explained that "*AI has the ability to aggregate enormous amounts of information coming from different sources depending on the different factors at stake, analyze quickly all those information, and make a decision accordingly*." Moreover, IBM employee 1 argued that AI can act fast and has the ability to forecast what is likely to happen thank to its analysis. IBM employee 1 explained that "if *we consider trading, it is a complex environment because it depends on different factors, the market evolution and other events. Trading firms choose to give the decision to machines instead of humans in order to gain profits because machines can react faster than humans thanks to the power of computer and the speed of their analysis.*" Moreover, IBM employee 1 added that nowadays, trading operations occur in less than one nanosecond, that is why humans cannot compete with such speed of calculation. However, the final decision should be made by humans even if machines have a better analysis according to IBM employee 2.

4.2.7.3 Overcoming ambiguity

To overcome the challenge of ambiguity, IBM employee 1 believes that humans can solve the problem thanks to their sense making, their critical thinking, and their contextualization. On the contrary, IBM employee 2 considers that the most qualified decision maker is the machine, notably because "*the machine will stay objective about the decision, so the source of ambiguity will be removed. Besides, the analysis will be better, but the final decision should come from humans*." Because of the three limits of AI, technical, legal and societal, IBM employee 1 thinks it is not possible to let a machine decide in ambiguous context, indeed "*We do not know how to code a machine to solve an ambiguous situation, and if it was the case, legal limits would not allow a machine to decide because we never know when a dysfunction can occur and who would be hold responsible for this failure.*" Also, according to IBM employee 1, the society has not accepted yet the use of machines in the decision making process.

4.3 KNOCK & Loogup

4.3.1 Presentation of KNOCK & Loogup

KNOCK and Loogup are two startups in the real estate industry. The first one is located in France, and the latter in Sweden. Both are working on their national market. These companies share many similarities, that is why we decided to group the results of their interviewees. KNOCK and Loogup aim to improve the quality of property search using machine learning. People seeking a property first have to explain what they are looking for, on the website. Then, as their AI learns about user's preferences, it is able to propose them property choices that are more and more accurate. Both companies are early-stage startups.

4.3.2 General background of the interviewees

KNOCK employee is a business developer. Nevertheless, given the size of the company, his activities are broader. His main mission is to find funding for the company, through banks, investors, or subventions. Other activities include management, and to some extent, marketing and communication. KNOCK employee has a business-oriented educational background. He specialized in finance and entrepreneurship, with previous experiences in venture capitalist firms and another finance firm. Loogup employee 1 is the CEO. He has a business background. His missions include business development, communication, and defining the overall strategy of the firm. Loogup employee 2 is a full stack developer. He has a technical background and studied computing sciences. His missions are to code the machine learning AI, as well as the website, and test it. It is important to keep in mind that since the interviewees are working in early-stage startups, their missions are overlapping.

4.3.3 A definition of AI

KNOCK employee sees AI as a machine that can make considered decisions. According to him, "i*t is not binary anymore [...], it is the machine ability to be agile; it means questioning the decisions made and learn from its mistakes, it is this capacity of thinking.*" Loogup employees 1 and 2 refer to AI as the "*capability of computers to replicate human behaviours, specifically related to cognitive performance*". They both outline the importance of thinking abilities.

4.3.4 KIF and organizational design

KNOCK's organizational design is highly flexible. The hierarchy is flat, everyone can make a decision, expose their ideas, give and receive feedbacks, etc. Decision making is highly decentralized, and collaboration is encouraged as part of the decision making process. According to KNOCK employee, part of that situation can be explained by the small size of the company; for instance, a pyramidal hierarchy would not have any meaning in such a small organization. Thus, commons are loose, and employees regularly work together as they do not have strictly defined tasks. Nevertheless, KNOCK employee states that efforts are made in order to structure the organization as it develops. If he thinks that "*KNOCK is agile just as every startup today*", he also argues that "*it is very important to be agile [for an AI startup]; it means being able to code something, develop a process, and then realize that it doesn't work or not as good as expected, so that you can change method*". Loogup employees 1 and 2 also said that their organization has no other choice than to be flat since it is an early-stage startup of only three persons. According to them, key skills that they need are soft skills such as reactivity, fast-learning, proactiveness, motivation, passion, not being afraid to fail, along with some hard skills. Their commons are informal: since all the members of the organization have distinct and complementary roles, they are constantly overlapping with advice, feedbacks, etc. The use of the communication and sharing platform Slack seems to be the most formalized common. Both employees think that agility is a necessity for Loogup given the size and stage of the company. It comprises a high level of communication and consultation in order to take decisions for instance.

4.3.5 Decision making approach, process and organizational challenges

KNOCK employee explains that the way he makes decisions is fully rational. He relies on facts that he will analyze in order to make a decision. According to him, each decision depends on the context, so that a preliminary analysis is necessary. "*A non-contextual decision is a decision without any impact; it doesn't work, it can even result in lower* *performance*". Loogup employee 1 adapts his approach depending on the stakes related to the decision. Thus, he does not follow a methodological way for little stakes. For important stakes, he will think in terms of opportunity costs, especially when there are many variables. He prefers choosing things that he already knows, because in that case he already knows the impact of his decision. Loogup employee 2 often trusts his gut feelings to make decisions, based on intuition and experiences. But when it comes to big decisions, like choosing an apartment, he will be more rational, compare options, etc. Both Loogup employees have decision making approaches and processes that depending on what is at stake and on the number of variables.

4.3.6 Decision maker: humans and AI in the process of decision making

4.3.6.1 Human processes in decision making

KNOCK employee thinks that humans should keep dominating the decision making system. Loogup employees 1 and 2 point out that the biggest lack of machines in decision making is about common sense and intuition, that are both crucial in decisions related to management. That's why managerial decisions are not suitable for machines: it should remain a human task according to them.

4.3.6.2 AI decision making processes: autonomous AI in decision making

KNOCK employee thinks that at the moment we cannot entrust decision making to machines. He took the example of his company, in which AI only makes a property proposition to the user; a value proposition. The user can then accept to visit it, or decline. He argues that, if decision making were to be fully entrusted to AI, the mistakes done by machines would strongly question the trust of users in the power of AI. Nevertheless, he believes that this problem could be solved in the future thanks to the rise in the training and relevance of machines, and because it improves the user experience. Loogup employees 1 and 2 think that machines can make decisions on their own if they are concerned with decisions that are repetitive for humans and act on a small scale. They argue that machines are better than humans to find patterns, to give meaning to data, as well as to treat huge amounts of data.

4.3.6.3 Partnership between humans and AI in the decision making process

KNOCK employee emphasizes that it is crucial that the use of AI remains invisible for users, i.e. users should not be aware of the use of AI in a purpose of simplification. He thinks that AI should always remain at the service of users. According to him, the human/machine decision making process is: 1) humans pose a question; 2) machines facilitate solving the problem; 3) humans decide in the end. Loogup employees 1 and 2 share the same view about human/machine collaboration. They think that "AI allows to enhance human capabilities, to find patterns that humans could not find alone" They see AI as a tool for humans in the decision making process. They also share the vision of the human/machine collaboration in decision making that AI analyzes the data, and humans take the final decision.

KNOCK employee thinks that the only people who may be scared about the use of AI are those who could lose their current job. He referred to the automated warehouse of Amazon in which machines are doing almost everything. Yet he argues that in the end it does not suppress jobs: instead it modifies them and morphs them into something new. Loogup employee 1 believes that ethics is not the main issue in the development of AI at the moment. He thinks that there is today no limit for research on AI; research is ongoing. On the contrary, Loogup employee 2 believes that AI is a revolution, both technological and societal, and that the main challenges are not technical, but about to find a consensus to say what is right and wrong. He thinks this is particularly hard because we are already not able to define it for humans… So, what about for machines? He referred to "wrong" uses of the technology, such as the use of personal data by Cambridge Analytica, and the AI Tay by Microsoft who turned out to become racist. Both Loogup employees agree on safety issues about AI.

4.3.7 Decision making within KIFss

4.3.7.1 Overcoming uncertainty

As he thinks that decision making has to be rational and must rely on facts, KNOCK employee said, "*when I have to make a decision, I want numbers*". In a situation of uncertainty, AI, like other technologies, can help humans by making predictions about the outputs of each alternative. KNOCK employee argues that machines can provide the decision maker - a human being - with probabilities of success and failures of the alternatives, with the margin of error, based on statistics, in order to reduce uncertainty for humans. Loogup employees 1 and 2 address that there is some uncertainty about what machines can do. For instance, neural networks can make propositions using patterns that we will never know nor understand. This process - black box - raises important issues for decision making.

4.3.7.2 Overcoming complexity

KNOCK employee said that "*it is in the nature of AI to analyze a big number of alternatives and possibilities*". He believes that in complex and objectives situations, machines are more powerful than humans, so that they can take more accurate decisions. He used the example of Go game, which is made of binary choices - moving pieces forward or backwards - and in which AI defeated the human champion. Loogup employees 1 and 2 share this view as they think that machines are able to treat huge amounts of data that humans cannot, so that they are more relevant to overcome complexity.

4.3.7.3 Overcoming ambiguity

KNOCK employee argues that when dealing with human problematics - for instance whether firing an employee or not - AI cannot help, because it cannot bring objectivity where there is only subjectivity. He emphasizes this distinction between objective and subjective decision making situations by adding that most of people think that AI will do everything in the future, yet it cannot understand humans since they are too complex, in a subjective way. Loogup employee 1 thinks that machines cannot build empathy and that is why humans are better for decisions related to empathy, such as management and social decisions. In an ambiguous situation, Loogup employee 2 outlines the importance of the human/machine collaboration. Indeed, according to him, machines are more likely to make objective decisions in a situation that may have different meanings, while only humans are able to adapt their suggestions to the reality through their common sense.

We presented a summary of the findings in the appendix 4.

5. Analysis and discussion

In this chapter, the purpose is to analyze our results and findings developed in chapter 4 considering the theories that we developed in the theoretical framework in chapter 2. The cornerstone of our thesis, the roles of AI and humans in the organizational decision making process within KIFs, is analyzed and discussed through the following topics: (1) the role of decision maker and organizational challenges; (2) organizational design suited for AI in KIFs and; (3) new challenges linked to AI in decision making.

5.1 The role of decision maker and organizational challenges

5.1.1 The role of AI in decision making

5.1.1.1 AI unique capabilities in decision making

Most of the interviewees think about AI as a system that heads towards imitating the human brain, i.e. how humans think. Yet they also emphasized its unique capabilities. AI appeals to algorithms and machines in order to perform assigned tasks, giving to AI many advantages over humans. First, thanks to its computing power, AI can store more data and process it faster than human brains, leading to improved analysis. It can also access real-time data so that storage is not even a problem anymore. All of this makes AI able to find patterns, to give meaning to data, as well as to treat huge amounts of data more effectively than humans, which is consistent with our theory (Jarrahi, 2018; Parry et al., 2016). ML is empowered by data, so that the more AI is nurtured with data, the more precisely it will analyze. This is particularly useful in the era of Big Data and digitalization (Dejoux & Léon, 2018). Secondly, AI is objective, fully rational, and scalable. As outlined by Atos interviewees, machines are not concerned with human biases in decision making, such as conflicts of interests and fears, or language barriers and sociocultural idiosyncrasies (Parry et al., 2016, p. 576). AI analyzes the data in order to come up with the best solutions for a certain problem, following its algorithmic rules, and nothing else, so that its analysis relies only on verified facts (Parry et al., 2016, p. 577, 580). AI is scalable in the sense that when it has resolved one problem, it is able to strictly transpose its way of reasoning to a similar problem, while assessing the singularity of the new problem via its objectivity capabilities, which is consistent with Parry et al. (2016, p. 577). The objectivity and the superior analysis capabilities of machines make them able to efficiently predict future events basing on the current reality. Thus, one startup employee noticed that AI can make forecasts using probabilities and margins of errors, which may make them predict the future more accurately than humans (Parry et al., 2016, p. 580).

5.1.1.2 The scope of AI's autonomy in decision making

The advantages of AI discussed in the previous section suggest that AI possesses several skills that are necessary to make a decision, and that AI outperforms humans on some of these skills. Consequently, one can legitimately wonder if AI is able to make decisions in an autonomous way. When analyzing our results, we noticed that AI seems to be already autonomous regarding decisions taken at a limited scale, especially according to the IT consulting firms interviewees. These decisions are usually repetitive and thankless tasks for humans. They can be fully automated since they require only capabilities in which machines are better than humans, such as objectivity and dealing with a huge amount of data. In fact, AI is used in enterprises to deal with "routine operational decision processes that are fairly well structured" (Parry et al., 2016, p. 573) as part of GDSD, as mentioned in chapter 2.

Such automated decisions already exist within high frequency trading and stock management.

However, although AI is autonomous along the whole process of decision making, all the interviewees agree that its reasoning and decisions remain within the boundaries set by humans, i.e. the rules of the algorithms. This is called rule-based decision making. Machines make decisions only on what they have been programmed for. Thus, developers in fact already know the decisions that machines will take, because they programmed the algorithms so that they always bring the same solution to a given set of facts. The term 'decision' may then be inappropriate for machines because it is their designer who actually made the decision, and they simply reproduced it (Pomerol, 1997, p. 19). AI autonomous decision making today is restricted to the weak AI (Dejoux & Léon, 2018, p. 190, 191). Interviewees emphasized that AI does not have a global view of the problems and that humans still always have a role in the decision making process by making the final decision and controlling AI actions, like unplugging the machine if it turns very bad for instance. Indeed, without human last control, the current AI will make some mistakes so that users would question their trust in the power of machines.

5.1.2 The role of humans in decision making

There are many reasons to explain why humans should always have the last word in decision making. Machines follow a strictly rational decision making process, reproducing the reasoning of their designers. But through their intuition, humans can refer to their emotions and their automatisms derived from past experience to make decisions without using the rational processes (Kahneman, 2003, p. 698). They are then able to make decisions using thought processes that are inaccessible to machines (Dejoux & Léon, 2018, p. 206).

Intuition seems to be related to various characteristics that weak AI cannot imitate, such as empathy, creativity, common sense, critical thinking, or imagination. Neither of them can be transformed into code, so that humans keep dominating the decision making process. In rule-based decision making, ML morphs algorithms into experts of a particular field, but they are unable to think outside of the box, lacking intuitive capabilities (Dejoux & Léon, 2018, p. 206; Sadler-Smith & Shefy, 2004, p. 78). It appears from our results that, for this reason, humans are the 'owners' of the decision. They can mandate a machine in order to make the decision, but always within the framework they have defined. Thus, humans orientate the work of AI using their unique capabilities; for instance, they use their common sense in order to come up with decisions which are actually possible to implement. Humans also adapt AI decisions to the reality; for instance, they can use their understanding of moral and ethics to prevent AI to implement solutions that are not acceptable by the society.

Finally, it appears that humans have an advantage of legitimacy over AI in decision making, that was raised by interviewees from all the companies. People are more likely to accept decisions made by their peers than by machines, even if it may evolve in the future. Having a human being who has the last word to make decisions is then comforting both for users and employees. We will discuss this issue further in section 5.3.3. To summarize, using the two-system decision making approach as mentioned in the theory (Kahneman, 2003, p. 698; Johnson, 2017, p. 512), it seems that reasoning is imitated by machines while intuition cannot be imitated, and that, AI imitates human reasoning in a more narrow but powerful way. Thus, all the decisions directly related to human characteristics, such as managerial decisions, are not suitable for machines, and should remain human tasks. IBM employee 1 outlined that human intelligence is also unique and inimitable in the sense that humans always *"push the boundaries of what is possible"*.

5.1.3 Collaboration between AI and humans in decision making

All the KIFs interviewed agreed on the fact that the combination of the human and artificial intelligences is superior to the intelligences of humans and/or machines considered independently, stemming from the respective assets of human and machine intelligences as explained in sections 5.1.1 and 5.1.2. One of the most important challenge for organizations is then to successfully combine these two components. Our findings about the respective advantages of humans and AI confirm the theory developed in section 2.4.3 that machines should assume the role of rationality and humans the role of intuition within a mixed decision making system.

Consistent with Jarrahi (2018, p. 5), there is a need for a human/machine symbiosis in order to combine the superior ability of machines in collecting and analyzing information related to intertwined factors with the contextualization and experiences of the human brain. It appears from our study that humans state the problem to machines; then machines come up with suggestions among those humans will choose. The challenge is about to state it properly. The whole process starts with the decisions owner, who is responsible for the decision. He chooses a machine as the executor of this decision. The executor analyses the situation using its advanced computing power. The executor then proposes a solution to the human decision maker, who examines it. The decision maker can choose to implement the solution directly, to adapt it before implementing it, or to refuse it and ask for a new solution to the machine. (Pomerol, 1997, p. 22). This process is illustrated in Figure 13. The main difference with the process presented in Figure 9 (section 2.4.3) is that humans can find AI's proposition unsatisfying and start the process again. In any case humans have the last word so that they can gauge the fit between AI's suggestion and the context which some of the parameters are imperceptible for algorithms. AI is a tool for humans, whose decision making is augmented. According to the situation, the decision owner can also choose to mandate humans to propose solutions.

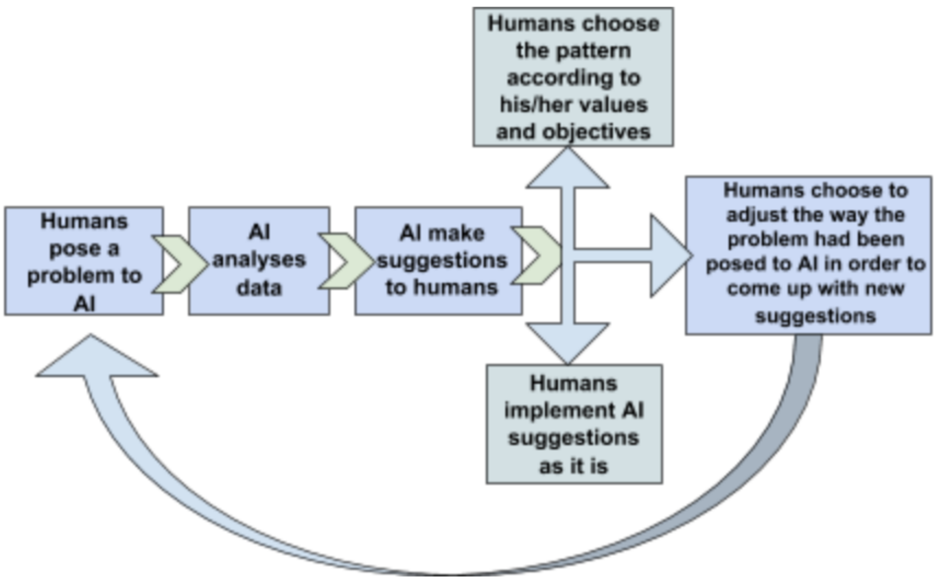

Figure 13: Process of decision making between AI and humans: AI as a tool for the human decision owner (framework developed from Figure 9 and adapted from Dejoux & Léon, 2018, p. 203)

Current AI need to be asked precise questions, they are not generalist. According to Atos employee 2 they are" *narrow in their decisioning"* in the sense that their algorithms are trained to possess specialized knowledge. That is why humans also have a role at the beginning of the process. That is also why AI needs continual tweaks in order to be adjusted to changing circumstances, such as rules and regulations, the market, etc. Our findings reveal that machines should replace humans in thankless and repetitive tasks so that they will be able to focus on the core of their job, i.e. what truly matters (Dejoux & Léon, 2018, p. 218) This type of tasks mainly comprises finding, analyzing and presenting a huge amount of data, and making sense from it through pattern recognition. This combination of decisioning systems allows humans to be augmented in their decision making (Dejoux & Léon, 2018, p. 218; Jarrahi, 2018, p.7).

5.2 Organizational design suited for AI in KIFs

On the one hand, the real estate tech firms have a flexible and flat organization. On the other hand, the structure of IT consulting firms interviewed are matrix organization, as employees described to be working with a project team, in an autonomous way and making decentralized decisions (Fjeldstad et al., 2012, p. 738). Their organizations comprise different units and dimensions according to countries and departments. Particularly, one of the employee described the organization design as being in between of Taylorism and Holacracy. Besides, one of the employee in one of the IT consulting firms stressed that the concept of decentralized decision making, collaboration and flat hierarchy with self-organizing employees are concepts that his firm wants to implement. Matrix organizations are also characterized by control and processes (Fjeldstad et al., 2012, p. 738). Holacracy is based on collective intelligence, the absence of hierarchy and the absence of managers. The real estate tech firms interviewed rely on the concept of collaboration, flat hierarchy and decentralized decision making with autonomous employees. On the face of it, it appears that the interviewed firms adopt or move towards an actor-oriented architecture for their organizational design when using AI (Fjeldstad et al., 2012, p. 739).

5.2.1 Actors in KIFs

As aforementioned in the chapter 2, actors in an actor-oriented architecture have knowledge, skills and values for digital organization where they can work with digital co-workers (Snow et al., 2017, p. 8). When analyzing our results, the hard skills that appeared to be the most important in KIFs are sensitivity to digitalization and a basic knowledge of what AI can accomplish in order to avoid any AI fantasy or to have a misjudgment about AI capabilities - mainly due to the fuss made by media - (Dejoux & Léon, 2018, p. 209, 219). In fact, humans and AI can collaborate in decision making if humans have a basic knowledge about AI abilities and mechanisms (Snow et al., 2017, p. 8; Dejoux & Léon, 2018, p. 209, 219). Then, one interviewee mentions a hard skill related to computational thinking, and information and communication technologies literacy mentioned by Snow et al. (2017, p. 8). Finally, IT consulting employees mentioned how important the knowledge management is for their organization, indeed one of the employees at IBM qualified it as a strength as employees share at their best, knowledge to create benefits for the organization (Snow et al., 2017, p. 8; Hendarmana & Tjakraatmadjab, 2012; Liebowitz, 2001).

For the soft skills, it appears that the collaborative skills and the social intelligence are the most important skills as all interviewees referred to the use of digital tools - notably Slack, intranet- to collaborate, communicate, share and create knowledge with actors and digital co-workers. The sense-making is also a skill that most of the interviewees mentioned. Sense-making enables actors to make decisions according to their critical thinking; for example, actors with a common sense can control AI suggestions in the process of decision making. The abilities to contextualize and to be empathic are also paramount for the decision making process especially coupled with AI that lacks emotions and an overview of the situation. The transdisciplinarity and design thinking have been discussed by one interviewee, he considered that actors should demonstrate more than transversal skills and design thinking is a method to achieve the ultimate organization. In fact, Dejoux & Léon, (2017, p. 57, 219) presented the manager in the digital age as a person able to demonstrate transdisciplinary, but also three other skills that are all related to the skills of design thinking. Moreover, when analyzing the findings, it appears that interviewees believed that soft skills are specific to humans, soft skills cannot be imitated nowadays by machines and soft skills are competitive advantages humans have over machine.

However, one of the IT consulting employee underlined that hard and soft skills are notions that are not enough to define actors in KIFs, "*in IBM they tend to give more interest to the attitude to continuously learn and having the intellectual agility to learn things*". Indeed, actors in KIFs should consider attitudes instead of hard and soft skills because such organizations are evolving and adapting continuously to the need of the market, as their environment is characterized by fast-pace & ever changing. That is why, one interview said that a paramount attitude is to be agile, that is to say to be able to continuously learn new knowledge, to be open-minded to new practices and to be able to go out of its comfort zone.

The analysis of the findings supports Snow et al., (2017, p. 10), Brynjolfsson & McAfee, (2014, p. 16-20) and Dejoux & Léon, (2018, p. 55, 210, 211) theories about soft skills in KIFs including social intelligence, collaboration capabilities, transdisciplinarity, sense-making, critical thinking and design mindset that includes empathy and creativity. Also, the findings confirm that soft skills cannot be emulated by machines and are a competitive advantage for humans (Brynjolfsson & McAfee, 2014, p. 16-20). Besides, it is in line with the theory of Snow et al., (2017, p. 10), digital technologies are integrated into internal tools in the organization to enable actors to collaborate between them and with digital co-workers.

5.2.2 Commons in KIFs

The first common concerns the share situation awareness, on which only one employee mentioned committees happening in his organization in order to know what is happening at a global strategy scale. Instead, all interviewees have mentioned digitally shared awareness through digital platforms like Slack, intranet, internal social networks and websites of communities of interest to enable them to create and share resources with all the members of the organizations. That so, in KIFs actors share situation awareness mainly thanks to digital tools (Snow et al., 2017, p. 7, 10).

The second commons, knowledge commons, have been discussed by the two IT consulting firms as being of high importance. Indeed, one of the interviewees said that one of the strength of IBM was the ability of the company to create and share knowledge and that this knowledge comes from different sources like platforms, networks, websites, communities of interests. Regarding explicit knowledge, all IT consulting firms mentioned training thanks to e-learning, workshops and digital training platforms based on AI. One IT consulting firm elaborated more saying that they created a "*Netflix for the employee training based on AI*" and that "*This platform is a hub that will search unstructured information coming from communities of practices, documents shared between employees, in the database, and in the training catalogue*." Besides, all IT consulting firms also create explicit knowledge based on their employees' activities, indeed actors share knowledge from previous projects and experiences and they share through digital platform to the organization. However, the whole organization cannot access to information but only teams and departments, in order to preserve the confidentiality of customer data. With regards to tacit knowledge, one of the IT consulting firms said that tacit knowledge is not possible to code as it is based on experiences, feelings, mindset, etc. To cope with this loss, organizations can rely on collective intelligence through (1) digital platforms that can connect people according to their tacit knowledge; (2) communities of interest; (3) and workshops organized by employees. Thus, the findings and analysis are in line with the theory of the chapter 2, even if the chapter 2 did not emphasize the loss of tacit knowledge. This loss is balanced by the use of communities of interest animated by employees to share the best practices and the use of an open online platform to allow and ameliorate the sharing of knowledge throughout the different departments (Dejoux & Léon, 2018; Fjeldstad et al.,2012, p. 741; Galbraith, 2014; Snow et al., 2017, p. 10).

The two types of commons are in line with the theory of actor-oriented architecture in KIFs (Snow et al., 2017, p. 7, 10). Indeed, as we stressed in the second chapter, knowledge is a paramount concept and that is why the second common related to knowledge commons have been more mentioned and developed by the interviewees on average compared to the first commons. Knowledge commons enable actors in KIFs to evolve, to adapt and to learn within an organization (Snow et al., 2017, p. 10).

5.2.3 PPI in KIFs

As mentioned in 5.2.2 in the commons, all interviewees mention infrastructures i.e. communication networks and computer servers to smooth the collaboration and the sharing of knowledge.

The majority of interviewees said that protocols regarding the division of labor and decision making position: (1) the human as the final decision maker. Humans have an important role to play in decision making process; (2) AI as the assistant which suggests decisions. However, one IT consulting firm believed that AI could have a bigger role and that autonomous AI-based decision making could represent up 90 % of the operations within an organization, he explained by saying "*we elicit the knowledge to make the decisions, and we can automate decisions and then integrate these automated decisions in business processes*". Indeed, all interviewees agree with the fact that AI has a competitive advantage when considering analysis and aggregation of information within an enterprise. However, almost all interviewees agree with the competitive advantages of humans over machines when considering creativity, sense-making, critical thinking, empathy, notably because "*it is not possible to put those specificities into code.*" So, to a certain extent, AI can handle routine decisions, but humans still have an important role to play in the decision making process.

For the processes, all firms want to foster an agile organization and sometimes coupled with design thinking. Design thinking was mentioned only one time by an IT consulting company. Design thinking enables actors to create jointly with their customers by being empathic and innovative. Working with an agile management enables actors to work in project mode, with regular feedbacks and iterations in order to be reactive and proactive to market changes. Within one IT consulting firms, all the projects are agile, and the protocols and processes are based on agility. For one real estate tech firm, agility is of importance as it allows to develop a process, test and experiment it in order to reach the optimal state, indeed "*Knock is agile just as every startup today*"; he also argues that *"it is very important to be agile [for an AI startup]; it means being able to code something, develop a process, and then realize that it doesn't work or not as good as expected, so that you can change* *method*". Agile management enables actors to be autonomous in their decision making because the decision is decentralized to the individuals or the teams. Agile management is suitable for KIFs because it enables KIFs to act fast and adapt. Furthermore, the findings are in line with the theory of Staub et al., (2015) that linked AI and specifically ANN to agility; all firms using AI adopt an agile management. However, one IT consulting interviewee was quite critical towards agile management saying that agile management is not just a process but a mindset and an attitude as we have presented in section 5.2.1.: "*Agile, it's a trip, it's in your character. It goes much deeper than just doing some rituals.*"

In the process of knowledge management, the IT consulting firms use infrastructures and protocols to share the common knowledge as we have presented it in the part 5.2.2. and they utilized the four categories involved in knowledge management process. In fact, the first category is externalization and actors are completing it by sharing their previous project and experiences thanks to knowledge commons and infrastructures. Then, the second category combination refers to the aggregation of knowledge commons created by actors coming from different sources and accessible via platforms like Slack, or intranet. Next, the third category, internationalization, occurred through e-learning, workshops, training platforms. Finally, socialization happened thanks to collective intelligence enabled by the communities of interests, internal social networks, intranets and workshops. One IT consulting firm highlighted the usage of workshop ("*I had a training about the blockchain by IBM consultants*") and of communities of interests ("*let us consider the theme of agility, you can enrol to the group related to agility and you will have access to their resources and assets*").

PPI described in the findings and analysis correspond to the theories. Indeed, infrastructures in KIFs are mainly represented by communication networks and computer servers (Snow et al., 2017, p. 11). Infrastructures are paramount to enable actors to have access to knowledge commons and experience knowledge management processes (Fjeldstad et al., 2012, p. 739; Alyoubi, 2015, p. 281). Besides, with the rise of AI within enterprises, protocols describing tasks attributed to humans vary from one company to another but on average it is consistent with the new division of labor described in the chapter 2 where AI does the analysis and repetitive tasks while humans use their competitive advantages to make the final decisions (Brynjolfsson & McAfee, 2014, p. 16, 17). Moreover, regarding the processes within KIFs, the fast-changing environment tends to foster an agile organization in all the firms that we interviewed, which enables the actors to adapt and change rapidly, and to make decentralized and local decisions (Snow et al., 2017, p. 6; Dejoux & Léon, 2018, p. 42, 46). The agility process can be completed by design thinking - allowing actors to think differently and innovate – and it could be coupled with actors' attitude towards agility (Dejoux & Léon, 2018, p. 52, 53). We have also identified that PPI are paramount for decision making and knowledge management in KIFs, because knowledge management is based on knowledge commons that actors can access thanks to protocols and infrastructures (Fjeldstad et al., 2012, p. 744).

5.3 AI & challenges that arise in decision making processes

5.3.1 Decision making processes and organizational challenges within KIFs

5.3.1.1 Overcoming uncertainty

Situations of uncertainty are characterized by a lack of facts on which to base decisions. Our analysis revealed that it is problematic for AI since it mainly relies on facts. However, even in the most uncertain situations, there are some components that are certain. Thus, basing on these facts, AI can make forecasts, using probabilities (Pomerol, 1997, p. 12). It predicts the future in order to reduce uncertainty for humans (Jarrahi, 2018, p. 4), as well as it reduces uncertainty caused by human biases, so that humans can make more appropriate decisions. Humans, thanks to their global perspective and wide experience, are more suitable to take the final decision. This is particularly true in the case of problems that do not look like any occurred situation, where human intuition and its speed are valuable assets.

Interviewees raised the issue of black boxes, which refers to NN that make decisions in ways that the suggestion made by the machine is not understandable for humans. This phenomenon calls for uncertainty, as it is difficult for humans to justify a choice when they do not know the actual reason of this choice. Nevertheless, one of the IT firms has recently found a way to overcome this problem and fully understand the patterns found by AI. We can then think that black boxes will eventually fade away.

5.3.1.2 Overcoming complexity

It appears from our interviews that it is in the nature of AI to deal with complex situations. Indeed, consistent with Jarrahi (2018, p. 5) and Parry et al. (2016, p. 579), machines have superior abilities to analyze huge amounts of data and recognize hidden patterns, and at a faster pace. AI is also better at taking multiple factors in consideration and make forecasts regarding various alternatives and possibilities (Jarrahi, 2018, p. 5).

Yet AI is still narrow in its decisioning, in the sense that it is curbed to its field of expertise (although it has broader knowledge than humans in that particular domain obviously) and to the problem posed by the decision owner. Thus, AI's superior complexity-solving abilities do not question the leading role of the human decision maker in the final decision.

5.3.1.3 Overcoming ambiguity

Our results highlight that decision making in situations of ambiguity require intuition, critical thinking, contextualization, empathy, these qualities being specific to humans. As these situations are characterized by subjectivity, decision makers who can let their rational thinking out have more chances to fulfill the various and different objectives of multiple parties (Jarrahi, 2018, p. 5).

Nevertheless, it also stems from our study that AI is able to clarify ambiguity if the problem has been correctly stated to it. In these situations, we experience ambiguity because we are humans, but AI will remain objective and clarify our perceived dilemmas according to probabilities and binary laws. If the answer of the machine is still ambiguous, it means that the decision owner has to adjust his/her question until ambiguity is clarified. Situation modelling is implemented within IT consulting firms in order to find the right question to ask to machine.

5.3.2 New challenges linked to AI in decision making

5.3.2.1 Ethical considerations of AI's role in decision making

All the firms mentioned the challenge of ethics in the decision making process. In fact, one of the IT consulting employees included ethics in his decision making process "*First, you have to quantify both your targets and the different levers upon which you can act. Then, you try to reach an optimal match between the targets and the levers. Knowing that in the reality there is not just one optimal solution, there might be several. Between all these alternatives, you will have to choose and apply other criteria, related to ethics for example.*"

Indeed, when talking with the interviewees about an autonomous AI or a partnership between humans and AI in the decision making process, ethical considerations are considered as a limit. One of the interviewee qualified ethics as being one of the biggest challenge for AI. Indeed, the interviewee explained that at the moment humans are not able to define what is wrong or what is right, so how can we humans teach in machine ethics? One interviewee to illustrate his thought mentioned Cambridge Analytica and the racist AI of Microsoft as unethical use of AI. Besides, according to interviewees, ethics are of importance in the process of decision making because ethics enable the decision maker to make the final decision by evaluating if the decision is right in accordance with moral and values. Interviewees also put forwards that ethics are specific to human kind since ethics cannot be put into codes and so machines cannot evaluate if the decision is ethical. Indeed, Dejoux & Léon, (2018, p. 182) questioned to what extent the machine could integrate ethics and moral values in their codes. That is why, in decision making process, humans still have an important role to play in order to assess the ethical aspect of the decision. The findings are in line with the theory that the role of humans in decision making is important since humans make the final decision according to their values (Dejoux & Léon, 2018, p. 202).

5.3.2.2 Consideration of AI's responsibility in decision making

As we discussed in the previous sections, today in most of the situations, AI does not directly take decisions but rather makes propositions to humans. The real decision maker is then the human being who accepts whether to implement the decision suggested by the machine or not (Cerka et al., 2015, p. 387) However, one can wonder to what extent the overall decision making system, including AI, is responsible for this decision. Indeed, humans without machines support may not come up with the same decision.

Autonomous AI, even constrained in a narrow field of action, raises important issues about the responsibility for the decisions. If we take the example of high frequency trading and imagine that an AI made a big mistake that led to substantial losses for the organization that mandated it; who is the responsible? It seems from our results that the 'real decision makers' in this case, the decision owners, are not the people who designed the AI but rather those who trained it. Interviewees from IT consulting firms explained that they can sell similar AI solutions platforms to their customers, so that customers can then train them in order to answer to their specific needs. The responsibility issue within organizations is closely related to the issue of responsibility towards society and so to laws and regulations.

5.3.2.3 Juridical considerations of AI's role in decision making

Regarding law, all firms referred to the challenge of jurisdiction when making a decision involving AI. In fact, one IT consulting employee stated, "*We do not know how to code a machine to solve an ambiguous situation, and if it was the case, legal limit would not allow a machine to decide because we never know when a dysfunction can occur and who would have been held responsible for this failure.*" Juridical considerations deal with the consequences of a decision made by or with a machine. Indeed, when an individual makes a decision, afterwards people can hold this individual responsible if something goes wrong and blame him for it; but in the case of an autonomous AI, how can humans blame AI for a decision? Most of the interviewed KIFs mentioned the example of the self-driving car to assess the question of the juridical status of the machine. If the machine makes a bad decision and an accident occurs, who will be responsible of this action? That confirms that a juridical status should be defined for machine especially if they make a wrong decision (Dejoux & Léon, 2018, p. 182). One of the IT firms puts forwards that because AI is a revolution, AI is not yet adopted by the jurisdiction. This finding is in line with the current void of law concerning AI and the challenges that arise from it (Zeng, 2015, p. 4).

5.3.2.4 Societal acceptance of AI's role in decision making

Stemming from our study, it appears that the societal acceptance of AI can be an obstacle to its development within organizational decision making. The first concern is about the legitimacy of AI to make decisions. As one of the interviewed noticed, "*nowadays, nobody has seen a machine making a clear-cut decision.*" That is why society is not ready to accept fully autonomous decision making in its daily life, and people even struggle with accepting decisions in which AI played a role. However, as another interviewee confirmed, it "*will come a time when machine will gain legitimacy and we may change our opinion about AI [being] autonomous in decision making*."

People are not ready to entrust important decisions to machines yet. The main reason why humans do not trust machines is because they do not understand how they work (Hengstler et al., 2016, p. 106, 112, 113). That is why today the use of AI remains invisible to users in most of the cases, in order not to scare them, and for simplification purpose: AI in decision making is thus restrained to areas where customers are not involved. Thus, autonomous AI decision making concerns services which are not available to the general public, for instance high frequency trading. Another example of the lack of trust towards machine, and of legitimacy, stemming from our interviews, is some law firms in which AI suggests strategies based on laws and case law, but it is a human lawyer that defends them in front of the court.

This lack of trust towards machines combined with their low legitimacy justifies again more the need for collaboration between humans and machines where AI is a support giving recommendations to humans. Indeed, AI, as every technological innovation, must be introduced gradually (Hengstler et al., p. 107), which goes against autonomous AI.

Finally, another reason why people may be reluctant to accept AI, is not concerned with users but rather with workers. People are scared that the automation wave of AI will lead to numerous job cuts (Susskind & Susskind, 2015, p. 281, 283), so that they will lose one of their most meaningful activities (Brynjolfsson & McAfee, 2014, p. 128). Yet, if AI will indubitably lead to job transformations, it will not necessary be for the worse. AI is a tool for humans in decision making, it will remove repetitive and thankless tasks from human jobs, allowing them to focus on the core of their job (Dejoux & Léon, 2018, p. 218; Galily, 2018, p. 3, 4) We are at the premises of a revolution on the labor market, so it is logical that some people are afraid and need some time to accept it.

5.3.2.5 Smart decisions

Resulting from our analysis, we have completed the Figure 11 built in section 2.5.3 and depicting interactions between decision makers (humans and AI), organizational design and decision making (Figure 14). It appears that the combination of AI and human capabilities (section 5.1), together with an appropriate organization design (section 5.2) and the consideration of specific challenges related to AI and organizational decision making (section 5.3), allow humans to be augmented by AI and make 'smart decisions'. Thus, we consider as 'smart decisions' decisions that: (1) are made in accordance with the nature of the decision maker; (2) are made within an organization that implements policies in order to optimize the use of AI; (3) and take in account and tackle the new challenges that AI brings along the decision making processes. In this framework, the nature of decisions determines the respective roles of humans and AI within decision making. Smart decisions, through collaborative and loose organizational design, allow the decision maker to make the best possible use of its/his knowledge, as well as they are more relevant to deal with the organizational decision making challenges - uncertainty, complexity, ambiguity - since they are based on augmented humans. Finally, smart decisions are made in accordance with the new challenges raised by AI thanks to organizational awareness, society attentiveness, and appropriate answers from business organizations.

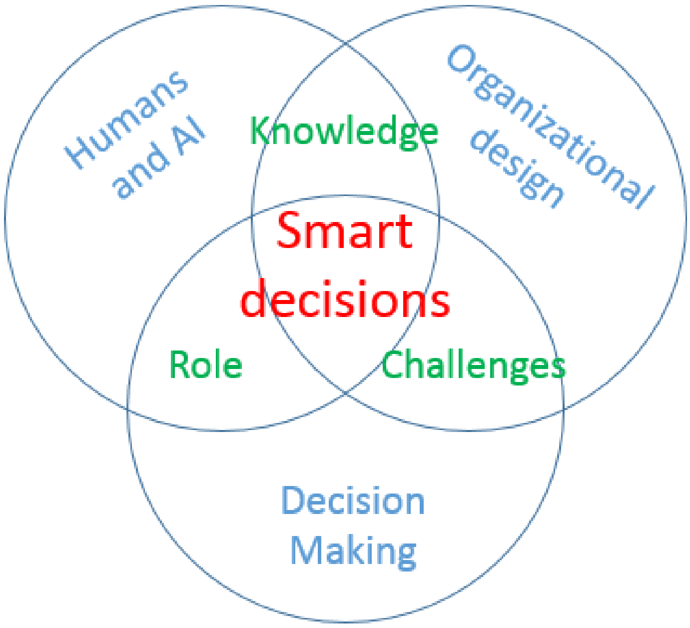

Figure 14: Smart decisions resulting from the collaboration of humans and AI within organizational context (developed from Figure 11)

6. Conclusion and contributions

In this chapter, the purpose is to answer our research questions stated in the introduction part. We start by drawing conclusions and answering our main research question and its three underlying questions. Then, we discuss the several contributions of our thesis, i.e. the theoretical, practical, societal and managerial contributions. Next, in a third part we outline the truth criteria of our research. We finish by presenting how further research could contribute and the limitations of our thesis.

6.1 Conclusion

The main purpose of this master's degree project is to develop a deeper understanding and to gain deeper knowledge about the role of artificial intelligence and humans in the organizational decision making process within KIFs. In the introduction, we have defined our research question as: "How can AI re-design and develop the process of organizational decision making within KIFs?" In order to make it precise, we have formulated three underlying questions: (1) What are the roles of humans and Artificial Intelligence in the decision making process? (2) How can organizational design support the decision making process through the use of Artificial Intelligence? (3) How can Artificial Intelligence help to overcome the challenges experienced by decision makers within KIFs and what are the new challenges that arise from the use of Artificial Intelligence in the decision making process?

Several insights stemmed from the findings of our qualitative study. We found that currently, AI cannot replace humans in the decision making process. Indeed, although AI offers a faster and deeper analysis on very specific topics compared to humans, it cannot integrate parameters that are emotional and ethical, and AI cannot solve a dilemma or solve a new problem out of its scope of expertise without having human's inputs and training. Consequently, AI's role in the decision making process is the one of an assistant and a support to humans in the analysis and the formulation of alternative decisions, so that humans still have an important role to play in the decision making process. The first role of humans in the decision making process is to pose the problem to AI and to formulate a question thanks to their critical sense, common sense and contextualization capabilities. Then, humans assess the alternatives proposed by AI and choose the best solution to implement or choose to think about another alternative not proposed by AI thanks to their grid of values, ethics, creativity and intuition.

Besides, the results highlight that actor-oriented organizational design is suitable for supporting the decision making process with AI within KIFs. In fact, this organizational design supports the keys concept of KIFs, knowledge, and enable actors to make decisions. Actors in KIFs have basic knowledge of what AI can do, with a sensitivity to digitalization; besides, actors possess soft skills including social intelligence, collaborative capabilities, transdisciplinarity, sense-making, critical thinking and design mindset that includes empathy and creativity. However, the results stress that soft and hard skills are not enough to define actors in KIFs nowadays, actors should have agile brains to adapt and continuously learn new knowledge. Regarding the commons, knowledge commons are of high importance and they enables them to handle the creation and sharing of knowledge. Regarding PPI, the communication networks and computer servers, agile management, and knowledge management processes are paramount elements for the management of explicit and tacit knowledge. PPI also enable to effectively handle knowledge commons. Actors in actor-oriented architecture make decentralized decisions in an autonomous way supported by AI present in the PPI and knowledge commons.

We have considered three challenges experienced by organizations in decision making: uncertainty, complexity, and ambiguity. We have discussed the respective roles of AI and humans to overcome these challenges. Our analysis shows that (1) AI can reduce uncertainty through its ability to make objective forecasts while humans experience and their comprehensive approach are vital to make decisions within this context; (2) machines have superior abilities to analyze complex data and give sense to it , but their decisioning is curbed to their specific field of expertise; (3) AI can clarify ambiguity as long as it is asked the right question but they lack critical thinking, empathy and contextualization that are human characteristics in order to resolve these situations. Our results highlight new challenges for organizations and society related to the development of AI. The responsibility of AI in decisions it have made or have helped to make must be clarified, both within organizations and in front of the law. This is closely related to ethics as giving moral values to machines raises many issues. AI is a new technological revolution that will deeply modify organizational practices and society, and due to the reasons stated above, people are sometimes reluctant to these changes. Our study was concerned with 'weak AI', which is the type of AI applications that are used today within organizations. The development of 'strong AI', also called superintelligence, is already ongoing. It will heighten these challenges and speed up the need for concrete answers from both organizations and society.

6.2 Contribution

The contributions of this study are fourfold, and the insights given in this study are of value for many stakeholders. These insights are presented and discussed in the following parts of the 6.2.

6.2.1. Theoretical contribution

Through our qualitative analysis, we provided a deeper understanding of the role of AI and humans in the organizational decision making process. That so, we have contributed to theory both to the fields of research of decision making and organizational design. We investigated specifically KIFs and their organizational design related to the use of AI. To have different point of views on our research question, we have interviewed companies using AI coming from two different sectors, IT and real estate, and of different size, global firms and startups. By doing so, we enriched existing literature about KIFs and AI related to organizational decisions. Furthermore, our thesis highlights several new challenges that AI raises in decision making process that we will discuss in the societal contributions.

6.2.2. Practical contribution

Our research provides practical contributions to KIFs and especially to the IT and real estate sectors. We would advise KIFs to adopt a specific organizational design based on actor-oriented architecture were actors could access knowledge commons supported by an efficient configuration of PPI. We would also recommend KIFs to consider in the collaboration between AI and humans in decision making process the following roles: integrate AI as an assistant in the process of the decision making and strengthen humans as the owners of the decision, those who can control AI. By doing so, the benefits for KIFs could be to overcome organizational challenges in decision making processes related to uncertainty, complexity and ambiguity. Furthermore, in the decision making process humans could be augmented in their decision making and could make smarter decisions.

Nevertheless, KIFs should consider the four new challenges - ethics, law, acceptance and responsibility - raised by AI. Ethics and responsibility are two paramount parameters when making a decision in collaboration with AI. Indeed, it is important to know if the decision is right and who is the owner of the decision. AI does not incorporate such metrics as ethics. Because AI is not fully accepted by the society and does not have a juridical status, law and acceptance are two subsequent questions to decision making process with AI. However, regarding ethics and acceptance, private incentives, such as the Partnership on Artificial Intelligence initiated by GAFAM and IBM or Elon Musk's association Open AI, are taken to ensure that AI will contribute to society and will not be misused. To tackle the juridical status of AI, its rights and duties researchers all over Europe proposed laws to construct a legal frame to AI (see the part 2.4.2.2).

6.2.3. Societal contribution

Generally speaking, our research provides a broader scope to all firms that are interested in the role of AI in decision making and the type of organizational design they should adopt to optimize their use of AI. AI is of strategic importance today and our conclusions could help to design the overall strategy of any firms that want to incorporate AI in its structure and decision making processes.

Besides, all citizens that are interested in AI could benefit from our research as we present four new challenges that arise from the use of AI in the decision making process, related to ethics, law, society acceptance and responsibility. We draw the conclusion that there is a lot of vagueness around AI when considering the ethical and juridical levels. Moreover, AI has not been fully accepted by the society and the question of responsibility when making a decision stays widely unanswered. AI will not be anytime soon a substitute for humans, and least of all a substitute to human decision making. Instead, AI contributes to augment humans and make smarter decisions.

6.2.4. Managerial contribution

As we mentioned in the purpose of the introduction (sections 1.5), our research is relevant for the KIFs that want to get a better and deeper understanding of the role of AI and humans in the organizational decision making process. Indeed, our research explains how managers can deal with AI in the decision making process by defining the roles of AI and humans. Nevertheless, even though our study focuses on KIFs, especially IT and real estate sectors, and our data was collected with mainly French interviewees, we hope our study can contribute to other sectors and types of firm interested in AI and their role in the organizational decision making process.

6.3 Truth criteria

Researchers must assess the quality of their work when they conduct a study. In this part, we present the different criteria to evaluate the quality of our qualitative study.

6.3.1. Reliability and validity in qualitative research

Both reliability and validity are important criteria when evaluating a business research under an interpretivist and a positivist paradigm (Collis & Hussey, 2014, p. 52). Reliability is related to "the accuracy and precision of the measurement and the absence of differences if the research were repeated." (Collis & Hussey, 2014, p. 52). The concept of reliability is split between external reliability and internal reliability. (Bryman & Bell, 2011, p. 395). On one side, the external reliability of the study is related to the extent to which a study could easily been reproduced (Bryman & Bell, 2011, p. 395). As one of the researchers has his brother working in one of the companies interviewed, this previous link with one of the companies interviewed is hard to replicate. However, during the interviews with the employees of this firm, we made sure that the interviewees were not influenced. We asked them the same questions as to any other employees interviewed. So, another study with the structure of our thesis could be undertaken easily but with different people interviewed. On the other side, the internal reliability refers to the coherence of the study if other researchers, with the same constructs and data, would have conducted the research the same way as the researchers did (Bryman & Bell, 2011, p. 395). As we have acknowledged the influence of our values in section 3.1.4.1 (authors' preconceptions), we are aware that we could have modified the research. Knowing that, we made sure all along the study to stay as coherent as possible to ensure the internal reliability of the study.

Nevertheless, in a qualitative study, reliability is often of little significance compared to validity, notably because the researchers' activities can influence the phenomenon under study (Collis & Hussey, 2014, p. 53). Validity, the second important criteria in any type of research, either qualitative or quantitative, refers to "the extent to which a test measures what the researcher wants it to measure and the results reflect the phenomena under study." (Collis & Hussey, 2014, p. 53). As for the reliability, validity can be divided into two types, the external validity and the internal validity (Bryman & Bell, 2011, p. 395). On the one hand, external validity is about generalizing, that is to say, "the degree to which findings can be generalized across social settings" (Bryman & Bell, 2011, p.395). A qualitative study is hard to generalize. Besides, as we stated right from the beginning and in the title of the thesis, we made a focus on a particular type of firms, KIFs. To that extent, we are conscious that our results can hardly be generalized. On the other hand, internal validity is defined by "whether or not there is a good match between researchers' observations and the theoretical ideas they develop", i.e. internal validity refers to the fit between theory and data (Bryman & Bell, 2011, p.395). We think that the internal validity of our research is medium. In fact, we have reviewed previous literature to assess whether our qualitative study would be supported or rejected according to the theory. However, we are well aware of the fact that the topic chosen is rather new in the literature and few companies are using AI. As a consequence, we have based our literature on existing articles and books that are rather limited in number.

6.3.2 Trustworthiness in qualitative research

Trustworthiness is considered as being an alternative way to assess the quality of qualitative research (Bryman & Bell, 2011, p. 395). Trustworthiness compromises the following four factors: credibility, transferability, dependability and confirmability (Bryman & Bell, 2011, p. 395).

First, credibility is concerned with "the respondent validation" to ensure the credibility and validity of the findings (Bryman & Bell, 2011, p.396). Researchers can obtain respondent validation by submitting their results to each participant. As we conducted semi-structure interviews, we had the possibility to ask further questions in order to clarify unclear answers and/or to reformulate the answer to ensure we understand the answer.

The second factor to ensure trustworthiness is transferability. Transferability refers to the possibility of transferability of the findings from a specific context to another one (Bryman & Bell, 2011, p. 398). In order to complete this criterion, researchers are expected to build a “thick description” that is defined by Guba and Lincoln (Bryman & Bell, 2011, p.396) “as a database for making judgements about the possible transferability of findings to other milieu”. As our research made a specific focus on KIFs and particularly on IT and real estate firms, the results and findings are hardly transferable to other firms.

Then, dependability is defined by Bryman & Bell (2011, p. 398), to rely on an “auditing approach”, that means that “complete records are kept of all phases of the research process— problem formulation, selection of research participants, fieldwork notes, interview transcripts, data analysis decisions, and so on—in an accessible manner”. Adopting an auditing approach entails to keep every document during the process of research in order to prove the trustworthiness of our approach. During the constitution of our thesis mainly done via computers, we have kept and saved every document. Regarding our qualitative study, we paid careful attention to save every mail, vocal records of interview, transcriptions of interviews and analysis.

Finally, the last factor is confirmability. According to Bryman & Bell (2011, p. 398), “confirmability is concerned with ensuring that, while recognizing that complete objectivity is impossible in business research, the researcher can be shown to have acted in good faith; in other words, it should be apparent that he or she has not overtly allowed personal values or theoretical inclinations manifestly to sway the conduct of the research and findings deriving from it.” We have decided to transcribed interviews in the language used to conduct the interview in order to stay as objective and honest as possible regarding what the participants stated during the interviewee. Then, when the interview was conducted in French, we thoroughly translated it in English in order to not modify the sense of the answer given by the interviewee. While translating and analyzing, we stay as objective as possible.

6.4 Future Research

Conducting this study was interesting on both theoretically and practically levels. Besides, this study really enlightened us about the role of humans and AI in the organizational decision making. We think it is of importance and very interesting to know about the potentiality of AI within enterprises as it may become a strategic asset in the future. We think that being two researchers in the study was an advantage and a guarantee of quality. Indeed, as we were two researchers writing the thesis, searching for information and conducting the study allowed us to discuss and debate about the topic in order to balance each other’s views and to broaden the scope of the study. This research was very fruitful for us as we gained a lot of knowledge regarding our research topic. That is why we think that the research field of AI, strategy, organization and management is full of inspiring topics. That so, many researches could be conducted within this field in the future.

Future research could explore further our topic by conducting a case study within a single firm. Besides, further research could investigate other firms or industries within the topic of our research. Indeed, further research could compare if the role of artificial intelligence and humans in the organizational decision making process is the same from one type of firms to another as our research is restricted to KIFs. Future qualitative studies are needed in order to explore further the new challenges raised by AI regarding ethics, law, societal acceptance and responsibility.

We made the choice to conduct a qualitative study in order to reveal insightful knowledge about AI within organizational decision making, since this topic is still widely unexplored. Nevertheless, we believe that some quantitative studies should be conducted in the future, in order to quantify the impact of AI within decision making for companies, such as its level of speed, accuracy, etc. For instance, comparing the results of firms according to their level of implementation of AI could be particularly interesting. Further research could also explore the field of the new challenges arisen by AI in decision making and measure the level of acceptance of AI within decision making among society and employees. On the same topic, future research is needed regarding the policies implemented by business and legal institutions in order to tackle these challenges.

6.5 Limitations

Our study has several limitations. The first limitation concerns our typology of interviewees. Our qualitative study was mainly conducted with French interviewees. There is no big diversity among our interviewees. Furthermore, as we wanted the interviewees to perfectly fit our theoretical review, we took time to choose carefully and thoroughly our participants. That is why our second limitation is related to the relative low number of interviewees that might jeopardize the standard of quality of our research. We had a hard time finding people that could answer our questions regarding AI, decision making and KIF organizational design. The second limitation can be mainly explained by two other limitations that are lack of time and the fact that AI is a very recent phenomenon in enterprises and within the field of research. Besides, we identified another limitation linked to our type of interviews. Indeed, choosing a semi-conducted interview can orientate interviewees in their answers and it can prevent them from expressing truly what they think, so that one can question the honesty of the interviewees.

Another limitation of our study is the lack of industry diversity among the companies from which come our interviewees. Indeed, for sample convenience purposes and because we think that they are fertile ground for our study, only high-tech service firms and real estate companies are represented. This may obscure other realities in industries that we have not explored. Finally, we conducted only one interview in face-to-face. Most of our interviews were conducted via video conferences, and two of them audio calls. One can say that these methods may prevent the interviewees from feeling comfortable and fully focus about the interview, and also prevent the researchers from understanding all the information due to the lack of body language, so that it could lower the quality of the data collected. For instance, Saunders et al. (1997, p. 215) argue that conducting interviews allow the researcher to go more in depth due to personal contact with the participants.

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Appendix

Appendix 1: Interview guide

Introduction of the topic: field of research, purpose and procedure

Hello, we are Dorian and Mélanie, two master students at Umeå School of Business, Economics and Statistics and we are conducting a research for our master thesis. We would like to thank you for your time and for your support in our research, that is of crucial importance for our study.

We have starting the research with the observation that AI is on the verge to become a strategic competitive advantage for enterprise and will change our society. The topic of our research is the role of human and AI in the organizational decision making process within knowledge-intensive firms. In that purpose, we will interview employees from knowledge-intensive firm that make decisions.

Umeå University has ethically approved the research. The participation in our study is based on volunteering, that means that you can withdraw from the study at any time without precising the reason and without having implications for yourself. We will preserve your anonymity and we will ensure the confidentiality of the data and information that you will discussed with us. We will use the information that you will share with us for our analysis. Consequently, this interview will be recorded for practical and ethical reason as we do not want to misunderstand your words. Would you accept to be recorded?

If you would like to have further information about our study, how the data collected will be used and the conclusions of our research project, please just ask us.

By signing this information paper and responding our questions, we assume that you agree to all these terms and that you take part in the study with full consent.

Yours sincerely,

Signatures

Appendix 2: Interview questions

Part 1: general questions:

1. What is your current position?
2. What are your mission/tasks/ day-to-day activities? Do you make decision within the enterprise?
3. How much time have you been working in that company?
4. What is your educational background?
5. How would define AI in few words?

Part 2: KIFs organizational design

6. Would you say your company rely on the concept of collaboration, flat hierarchy and decentralized decision making with self-organizing employees?
7. According to you, what are the key skills (hard and soft) that people in digital enterprise need to have?
8. Can you describe how your company manage knowledge and the extent to which you can access / share / create it?
9. Do you know what ‘agile management’ refers to? Do you consciously work about it? IF YES: What are the benefits of agile management?

Part 3: decision making approach, process and context

10. Can you describe how you make a decision?
11. To what extent your decision depends on the context?

Part 4: Decision making and decision makers

12. According to you, can decision making be fully given to robots?
13. *Depending on the answer to 12:* Should decision making remain a human task?
14. *Depending on answers to 12&13*: Should human collaborate with machine in decision making?

Part 5: Decision making and organizational challenge

15. Do you think humans or machine is the most relevant decision maker in uncertain situation? Why?
16. Do you think humans or machine is the most relevant decision maker in complex situation? Why?
17. Do you think humans or machine is the most relevant decision maker in ambiguous situation? Why?

Part 6: Conclusion

18. Any conclusion about the future of AI? The future of AI within decision making?

Appendix 3: Details of interviews

<table>
<tr><th>Company</th><th>Employee</th><th>Spoken Language During Interview</th><th>Educational Background</th><th>Position</th><th>Date</th><th>Duration</th><th>Means Of Communication</th></tr>
<tr><td rowspan="2">Atos</td><td>1</td><td>French</td><td>Computing Science</td><td>Big Data Integrator</td><td>08/05/18</td><td>77 min 46s</td><td>Conference call</td></tr>
<tr><td>2</td><td>English</td><td>Computing Science & Business</td><td>Business Information Analyst</td><td>16/05/18</td><td>48 min 19s</td><td>Audio call</td></tr>
<tr><td rowspan="2">IBM</td><td>1</td><td>French</td><td>AI & Education Science</td><td>Subject Matter Expert</td><td>09/05/18</td><td>82 min 42s</td><td>Conference call</td></tr>
<tr><td>2</td><td>French</td><td>Strategy & Management</td><td>Watson Consultant</td><td>14/05/18</td><td>41 min 26s</td><td>Audio call</td></tr>
<tr><td>KNOCK</td><td>1</td><td>French</td><td>Management</td><td>Business Developer</td><td>11/05/18</td><td>57 min 17s</td><td>Audio call</td></tr>
<tr><td rowspan="2">Loogup</td><td>1</td><td rowspan="2">English</td><td>Management</td><td>CEO</td><td rowspan="2">14/05/18</td><td rowspan="2">65 min</td><td rowspan="2">Face-to-face</td></tr>
<tr><td>2</td><td>Computing Science</td><td>Full Stack Developer</td></tr>
</table>

Appendix 4: Overview of the findings of chapter 4

THEME	ATOS		IBM		KNOCK	LOOGUP
	EMPLOYEE 1	EMPLOYEE 2	EMPLOYEE 1	EMPLOYEE 2	EMPLOYEE 1	EMPLOYEE 1 & 2
PART 1						
DEFINITION OF AI	"AI includes a set of techniques that enables a machine to cope with a problem that is not clearly stated by humans that, so the machine can adopt its behavior according to the stated problem. AI is to oppose to a simple algorithm."	At the stage of right now: "it is just to mimic the cognitive aspects of what a human can do, or several humans." Yet this definition narrows down to neural AI, so it comprises in fact many capabilities	→ Reference to the Turing Test. → Though, within IBM Employees don't talk about AI, but they rather say cognitive systems. "Cognitive systems are based on algorithms that can learn and they are rather oriented on neural network."	"Nowadays, AI is to put the intelligence of a robot to fulfil human off-putting tasks. AI won't replace humans, AI will assist humans in their basics tasks. Also, currently AI exists in every sectors of the economy but in a rather limited way."	"AI is a considered decision. It is not binary anymore [...], it is the machine ability to be agile; it means questioning the decisions made and learn from its mistakes, it is this capacity of thinking."	"Capability of computers to replicate human behaviors, specifically related to cognitive performance"
PART 2: KIFs ORGANIZATIONAL DESIGN						
ACTOR-ORIENTED ORGANIZATIONAL DESIGN PRINCIPLES: collaboration flat hierarchy decentralized decision making	→ collaboration: working with a project mode → decentralized decision making : autonomous actor	→ Very self-stirring team, able to make its own decisions. → The expertise holders of the team are those who are supposed to make the decision in a particular field. → Dynamic team.	→ organizational design between Taylorism and Holacracy → Holacracy system of organizational governance based on collective intelligence, that is to say, there is no hierarchical pyramid, no manager → IBM currently has a matrix organization	→ the concept of collaboration, flat hierarchy and decentralized decision making with self-organizing employees are concepts that IBM is willing to implement. → startup spirit → digital transformation	→ flat hierarchy due to the small size of the company. → Everyone can make a decision, expose their ideas, give and receive feedbacks… → Decision making is highly decentralized, and collaboration is encouraged as part of the decision making process.	→ flat organization due to the size and stage of the startup → High level of communication and consultation in order to take decisions
ACTORS Soft Skills Hard Skills	→ Soft Skills: have common sense to judge ethics and moral → Hard skills: know what AI is able to do in order to avoid AI fantasy	soft skills that AI does not possess: → critical thinking: ability to assess whether information is valid or not → systemic thinking: "always keep the whole in consideration and not only	→Soft skills outdated term → Instead of hard/soft skills: aptitude → agile brain i.e. people that are open-minded, can go outside of comfort zone, learn and adapt continuously	Soft skills: → proactive → curious → cultivate the difference Hard skills: → what AI can do or not	Teamwork	→ complementary hard skills → soft skills: reactivity, fast-learning, proactiveness, motivation, passion, not being afraid to fail

		your own task or perspective" → empathy : the human measure				
COMMONS Shared situation awareness Knowledge commons	→ Digitally Share awareness: internal tool for communication → Share awareness thanks to committee for the global strategy → Explicit knowledge: previ ous projects and experiences → Tacit knowledge: internal social networks, community of interest	→ Development of e-learning → Trainings, workshops in order to "train our people to go beyond what is common, what is mainstream". → He gives courses about enterprise decision management → Tool with common interest groups.	→ Explicit knowledge: Netflix training system → Tacit knowledge is impossible to code → Collective intelligence thanks to intranet based on AI	→ Digitally Share awareness: internal tool for communication (Slack) → explicit knowledge: e-learning & platform to share previous projects → Tacit knowledge: training among IBM consultants & community of interest	→ Commons are loose, employees regularly work together as they do not have strictly defined tasks. → Attempts to structure it more	→ People have distinct and complementary roles, but they are constantly overlapping with advice, feedbacks, etc. → Internal tool for communication (Slack).
PPI Protocols Processes Infrastructures	Agile management → Feedbacks and iterations	→ "There are a lot of things that are called agile and are not." → Agility is not about picking out one or two agile tricks in order to follow the trend. → "Agile, it's a trip, it's in your character. It goes much deeper than just doing some rituals."	→ IBM heads towards a more agile organization, the more flexible, the more design-thinking → To head towards Holacracy	Agile management → Every project in agile mode → Process and protocols	→ Every start up is agile → "I think it is very important to be agile [for an AI startup]; it means being able to code something, develop a process, and then realize that it doesn't work or not as good as expected, so that you can change method"	Agility is a necessity given the size and stage of the company
PART 3: DECISION MAKING APPROACH, PROCESS AND CONTEXT						
INTERVIEWEE DESCRIPTION OF decision making approach, process within a context	→ Rational decision making approach and process. "*First, you have to quantify both your targets and the different levers upon which you can act. Then, you try to reach an optimal match between the targets and the levers. Knowing that in the reality there is no just one optimal solution, they might be several. Between all these alternatives, you will have to choose and apply other criteria, related to ethics for example.*"	→ "visual thinker" → He first appeals to his intuition, then attempts to figure out the cause of what he intuited, in order to transform intuition into an idea. He tries to find the rational roots of his intuition, thinking backwards; then he decided to follow or not this intuition. Intuition "comes from my feeling, and this feeling is often based on experience"	→ Depending on the context, both approaches	→ Both approaches: irrational & rational → Based on feeling, experience, intuition → Rational process at work "The context will influence the decision making as well as the importance of the decision"	→ Fully rational decision making: relies on fact that he analyses to make a decision → "you cannot make a decision without a context, and so without a preliminary analysis. You cannot make a decision and implement it without considering its context." → "A non-contextual decision is a decision without any impact; it doesn't work, it can even lower performance"	→ Employee 1: it depends on what is at stake and number of variables. For important stakes, he thinks in terms of opportunity costs especially when they are many variable, while for little stakes he is less methodical. He prefers choosing alternatives whose he already knows the impacts → Employee 2: he will often trust his gut, basing on intuition and experience. But when it comes to big decisions, like choosing an apartment, he will be more rational, compare options, etc.

PART 4: DECISION MAKING AND DECISION MAKERS						
AI AS AN AUTONOMOUS DECISION MAKER	→ AI has a consistent advantage through ML: Watson example → Cannot give fully the decision making to machine because machine does not have a global view	→ "If you can define it in business rules, then you can make a full automated decisioning service based on these rules" → "we elicit the knowledge to make the decisions, and we can automate decisions and then integrate these automated decisions in business processes" → up to 90% of operational decisions can be automated. → Machines have no bias, and they are scalable	→ AI autonomous in trading → AI advantages (speed, storage) → AI limits (tech, law, societal) → AI as a support "In IBM, with cognitive system it is important to stress that it is never the machine that make a decision."	→ Not possible at all to give the decision making to the robot "AI is a learning machine, so humans make the decision, that is to say that humans choose what raw data they will give to the machine in order to have suggestions. "	→ At the moment we cannot entrust decision making to machine; KNOCK'AI only makes propositions → AI not ready yet, and humans may be scared by its mistakes. But it will get better in the future and improve user experience.	→ Machines can make decisions on their own if it is decisions that are repetitive for humans and are concerned with a small scale. → Machines are better than humans to find patterns and treat huge amounts of data.
HUMANS DECISION MAKER	Human advantages → intuition → instinct → moral → ethics → legitimacy, example of Cambridge Analytica & link to black box	→ "the human still has a very important role, because he is still the owner, he is still responsible." → The owner of the decision defines the rules (of decisioning), and mandates a decision maker - human or machine - to execute a decisions according to these rules; this is called rule-based decisioning. → It is the role of the business information analyst to elicit the knowledge in order to define the rules. → The human is in charge and let the machine do autonomous decision making within the boundaries of his rules.	Human advantages → intuition → creativity → common sense → critical thinking → solve a dilemma → contextualizing → innovation "*it is not possible to put those specificities into code.*" → push the boundaries & thrive for progress "*they did not know it was possible, until they realized it*" "*humans are proved in History their desire to push the boundaries and to do the impossible, for example when the first man land in the Moon or when we first discover the first vaccine.*" → Limit: brain plasticity "*their brain plasticity in the*	"Nowadays, I will say yes, but in 10 years I will say no." talking about the fact that decision making should remain a human task. → On an ethical level, humans will still have a role to play and the society is not ready to accept a decision coming from a machine "one of the most complex challenge towards AI is the society acceptance, it will come a day, but it is like a fourth revolution, so as Internet we have trouble to adopt it, AI has to be accepted, be democratized, and be adopted by the jurisdiction." "acceptability rate of AI is really low, especially among the young." → AI has limits towards technic,	"Humans remain dominating the decision making system."	Managerial decisions should remain human tasks: the biggest lack of machines is about common sense and intuition, that are both crucial in decisions related to management.

			sense that a person is accustomed to make a decision in a certain way due to his cognitive system and what he learnt during his life."	societal and ethics		
COLLABORATION BETWEEN AI & HUMANS	→ Legitimacy: "*as a first step, the optimal decision making is a combination of both humans and AI*" and because "*Nowadays, nobody has seen a machine make a clear-cut decision.*" "*will come a time in which machine will gain legitimacy and we will may change our opinion about AI autonomous in decision making*." → Process and roles: " *first the human has to state the problem. Then, he will use different tools in order to for his algorithms suggest solutions. Finally, the human will chose among the solutions proposed even if there is only one solution proposed. It is of importance that the humans choose because he can put his subjectivity on the rational decision taken by the machine.*"	→ The responsible mandates the machine only when all its rules have been evaluated and validated. In a way he has to know what the machine will decide. → "the decision always keeps explainable to the last detail" ⇒ no black boxes ⇒ able to understand the patterns. → Asking the right question to the machine is a key element → AI need continual tweaks in order to be adjusted to changing circumstances, such as rules and regulations, the market, etc..	"*the combination of the machine and the man is superior if we consider just the man or just the machine. We can hypothesize that in the decision making process, the human decision making and the machine decision making are less effective than the decisions made by the human augmented thanks to the machine*" "*augmented intelligence rather than artificial intelligence*" "*IBM has identified that when asking to a human and a machine to diagnose on their own cancer cells, the human was able to identify up to 90% of cancer cells, the machine up to 95% but the partnership between humans and machine was able to identify up to 97%.*"	"machine will replace humans in off-putting tasks to enable the humans to focus on what truly matters in their job, on the core business, on the added value, while nowadays we have lost this added value "the machine will make the analysis and the human will make a decision thanks to his larger spectrum of knowledge." → Human advantages: humanity, their emotions and how they can be empathetic towards one another while the machine stay impartial. → AI advantages: ability to analyze a huge amount of data in order to be more accurate and have a thorough analysis.	→ The use of AI must be invisible for users, for simplification purpose. → AI should always remain at the service of users. → Humans should pose a question, and machines should then facilitate solving the problem.	→ "AI allows to enhance human capabilities, to find patterns that humans could not find" AI is a tool for humans. → AI analyses the data, and humans take the final decision. → Employee 1: safety issues problems with AI → Employee 2: AI is a revolution, and the main challenges are not technical, but about to find a consensus to say what is right and wrong. This particularly hard because we are already not able to define it for humans… So for machines? ⇒ problems about "wrong" uses of AI: Cambridge Analytica and the racist AI by Microsoft.
PART 5: DECISION MAKING AND ORGANIZATIONAL CHALLENGE						
OVERCOMING THE CHALLENGE OF UNCERTAINTY	rationality is the key to overcome uncertainty and the machine is the most suitable in this situation	→ AI can cut out uncertainty → "the machine is quite strict on its decision making, but it always depends on the question you ask". → You have to ask the right question otherwise you will not get the	→ AI can be a support in the decision making process or can replace humans in the process by being objective and reducing humans biases. → To do so, at the beginning, a firm can decide the level of	"humans can decide because humans can embrace and visualize the decision and humans will understand the current trends"	→ any decision must rely on facts → "When I have to make a decision, I want numbers" → AI, just like other technologies, can help humans by making predictions about the	there is some uncertainty about what machines can do. For instance, neural networks can make propositions using patterns that we will never know nor understand. This process, called black box, raises important

		appropriate answer.	involvement of a machine in the decision making process and then, the firm will integrate this parameter in its information systems, mechanic and computerization		outputs of each alternative. It can give to the decision maker probabilities of success and failures of the alternatives, with the margin of error, based on statistics	issues for decision making.
OVERCOMING THE CHALLENGE OF COMPLEXITY	→ Machines: ES, ML combined with Big Data like Watson's IBM platform "*the more data, the more precise the decision making will be*"	→ AI can manage really huge amounts of complexity, but only if the question you ask to AI is the right question. → AI is still narrow in its decision.	→ AI can act fast and has the ability to forecast what is likely to happen thank to its analysis "*AI has the ability to aggregate enormous amounts of information coming from different sources depending on the different factors at stake, analyze fast all those information, and make a decision accordingly.*"	"machine can manage better the variability and several factors in order to make a more accurate and reliable decision". In fact, she explained that the machine can handle better several factors at a time compared to humans. However, the final decision should be made by humans even if machine have a better analysis."	→ "It is in the nature of AI to analyze some big amounts of alternatives and possibilities" → In complex and objectives situations, machines are more powerful than human, so that they can take more accurate decisions ⇒ Go game example, with its binary choices.	Machines are able to treat huge amounts of data that humans cannot.
OVERCOMING THE CHALLENGE OF AMBIGUITY	→ Humans advantage, the situation will require a decision that is related to intuition, instinct and the personality of the decision maker → Example: the case of the self-driving car	→ If you ask the right question to AI, it will clarify ambiguity. → Finding the right question by modelling out the decision. → Adjust your questions: "If you get the results and that the machine gives you ambiguous answers, then you have to think back, and figure out how could I ask questions in that way that ambiguity gets clarified ?"	→ Humans can solve the problem thanks to their sense making, their critical thinking, their contextualization "*We do not know how to code a machine to solve an ambiguous situation, and if it was the case, legal limit would not allow a machine to decide because we never know when a dysfunction can occur and who would have held responsible for this failure.*"	"the machine will stay objective about the decision, so the source of ambiguity will be removed. Besides, the analysis will be better, but the final decision should come from the humans."	→ When dealing with human problematics, like firing an employee, AI cannot help, because it cannot bring objectivity where there is only subjectivity. → People think that AI will do everything in the future, but it cannot understand humans since they are too complex, in a subjective way.	→ Machines cannot build empathy; that's why humans are better for decisions related to this. → importance of human/machine collaboration: machines are more likely to make objective decisions, while only humans are able to adapt it through their common sense.

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