

Louvain School of Management

Artificial Intelligence: Some managerial implications and recommendations

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Abstract

Artificial intelligence is a trendy concept that attracts the attention of many people. However, some managers are not familiar with this technology and are therefore unsure whether they should consider it for their firm and what they should pay attention to. For this reason, the purpose of this paper is to clarify the concept, highlight some attention points (application fields, potential barriers and (dis)advantages) and make some recommendations.

This paper's approach to this problem is to complete a literature review in order to first define what AI is and frame it among other related concepts. Secondly, the industries where this technology seems applicable are highlighted and compared. Thirdly, potential barriers to its implementation and adoption are mentioned. Fourthly, some advantages and disadvantages of using this technology are explained. Then, a few key issues to address for AI implementation and adoption are provided and all these steps are then confronted to 7 field experts with different backgrounds to compare this literature research with on-field expertise.

By following this approach, it seems that artificial intelligence can be broadly defined as a technology that can perform tasks that would require intelligence when done by humans. Additionally, it could be said to be a general-purpose technology that seems to have currently a particular potential in industries that can benefit from image recognition applications. The barriers to its implementation and adoption are plural, can occur prior, during and after the implementation of AI and depend on the application, the resources and the culture of the company. Lastly, the (dis)advantages can be general and inherent to AI, but also application specific.

To conclude, it is important for a manager willing to implement and adopt an AI solution to understand the technology, to define a precise goal for its application and to make sure that it can meet the expectations as well as have an actionable output.

Then, the manager should check if the company has the right set of data, access to computational power and human skills. Lastly, the manager should verify whether the technology will fit the company culture and processes as well as answer to relevant ethical questions.

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Introduction

Mark Zuckerberg said in an online video on Facebook:

I am optimistic. I think you can build things and the world gets better. But with AI especially, I am really optimistic. I think people who are naysayers and try to drum up these doomsday scenarios — I just, I don't understand it. It's really negative and in some ways, I actually think it is pretty irresponsible (Zuckerberg, 2017).

Whereas, Elon Musk shared during a conference for South by Southwest (SXSW):

I am really quite close, I am very close, to the cutting edge in AI and it scares the hell out of me. It's capable of vastly more than almost anyone knows, and the rate of improvement is exponential. I think the danger of AI is much greater than the danger of nuclear warheads by a lot (Musk, as cited in South by Southwest, 2018).

Lastly, Bill Gates mentioned that “the world hasn't had that many technologies that are both promising and dangerous — you know, we had nuclear energy and nuclear weapons” (Gates, as cited in Stanford University, 2019).

The word “artificial intelligence” has had opinions, ranging from positive to negative extremes, by many top CEOs of technology companies. Hence, the future of this technology seems to still be blurry and not unanimous. Even if not everyone shares the same opinion, a lot of companies are investing heavily in this new technology in the hope to keep up against competitors or gain competitive advantages. But what can AI bring to a company? What are its application fields, business barriers, advantages and disadvantages? Hence, what are some key issues and opportunities to address that could be shared with managers for an AI solution implementation and adoption?

The objective and motivation for this paper is to contribute to a better understanding of artificial intelligence for managers who are not familiar with this concept and are questioning the relevance of this technology for their business. Therefore, the scope of this paper is to discuss the concept, its application fields, review a few of its limits, identify some key advantages and disadvantages of using this technology and give some recommendations for firms. It will not discuss other topics about artificial intelligence as, to cite some examples, its regulation, its weaponization or guidelines to code an AI algorithm.

The methodology that was used for the writing of this paper is the following. The author started with a theoretical analysis to review current insights from the literature.

The used literature ranges from business articles from the Harvard Business Review to articles from more scientific journals as Artificial intelligence, Intelligence, IEEE Intelligent Systems, etc. Besides, other sources were also used as, to cite some, reports from the European Commission, OECD data, reports from consulting companies, a conference organized by Stanford University, books, etc. Also, a bibliometric analysis was done based on the Harvard Business Review, the IEEE Computational Intelligence magazine, the Technological Forecasting and Social Change journal and the Research Policy journal. Then, these acquired insights were confronted to interviews with AI knowledgeable people to analyse the literature findings and compare it to their opinion. The on-field research was done by interviewing different people with varying backgrounds (CEOs, digital entrepreneurs, consultants, coders and a professor in digital business transformation) who therefore have divergent approaches to AI.

The structure of this paper begins with the theoretical part and provides a brief overview of the history of the emergence of artificial intelligence and its developments until deep learning. Then, artificial intelligence is defined as well as other closely related concepts AI is often confused with. Following, the application field of AI is analysed through a bibliometric analysis and the construction of a matrix with two variables: data generation and digital maturity of industries in order to try to highlight the relevant industries to provide a sense of the application and exclusion of AI. Some key barriers are then defined to track the potential success of the implementation of this technology. Next, advantages and disadvantages of the technology are analysed, summed up and described.

This theoretical approach is then confronted with on-field practices and knowledge. Interviews were done, using an interview structure that follows the chapters of this thesis to analyse the current on-field AI implementation experience. Then, the interviews are confronted with the theoretical analysis made previously to complement, confront and question what was found in the literature and to come up with some key issues to address for managers willing to integrate AI in their firm. Lastly, a conclusion is drawn from the main contributions of this paper and its implications as well as its limits and the possibilities for future research.

Chapter I: Artificial Intelligence: a brief history

Even though it is difficult to highlight a precise birthday for AI, the origin of AI came from the 1940's. Artificial intelligence finds premises in science fiction. Isaac Asimov published in 1940 the book "Robbie" which narrates the story of a young girl, Gloria, and her relationship with a robot, Robbie. This thought-provoking book fosters the imagination of intelligent non-humans, but also promotes the thinking about human characteristics. This book introduced the consideration of how people will have to interact with robots (Asimov, 1940).

Later, there were two major events in 1942 that contributed to the emergence of artificial intelligence. The first one, is the publication "Runaround" from Isaac Asimov in which he defined three laws of robotics. The first law says that a robot may not harm a human or allow a human to come to danger. The second law dictates that a robot must conform to the instructions of a human except if these counter the first law. The third law is that a robot must protect itself except if this implies an abuse of one of the two first laws (Asimov, 1942).

The other event that marked the beginning of AI, is the famous Turing machine, made by Alan Turing in 1942. Thanks to this conceptual model, the Allies were able to break Enigma code to decode the German ciphers which was their encryption machine for communication during the Second World War. Enigma was known to be impossible to decode for humans, even for the best mathematicians. This made Turing wonder about the potential intelligence of machines. In 1950 he published the article "Computing machinery and intelligence". In this publication he asks whether machines can think. His approach to this question is to apply the imitation game. This game requires someone to identify if the interlocutor is a person or a machine. The person must converse, without seeing or hearing its counterpart, by asking questions to its counterpart. Doing this will avoid any bias that could compromise the game as tone in voice and physical appearance. This test is the "Turing test" and stipulates that an artificial system is considered as intelligent if it's able to communicate with a human being without the human being noticing, for at least five minutes, that he talks to a machine (Turing, 1950).

The word "Artificial Intelligence" has only been used later, in 1956, when Marvin Minsky and John McCarthy organized the Dartmouth Summer Research Project on Artificial Intelligence

(DSRPAI). The purpose of this event was to gather researchers from different fields in order to develop machines able to imitate human intelligence. They wanted to focus on current problems for improvement in the artificial intelligence field. The issues they highlighted in their proposal for the Dartmouth Summer Research Project on Artificial Intelligence are the following. The first issue is about automatic computers. They mention that a critical obstacle we face is our lack of capability to write programs able to benefit fully from what we have. The second issue was to understand how a computer can be programmed to use a language. The third one is about neuron nets. They highlighted the difficulty to build a neural network that would be able to form concepts. The fourth issue is the theory of the size of a calculation. This theory implies that to be efficient one should be able to compute the complexity of the issue to assess the efficiency of the calculation. The fifth issue is the question of self-improvement. A truly intelligent machine should be able to improve itself from experience. The sixth highlighted issue is abstraction. This relates to the question of how machines could deal with abstract events. The last problem they highlighted is about randomness and creativity. This issue rests on the idea that creativity relies on a form of randomness and this randomness is guided by intuition which can difficultly be imitated by machines (McCarthy, Minsky, Rochester, & Shannon, 2006).

Later, around 1966, Eliza program was created which was the first program that could attempt to pass the Turing test. Eliza could simulate a conversation with a human being. It didn't pass the test, but it showed great progress in that domain (Weizenbaum, 1966). Another success story is the General Problem Solver program developed by Herbert Simon, Cliff Shaw and Allen Newell. This program was supposed to be a universal problem-solving machine (Shaw, Newell, Simon, & Ellis, 1958). Resulting from these successes substantial funding was made in AI research.

However, in 1973, strong critics were made from the U.S. Congress about the high spending on AI research versus its potential. Following this, the British government stopped to finance research on AI except for 3 universities. This was a downturn in research on AI and led to improvements in this field to stagnate till the 80's with the emergence of expert systems (Hendler, 2008).

One of the reasons for AI slowing to progress is because previous researchers tried to copy human intelligence through an expert system approach. This means that they applied a series of top-down conditions using "if-then" statements. Expert systems were impressive at that time

though. In 1997, IBM developed Deep Blue chess playing program which beat Garry Kasparov, the chess world champion and grandmaster who has been world champion for 225 out of 228 months of his career. The program could process up to 200 million moves per seconds and choose the best move looking 20 moves ahead thanks to tree search (Campbell, Hoane & Hsu, 2002). However, because of these “if-then” statements, an expert system could not do face recognition. For image recognition, the machine has to learn from data to adapt to different cases and this is what seems to define AI nowadays. To make AI able to learn from data there is a need of statistical methods. This concept was introduced in the 1940’s by Donald Hebb, who introduced the replication of human brains by using neurons and this conducted to researches in Artificial Neural Networks and this concept was further developed under the term perceptron by Bernard Rosenblatt in 1962 (Hebb, 2005; Sandler & Rosenblatt, 1962). However, researches in this domain slowed down because of a lack of sufficient computing power back in 1969. In 2016, AlphaGo, a program developed by DeepMind, defeated Lee Sedol, the Go world champion at that time, who was dan-9 level and won 18 international titles, four games to one. It was able to do so by using tree search and deep learning, which is also the basis for image recognition. This breakthrough led to advances in other domains as scheduling, planning and constraint satisfaction (Silver et al., 2016). Later, AlphaGo Zero, the newest version of AlphaGo, beat AlphaGo 100 to 0 by learning by playing against itself for 21 days (Haenlein & Kaplan, 2019). These events relaunched all discussion and researches about AI and generated again hype for artificial intelligence.

In a nutshell, artificial intelligence has evolved over time and has gone through periods of enthusiasm and deception due to expectations and the realization of what is feasible with current means. Thus, AI seems to be a continuously evolving concept that includes a lot of different techniques. For this reason, in the next chapter the concept will be defined in a managerial context and boundaries to the concept will be explained in order to work further with a commonly understandable term.

Chapter II: Definitions

As the concept of artificial intelligence seems to be broad and amalgamed with different other concepts, this chapter aims at understanding the common characteristics and differences with often-related notions and defining what artificial intelligence will mean for the further discussion in this thesis.

1.1. Artificial intelligence

The Oxford dictionary of computer science defines artificial intelligence as “A discipline concerned with the building of computer programs that perform tasks requiring intelligence when done by humans...” (“artificial intelligence”, 2016).

This definition talks about intelligence done by humans. But what does intelligence mean? To answer this question, we could write a whole thesis citing all the different experts that have their own perception of what intelligence is. “Viewed narrowly, there seem to be almost as many definitions of intelligence as there were experts asked to define it” (Gregory & Zangwill, 1987). To keep it simple, intelligence will be defined by John McCarthy, a founding father of the “artificial intelligence” term, as followed: “The computational part of the ability to achieve goals in the world. Varying kinds and degrees of intelligence occur in people, many animals and some machines” (McCarthy, 2004) .

Besides, the term “artificial”, on a stand-alone basis, could be defined as “Made or produced by human beings rather than occurring naturally, especially as a copy of something natural” (“artificial”, 2019).

Moreover, one should keep in mind that artificial intelligence can be nuanced in terms of “strong” and “weak” artificial intelligence. The first one refers to the ability of AI to be conscious, self-aware and sentient on top of “weak” AI. This would make AI human-like. Hence, this kind of AI seems quite futuristic and improbable as it would imply that machines could become perfect substitutes for people in every job. In other words, the AI program should pass the employment test as was introduced by the Stanford Professor, Nils John Nilsson. This test implies that the program should be able to get a job on its own going from application

procedure through the interviews to the acceptance for the position (Nils, 2005). More reasonable and feasible is “weak” AI, which refers to the transfer of cognition abilities to machines. Cognition abilities are the mechanisms to process thoughts by learning based on experience, remembering and problem-solving (Gottfredson, 1997). Hence, only “weak AI” will be the focus of this paper.

Before giving a final definition of artificial intelligence for this thesis, this paper will go through several related concepts that are often confused AI.

1.2. Related concepts

As Rav Ahuja¹ highlights, artificial intelligence, machine learning, neural network and deep learning are often used interchangeably, but they do not refer to the same things (Ahuja, 2019). For this reason, these concepts as well as a few others will be defined and compared to start on a common ground of what AI is, what it includes and what specifies this technology.

4.1.1. Expert system

“Expert systems are computer programs emulating human expert decision processes in a specialized domain. Expert systems are designed to produce decisions comparable to, and hopefully better than, human experts... Rule-based systems, using If-Then logic, are the most prevalent” (Coursey & Shangraw, 1989). In other words, expert systems follow a series of explicitly programmed rules following a certain logic, using, for example, “If – Then” conditions to take simple or complex decisions as an expert would. This task does not involve any learning from new data for the programmed system.

An expert system is part of the family of symbolic artificial intelligence which is an ensemble of approaches in artificial intelligence that are established based on human-understandable representations of problems. This was the first form of artificial intelligence and was leading from the mid-1950s until the late 1980s (Haugeland, 1989; Kosko, 1994). It is built to take complex decisions based on human expertise. Hence, it mimics the thinking of human experts who would have to analyse, design and monitor to perform the given task.

¹ Rav Ahuja is a Global Program Director at IBM and Co-founder of Cognitive Class

Even though it is a forerunner of AI, as it mimics the human way to solve a complex problem in a specific context, it does not rely on learning as data and the rules to handle this data are provided up front (Cf. Figure 1). Hence, there is no learning mechanism (Chollet, 2018).

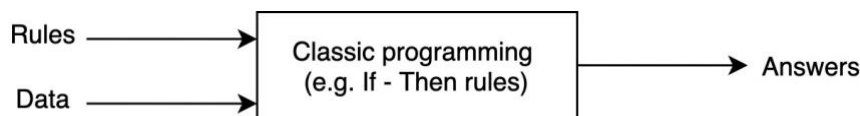


Figure 1: Concept of expert system - Adapted from "Deep learning with Python" (p. 5), by Chollet F., 2018, 20 Baldwin Road, Shelter Island: Manning Publications Co.

4.1.2. Machine learning

The Oxford dictionary of computer science defines machine learning as follows:

Machine learning is a branch of artificial intelligence concerned with the construction of programs that learn from experience. Learning may take many forms, ranging from learning from examples and learning by analogy to autonomous learning of concepts and learning by discovery. Incremental learning involves continuous improvement as new data arrives while one-shot or batch learning distinguishes a training phase from the application phase.

Supervised learning occurs when the training input has been explicitly labelled with the classes to be learned. Most learning methods aim to demonstrate generalization whereby the system develops efficient and effective representations that encompass large chunks of closely related data ("machine learning", 2016).

François Chollet, author of the book "Deep learning with Python", argues that machine learning is a subfield of artificial intelligence that arouse with the question to understand whether a computer could go beyond what it is ordered to do and learn by itself to perform a specific task. For a machine to learn how to perform a specific task, humans must input data and answers so that the algorithm can generate its own rules (Cf. Figure 2). These rules will then be applicable to new data and again adapted because of these new inputs. Therefore, a machine learning algorithm is trained rather than explicitly programmed. Even if machine learning is tightly related to mathematical statistics, it is dealing with large and complex sets of data as, for example, millions of images made of thousands of pixels, which would make it difficult for classical statistical analysis to process. Consequently, machine learning, and especially deep learning, rests on comparatively limited mathematical theories (Chollet, 2018).

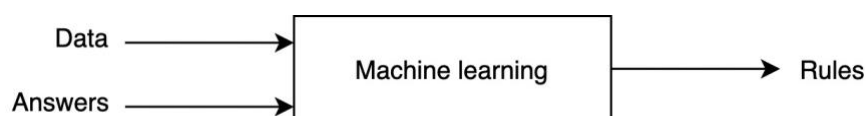


Figure 2: Concept of machine learning - Reprinted from "Deep learning with Python" (p. 5), by Chollet F., 2018, 20 Baldwin Road, Shelter Island: Manning Publications Co.

According to François Chollet, to work with machine learning, three things are required:

1. Input data: Imagine the AI application that is to be integrated is a solution that will automatically label some pictures. In this case the input data will be the images that we seek to label (Chollet, 2018).
2. Examples of expected output: These expected outputs will provide the algorithm with a possibility to train and get better at its predictions. It will allow the algorithm to create situation-solution couples from which it will learn the relation in order to apply this to new, known and unknown data (Prosperio, 2019). Using the same examples, the expected output will be labels that will be linked to the pictures.
3. The last necessity is a way to measure if the algorithm is performing well: It is required to compute the difference between the current output and the desired output. This distance will then be communicated, as a feedback, to the algorithm in order to adapt and correct the way the algorithm runs. This correction is called learning and learning in machine learning express an automatic search process for better representations. So, machine learning is the searching for useful representations of some input data, within a predefined space of possibilities, using guidance from a feedback signal. This specific way of feeding back the algorithm with this error measure makes machine learning different from expert systems (Chollet, 2018).

Nowadays, when referring to AI, people have in mind machine learning and not expert systems. Even though both are still part of artificial intelligence.

4.1.3. Deep learning

“Deep learning is a specialized subset of machine learning that uses layered neural networks to stimulate human decision-making” (Ahuja, 2019).

Deep learning is a subcategory of machine learning. It puts the emphasis on learning successive layers of increasingly meaningful representations. Hence, the “deep” stands for the successive layers of representations and is defined by the depth of the algorithm, which is the number of required layers to form a model. These layers of representation are automatically determined thanks to the training data set. Through these different layers of representation, the information will be purified by passing through a succession of filters to get a progressively better outcome. These layers are parametrized by weights to transform the data with a different impact. Therefore, learning in this context is updating the weight of the different layers in order to reach

a better representation of the input and its associated output (Cf. Figure 3). Hence, deep learning is a structure of multiple levels to learn data representation (Chollet, 2018).

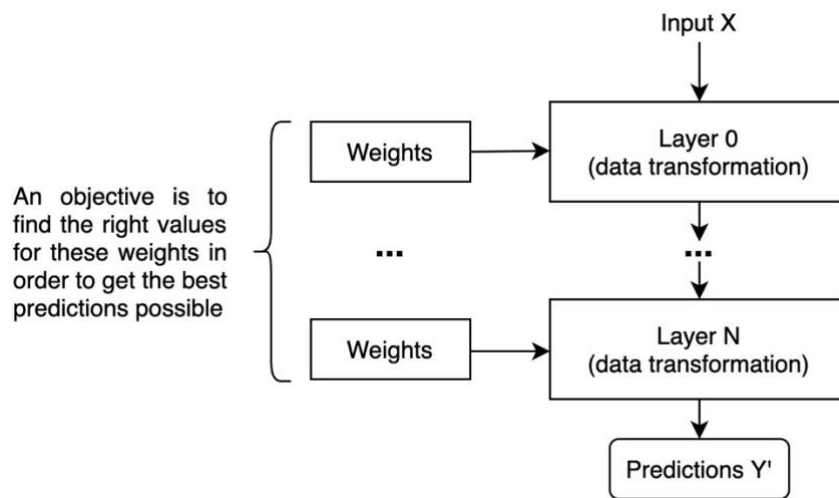


Figure 3: A neural network representation parametrized by its weights - Adapted from "Deep learning with Python" (p. 10), by Chollet F., 2018, 20 Baldwin Road, Shelter Island: Manning Publications Co.

As illustrated by the red arrows in the figure below, a fundamental goal of deep learning is to use the loss score, resulting from the difference between the prediction and the true target from the training set, as a feedback to lower the loss through the optimizer which allows backpropagation to adjust the value of the weights. This loop is repeated in order to minimize the loss score (Cf. Figure 4).

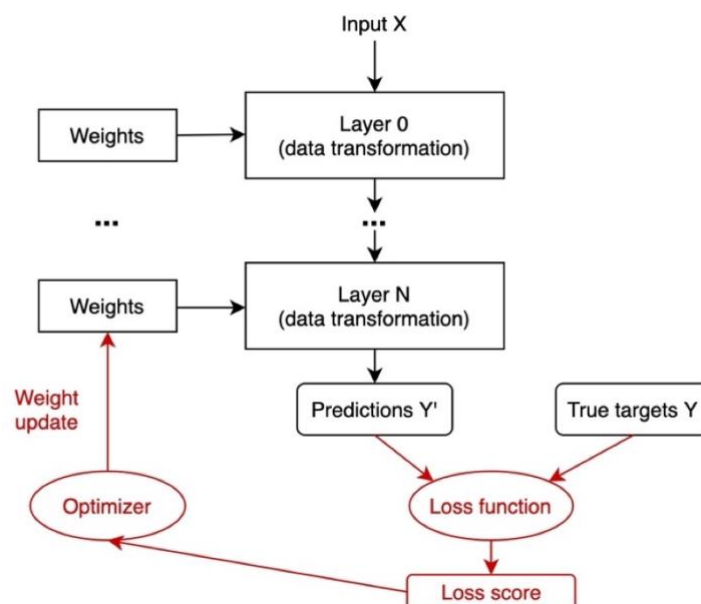


Figure 4: Optimization of the weights through the backpropagation of the loss score - Adapted from "Deep learning with Python" (p. 11), by Chollet F., 2018, 20 Baldwin Road, Shelter Island: Manning Publications Co.

Deep learning made near-human-level image recognition, natural language processing, natural language understanding, natural language generation, handwriting transcription, better machine translation, digital assistants (e.g. Amazon Alexa), autonomous driving, ad targeting and superhuman Go playing machine possible (Chollet, 2018).

4.1.4. Artificial neural network

The Oxford dictionary for computer science defines neural network as follows:

A neural network is a form of computation inspired by the structure and function of the brain. One version of this is as follows. The topology is a *weighted directed graph. *Nodes in the graph can be on or off. Time is discrete. At each time instant all the on nodes send an impulse along their outgoing arcs to their neighbour nodes. All nodes sum their incoming impulses, weighted according to the arc. All the nodes at which this sum exceeds a threshold turn on at the next time instant; all the others turn off... Nodes can be trained, using examples, to recognize certain patterns, for instance to classify objects by features... (“neural network”, 2016).

A neural network is a construction used in deep learning to form layers of representations. They are inspired from neurons and our understanding of the functioning of brains. However though neural networks are not modelled after brains but are only influenced by brain’s mechanisms (Chollet, 2018).

To sum up, an artificial neural network is an ensemble of layers, and its associated nodes, also called neurons, that together form the learning system (Cf. Figure 5).

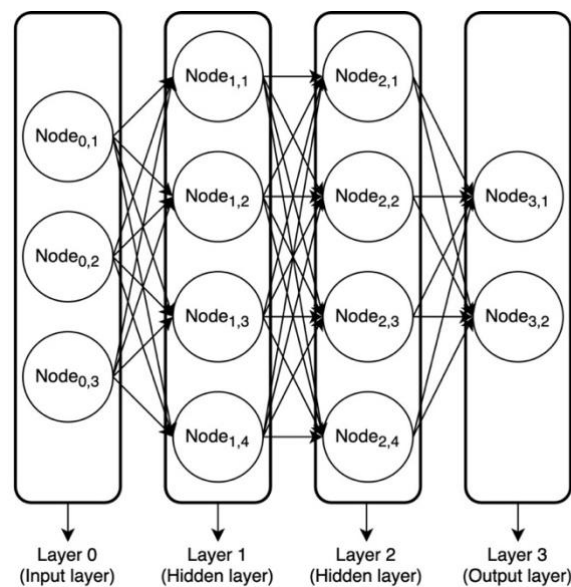


Figure 5: Representation of an artificial neural network of 4 layers, including one input layer, two hidden (computational) layers and one output layer. Each layer is made of neurons that will be activated or not (0 or 1) depending on the sum of the incoming values.

4.1.5. Adaptive systems

In their book on stable adaptive systems, Kumpati Narendra² and Anuradha Annaswamy³ define the concept as:

a system which is provided with a means of continuously monitoring its own performance in relation to a given figure of merit or optimal condition and a means of modifying its own parameters by a close-loop action so as to approach this optimum (Koditschek, as cited in Narendra & Annaswamy, 2012).

This system should be sufficiently intelligent to adapt, on its own, its parameters to a changing environment in order to function in the best possible way depending on specific criteria (Drenick and Shahbender as cited in Narendra & Annaswamy, 2012).

Adaptive systems differ from machine learning in the sense that the concept is broader than machine learning. Actually, adaptive systems include all the systems capable of adapting oneself to external stimuli. Therefore, these systems can be found in several domains as in biology (e.g. immune system), social science (e.g. group), computer science (e.g. machine learning), etc. (Holland, 2006; Lansing, 2003).

4.1.6. Statistics

“The practice or science of collecting and analysing numerical data in large quantities, especially for the purpose of inferring proportions in a whole from those in a representative sample” (“statistics”, 2019).

It is a scientific method to gather, summarize, represent and analyse data to take conclusions or make predictions based on the analysis. This scientific method can be applied in a variety of areas (Cf. Chapter 3). (Srivastava, 2008)

Some of the concepts that are most often confused with artificial intelligence were defined in this sub-chapter. The following sub-chapter aims at comparing all those concepts.

² Kumpati Narendra is the Harold W. Cheel Professor of Electrical Engineering and the Director of the Center for Systems Science at Yale University.

³ Anuradha Annaswamy is the Director of the Active-Adaptive Control Laboratory at MIT and a Senior Research Scientist in the Department of Mechanical Engineering

2.3. Comparison of these close-related concepts

In the previous section the related concepts were defined. This section will compare these concepts by laying down the similarities and differences among them. The purpose here is to provide the big picture and the connections between all these previously defined concepts.

AI has been widely used to discuss about everything. It has become a hype word that is often used for credibility and marketing purposes. Actually, for some companies, artificial intelligence has become a must-have, an argument for sales. However, people often misuse the term with machine learning, deep learning, etc. This can be due to the amalgam in the jargon or because of a lack of knowledge of the characteristics of each and about how they are related. To put it simply, while the terms “artificial intelligence” (AI), “machine learning” (ML) and “deep learning” (DL) are sometimes used as synonyms, they are in fact subsets of each other. Hence, these concepts are not mutually exclusive. They have some similar characteristics, and this is why they are often confused. Artificial intelligence includes machine learning and deep learning, but also approaches that do not involve learning and follow predefined rules instead. Expert systems, which run according to hardcoded rules of “If-Then” conditions, are examples of artificial intelligence that are not machine learning. Machine learning includes deep learning and this, as machine learning, can be used through other mechanisms than neural networks, which makes this family broader than solely deep learning as DL is defined by its use of neural networks for its functioning. Similarly, artificial intelligence and deep learning are not exact substitutes. To sum up, artificial intelligence is broader than machine learning which in turn is broader than deep learning (Cf. Figure 6) (Chollet, 2018; Marr, 2019b; Simplilearn, 2018).

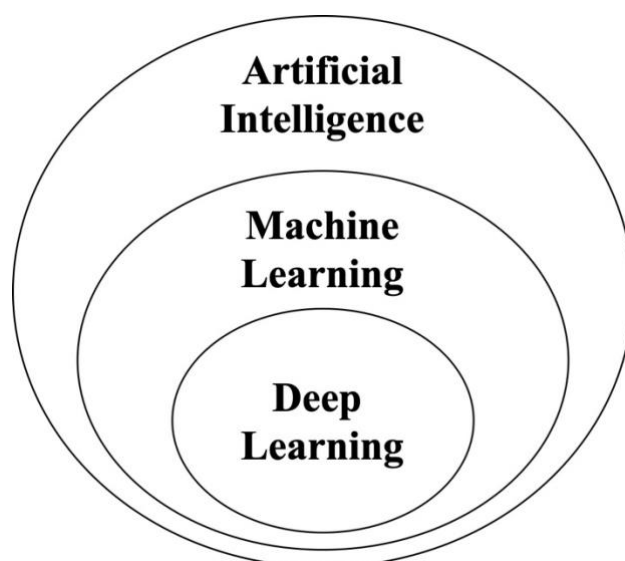


Figure 6: Relationship between artificial intelligence, machine learning and deep learning

As artificial intelligence tries to replicate human intelligence, a lot of discussion emerged trying to understand to what extent AI should be similar to humans' intelligence. This made people distinguish two categories of AI, "strong" and "weak" AI. Often also referred to as "general" and "narrow" AI. The first one implies that the machine would be able to think and understand the meaning of symbols instead of solely using them. However, current programs can only manipulate those symbols which does not guarantee the presence of understanding. To support this idea, John R. Searle⁴ gave as example that a machine could answer to questions asked in Chinese by using a rule book to associate the correct Chinese symbols without actually understanding any of the symbols dealt with. Therefore, weak AI refers only to this manipulation of symbols which represents the cognition part of human intelligence (Searle, 1990). This is what can currently be achieved to some extent and this paper focus solely on this type of AI.

Weak AI, which we will abusively refer to as AI later on, has existed since the early 40's with the Turing machine. However, back then we were truly speaking about expert systems. As the programs were coded to perform exactly what was asked from them by following pre-set rules. Those were fixed systems that would not evolve with its environment and new data. Because of its inability to learn by itself, there is a lot of deliberation about whether or not expert systems

⁴ John Rogers Searle is a Willis S. and Marion Slusser Professor Emeritus of the Philosophy of Mind and Language at University of California, Berkeley

can be considered as part of the AI family. The actual hype of what we nowadays understand as being artificial intelligence came later, in 2016, when DeepMind beat the world champion in Go. At that time, we had enough computational power to create a deep learning algorithm that would learn from experience and new data in order to perform a task in a way that was not explicitly programmed. This technology entered the family of adaptive systems that are able to listen to their environment and change accordingly. Machine learning can also be divided into two groups depending on the structure of their algorithm. A technique of machine learning implies the use of several interconnected layers of nodes that look like the functioning of human neurons. Using this technique, we speak about deep learning. However, machine learning can also be used by other statistical methods as regressions, decision trees, Naive Bayes classifier, etc. As mentioned, deep learning is characterized by a method using different layers of nodes resembling to human neurons. Therefore, this structure is called an artificial neural network (Microsoft Developer, 2019; Ramesh, 2017).

To summarize this approach to artificial intelligence and its related concepts, the author created a framework that provides an idea of the big picture gathering and connecting the previously defined concepts (Cf. Figure 7)⁵.

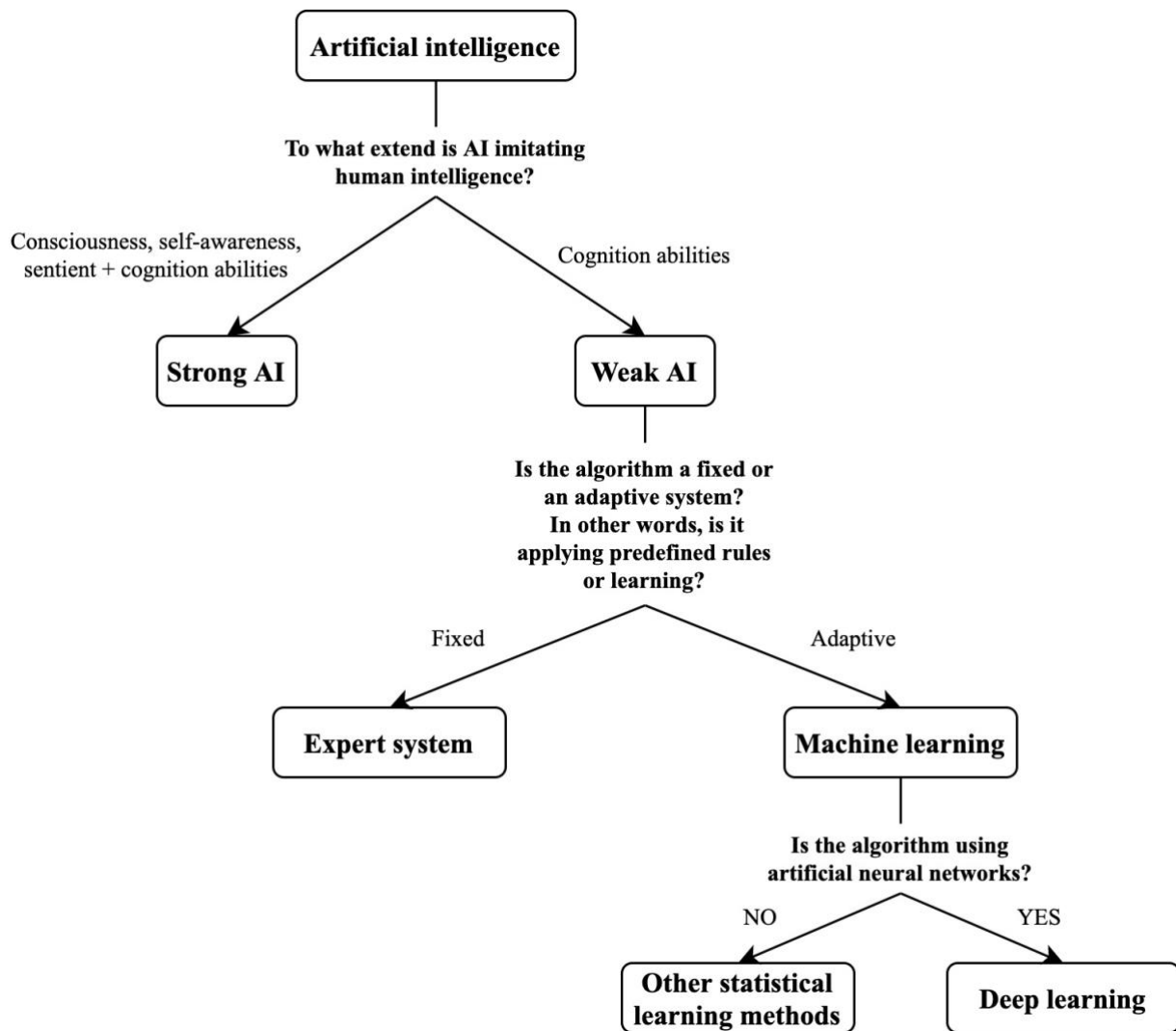


Figure 7: A schematic approach to decomplexify artificial intelligence and its close-related concepts

Given this brief background of the distinction between the different concepts, following is a table of comparison of the three big concepts that are often confused: artificial intelligence, machine learning and deep learning. The other defined concepts will be included in the explanations of the three to enrich the comparison of their meaning.

⁵ The question « Is the algorithm using artificial neural networks?» is here simplified to facilitate the comprehension. However, the true question should be “Is the algorithm using artificial neural networks with multiple hidden layers?”.

	Artificial intelligence (AI)	Machine learning (ML)	Deep learning (DL)
Time context	1940's (e.g. Turin machine), but the term artificial intelligence was used for the first time in 1956 at the Dartmouth conference	1950's, Arthur Samuel first introduced the concept in his paper about machine learning for the game of checkers) (Samuel, 1959)	1960's (Frank Rosenblatt introduced the perceptron, which is based on neurons, as part of the artificial neural network, which became core to the design of deep learning algorithms (Rosenblatt, 1960)
Abbreviated definition	Partly imitation of human intelligence that is artificially reproduced.	Ability of a machine to learn in order to perform a task in a way it was not explicitly programmed to.	Ability of a machine to learn through an artificial neural network to solve complex problems.
Is it part of AI?	YES	YES	YES
Is it part of ML?	NO	YES	YES
Is it part of DL?	NO	NO	YES
What is the system's structure? (for the exclusive part)	Algorithm of "if – then" rules	Regressions, decision trees, support vector machine, random forest, etc.	Multiple layers of neurons (= Artificial Neural Network)
Able to change with environment?	Not per se as AI can also be an expert system. Hence, it will be hardcoded to reproduce an expert's reasoning for a complex problem.	Yes, machine learning is an adaptive system. This means that through experience and by the use of statistics it will learn to adapt to its environment.	Yes, as deep learning is part of machine learning. Deep learning is a learning method that relies on a neural network structure to adapt to its environment.
Keywords	Intelligence, cognition ability	Learning, statistics	Learning, neural network
Examples (Cf. examples)	Components sorting process for assembly	House pricing determination	Image & speech recognition

2.4. Definition of artificial intelligence in a managerial context

To conclude this chapter about definitions, for this paper, artificial intelligence will be defined in a managerial context, based on the previous chapters, as the computer-based techniques that improve the speed, reliability or accuracy of processes that would require intelligence when done by humans, to help a company in its business activities by automating processes, supporting analyses through gains in insights or engaging with employees and customers (“artificial intelligence”, 2016; Davenport, Ronanki, 2018; Tarafdar, Beath, Ross, 2019).

As this definition suggests, this paper will not discuss strong artificial intelligence, other types of automation that would not require a certain type of intelligence, legislation of artificial intelligence and other topics related to artificial intelligence that do not refer to the implementation and adoption of this technology in companies.

2.5. Examples

Following are three examples of how artificial intelligence can be applied in a company. One example will be given at each level of artificial intelligence (expert system, machine learning (that is not deep learning) and deep learning).

The first example concerns expert systems. Digital Equipment Corporation developed XCON (for eXpert CONfiguration) program, which is an expert program. The company used to produce a wide range of computer components that could be configured in different ways depending on customer's orders. In the 1970's, experts had to gather all the components from a customer's order. Then they made a schema on how to assemble these parts. But this process contained human errors and omissions. Therefore, 90% of the company's components gathering were checked before assembly. This process costed a lot. This is why the company decided to automate the gathering part in order to avoid double check and minimize human errors. They implemented XCON program, which would automatically analyse a customer's order and gather the required components. This allowed to ship the order directly to the client without needing a double check. But also, generated a data base and increased the component's quality (Leonard-Barton & Sviokla, 1988).

The second example is one of machine learning that is not deep learning. Imagine a real estate agency that continually has to evaluate house prices based on different criteria as location, characteristics of the house (m², etc.), commodities, etc. No two houses are exactly the same. This is why estimations need to be made as it will never be the perfect match of what the agency already has encountered. To help a real estate agent with this a regression model could be used. By gathering all the information about the current houses in its management and comparing it with the new house. Thanks to a machine learning technique as a regression model, a prediction can be made for a new house's price. This is a valuable supportive function to win time, be coherent and avoid mistakes.

The last example illustrates deep learning. An example of a deep learning application is object detection in factories. This can have several purposes as for security, sorting, packaging, etc. Object detecting can help to sort and take out every product that is unwanted and not sellable. It can also help for security purposes as detect potential danger or failure to alert on time and act directly upfront.

While the previous pages had as goal to briefly outline the history of artificial intelligence, going from science fiction to weak AI, and to define the concept as well as the related ones to frame their relationships for the readers, the following chapters will discuss the relevance of this technology in business and management by highlighting domains of application and exclusion, barriers to its implementation and advantages and disadvantages of this technology.

Chapter III: Domains of application and exclusion of artificial intelligence

The approach in this paper to assess the potential scale of the application of AI in business is evaluated by analysing its potential for different industries. In order to do so, two analysis were done. The first one is through a matrix mapping the industries based on the two axes: data generation and digital maturity of the industry. The second analysis is a bibliometric study to get an idea of the number of AI-related articles published per industry. But first, the industry-based approach is put into context.

3.1. Industry-based approach

Artificial intelligence seems to foster a great interest in some industries as in the medical sector with its help for diagnoses, automotive sector with the autonomous cars, etc. However, the expectations in the short term are higher than what is often really achievable. Indeed, a hype has been created around artificial intelligence and its potential achievements.

Nowadays, deep learning is generating a third wave of fame for artificial intelligence. Therefore, companies tend to invest again in this technology and especially in deep learning (Chollet, 2018). As for example IBM was investing, in February 2019, \$2 billion in New York research hub for AI (Carville, 2019).

François Chollet argues that companies need to make sure they have a clear idea of what they can hope from this technology and what is not to be expected or, at least, in the short-term (Chollet, 2018).

The long-term, however, seems more optimistic, as we only recently started to apply deep learning algorithms for autonomous driving cars, for medical diagnoses and we still have a long way to go. This rapid increase in evolution and performance of AI is mainly due to increased funding in AI (Chollet, 2018).

AI seems to be already quite present in our daily lives even if people do not always notice it. People might be using it to filter out their Google pictures looking for specific objects and people or might be using digital assistants as chatbots to ask questions to companies or even using voice assistance for example.

It could be that, in the future, AI will have an even bigger importance in our lives and will be in almost every process. Trust, time and investment could make this happen. Some compare

the influence of AI in our lives as the Internet had a few decades ago as it could help out doctors, researchers, companies, etc. in their daily activities. Hence, which industries will be impacted by this technology?

3.2. Which industries have AI implementation opportunities?

According to the International Labour Organization⁶ (ILO), the industries can be grouped in the 22 categories that are enumerated in the appendix (ILO). This list is used with the hypothesis that it is exhaustive, hence that every business fits, at least, in one of these categories. In each one of these categories, an example of a potential artificial intelligence application specific to the industry is provided (Cf. Appendix A).

To better understand the trends that make an industry technologically prone to AI applications, an analysis was made through the mapping of a sample of industries according to two axes: the datasphere generation and the digitalization of the industries. Then a bibliometric research was done to support the mapping.

The mapping of the sample of industries was made by ordering these industries according to the amount of data that an industry generates and the digitalization maturity of that industry. These two axis were chosen as, per definition, in order to have artificial intelligence there is a fundamental need of data to process and digital capabilities to handle this data.

The first axis, the datasphere of industries, represents the volume of data that can be generated by an industry. As the datasphere refers to data being generated, it does not mean that this data is stocked, structured or ready-to-use. In a 2018 white paper from the International Data Corporation⁷ (IDC), the authors analysed the datasphere creation per industry. By making a global datasphere research and interviewing 2,400 worldwide companies' managers knowledgeable about their ICT system and management, they ranked some industries according to their data creation. According to their results, the first industry that generates the most data is manufacturing. This sector was estimated to generate 3,584 Exabytes yearly. The second

⁶ The International Labour Organization (ILO) is a agency from the United Nations which strives for more justice in labour by setting international labour standards.

⁷ The International Data Corporation (IDC) is a market research company specialized in information technology, telecommunications and consumer technology markets.

sector is retail and warehousing with 2,212 Exabytes. The third one is the financial services sector with 2,074 exabytes. The fourth one is information and communication technologies with about 1,555 exabytes. The fifth one is media and entertainment with 1,296 exabytes. The sixth one is healthcare with 1,218 exabytes. The seventh one is transport with 717 exabytes and the last one is resources (including oil and gas mining and transportation, resource industries and petroleum and coal refining) with 280 exabytes (Reinsel, Gantz, & Rydning, 2018).

Manufacturing is realistically topping in terms of yearly data generation as it is supported by different drivers. Firstly, manufacturing is widespread and also mature as it has been through several industrial revolutions. Secondly, it also knows long hours of operations as it might be running 24 hours, 7 days a week. Besides, the emergence of the Internet of Things (IoT) makes it possible to gather even more and better data from machinery (Mourtzis, Vlachou, & Milas, 2016). Next to generating data, manufacturing is also one of the sectors that stores the most data and is therefore helped by technologies such as cloud services (Yin & Kaynak, 2015).

At the other end of the spectrum, according to the IDC in 2018, resources generate the least data among the ranked industries. Oil & gas mining, as an example of the resource industry, could illustrate the complexity of generating data in that sector. Even though there are Big Data opportunities in drilling, exploration, transportation, etc., this sector might be confronted to some challenges (Mohammadpoor & Torabi, 2018). Those can be lack in knowledge of the employees and ownership of the data (Cameron, 2014).

Also, even though the sensors can generate millions of data per day, there might be problems with the sending of these generated data from the field to the Big Data computing infrastructures and these issues vary according to the data format, quantity and protocols (Neri, 2018; Gidh, Deeks, Grovik, Johnson, Arumugam, Schey & Hollingsworth, 2016).

Besides, lack of business support, because of low consciousness about big data in this industry, could also refrain the sector from moving towards more data creation. Next to this shortfall, there could also be a lack of relevant data and skilled people as well as high costs for Big Data infrastructures (Feblowitz, 2013).

Another challenge can be the interpretation of the output. Therefore, the data scientists should work closely with the petroleum engineers (Maidla, Maidla, Rigg, Crumrine & Wolf-Zoellner, 2018).

Other rationales for this low position in data generation could be, looking at the electricity industry, because the industry is conservative, preoccupied with system reliability and heavily regulated (Schuelke-Leech, Barry, Muratori, & Yurkovich, 2015).

The second axis represents the digital maturity of an industry. To illustrate this, a ranking was made by the McKinsey Global Institute (MGI) based on the digital level of assets, usage and labour for the industries in the US. According to this research⁸, the sector that seems the most digital is ICT (information and communication technology). The pool of industries that comes next in the ranking is media, financial services and professional services. The next group of industries is wholesale trade, advanced manufacturing, oil & gas and utilities. The group coming next is retail trade, real estate, education, government and personal services. The next pool is basic goods manufacturing, chemicals & pharmaceuticals, transportation & warehousing and healthcare. The last group is mining, entertainment & recreation, hospitality, construction and agriculture. As this analysis was made in December 2015, the industries have evolved and might have gotten a bit more digital, nonetheless this ranking provides a rough idea about the digital advancement in the different sectors and how they compare to each other (Gandhi, Khanna, & Ramaswamy, 2016).

The hiring of ICT specialists, the purchasing of computational power and the performing of big data analysis are some of the drivers that testify of the digital level of an industry and its digital readiness to adopt AI solutions. For these three drivers, the Organisation for Economic Cooperation and Development (OECD) published the percentage of companies' adoption per industry (OECD, 2018a, 2018b, 2018c). These results, for the European countries in 2018, could suggest that with 73,5% of the businesses hiring ICT specialists, 64% businesses purchasing computational power and 27% businesses performing big data analysis, ICT is the industry that is the most digital (Cf. Appendix B1, B2, B3). By averaging the ranking position of each industry for the 3 drivers, the global ranking of digital level, from top till down would be: ICT, professional services, Wholesale trade, administrative and support services, real estate, transportation and storage, manufacturing, retail, construction and food and beverages (Cf. Appendix B4). This ranking is the same for weighted (per percentage) as unweighted (per

⁸ The referred to research paper made by McKinsey Global Institute (MGI) in 2015 is "Digital America: A tale of the haves and have-mores". Part of this paper was summarized and discussed by two of the papers' authors, Somesh Khanna and Sree Ramaswamy, and published on Harvard Business Review (HBR) under the title "Which Industries Are the Most Digital (and Why?)".

position) averages, meaning that the ranking remains the same in absolute as well as in relative terms. The only minor exception is a switch in real estate and administrative and support services positions. However, this does not affect the general highlighted trend in industries' positions. This global ranking highlights the same trend, in terms of comparative digital levels between industries, as the analysis made by the McKinsey Global Institute for the US. Also, in both rankings ICT is a topper with a substantial advance on the other industries.

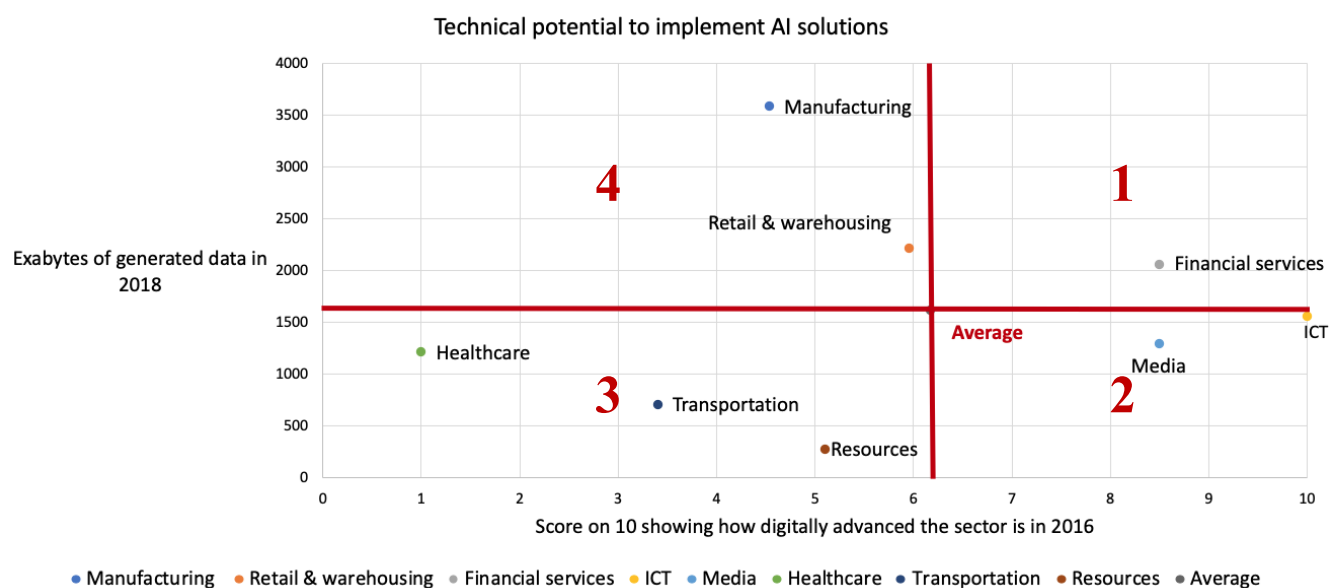


Figure 8: Mapping of industries* based on the two axes: data generation and digitalization maturity. *The mapped industries are those presented in both rankings (each axis).

By mapping the different industries that match in the ranking of both axis, digital maturity and datasphere, the following matrix can be generated (Cf. Figure 8).

This matrix shows the technological potential of industries to use AI solutions. Being below average does not mean that there is no AI potential. It just means that the industry is generating relatively lower data or is relatively less digitalized. From this matrix, manufacturing seems a good candidate for AI as it generates a lot of data yearly. As discussed above, this is mainly due to its characteristic to run for long hours (sometimes 24 hours for 7 days), but also because of the increasing connectivity and digitalization of machinery. ICT seems to be a good candidate as well by being on the edge of new technologies, hence digitally mature. Financial services appear to be one of the bests in class by being above average for digital maturity and data generation. Resources is low on data generation and this could be due to the challenges that the sector faces, as mentioned in the previous paragraphs. Healthcare seems to be lacking behind as well in terms of digital maturity as in terms of data generation.

This matrix could be a basis for building clusters of industries with the same characteristics and then analyse whether these clusters are driven by similar trends and are similarly impacted by AI opportunities and threats. Following the boxes created by the red lines on the matrix (Cf. Figure 8), these potential clusters could be: highly digital and higher data generation (financial services); highly digital and lower data generation (ICT and media); lower digital level and lower data generation (resources, transportation and healthcare) and lower digital level and higher data generation (manufacturing and retail & warehousing).

The technological potential of industries to implement AI solutions being mapped out and potential clusters being defined, the next step would be to look for similar trends in each cluster by highlighting the artificial intelligence interest for each mapped industry. In order to do so, a bibliometric analysis is done to evaluate which industries have more articles published about AI.

The online Harvard Business Review (HBR) magazine was analysed in order to get an idea about the business sense of AI in industries. The 21st of March 2020, the keywords “artificial intelligence”, “machine learning” and “deep learning” were searched on the HBR website and their results aggregated. A result of 11,017 articles was given from which 5,899 articles were allocated to industries (no time filter was applied). HBR automatically filters the articles per industry if relevant. The top 3 industries that had articles allocated are retails & consumer goods, manufacturing and financial services. On the contrary, the low 3 industries are real estate, marketing & public relations and travel (Cf. Appendix C1). This top three corresponds to the top three industries according to the data generation axis from the matrix analysis.

In order to complement this research with a more engineering point of view, a bibliometric research was made by selecting the IEEE computational intelligence magazine. This journal was chosen as it is a renowned engineering journal and as it was possible to compare it with HBR as it does not limit itself to machine learning or deep learning but includes all the AI family. Also, it had a reasonable number of articles to analyse without setting a time filter. The result was of 302 articles from which 72 articles could be allocated to industries based on the same industry categories as HBR divides it. The top 3 industries from this bibliometric research is, top-down, healthcare, aerospace & defence and, lastly, with a same score, media, telecommunication and financial services (Cf. Appendix C2). The low 3 on the contrary is hospitality, construction & infrastructure and food & beverages.

Healthcare is topping with 17%, of the articles attributable to an industry. This suggests that there is a lot of research being done in AI for healthcare from an engineering point of view, even though healthcare seemed relatively low on the technological potential matrix. Moreover, looking back at the HBR ranking, healthcare holds the 6th position.

Therefore, a last bibliometric research was made with the business innovation-oriented journals “Technological Forecasting and Social Change” and “Research Policy” in order to understand and bridge the gap between the two previously made bibliometric researches. The keywords used on the 14th of April 2020 were “artificial intelligence”, “machine learning” and “deep learning” and there was no time filter. This resulted with 664 articles from which 184 articles could be allocated to industries. The top 3 industries here is: healthcare, transportation and engineering, infrastructure & construction. The last category (engineering, infrastructure & construction) was driven by a lot of publications concerning smart cities. The low 3 here is: hospitality, sport and food & beverages (Cf. Appendix C3).

Healthcare comes again in top position with 16% of the articles that can be attributed to this particular industry.

Healthcare is low on the matrix as well in data generation as in digitalization and this could be because of several factors. Healthcare is a labour-intensive sector that uses sophisticated technology for diagnostics and treatments, but only a minority of the workforce uses technologies to perform their work. For example, less than 20% of the payments to healthcare is made electronically in the U.S. (Gandhi et al., 2016).

However, even though healthcare is low as well in terms of data generation as in terms of digitalization, there is a lot of research done in this field as well in engineering journals (as the IEEE Computational intelligence magazine) as in more business innovation-oriented journals (as Research policy and Technological forecasting and social change). This could be due to several reasons. First, an analysis on Scopus made the 14th of April 2020 shows increasing publications of articles discussing artificial intelligence in healthcare. Whereas in 2010 there were 5,484 articles published on Elsevier, in 2019 there were 25,698 articles published. The increase over the years follows an exponential trend, with an increase from 2018 to 2019 of 37% . This could testify of an increasing interest for artificial intelligence in healthcare (Cf. Appendix C4). Secondly, people get more and more connected and share information with new smartphone’s health applications or even with connected wearable products that measures people’s activity as the Google watch and the Apple watch which releases were respectively in 2014 and 2015, for instance. These telehealth devices enable to capture additional health

information as heart rate for example (Vesselkov, Hämmäinen, & Töyli, 2018). Also, new technologies are constantly created to measure health condition and also for imagery which brings new opportunities for analysis (Lapão, 2019). These are some examples of plausible rationales behind a potential growth in the healthcare datasphere. Additionally, the International Data Corporation (IDC) expects healthcare to have the biggest 2018 – 2025 CAGR in data generation with 36%. This is just before manufacturing with 30%, financial services with 26% and media and entertainment with 25%.

The following table (Cf. Table 1) summarizes the main results from the analysis described in this chapter for the industries that are mapped on the matrix. Three main categories are here published. For the first one, data generation, manufacturing stands in first position. For the second one, digital maturity, ICT is leading and for the last one, amount of AI articles published per industry, even though it depends on the journal, retail is a topper for HBR while healthcare had the most assigned articles in the IEEE Computational Intelligence Magazine and in the Technological Forecasting and Social Change & Research Policy journals.

Industries from matrix (Cf. Fig. 8)		Resources	Transport	Healthcare	Media	ICT	Financial services	Retail & warehousing	Manufacturing
Data generation	IDC - data generation (2018) (Exabytes)	280 EB	710 EB	1218 EB	1296 EB	1555 EB	2074 EB	2212 EB	3584 EB
	MGI - digital maturity (2016) (score on 10)	5,1	3,4	3,4	8,5	10	8,5	5,94	4,53
Digital maturity	OECD - Businesses hiring ICT specialists (within < 12 months) (%) (2018)		13,10%			73,51%		13,29%	19,99%
	OECD - Businesses purchasing computational power (%) (2018)		21,02%			63,99%		19,92%	21,99%
	OECD - Businesses performing big data analysis (%) (2018)		18,78%			27,01%		11,53%	8,89%
Artificial intelligence publicity per industry (as per published articles)	HBR* (2020)	2,89%	2,46%	6,59%	4,44%	2,97%	8,58%	14,87%	9,90%
	IEEE Computational Intelligence magazine* (2020)	2,78%	5,56%	16,67%	6,94%	6,94%	6,94%	1,39%	5,56%
	Technological Forecasting and Social Change & Research Policy* (2020)	7%	10%	16%	6%	6%	5%	2%	7%

Table 1: Summary table of the main results from the analyses done in this chapter for the industries presented in the matrix.

*The publicity of AI was measured per respective journal and the percentage stands for the amount of AI articles that were assigned to that particular industry among all the HBR-defined industries.

Finally, the main take-aways and discussion points from this analysis are plural. Firstly, the examples per ILO (International Labour Organization) industry and the fact that there are at least a few articles about artificial intelligence in each industry category on HBR testify that the application of AI is wide and not pre-determined for a few industries. However, there are gaps between the industries as well in terms of the mapping criteria as in terms of the number of published articles. This shows that even though AI is applicable to a certain extent everywhere, there are differences in terms of potential and attractiveness. Based on the matrix and the HBR classification, which classified the most articles (5,899 articles) to industries, their top 3 of industries (manufacturing, retail and financial services), which is similar for both, seems to be more driven by the axis of data generation. Thus, the manufacturing industry is likely to benefit substantially from AI. However, the other bibliometric analyses show a trend towards publications in healthcare. High publication levels of articles about AI in different clusters, namely for manufacturing (cluster 4) as well as for healthcare (cluster 3), could advocate that the previously defined potential clusters are not the only indicator for AI opportunities. Indeed, even though there is increasing data generation in healthcare, this interest in healthcare could indicate that data generation is not the only driver for AI opportunities and that besides technological implementation potential, other drivers could be important as for example the potential added value, return on investment or ethical issues.

3.3. AI as a General-Purpose Technology

Boyan Jovanovic and Peter L. Rousseau⁹ explain the term general-purpose technology as the following:

The term “general-purpose technology”, or GPT, has seen extensive use in recent treatments of the role of technology in economic growth, and is usually reserved for changes that transform both household life and the ways in which firms conduct business. Steam, electricity, internal combustion, and information technology (IT) are often classified as GPTs for this reason. They affected the whole economy (Jovanovic & Rousseau, 2005, p. 1184).

General-purpose technologies present the following characteristics. They have a scope for improvement, are widely used, have a broad variety of use cases and have technological

⁹ Boyan Jovanovic, Professor of economics at New York University, and Peter L. Rousseau, Professor of economics at Vanderbilt University, wrote together chapter 18 – “General Purpose Technologies” of the Handbook of Economic Growth, Volume 1, Part B, 2005.

complementarities, meaning that its environment needs to be adapted (Helpman, 1998). Artificial intelligence presenting all of these characteristics, it is probably the most important general-purpose technology of this era. Its impact will not only be reflected by its direct contributions, but also by its possibility to empower and stimulate complementary innovations (Davenport, Brynjolfsson, McAfee, & Wilson, 2019).

As analysed in the chapter about the domain of applications and exclusions, AI can be widely used across the industries if it meets two key technological criteria of success which are useable data and digital maturity to be able to leverage on the data.

From the examples of AI applications in each ILO industry, it is clear that AI has a general-purpose characteristic. This characteristic comes from the fact that AI can support companies in three major business needs, which are: process automation, cognitive insights and cognitive engagement. In 2018, Thomas H. Davenport¹⁰ and Rajeev Ronanki¹¹ analysed 152 AI implementation projects to assess to which AI application these projects related and got the following results (Thomas H. Davenport & Ronanki, 2018):

- Process automation accounts for 47% of the AI implementation projects and includes the automation of digital and physical processes. The automated digital processes are often administrative and financial activities.
- Cognitive insights accounts for 38% of AI implementation projects and its purpose is to detect patterns in the vast amount of data that companies can have access to and interpret those to support people in their decision-making.
- Cognitive engagement accounts for 16% of AI implementation projects and has as objective to engage employees and customers for efficient and effective customer service as well as support for technical questions.

In a nutshell, artificial intelligence could be defined as a general-purpose technology and finds special utility to automate some activities, bring additional insights through better analysis and enhance engagement with clients. Therefore, artificial intelligence finds a wide set of cases for its application, but then what could potentially refrain from using this technology? In the next chapter, the barriers to implementing and using AI will be discussed.

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Chapter IV: Barriers to the application of artificial intelligence

“Artificial intelligence has the potential to transform business. But the key to utilizing it will be realizing its limitations” (Lashinsky, 2019, p. 4).

Sunday 18th of March 2018 at 10p.m., a 49-year old woman was killed by an autonomous Uber car in Arizona. Uber has been testing its autonomous cars in several regions in North America to get its cars better at driving and overcoming potential sudden dangers. As car accidents are 94% of the time due to driver errors, self-driving cars promised to be safer in the future. However, cars require image recognition in order to operate autonomously and in this concrete example of an AI failure, the car could not identify the woman who was walking next to her bike. The car system detected the woman 6 seconds before the impact but was confused. It was first classified as an unknown object, then as a vehicle then as a biker whose trajectory was unidentified. At 1.3 seconds before the impact the system realized that it needed to use the emergency brake, but it was disabled to avoid conflict with the self-driving system. This is why there is a back-up driver to take over the driving if necessary. As this is the first pedestrian killed by a self-driving car it aroused some questioning about the used technologies, its reliability and responsibility (T.S., 2018; Wakabayashi, 2018).

This example of a dramatic AI failure keeps human down to earth by highlighting that AI applications are not perfect. They need a set of prerequisites, training and are confronted to limits. Even though in this example the AI application, generally speaking, works relatively well, except for that one tragic time, some AI applications are difficult to implement, because they are confronted to barriers. Following are some of the most mentioned potential barriers for an AI implementation. These barriers are here divided into 4 categories: the expectations, technological necessities, the new cultural environment and ethics.

4.1. Expectations

Andrew Ng¹² said concerning the expectations about what can be achieved through AI that “lately the media has sometimes painted an unrealistic picture of the powers of AI. (Perhaps soon it will take over the world!)” (Ng, 2016, p. 1).

Overestimation and misalignment of expectations is a barrier to an effective implementation of AI. An example of this overly expectations is the machine Watson from IBM that wanted to develop an algorithm to “cure cancer”. The product had as goal to recommend the best treatment for a patient by analysing his cancer. After having spent \$62 million, doctors from Jupiter Hospital in Florida said that the tool is unreliable and even unsafe for patients in some cases. Therefore, they had to put the collaboration on hold (Chen, 2018; Strickland, 2019). This mismatch between what they expected from the development of the tool and what machine learning could actually provide was an expensive way to learn that expectations need to be thoroughly confronted with reality.

Besides, AI is currently facing a huge hype and people’s expectations are surpassing its current potential. According to Gartner’s yearly technology hype curve of 2019, most of AI applications are still in the expectations peak (Cf. Appendix D) (Gartner, 2020).

Consequently, before starting to implement an AI application, a company should make sure that the technology will bring additional value, that the objectives of using it are well-defined and clear and that these objectives are achievable through the implementation of AI (Guttman & Galyardt, 2019).

4.2. Technological necessities

Barriers in technological necessities to provide an AI output can occur at two different stages: input and process.

4.2.1. Input

The potential barriers to correct implementation and running of AI at the input level concerns data. Data itself can represent a barrier in different ways. Non-accessible, incomplete, non-

¹² Andrew Ng, *Founder and lead Google brain (deep learning) project, former Chief Scientist at Baidu, Professor of Computer Science at Stanford University, Co-founder and Chairman of Coursera, Founder & CEO of Landing AI*

codifiable and biased data form the input-wise constraints that block companies from using AI in specific contexts.

Non-accessible data

Non-accessible data can occur because a company simply does not possess the required data or the data might be protected by GDPR¹³ legislation, which makes the data unusable towards certain ends (Wiewiórowski, 2019).

Incomplete data

Incomplete data is also a major issue. In order to make an AI application, it is required to provide the algorithm with sufficient input and output examples for it to learn by itself. To build a photo tagger, the algorithm should be fed with tens to hundreds of thousands of images and tags (Ng, 2016).

Non-codifiable data

Emotions, moods, smells, sounds, tastes, touch and visual cues are some types of data that human perceive, understand and are able to link to a certain reaction. However, in order to have AI deal with these types of data, the conversion from these inputs to code must be accurate. Whereas, visual cues and sound have already been codified to some extent, other types of data, as emotions, smell and tastes are more difficult to translate into computer language. Even though, codifying visual cues through image recognition has shown great progress in some industries as in agriculture for grain production (Patrício & Rieder, 2018) and automotive for autonomous cars, the codifying of other types of data is still in progress or faces some barriers. Google, for example invested in the creation of an algorithm that can classify smells by molecule's structure (Sanchez-Lengeling et al., 2019).

As Will Douglas Heaven¹⁴ suggests in his paper that was published in the scientific journal *Nature*:

Human faces pop up on a screen, hundreds of them, one after another. Some have their eyes stretched wide, others show lips clenched. Some have eyes squeezed shut, cheeks lifted and mouths agape. For each one, you must answer this simple question: is this the face of someone having an orgasm or experiencing sudden pain (Heaven, 2020, p. 502)?

¹³ GDPR = General Data Protection: EU law on data protection, privacy and usage

¹⁴ Will Douglas Heaven is a senior Editor for AI at the MIT Technology Review

As this quote suggests, several attempts have already been made to codify emotions, but these encounter the criticism that face expressions are not a one-to-one relationship with emotions as these rely on context and culture. A face alone cannot provide accurate information about the emotions of a person if the context is left aside. An example would be the face of someone crying. Only by looking at his face someone would tell that the emotion that the person is showing is sadness. However, by taking into account other factors as skin tone, body language, voice tone and background scene, it could become clear that the person is crying tears of joy because his favourite football team just scored (Cf. Appendix E) (Heaven, 2020). Hence, some data types cannot, or are hard, to codify yet and therefore cannot be used with high standards of accuracy for AI applications.

Format of data

The format and syntax of the data can also be a barrier to overcome. As an illustrating example, Ford Motor Company experienced this issue while outsourcing the building of an AI application to a small IT company. They encountered that these companies might be using their own language or software and in case they get bought out by another company, go out of business or change strategy, there is no support anymore and everything needs to be modified or re-written (Rychtycky & Turski, 2008).

Biased data

Biased data is a fifth problem that will provoke the malfunctioning of an AI application. This can be, for example, the cause for discrimination in CV screening. The challenge is that biased data is often undetected in first instance and is only noticed once going through the output of the AI application. Whereas biased data do not refrain from developing an AI application, it will provide a company with non-qualitative output, hence an algorithm will need to be retrained based on non-biased data (Roselli, Matthews, & Talagala, 2019a).

4.2.2. Process

In order to process the data to a wanted output, hardware and humans are needed. However, these can also be outsourced to third parties and cloud-services, but this will depend on the uniqueness, privacy of the data set used and the potential value to the business. All of these which reflect the sensitivity of the data (Foglia & Proserpio, 2019).

Hardware

The speed of learning and processing is driven by the computational power which is determined by the underlying hardware. Speed is important and can even become critical in some scenarios. Example given, an autonomous car needs to be able to react in a fraction of a second, hence it requires good computational power. Because most AI applications run based on a huge pool of data, running it on a simple Portable Computer (PC) is not sufficient. In fact, whereas historical data has been around for a while, it is because of the recent evolutions in computational power that neural networks have been able to work. Besides, hardware is also required for stocking all the data (Hofstee, 2019; Hwang, 2018). This requirement for speed and capacity might likewise lead a company to review its legacy system. The company might therefore check whether moving to cloud-based AI or edge AI (embedded AI) will make more sense for its application depending on some criteria as efficiency, latency, availability and privacy (Lee, Tsung, Wu, 2018). In order to even further enhance speed, required by Artificial Neural Networks for example, a hardware could be fully dedicated to an AI application instead of running it on a computer (Dias, Antunes, Mota, 2004).

Human skills

Talented employees in AI are needed to translate business needs into code. Even though this can be done by a third party as consultants or a small IT company, a company should pay attention before outsourcing. Ford Motor Company experienced several failures in the development of AI applications and explains the rationale of their failure in the paper: “Reasons for Success (and Failure) in the Development and Deployment of AI Systems”. They mention that AI consultants might not know the business very well which makes it harder for them to advise on the AI application to use. Hence, the importance of good communication of a company’s goals and experts’ advice on how to achieve it if possible. Besides, when costs are cut in a company it is often the advisory services that are cut first. Hence, this can happen before the knowledge from the third-party company is completely transferred. Concerning outsourcing to a small IT company, as discussed in “4.2.1. Input” chapter for data format, they experienced that these companies might be using their own language, and this might lead to the necessity of adapting the code in case the company changes. Moreover, having internal skilled employees is important for maintenance issues and to not remain dependent of a third party (Goasduff, 2019; Rychtycky & Turski, 2008).

4.3. Cultural environment

Barriers to artificial intelligence are not solely due to the technology itself, but the environment can also be a barrier to adopting a new technology in a company. An important job for the responsible of the AI solution implementation is therefore to limit the potential obstacles that might occur in an organization and go against the project. Obstacles to change in a company can occur at three levels: individual, team and organization levels (Pennarola, 2019).

4.3.1. Individual level

People are driven by fear for change. They like to remain in their routine and are against everything that could alter that. Besides, with AI, people fear the newness and to lose control over their tasks or even to lose their job. Therefore, it is important to communicate to employees the rationale behind using AI, in what aspects it will change their job and how they are going to proceed for the change (Marr, 2019a). Also, employees and executives need to understand what AI is as well as the basics of how it works. Finally, this technology will require a change in the needed knowledge and set of skills to work with it (Pennarola, 2019; Ransbotham, Kiron, Gerbert, & Reeves, 2017).

4.3.2. Team level

Teams will have to adapt, learn new skills and be more flexible in order to adopt new forms of collaboration. These new teams will have a more integrated way of working by joining human and machine forces. This also defines the intrinsic challenge of having humans and machine to work more closely (Ransbotham et al., 2017).

4.3.3. Organizational level

An AI strategy is required to get the most of this new technology. However, this requires executives to understand the added-value of the technology as change is often implemented top-down. This also refers to the individual challenge of getting people to know more about artificial intelligence. Besides, depending on the extent to which AI is rooted in the business model, the importance of change on an organizational level will vary. It could alter the organizational structure to become a more hybrid model as companies would require AI to be at a central and local level. Also, it could encourage organisations to review their structure in order to promote cross-sharing of data and to avoid that it remains locked in one silo. Also, access to data and data management will need to be reviewed to get the most out of the

technology (Pennarola, 2019; Ransbotham et al., 2017). Additionally, data governance should be checked in order to answer to responsibilities concerning data security, transparency, privacy, accountability, etc. (Kroll, 2018).

4.4. Ethics

4.4.1. Why is it relevant for AI?

Machine ethics, the study of ethical considerations due to the emergence of new machines and technological advances, has had a plurality of researchers writing about the subject these last decades and this goes back to Asimov's three laws of robotics when discussing automation of decision-making (Green, 2018). But lately these machines have been confronted to new progress with the creation of machines that can "think" and therefore take over some tasks requiring cognitive skills (Frankish & Ramsey, 2014). These advances, being even more pushed forward thanks to machine learning and deep learning, succeed to do and to excel in some tasks that, as previously thought, could only be done by humans. Some of the activities that machines can now take over to some extent are problem-solving, interaction with humans, communication through natural language, and perception recognition. These advances have brought new possibilities of improvements in different fields as healthcare, mobility, education, etc. However, the way in which those self-learning systems work is not always understood and more particularly for deep learning applications. The algorithm tends to be opaque for human comprehension (Vallor & Bekey, 2017).

Besides this inherent characteristic of opacity of deep learning, AI can present dual usages in some cases for the good and the bad. For example, it could be used in order to identify and classify wildlife as to target wildlife as is currently being done to fight against a particular type of starfish that is endangering the existence of the Great Barrier Reef (Platt, 2016). However, some day the machine could be targeting other animals, also humans (Green, 2018).

With the development of this technology opening doors to new opportunities comes also new responsibilities. Therefore, ethical questions and problems, concerning the usage of AI, are discussed and these could be said to be related to two goals. The first one being to make sure that AI will do no harm to moral beings and the second one being the definition of the moral status of AI (Frankish & Ramsey, 2014). As a concrete example from a particular industry to testify of the relevance of these goals and questionings is the famous trolley dilemma that was

suggested by Philippa Foot¹⁵ in 1967. In this dilemma, one should choose between doing nothing in which case a train kills five persons and pulling a lever to redirect the train towards one person. This scenario that was purely for philosophical purposes at the time and is becoming now a real question that autonomous cars manufacturers are facing. Of course, this example is food for thoughts, but it is not the only ethical question and problem that arise from the emergence of AI.

4.4.2. What are common ethical questions for AI?

So, what are these ethical questions and problems that arise with artificial intelligence?

By reading and confronting the book *“Robot ethics 2.0.: From Autonomous Cars to Artificial Intelligence”* with the article *“Ethical Reflections on Artificial Intelligence”* and the *Cambridge Handbook of Artificial Intelligence*, arguments from these three sources could be grouped into three main categories: ethical questions, attention points and goals. The first one refers to ethical questions a company might have prior to implementing an AI solution. The second category deals with aspects to focus on while implementing AI to avoid ethical issues. Finally, goals involve objectives to have the application perform ethically.

The focus being clearer, some of the ethical goals that can lower the concerns for this technology are impartiality, transparency and robustness (Bostrom & Yudkowsky, as cited by Frankish & Ramsey, 2014).

Impartiality refers to the aspect of the algorithm to not take a decision in an unjustified and unobjective way. This goal would foster the idea that the algorithm runs correctly on its own. However, to achieve impartiality it is key that there are no biases, and these are not always explicit. They are sometimes hard to highlight.

A second goal is transparency. This is core to a legal system. For legal systems going even a step further by being predictable is also often required as legal systems do want to understand what the consequences of a contract being defined and executed are.

A last goal would be to have an algorithm that is robust against manipulation. This criterium is needed to make sure that nobody could un- or intentionally mess around with the algorithm by providing misleading inputs. An example for this would be by adding a shape to a weapon to

¹⁵ Philippa Ruth Foot was an English philosopher who published in 1967 in the Oxford Review the paper “The Problem of Abortion and the Doctrine of the Double Effect” in which she introduced the famous trolley case that has been tackled by several philosophers since then.

make it look like something else while passing through security gates resting on image recognition (Bostrom & Yudkowsky, as by Frankish & Ramsey, 2014).

The goals discussed above, together with other potential goals, could help to create an environment that would lower the ethical concerns by assuring a well-functioning system, that can be checked upon and that is robust for deceit. However, this would be an ideal scenario and is realistically difficult to achieve due to implicit biases, the unpredictable characteristic of deep learning, unknown sources and methods to deceit, etc.

Besides ethical goals, there are also ethical questions to AI solutions (Bhargava & Kim, 2017). A first question is, who get to choose for the ethical criteria of the AI solution? Is it the company, the end-user, the government, the public opinion, etc.? To come back to the trolley dilemma example, who gets to choose how the autonomous car should behave in this scenario? Is it the developer, the driver, the company, the State, etc. (Bhargava & Kim, 2017)?

Besides the decision power to set the ethical criteria, a second question is about responsibility. Who is responsible for a faulty or unethical outcome from the AI algorithm and its consequences? In other words, who takes the blame? To stay with the autonomous car example, if one does an accident and kills someone, who will take the responsibility for it? Is it the driver, the developer, the company or even the AI solution itself (Frankish & Ramsey, 2014)?

This leads to another ethical question which is can the AI system be blamed? Does it have a moral status? This debate about whether AI has a moral status or not could be compared to the debate about the moral status of animals and what differentiate humans from animals. Similarly, AI crossing borders of some characteristics that used to differentiate humans from the rest forces us to reconsider what makes human beings unique and to re-define the extent of the moral status of the rest (including artificial intelligence) (LaBossiere, 2017).

Lastly, besides ethical goals and questions to consider, companies might also have to look out for some ethical “attention points”. These concern the algorithm’s input, functioning, output, controllability and consequences as is explained hereafter (Green, 2018).

A first attention point is about the functioning of the AI application. Does the application work and is it safe? Is the solution safe when it works and when it doesn’t? An autonomous car that crashes when it fails might be judged as unsafe for example. Besides, does it have any “safe exits”? Meaning that when the algorithm fails it can rely on a second option which might be to hand the situation over to a human. And is this done in a safe way? For example, handing over

the situation of an autonomous car going too fast in a hairpin turn while the car is at a speed of 80km/h is not a safe exit (Green, 2018).

A second attention point is the controllability of the algorithm by discussing its transparency/opacity. Will AI be able to tell why it did something or took a particular decision? And if it does, will we be able to understand it? To illustrate this, in 2014, two mathematicians, Alexei Lisitsa and Boris Konev, from the University of Liverpool, U.K., established a program that would resolve the “Erdős Discrepancy Conjecture” problem that was posed by Paul Erdős in the 1930s. To solve this problem the computer generated a proof that is a document of about 13 gigabyte, which is similar to the size of all Wikipedia (Green, 2018). Hence, no human could read all of it to check the correctness of the proof. Should therefore, the proof be taken as granted even though it is too complex or too long for a human to understand it? Should we accept something from a computer and take it as granted even though humans won’t be able to confirm it and therefore let the computer outsmart us to handle things for us (Konev & Lisitsa, 2014; Yirka, 2014)? This opacity gives some privacy to AI, but humans often want to have an understanding and justifications of the decision-making process of the algorithm. Besides, this right for explanation is also supported by the EU’s GDPR (General Data Protection Rule) and is therefore a necessity to some extent (Green, 2018).

A third attention point refers to the input. Is there any bias in the data, in the training set? Because as often mentioned “garbage in, garbage out”, hence bias can bring an algorithm to be trained to do unethical things as discriminating in the screening of applications.

A fourth attention point is concerning the output of the algorithm. AI has the potential to achieve great things, but the same AI application could also be used at bad and unethical ends or work correctly but for an ill-defined problem (Green, 2018).

A last attention point concerns the consequences of AI implementation in companies. Unemployment is an often-discussed consequence of AI as this could hit cross industries and have a potential big impact. People have feared unemployment with the industrial revolution, the emergence of computers and now artificial intelligence. However, AI comes with a special twist which is that it does not only have the possibility to automate some physical tasks, but also some mental ones (Vallor & Bekey, 2017).

In a nutshell, a society, but even a company, getting more and more digital should take into account ethical goals, questions and attention points in order to define and set rules to guide a company’s do’s and don’ts and responsibility setting.

4.4.3. Potential approaches and answers

Different methods, to get closer to the afore-mentioned ethical goals as well as ways to approach the ethical questions, are suggested in the book “*Robot ethics 2.0.: From Autonomous Cars to Artificial Intelligence*” and in the *Cambridge Handbook of Artificial Intelligence*. Following are some of these suggestions and their potential complications.

Concerning the ethical goals of impartiality and transparency, some methods can be helpful. For impartiality, potential bias in data should be looked up for prior to its usage, while for more transparency, some types of machine learning tools can be used as decision trees for example (Frankish & Ramsey, 2014). However, biases cannot always be noticed up front. Also, even though some tools of machine learning are prone to more transparency, deep learning, and its underlying artificial neural network (ANN) structure, has a lot of fame lately due to its capability to deal more accurately with complex situations. These ANNs have as characteristic to be less transparent. Hence, there is here a trade-off between efficacy and transparency. Besides these more technical approaches, there could also be someone for human oversight over the running of the AI solution. But, here again, there could be some complications. A first one being time. One of the main purposes of introducing AI solutions is to win time. By introducing someone to check for the correct running of the solution, there would be a reduction of the time-sparing by automation. A second issue would be the cost of having a supervisor for the solution. A last problem is the efficacy. Is the human judgement always better than the computer decision? If a human would correct what the machine did, thinking that the machine was wrong, it might delete the sole purpose and added value of the algorithm itself (Vallor & Bekey, 2017).

Regarding the ethical questions about how to set the ethical criteria and responsibility, there are no right or wrong answers, but only suggestions that some might accept while others will not. Dealing with the first question of who gets to choose the ethical criteria for the AI solution (end-users, government, companies, etc.), there is moral uncertainty. Actually, who has the power to say that if an autonomous car can't break it is better to turn and kill one person rather than doing nothing and killing five individuals? And does it change if the one person is a healthy young man, whereas on the other side these are five old woman? And if this young man is crossing the road at red light whereas the five old woman are crossing the road at green light and are therefore fully complying to the law? These are not easy questions to answer. Therefore, a fine way to address moral uncertainty is by having a methodical approach.

Some of these approaches could be: continuous deliberating, the “my favourite” theory and the expected moral value approach (Bhargava & Kim, 2017). The continuous deliberating approach would literally refer to the fact of continually debate with the different parties until a solution emerges. This method seems unrealistic and time-consuming. Therefore, because of lack of resources, this option does not appear as the most adequate. Then, the “my favourite” theory would suggest that the company or the person developing the AI solution set the rules for the AI application according to what seems for them the best thing to do. The last-mentioned approach is the expected moral value approach. This approach suggests that the ethical rules that are set are those that will maximize the expected moral value. This could be done by weighting all the potential scenarios and hereby define how to prioritize them (Bhargava & Kim, 2017). A concrete example of trying to reach the maximum moral value is something that the MIT did with their moral machine¹⁶. This moral machine requires people to choose between two scenarios. Specifically, they ask for the people’s perspective on what is the best thing to do for an autonomous car, in case of an incident, by applying the trolley case dilemma to different autonomous car scenarios. Therefore, in the end, with the people who participated, they could average what is the best thing to do in particular situations and therefore, in a sense, maximize the expected moral value (Awad, 2017). Even though this seems a reasonable way of proceeding, one should pay attention that there could be some bias with this method as well. Actually, who is in the panel of respondents? Is it composed of 80% Western Caucasian 40-years old right-winged men? Or does it present a more mixed set of cultures, ages, genders, nationalities, etc.? To deal with the second question about responsibility, we could look at the control of operations. To stay with the example of autonomous cars, as there is a shift in control of operations from the driver to the company’s AI system, there should equally be a shift in responsibility of the operations. However, it would be more debatable in a situation with a safe exit where the driver would take over the control as a last resort (Bhargava & Kim, 2017).

In short, there are several barriers that come at different stages of the implementation and adoption process. Barriers go from expectations prior to the usage of the technology to gathering the right set of tools, data and people for its implementation, to effectively integrating the technology in a company’s culture and using it in an ethical way. Even though these barriers could be solved to some extent, a manager might also have to pay attention to the potential advantages and disadvantages of using such a technology.

¹⁶ This is the link to MIT’s moral machine: <http://moralmachine.mit.edu/>

Chapter V: Advantages and disadvantages of AI

Although artificial intelligence seems to be the new hype and appealing to some companies, a manager could be willing to discern the advantages from the disadvantages of AI to understand its implications for his business.

To discuss this and in order to write this chapter, the advantages and disadvantages were separated into 2 categories: general and (non-general) ones. This is done because some are intrinsic to the concept and therefore generally valid for all the AI applications, while others remain more specific to the utilization of the technology. Then, a panel of 18 articles from diverse sources (business and scientific journals, consulting reports, EU documents, use cases, etc.) were analyzed in order to get a wide view over the different advantages and disadvantages cited from different backgrounds. The arguments highlighted in these sources were allocated accordingly to the different categories. Finally, those that were not directly selected is mostly because they joined (directly or indirectly) other arguments.

5.1. General advantages

A McKinsey analysis stated that, generally speaking across industries, artificial intelligence might have a big impact in differentiating companies by creating a gap between early adopters and late runners. Early adopters, fully embracing the technology in their business by 2025, will be able to double their cash flow by 2030. This implies that the companies would have an additional 6% growth for the next decade (Bughin, Seong, Manyika, Chui, & Joshi, 2018).

According to a survey of 1,600 business executives done by Infosys¹⁷ and cited by Joe McKendrick¹⁸, 71% of decision-makers believe that artificial intelligence will or is disrupting their business. 55% of them believe that AI can help on several domains as creating new improved products and services and business models and getting information faster. 50% of them believe that it will resolve problems quicker and 42% think that it can help out with personalization (Infosys, as cited in McKendrick, 2017). Even though this gives a first insight

¹⁷ Infosys is a global multinational information technology consulting company.

¹⁸ Joe McKendrick is part of the organizing committee for the IEEE International Conference on Edge Computing.

of why AI can be an advantageous technology for companies, following are some of the main advantages to implement artificial intelligence in a company.

5.1.1. Increase efficiency and productivity

A first advantage of using artificial intelligence is the ability to increase the company's efficiency and productivity. This can be done by automating some processes and make these faster than if human beings had to perform the same task. Besides making some processes faster and more precise it can also let employees focus on other tasks that require other human skills as creative thinking. Artificial intelligence can also lead to increasing productivity by providing recommendations based on quicker analysis to support decision making. Supporting this idea, a study made by Accenture suggests that by 2035 artificial intelligence can boost employees' productivity up to 40% in some of the countries analysed and that it can reach up to 17% in Belgium (Purdy & Daugherty, 2017). Next to freeing employees from some tasks, it can run without interference for 24 hours, 7 days a week.

5.1.2. Increase quality of outcome

Besides decreasing cost and operating time, artificial intelligence has also the capacity to increase the quality of outcomes. This comes due to the fact that it can perform tasks with more precision looking at more parameters at the same time. Actually, it can explore greater complexity and reduce it to make it more human friendly. In addition to being able to explore more it can also leave human biases and errors, as for example human judgement errors, aside. However, to avoid biases the data must be qualitative. This is because, even if the algorithm is excellent, providing biased input will give biased output. Even worse, the algorithm will learn from that bias and reinforce the error (European Union Agency for Fundamental Rights (FRA), 2019). This issue can cause infraction of fundamental rights, for example, as discriminating the screening of some applications based on ethnicity.

5.2. General disadvantages

Artificial intelligence also presents some disadvantages. These disadvantages can often be described as fears. Employees fear job loss by being replaced by this technology, but also fear to work with this technology for which they have few or no knowledge. Besides, big controversial thematic in the adoption of artificial intelligence are ethics, security and privacy

issues (Uden, Ting, & Corchado, 2019). Following are 6 often discussed general disadvantages and attention points for AI.

5.2.1. High investment

Developing an artificial intelligence algorithm implies high investments as it requires a specific set of skills, gathering and cleaning data and developing the algorithm. Moreover, it takes a lot of time to go through the whole process (gathering data, developing the algorithm, training the algorithm, ready for usage). While developing a website takes on average 60 man-days, developing an AI algorithm can take up to 600 man-days (Foglia & Prosperio, 2019). This being said, the initial investment can vary a lot depending on three main variables: the complexity of the required AI application, the data set availability and the needed set of skills for the development of the algorithm. Following are two tables (Foglia & Prosperio, 2019). The first one is for the scenario in which a company decides to develop an AI solution with internal means. The main costs here are for the human resources and technology licenses. The cost of changing the current processes are not taken into account in this table. Also, the actual cost will vary with the complexity of the project (Cf. Table 1).

Make Approach	Scenario 1	Scenario 2	Scenario 3
Data set	Available and ready to use	Available and ready to use	Still need to be gathered and formatted
Complexity of AI technology	This AI technology has already been developed internally or by competitors	Research and development activities are required	Research and development activities are required
Range of cost	€ 100k – 250k	€ 350k – 650k	€ 500k – 800k

Table 2: Estimated cost of developing the AI solution internally – Reprinted from Foglia, F., Prosperio, L. (2019). Digital Business Transformation: Artificial Intelligence (module2) [PowerPoint presentation]. Milan, University: Università L. Bocconi, 20

The second one is for the scenario in which a company decides to outsource the development of the AI solution. In this scenario the company will have a 3 different types of costs for the full integration of the AI solution (Cf. Table 2).

Buy Approach	Total solution cost		
Steps	1) Proof of concept Development	2) Final development and integration	3) Cloud service cost (pay per use approach)
Range of cost	€ 30k – 60k	€ 70k -150k	Expected number of uses * cost/use

Table 3: Estimated cost of outsourcing the AI solution development – Reprinted from Foglia, F., Proserpio, L. (2019). *Digital Business Transformation: Artificial Intelligence (module2)* [PowerPoint presentation]. Milan, University: Università L. Bocconi, 20569

5.2.2. One task-oriented

This characteristic is specific to weak artificial intelligence. In essence, it is one of the main differences with general and super intelligent AI. As today only weak artificial intelligence exists, one should keep in mind that the algorithm will excel at one specific task only. To give an example, the algorithm will be good at clustering emails to sort out the spam. But the same algorithm won't sort all the other emails in different mailboxes per theme, delete automatically the spams and answer automatically to some emails to set appointments (Ng, 2016).

5.2.3. Implementation time

From the moment a company decides to use artificial intelligence to its actual application requires some time. Compared to other programming scripts, artificial intelligence requires the gathering of a varied and big enough data set, the coding of the actual algorithm, the training, the testing and the implementation phase that requires some change management as well. Hence, as mentioned previously, this can take up to 600 man-days in development efforts (Foglia & Prosperio, 2019).

5.2.4. Biases

Even though artificial intelligence reduces human biases, this technology can also come up with its own biases. These can come up unnoticed as they can be hard to track (Cf. Black box) and they can even worsen due to the algorithm constantly learning from these as it cannot differentiate a pattern from a bias (J. Manyika, Silberg, & Presten, 2019).

Biases can appear due to several factors. A first reason is a biased training data set. As an urban saying states “garbage in, garbage out”, if biased input is used to train the algorithm the output

will reflect the original error. One should be careful though as biases can be hidden. Taking the example of using artificial intelligence to screen job applications, common discriminating factors are easy to highlight as gender, race, religion or sexual orientation. However, implicit factors can also be found as Amazon, for example, stopped using this process because it found out that the algorithm favoured applications that included the words “executed” and “captured” as those words are often more on men’s resumes. A second way for biases to appear is the gathering method of data by for example collecting data only from a specific neighbourhood. Thirdly, bias can be generated due to societally unacceptable or illegal statistical correlations. An example for this is reducing mortgage lending based on age as the algorithm notices that older people are more likely to default their lending. Lastly, biases can appear due to the usage of a wrong AI model. Nonetheless, input data is the biggest source for biases. (Manyika et al., 2019; Manyika, 2019; Roselli, Matthews, & Talagala, 2019b)

To minimize these biases, different methods can be applied:

1. *Maintain transparency*: Processes to evaluate the functioning of an AI application should be freely accessible to any stakeholder. But also comprehensible for non-technical people to ease potential review by management and auditors as AI applications can be truly complex. This can be due to the fact that data scientists can use shortcuts without even needing to understand these shortcuts work.
2. *Ensure Data quality, safety and origin*: Making sure the collected data is independent from each other, varied and not biased is key for the functioning of the whole process.
3. *Perform regular bias controls*: Tools exist to assess the validity of the process at each step. This helps to validate the whole process, but also to explain to some extent the predictions.
4. *Compare expectations with reality*: In order to test the effectiveness of the model, using real data to compare the expected output with the real output can help to check the effectiveness of the model and if it doesn’t reach the expectation threshold, the model can be retrained with another training data set or the algorithm itself can be reviewed.
5. *Pay attention to feedback loops*: As the characteristics of artificial intelligence are that it is able to learn by itself, the algorithm will be reinforced by its learnings. Hence, the feedback loop, which makes the algorithm able to learn from previous input-output relations should be correctly built. A Bias here, will compromise the model in the long run even if the data is not biased.

6. *Counterfactual fairness*: This technique is used to assess the fairness of results by checking if the decision results of the model would be the same in a counterfactual world where the parameters that are qualified as sensitive (e.g. race, religion, gender, etc.) are altered.
7. *Human judgement*: In the end, human judgement will still be needed in some applications to make sure that AI decisions are fair and seem correct. Artificial intelligence rests on all the parameters that were programmed to be taken into account. However, it might happen that other environmental factors influence an output, hence the need of a critical point of view when dealing with recommended outputs.

(Hume & LaPlante, 2019; J. Manyika et al., 2019; Manyika, 2019; Roselli et al., 2019b)

5.2.5. Black box

The term “black box” refers to the fact that it is often difficult to understand the path that a machine learning algorithm took to end up with a particular result. Hence, it is hard to justify why it came up with a certain output. This lack of transparency in the machine’s decision-making makes it an important attention point to consider when dealing with critical matters. Being able to explain the rationale behind a prediction helps to create trust and to highlight potential mistakes to improve the model’s robustness.

In order to reduce the black box effect there are two possibilities. The first one is to use simpler models as linear regressions. Simpler models reduce complexity of understanding, but they prevent from benefitting from the full potential of artificial intelligence as other, more complex, models that use different methods and other paradigms to make the predictions, even though less explainable, more precise. The second method to reduce the black box effect is to create a synthetic explanatory model that, based on the given input, can help to understand why the machine learning application made a particular prediction (Akerkar, 2019).

As an additional precaution to limit negative impacts from the black box effect, Deloitte suggests establishing controls at each step of the algorithm life cycle as during the information gathering, preparation, model selection, model development, training, evaluation, validation and implementation. This will help to reduce the probability to follow blindly erroneous outputs due to misconception (Albinson, Thomas, Rohrig & Chu, 2019).

5.2.6. Disruptive competition

The digitalization of firms is responsible for the appearance of new business models and therefore also new competition landscapes. Besides, digitalization can also have as a consequence the rise of new barriers of entry because of network effects and access to data (Sørensen, 2018). It can also bring small companies to compete with bigger ones in an unexcepted way. As for example, Uber was able to compete with Taxi companies (Cramer & Krueger, 2016). Similarly, and as a next step, the driverless cars, that are based on AI technologies, will disrupt the automotive industry (Yigitcanlar, Wilson & Kamruzzaman, 2019).

5.3. Non-general advantages

5.3.1. Decrease long-term costs

Even though implementing artificial intelligence might require a heavy initial investment for the building, training and implementation of the algorithm, it will reduce costs in the long-term as it will increase efficiency and productivity. The greater decrease in long-term costs is especially valid for processes that are sought to be automated through AI as it can replace repetitive jobs as well as ease more complex ones. As the Infosys analysis highlights, more than half (51%) of the 1,600 executives that were surveyed about the main usage of AI acknowledge that cost-reduction is a primary reason for using that technology (Infosys, as cited in McKendrick, 2017).

5.3.2. Digital assistance

So far, artificial intelligence is more seen as a cost-cutting technology and less as a mind-expanding tool. However, the opportunities that artificial intelligence creates to support employees and managers in their work are wide as it makes it possible for them to focus on other tasks that require more creativity and intuition as strategic decision making and to rely on the technology to work on other tasks as administrative ones, for which the presence of a human-being adds less value (Pomerol, 1997).

5.3.3. Differentiation opportunities

AI can help in redefining one's business model and open doors for new differentiation opportunities. By being an enabler to access new functionalities it can create new jobs required

by the technology as data scientist, analysts and engineers, but also other jobs that require creativity and innovation.

Besides reducing costs, artificial intelligence has also the potential to increase revenues. Early artificial intelligence adopters expect to see a rise of 39% in their revenue over the next 3 years. These early adopters see AI as a long-term strategic priority for innovation and 76% of them say that it is fundamental for the success of their company (Infosys, as cited in McKendrick, 2017).

An example of a differentiation opportunity thanks to AI is Uber investing heavily in driverless cars which would mean a big change in their business model as drivers would not be needed anymore.

5.4. Non-general disadvantages

5.4.1. Jobs turnover

According to Andrew Ng¹⁹, Job displacement is the biggest harm AI can do in the short term to people, as the amount that can be automated through this technology is greater than before (Ng, 2016). Job loss due to this technology is a big fear of employees. Truly, a lot of repetitive jobs can be automated with AI. To reassure its employees, managers often state that adopting AI is not intended to replace employees but instead to free them to let them focus on other tasks. 80% of AI adopters say that instead of firing employees they will retrain them so that they understand this technology in order to work along with it (McKendrick, 2017).

However, Huard Smith²⁰ argues that 73% of the cubicle-related jobs will be automated by 2030 and that even programmers won't have secure jobs as coding might be automated to some extent. Hence, even though new jobs will be created as artificial intelligence needs data analysts, scientists and engineers, Forrester Research foresee a negative balance. While AI might create additional 13% jobs, the American market research company for technological impacts foresee that 29% of jobs will be deleted by 2030 (Forrester, as cited in Vanian, 2019).

This being said, it is unclear for the moment whether artificial intelligence will have a positive or negative balance regarding job loss and creation as many researchers and reports support

¹⁹ Andrew Ng, Founder and lead Google brain project, former Chief Scientist at Baidu, Professor of Computer Science at Stanford University, Co-founder and Chairman of Coursera, Founder & CEO of Landing AI

²⁰ Huard Smith is the Vice President at Forrester Research

different opinions about the subject. The only thing that seems sure for the moment is that it will have an impact on the workforce and that there will be a shift in required jobs.

5.4.2. Lacking out of the box thinking

Due to its programmed characteristic, AI lacks creativity in its performance. Even though there are some attempts to make this technology more creative, it will be difficult to bring it to the same level as human's creativity. This comes due to the fact that it is hard to come close to human's richness of associative memory and to identify our values in order to translate them into an algorithm (Boden, 1998). However, looking back at the Go game between AlphaGo and Mr. Seedol, at some point, the algorithm came up with some new, unexpected moves from which Go players learned to enrich their own game.

The two following specific disadvantages are not per se disadvantages but are more questions that need to be discussed and followed-up closely otherwise they might lead to some serious problems in the company itself, but also with its external environment if they are not defined up front.

5.4.3. Responsibility shift

A concrete example of a responsibility shift that could occur is concerning autonomous cars. The responsibility of hitting someone while driving could go from the person in the car (originally the driver) to the company conceiving the car. However, going even further into the question of responsibility shift, another interesting point of view is concerning the particular category of learning systems in artificial intelligence (machine learning and its subset deep learning). Due to autonomous learning and development, these systems can come out of reach of their conceiver and behave in inexplicable ways as for example AlphaGo did with some moves in 2016 against Lee Sedol. This might lead to the shift of responsibility from the conceivers to the machine. As, even though the conceivers gave the data and the parameters, the algorithm learns and evolves which makes it difficult for them to predict how the algorithm will answer. As a parallel, a student learns from his parents and professors and is guided by the government, but can they be accountable for what the student will become? Parents are responsible for their child until he, or she, is 18 years old. An age at which the child is assumed to be mature enough to take responsibility for his own behaviour. Could something similar be applied to AI? However, we should be careful when comparing humans to AI as perception

may be shared, but the way it is processed remains different (Skene, 2019). About this, Kathleen Richardson²¹ mentioned that the willingness to reproduce artificial intelligence-based systems that present similar characteristics to humans will make us re-think about what it means to be human (Richardson, 2015). But, to what extent can autonomous machines take legal responsibility? This is a question that Professor Mark Chinen²² develops in the paper “The Co-Evolution of Autonomous Machines and Legal Responsibility” published in the Virginia Journal of Law & Technology 20th volume NO. 2, Fall 2016. He concludes that there is no right answer for this associative responsibility, but that this will depend on the willingness of people to define at which degree of granularity they would like to assign responsibility to a legal entity. However, as a first step to decomplexify this issue, “responsibility” should be redefined, and machines should be built in an ethical and prosocial way (Chinen, 2016).

5.4.4. Decision power trade-off

As artificial intelligence deals with the automation of some processes, we could ask ourselves to which extent AI can play a role in the decision process. In order to tackle this question AI could be divided into the expert systems and the learning systems. Concerning the expert systems, AI could play a role for tactical and operational decision-making, but it is more complicated for strategic decisions. This is due to its pre-programmed characteristic that doesn't allow it to adapt to a changing environment without being manually adjusted. However, it could be useful as a support to decision making and this on the three levels (operational, tactical and strategical). This counts also for learning systems as, even though they can adapt and change with new circumstances, it is mostly unlikely to take all the new dynamics in the environment into account. Hence, it seems to be more effective in stable and known conditions. But this is still a question that persists, namely “how can humans and AI co-exist in companies to take decisions?”. Besides, research is being done to see how AI can become more transparent in its decision process, so that there could be a follow-up on the process and to make it more reliable in humans' eyes (Duan, Edwards & Dwivedi, 2019).

To conclude, advantages and disadvantages are varied and can be general or specific to applications. Even though people tend to think mostly about the advantages, managers should also be aware of different potential disadvantages of AI before its adoption.

²¹ Kathleen Richardson is a Professor of Ethics and Culture of Robots and AI at the Centre for Computing and Social Responsibility, De Montfort University.

²² Mark A. Chinen is a Professor of Law at the Seattle University School of Law.

Based on everything that has been discussed in these five first chapters (Cf. Table 4), some implications and recommendations could be suggested in order to go into the right direction of an AI implementation and adoption project.

Summary of the first five chapters	Key aspects
Chapter 1: A brief AI history	- Constant evolution from Asimov's science fiction to current deep learning - Definition of AI at the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) in 1956 - Expert systems -> Machine learning -> Deep learning
Chapter 2: Definitions	- A lot of confusion and amalgam with other related concepts - Computer-based techniques that improve the speed, reliability or accuracy of processes that would require intelligence when done by humans, to help a company in its business activities by automating processes, supporting analyses by gaining in insights or engaging with employees and customers.
Chapter 3: Application fields	- General-Purpose Technology (GPT) - Manufacturing seems to have the highest data generation - ICT seems the most digitally mature sector - Financial services seem to be the "Best-in-class" - Healthcare seems to be the one with the most publicity in the IEEE Computational Intelligence Magazine and the Technological Forecasting and Social Change journal and the Research Policy journal
Chapter 4: Main barriers	- Prior implementation: expectations - For implementation: technological (data, hardware & skills) and cultural (individual, team & organizational level) - Usage: ethical concerns
Chapter 5: Advantages and disadvantages	- General: advantages (increase efficiency, productivity and quality of outcome) and disadvantages (high investment, one-task oriented, implementation time, bias, black box, disruptive competition) - Non-general: advantages (decrease long-term costs, digital assistance, differentiation opportunities) and disadvantages (jobs turnover, lacking out of the box thinking, responsibility shift, decision power trade-off)

Table 4: Summary table of the 5 first chapters in the literature review

Chapter VI: Implications from literature and a few recommendations for managers

As justified in the chapter on the application field, artificial intelligence could thus be characterized as a general-purpose technology that can be applied across industries. However, it requires a thorough methodology of implementation as it is confronted to some barriers and presents different advantages and disadvantages.

Therefore, following is a set of chronological questions to take into account different attention points that were discussed in the five previous chapters (Cf. Table 4) that might help managers willing to implement an AI application in their company.

6.1. What is the company's goal?

Before considering whether to use AI or not, the goal a company is trying to achieve should be clearly determined. It is important not to succumb to the AI hype by willing to integrate the technology no matter what, but to make sure it will actually help to reach a specific goal and add value in the value chain. Therefore, even though it might seem logical, it is important to determine first the goal and then the AI technology that will be used and to not do the opposite (first think which AI technology, then determine where and how it could add value).

As already mentioned, it is important to not succumb to the hype. Therefore, a manager should not overestimate the capabilities of the technology and stay down to earth by confronting its expectations to what is realistically achievable. This could be done by getting more informed about the potential of the AI application or by consulting an internal or external IT expert.

6.2. Can AI help? If yes, which AI application(s) is required to achieve it?

Once the goal is defined, a manager can determine whether an AI application can help to achieve it. It needs to be clear whether the technology will add value and whether it will be hard to copy or not to sustain a competitive position. Broadly speaking, artificial intelligence applications can be used in order to automate some business tasks and processes, to support some functions by making predictions and to engage with customers. Moreover, Andrew Ng suggests, as a rule of thumb, that if a human can perform a mental task in less than one second, it can probably be done by an AI application today or in a near future (Ng, 2016).

If artificial intelligence can help to achieve a goal, a manager should be aware of which AI application(s) should be used. These AI applications can be image recognition (e.g. autonomous cars), natural language processing (e.g. chatbots), natural language generating (e.g. Amazon's Alexa), machine learning for prediction (e.g. stock market predictions), advanced robotics (e.g. Robotic Process Automation) or a combination of these. It is only possible to know which kind of data will be required when the AI application(s) that will be used and the goal are determined.

6.3. Does the company have the required data set(s)?

When the AI application(s) is defined, a company should make sure it has the adequate set of data. In case of a supervised learning algorithm (e.g. image labelling), the company should have a set of data A (inputs) and a set of data B (outputs) (e.g. A: images, B: labels). In case of an unsupervised learning algorithm (e.g. grouping customers by purchasing behaviour), the company requires one set of data that will be clustered.

These sets of data need to be accessible, big, structured, codified and not biased. These criteria are key as they are critical to have a functional AI application with worthy outputs.

- If the data is not accessible, then a manager should check if it is possible to buy the data set or to build it.
- If the data is not large enough, a manager should make sure to inflate the volume of data as the algorithm needs to learn on a big set of data to get mature enough.
- If the data is not structured, then a manager should engage in data management to have the data cleaned, standardized and ready-for-use.
- If the data is not codified, then a manager should check whether the data can accurately be codified.
- If the data is biased, then a manager should make sure the data is varied enough and does not present any form of bias anymore as it will get the algorithm to learn on a wrong basis and will provide the company with a useless output ("garbage in, garbage out").

In case a company cannot deal positively with one of the previous conditions, it will not be possible to use an AI algorithm or at least to get a useful output from it.

In case all of the previous conditions are met, a manager can determine the competitive position of its data set by reviewing its value, rarity, imitability and substitutability and structure. This will be decisive in a later step whether the solution development and the computational power can be outsourced or not.

6.4. Does the company have the required computational power and human skills?

Next to having a good data set, a company should make sure to have the required computational power to deal with the data manipulation and storage in a quick and efficient way. If a company does not have the required hardware, they should ask themselves whether outsourcing it through cloud services could be an option. This mainly depends on the competitive position of the data set and its added value as well as its core position to the company's business. If the data set presents a form of competitive advantage, then better is to not outsource the computation as the data is unique and should remain inside the company. Also, if the usage of the AI application becomes core to the company's business, then the company should not outsource the application to avoid becoming dependent on service provider (Prosperio, 2019). The same reasoning of whether to outsource or not applies to the necessary human skills. Having employees knowledgeable about the coding of AI is also valuable because the algorithm needs to be adapted to the company's context, culture and specificities. Hence, having someone from the company managing the algorithm is often better to have an output that fits the company's requirements better.

6.5. What are the implications of the AI implementation for the stakeholders?

Adopting an AI application often involves other parties who will have to change, adapt or be noticed about the new process. This requires the company to have a good change management plan. Employees need to be aware of the change, the rationale for it and what it will have as impact for them. Some employees will also need to be trained in order to work better with the AI solution. These steps are also critical in order to have the AI solution fully implemented and to not face reluctant employees that might become obstacles and have the project fail because of their resistance.

Moreover, a manager should make sure that the AI solution is aligned with all ethical concerns. Companies dealing with personal data, for example, might be at risk as they can be confronted to the GDPR rules and privacy concerns, which makes them legally unable to use some data and outputs. But privacy concerns are not the only ethical problems at stake as other concerns also emerge from AI solutions. As for an example, due to this new technology, the famous runaway trolley dilemma from Philippa Foot, in which one should choose whether to not do anything and kill five individuals or turn the wheel and kill one individuals (Foot, 1967), could become a real problem to deal with when programming an autonomous car.

These generic questions and recommendations could help managers to address an AI project by reducing omission of important steps in an artificial intelligence implementation and adoption plan. However, these being only based on the literature review made previously, it could lack of a certain feasibility and be exposed to some naivety as well as not be truly up to date anymore. Therefore, the next chapter aims at confronting the literature research with on-field expertise and knowledge in order to get an understanding of the extent of alignment and deviation between literature and on-field knowledge.

Chapter VII: Confrontation of literature with field research

In order to check the feasibility and reality of the insights brought by the literature, interviews were done to cover the previous chapters and go after experts' opinions to understand how these differ or are similar to the literature research in this paper.

7.1. Methodology

In order to confront the findings from literature with field expertise, 7 people with a different background and knowledge about AI were interviewed. The interviewees include 2 Country Managers of digital corporates (Didier Ongena, *Belux Country Manager of Microsoft*, and Thierry Geerts, *Belgium Country Manager of Google*), 2 CEOs and founders of digital start-ups (Sebastien Deletaille, *CEO & founder of Rosa*, and Thibault Helleputte, *CEO & founder of DnAnalytics*), 1 professor (Professor Luigi Proserpio, *Professor of digital business transformation at University Luigi Bocconi*) and 2 consultants in AI implementation (Ferdinand Casier, *Belgium digital group leader of Agoria*, and Dr. Mihailo Backović, *consultant at B12-consulting*). The rationale behind this variety in interviewees is to provide a wide view over the technology and its possibilities. The interviews were led using a same questionnaire for all the interviewees. The questionnaire consists of 7 open questions with 2 sub-questions (Cf. Appendix F). These questions were formulated in order to go through the different chapters that were covered in the literature review. All the interviews were held in French except from one in English. The transcription of all the interviews can be found in the appendix (Cf. Appendix G). Following, first the main results per question, hence per chapter, will be disclosed. Then, these will be confronted with the literature.

7.2. Main results from the interviews

Even though the 7 interviews were conducted using a same questionnaire, not every interviewee was able to answer to each question or, due to some time constraints, not all questions could be asked to each of the interviewees. Therefore, the number of answers per question varies. For a more detailed analysis, a summary of each interviewee's answer per question can be found in appendix H.

7.2.1 Definition

The interviewees were asked how they would define artificial intelligence as this is a broad concept and not everyone aligns on what it means and what it includes. From the 6 answers to question, half the interviewees would keep it broad by defining it as a technology which is able to take care of tasks which would require intelligence when done by humans, while the other half would scope it a bit narrower by focusing on the latest technological advances in this field, namely the learning ability of this technology and therefore put an emphasis on machine learning. Artificial intelligence was said to be a broad concept that results from a constant evolution of technology and statistical methods. Ferdinand Casier suggested to follow the definition given by the European Commission to harmonize understandings (Casier, personal communication, April 15th, 2020).

The European Commission defines artificial intelligence the following way:

Artificial intelligence (AI) refers to systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications) (European Commission, 2018).

7.2.2. Application fields

The next question refers to the main application fields of artificial intelligence and to see whether indeed it could be classified as a General-Purpose Technology (GPT). 4 answers were gathered for this question and all of them argued that the application of AI is wide and varied. Hence, it is difficult to give one concrete application field. Ferdinand Casier said that to have a better focus on the application field of artificial intelligence, it could be analyzed through 2 axes: per industry and per application as image recognition, NLP, NLG, RPA and advanced analytics (Casier, personal communication, April 15th, 2020). The 4 interviewees mentioned that it is a GPT as it is widely applicable. Whereas Ferdinand Casier and Luigi Proserpio would forecast AI as having a potential impact in the future to the same extend as the Internet and Thierry Geerts mentioned, while answering the question about the future role of AI in companies, that the impact of artificial intelligence will be more important than the arrival of computer science in the 60's - 80's (Geerts, personal communication, May 4th, 2020), Mihailo Backović said that he "isn't sure how to weight AI to the Internet" (Backović, personal

communication, April 16th, 2020). Even though comparing artificial intelligence to the impact that the Internet had might be seen as a bit exaggerated by some, the main take-away here is that the application of AI is broad and can have a potential impact on several industries for several business aspects. From these 4 answers, 3 highlighted the application of AI with as purpose automation of tasks and 2 mentioned that AI will play an important role as a support to the decision-making process (Casier, personal communication, April 15th, 2020). Mihailo Backović said that he believes that image recognition is the current AI application with the biggest impact (Backović, personal communication, April 16th, 2020).

7.2.3. Top 3 industries

From the 5 answers to the question “what would be the top 3 of industries were AI can be applied?”, Thibault Helleputte said that there are more typical scenarios of usage rather than typical industries. Artificial intelligence requires repetitive tasks that are actionable (Helleputte, personal communication, April 16th, 2020). All the industries that were mentioned by the 4 other interviewees are: manufacturing, media, telecommunication, healthcare, mobility, technology, education and security. All these industries were mentioned once except manufacturing that was cited 3 times. Interestingly, out of the 8 sectors mentioned, 5 rests on the potential of image recognition as was mentioned by Mihailo Backović to the previous question. These 5 sectors are: manufacturing, media, healthcare, mobility and security. All of these sectors rests on the potential to use IoT, images, videos and cameras to leverage from artificial intelligence. Further, Sebastien Deletaille argued that healthcare is an unconventional sector as even though it seems to have potential, it is dealing with two key constraints. These are: data quality and accessibility issues as data, in this sector, is sensitive, unstructured, not standardized and hard to access. Also, due to the sensitivity of medical data, this sector is confronted to a lot of ethical questions (Deletaille, personal communication, April 11th, 2020).

7.2.4. Main barriers to implementation

All the 7 interviewees answered to this question about the main barriers to the implementation of artificial intelligence in companies. To group and segment their answers. They could be divided into 3 exhaustive categories: Prior implementation, implementation and running of the artificial intelligence solution.

Prior implementation

Prior the implementation of the AI solution, 3 main obstacles were suggested. The first one is awareness of AI. There is a lack of awareness about artificial intelligence and its possibilities. Whereas Sebastien Deletaille and Thibault Helleputte suggested that managers often don't understand the technology and its benefits, Mihailo Backović added that the difference in level of knowledge about the technology is different from country to country. Whereas Western countries are more advanced in terms of understanding, the Balkans, for example, have much less knowledge about the technology (Backović, personal communication, April 16th, 2020).

Secondly comes the goal definition for the usage of AI. Sebastien Deletaille and Professor Luigi Proserpio argue that it is crucial to first highlight a business problem and use AI as a tool to solve the issue. This is important as some companies see the usage of AI as a goal in itself, whereas it should be the method to solve business problems (Deletaille, personal communication, April 11th, 2020; Proserpio, personal communication, May 4th, 2020).

Thirdly, the expectations should be managed correctly. This idea has been communicated by almost all the interviewees. It includes 2 action points. The first one being to clearly understand what AI can and can't achieve and the second one is relying on relevant use cases and potential return on investment (ROI). This unclear understanding of what AI can and cannot achieve is related to the lack of awareness and to the hype created around this technology. The second action point is to have an idea of the potential ROI that the project will bring. A company should have a use case at hand from a comparable company. When small companies see success stories from AI projects from GAFA companies, for example, it does not speak to them as they do not have the same means. Hence, they should look at use cases from similar companies for similar projects (Casier, personal communication, April 15th, 2020). Having a potential ROI to provide to the executives might help them to make the investment in AI projects and give them a more concrete idea of the possibilities that can be achieved through AI (Deletaille, personal communication, April 11th, 2020). Also, some companies have pilot projects and hundreds of use cases but have an issue with scalability of the AI project (Ongena, personal communication, April 21st, 2020). Even though having the opportunity to share use cases with the company is useful, it is not as easily done. Estimating the potential ROI up front is truly complicated as it depends on a lot of different variables as the quality of the input data and the added value of the output. Therefore, an ROI cannot be guaranteed up front (Backović, personal communication, April 16th, 2020).

Implementation

Deciding the scale of the project should be done up front as well. On this topic not all interviewees were aligned. On the one hand, it was suggested that to help companies get more at ease with the technology, they should try and experiment by starting with smaller projects and then scale those up once companies feel at ease using the technology. Then, they can also bring it closer to the core of their processes. Hence, they should start with the “low-hanging fruit” (Casier, personal communication, April 15th, 2020). On the other hand, other suggested to go directly for more important projects. As AI is expensive, companies need to use it for projects with high value (Geerts, personal communication, May 4th, 2020; Helleputte, personal communication, April 16th, 2020). Besides, if the projects start small, the company will never scale up the project as managers won’t see the added-value and the full potential of the technology. Hundreds of companies failed to use AI, because they started with the small projects of low value (Proserpio, personal communication, May 4th, 2020).

Next to the scale of the project, during the implementation process, there are two other barriers which are technological and cultural.

Concerning the technological barriers, these can be due to data, people’s skills and hardware. 5 of the 7 respondents mentioned data as a barrier. Having relevant well-structured data is a key criterion to success. They mentioned that data needs to be of quality, sufficient and structured. At Agoria, for example, they spend 80% of their time in a project of AI adoption for checking the data (Casier, personal communication, April 15th, 2020). “Having reasonable data is probably the biggest challenge in an AI project.” (Backović, personal communication, April 16th, 2020). A big issue with data currently is the way it is gathered and structured. For example, data has been used a lot to answer to regulatory requirements (e.g. car exhausts), but not enough yet with as goal to leverage from its value. Hence, the way it is collected and structured is different and need to be adapted to make the most out of it (Helleputte, personal communication, April 16th, 2020). Further, having skilled people is also a discussion point. Whereas 3 of the respondents mention the importance of having skilled people to work with this new technology, the 2 interviewed consultants are not sure this is so relevant anymore as they say that there are a lot of companies that can support in the building and integration of an AI solution. Having skilled people can come at two levels: artificial intelligence knowledgeable data scientists and businesspeople with a solid knowledge in the possibilities of this technology that can work as “bridgers” between business and technology. These artificial intelligence knowledgeable data scientists need to have followed the latest techniques in order to be on point

for an effective implementation. They shouldn't be regular statisticians as they might not have the latest insights about how to take the most out of this technology (Deletaille, personal communication, April 11th, 2020). The "bridgers" need to have a business background with a knowledge of how a business problem can be translated to coders. In other words, they have to bridge the gap between businesspeople and data scientists (Proserpio, personal communication, May 4th, 2020). The last potential technological barrier is the computational power, the hardware. Whereas two of the respondents said that there should also be paid attention to this aspect, the two interviewed consultants said that with cloud services, hardware is not an issue anymore. Companies can just pay for the usage of computational power. In 10 years, storing and computing in the cloud will become a standard. However, not all the companies should, or are willing to, put their data in the cloud. It depends mostly on the sensitivity of the data. So, companies are free to opt for cloud or not as it is a technology of convenience (Backović, personal communication, April 16th, 2020).

Concerning cultural barriers, these are mainly due to fear for the unknown and change. All the respondents mentioned a cultural aspect as being a barrier to an AI adoption plan. This cultural barrier ranges from the fear of employees for job turnover (Deletaille, personal communication, April 11th, 2020) to a lack of understanding and support from the managers (Helleputte, personal communication, April 16th, 2020) and a general impact on the whole business model (Geerts, personal communication, May 4th, 2020). Therefore, bottom-up driven projects often fade, because of a lack of investment, support and perceived added-value. Hence, there is a need for a top-down driven approach to adopt AI in a company. Managers need to be convinced of the added-value and being willing to make the investments as well as support the project through the whole implementation plan, train the employees to use the technology and inform them on how it will help them to be more efficient and effective in their work (Proserpio, personal communication, May 4th, 2020).

Usage of implemented AI tool

Before deciding to use AI for a certain goal, but also while using it, a company should check whether there won't be any ethical complications of using artificial intelligence at a certain end. 5 respondents discussed this point. Industries like healthcare face often a lot of ethical questions as it is dealing with personal sensitive data. However, on a general basis, a lot of industries, as media, telecommunication, security, etc. might be affected by the ways it would deal with personal data. Seemingly, efforts towards regulation and how to deal with ethical concerns are not clearly set yet. The ethical boundaries are not clearly defined yet (Backović, personal

communication, April 16th, 2020). Agoria is currently working with the European Commission to set a couple of questions a company should ask itself before implementing and using this technology (Casier, personal communication, April 15th, 2020). Meanwhile, it is important to train its teams on certain ethical guidelines the company wants to follow in order to avoid complex situations (Ongena, personal communication, April 21st, 2020).

7.2.5. Maturity of industry

This question was only answered by the two digital entrepreneurs who are operating in the healthcare industry. This industry showed relevance in the analysis made in the chapter “Domains of application and exclusion”, because of its low position on the matrix in terms of digitalization and data generation, but its high ranking in terms of published papers about artificial intelligence in the industry.

According to Sebastien Deletaille, healthcare is in the top 3 of not well digitalized sectors in Belgium. This top three would be healthcare, education and the government (Deletaille, personal communication, April 11th, 2020). However, over the past 5 to 10 years there has been an increase in consciousness that getting more digital is important in healthcare and might bring a lot of value. Whereas 5 to 10 years ago people weren’t interested, this has even been to the extreme inverse, people have been thinking that artificial intelligence, for example, would be like a magical formula that will solve all the issues (Helleputte, personal communication, April 16th, 2020).

7.2.6. Data generation capabilities

Here again, this question was only answered by the two digital entrepreneurs who have their own business in the healthcare sector. In the healthcare sector, the data has potential to deliver insightful information, but is confronted to several issues. These are of accessibility, quality and quantity. Accessibility refers to the fact that medical data is often sensitive personal data. The issue concerning quality is that data is not always enough structured, standardized, etc. (Deletaille, personal communication, April 11th, 2020). Data is also lacking in quantity. Healthcare is dealing with big amounts of variables. Hence, there is a need of a huge data pool for statistical inference as for every added variable, at least, 10 examples should be added. This leads to a scenario where there are more columns (variables) than rows (examples) to work with. This is what Thibault Helleputte refers to as “fat data”. There are ways to handle this situation with AI, but it is not perfect (Helleputte, personal communication, April 16th, 2020).

7.2.7. Advantages and disadvantages

Concerning the advantages of the usage of AI in companies, most of the 6 respondents mentioned that the advantages are broad and that it depends on the business needs. “It is as if you would ask me what the advantages of the Internet are” (Casier, personal communication, April 15th, 2020). Generally speaking, it has the same advantages as all the other technologies that were brought to companies. Therefore, the only real two generic advantages that are specific to AI are that it will transform non-structured knowledge into structured knowledge and that it will analyze connections between pieces of information (Proserpio, personal communication, May 4th, 2020). Now, there are also some general advantages that are linked to the business. These are plural and also depend, to some extent, on the business. The two general advantages that were the most mentioned are that AI will delete repetitive tasks by automation to have people focus on more added value activities and that it will work as a digital assistant to support for decision-making. These data-driven decisions will be even more supported by the Internet of Things (IoT) (Ongena, personal communication, April 21st, 2020). The other advantages that were mentioned are that it can make operations more efficient, bring outcomes of better quality and that it will improve client services. Then, on a company-scale, it can help a company to reinvent their business model and to achieve new things that wasn’t possible before (Geerts, personal communication, May 4th, 2020; Ongena, personal communication, April 21st, 2020).

Concerning the disadvantages of using AI in a company, from the 7 answers received, half of the respondents, among which the two country managers, said that there are no real disadvantages. The disadvantages that were highlighted and discussed are the following: black box, decision power trade off, bias, responsibility shift and high investment. Even though two interviewees agreed that the “black box” aspect of AI is an issue as we do not truly understand how the machine takes decisions which will not help to rationalize the recommendations or actions taken by the technology, it was not unanimous. Thibault Helleputte suggests that the black box aspect is not a disadvantage per se if it works well. As an example, a few years ago, AlphaGo beat the world champion at Go and people didn’t understand all the moves the program did. Even though, people didn’t understand its moves, it was still the time where machines became better than humans at a game that seemed too complex for machines at first. Also, making the AI solution more transparent is feasible, but it reduces its efficacy, so there is a trade-off to be made here (Helleputte, personal communication, April 16th, 2020). Regarding the bias, it was said to be a disadvantage and a hard one to notice as it is not always explicit in

the data provided. The bias can also be implicit by some terminology used on CVs for examples. Then, concerning decision power trade off and responsibility shift, two interviewees had a different opinion. Mihailo Backović supported the idea that indeed not all decision power should be given to AI. Especially in healthcare, for example, you cannot say that it is fine because there is only 2% chance that the algorithm gets it wrong. Because who will be responsible for these 2%? People want to have a certain degree of certainty and to rely on other people. The final decisional power should remain on human's side (Backović, personal communication, April 16th, 2020). On the contrary, if AI functions reasonably well, why should it not be given decision credit? If the algorithm does a better work at detecting a cancer on a scan than a human for example. In fact, the algorithm should be clinically tested, as medicine, to prove its efficiency. Then, it can take over some tasks that are done in the medical services. However, concerning the responsibility, it would go to the conceiver of the algorithm. The algorithm builder is responsible in the sense that he decided the parameters that were given to the algorithm as well as the objectives, the optimization function and the provided data. Hence, if AI has proven its efficiency through testing, it can have decision power and the responsibility would go to the person who made the algorithm (Helleputte, personal communication, April 16th, 2020). Lastly, concerning high investment, it was said to not always be the case and depending on the business project (Proserpio, personal communication, May 4th, 2020).

7.2.8. Evolution of AI in companies

In companies, artificial intelligence will have a growing importance. However, two of the five respondents mentioned that what will change towards the near future is the expectations of people for this technology. The gap between expectations and reality will decrease towards more realistic hopes. People will see that AI is no magic. Also, with time this technology will get more standardized and play a role for automation and support in decision making processes (Deletaille, personal communication, April 11th, 2020). Finally, the two country managers mentioned that AI will be a supporting tool in the daily activities of employees. So, there will not only be an impact on the company-level, but also on the individual level by having an impact on each employee. It will reinvent their way of working (Geerts, personal communication, May 4th, 2020; Ongena, personal communication, April 21st, 2020). At some point, people will use AI as they use Excel or any other tool. With the growing trend of “low code, no code”, people will be able to use their own model for their own analyses and other uses. It is comparable to websites. Previously, people needed to be expert coders in HTML to

create a website, but nowadays everyone can create a website (Ongena, personal communication, April 21st, 2020).

7.2.9. Recommendations for AI implementation and adoption

By ordering chronologically the different answers received by the 7 interviewees, the recommendations would be the following for an implementation and adoption timeline (Backović, personal communication, April 16th, 2020; Casier, personal communication, April 15th, 2020; Deletaille, personal communication, April 11th, 2020; Geerts, personal communication, May 4th, 2020; Helleputte, personal communication, April 16th, 2020; Ongena, personal communication, April 21st, 2020; Proserpio, personal communication, May 4th, 2020).

Awareness

First, employees and especially managers need to be aware of what AI is, how it works and what it can bring to their daily work as well as to their company, otherwise they won't make a step towards embracing the technology. Generally speaking, people fear the unknown and the change. Especially if they don't understand the advantages of adopting it.

Find an adequate business problem

Secondly, a problem is that some companies want to implement AI solutions in their business, but they link it to a wrong or non-relevant business problem. Therefore, the company should clearly define a business aspect that could be improved and impacted by AI. The idea is that a company first need a problem and then the according solutions, whereas some companies tend to be too much focused on the solution.

Find a potential AI solution

Thirdly, only after the correct definition of the business problem, a solution based on AI techniques can be searched for. AI is a tool to answer the initial problem or to seize a business opportunity. Besides finding an AI solution, it should be clearly defined what the expected results from the AI solution are, what the threshold for satisfaction is and how this can be measured. In other words, people should clearly define their expectations with numbers in order to define what a good system is. This is needed to make sure that a company forms right expectations from what can be achieved. For example, if the threshold of satisfaction is 99% of correct answers, this might not always make sense in every situation as for example some

diseases are only scanned as being positive 1 out of 140 000 times. Hence, by classifying everyone without exception as negative you will meet the threshold (Helleputte, personal communication, April 16th, 2020). Then, a company should also ask itself whether the issue can be solved through data or not. Lastly, it is important to get a sense of whether the output is actionable and valuable. Actually, having the expected result but not being able to use this result for anything is worthless. Hence, in a nutshell, when finding an AI solution, expectations should be clearly expressed in terms of satisfaction threshold and way of measuring this satisfaction as well as the output should be actionable and valuable.

Check for the requirements

When deciding to push the idea of implementing the AI solution forward, the company should make sure it has the right data that is accessible, structured and sufficient. Here, it is important to first have defined what the business problem and the AI solution to implement are before getting to this question. Too many companies gather too soon, up front, data, but the data does not match what is required in order to implement effectively the defined AI solution (Backović, personal communication, April 16th, 2020). Then, companies need to hire or train their employees to have the right set of new skills. These skills need to be knowledge in the programming of machine learning solutions, if a company does not want to work with consultants or any third-party company, and also people that will work as “bridgers” to translate business needs into understandable commands for data scientists (Proserpio, personal communication, May 4th, 2020).

Adopt AI

The last step before and during the actual implementation of AI is to make sure that everyone is going into the same direction. Meaning that employees and managers need to be confident that artificial intelligence is not a danger and is useful for them as well in terms of effective and efficient work as in terms of return on investment. To do so, use cases and potential ROI should be provided to the managing team to foster support and a top-driven approach. Also, people should be included early in the change process through awareness, exploration, experimentation and training sessions. This will allow people to accept and encourage the change.

7.3. Confrontation with this thesis' literature review

7.3.1. The concept of artificial intelligence (AI)

Whereas the literature review in this thesis suggests a broader approach to the concept of artificial intelligence, including more than the learning characteristic, during the interviews, the main focus seems to rest on this latest version of artificial intelligence. Currently, some solely focus on this learning aspect. In fact, this non-harmonized vision of what AI means shows that it is a vivid concept that has evolved a lot over time. Whereas the concept is broad and rests also on older systems as expert systems that emerged in the 50's, the focus has shifted towards later versions as machine learning and especially deep learning that have been promising in the 2010's and boost the hype and expectations. Even though this hype is decreasing lately as people start to get a more realistic view of the possibilities of this technology, there still remain some uncharted terrain to explore and experiment to push this technology forward.

In a nutshell, artificial intelligence is a broad concept, that is still evolving, where the latest focus has been on machine learning and more specifically on deep learning.

7.3.2. The application fields of AI

The applications of artificial intelligence are wide and plural. This was agreed by all the respondents. They agreed that artificial intelligence is a general-purposed technology and some of them would accept to compare it to the emergence of the Internet or computer science. This is not only because they believe in the wide scope of application, but also because they believe it will have a substantial impact in a lot of processes in the years to come. Therefore, it was hard for the interviewees to give a top 3 of industries as most of them mentioned that the technology could be used in every industry, but also at many different ends inside one industry. One suggested that AI should not be categorized per typical industry, but instead per typical usage. Another one suggested that all the industries that can benefit from image recognition will be impacted the most as image recognition shows big opportunities.

Concerning the mentioned industries, three of the four interviewees mentioned and topped manufacturing. Similarly to the analysis made in this paper, manufacturing shows a lot of potential for AI as it generates enormous amounts of data and there are even more automation opportunities thanks to image recognition that could filter out defects for example. All the other industries were mentioned once by the respondents. Next to manufacturing which was ranked the highest based on data generation, media and telecommunication were also mentioned and

are the highest on the digital maturity scale. However, healthcare and mobility were mentioned as well and are among the lowest on the matrix in terms of data generation and digitalization (cluster 3). As has been discussed for healthcare, in the bibliometric analysis, there has been an increasing number of research done in AI for healthcare and this is also supported by the interviews which said that people in that sector have had a growing consciousness over the last 5-10 years about the potential of this technology in healthcare. Also, next to this growing change in mindsets regarding the importance of digitalization, a new form of exploitable data that has emerged with this technology, is images. Nowadays, thanks to image recognition, images became a valuable source of data on which we can leverage more than a few decades ago. Therefore, sectors as healthcare and mobility are sectors that can now leverage on this type of data that couldn't be exploited as much before. Besides this potential growth along the two axes (digitalization and data generation), having these sectors (healthcare and transport) showing interest for AI could suggest that there might be a third axis that drives the decision to go for AI solutions. This axis would be return on investment as the importance of the potential ROI has been emphasized by almost all the interviewees. They said that some companies are reluctant to go for AI as they're unsure about the potential return on investment and this should be showcased to them through use cases from similar companies and similar projects. By adding this axis to the current matrix, that illustrates the technological requirements for AI, the sectors would be mapped according to two main ideas: "Do we have the requirements?" (data and digital (technology and skills)) and "Will it bring (financial) value?" (ROI).

7.3.3. Some barriers to AI implementation

The barriers of AI implementation ranges from technological barriers as data, technology and skills to more cultural ones as expectations, fear of change and also ethical questions. Most of the barriers that were given are similar to what was found in this literature review.

Here are the barriers that were equally mentioned in this literature review and by the interviewees.

A first barrier that was highlighted in the literature is having the right expectations. This was highly supported during the interviews as most of the interviewees mentioned the importance of having use cases and potential ROI to share with the management, because it is essential to have the managing team on board, so that they are not reluctant to this change.

A second barrier is the quality of data. This might be one of the most important aspects to focus on as it was emphasized in the literature as well as by the respondents. A company needs the right set of data for a particular business problem and this data must be relevant, sufficient, non-

biased and accessible under a right format. This was supported by the consultants in AI who mentioned that most of their efforts in projects are for data management, but also by other respondents as data quality is equally important for ethical questions and to effectively get value from it.

Ethics was also a criteria that was important for everyone. There should be clearly set rules of conduct. Some interviewees said that these should be set by the government, international organizations, etc. but also on a company level. People developing the technology should be aligned to implement it according to the values of the company. Currently, the European Commission is working on a set of questions a company should ask itself before implementing and adopting an AI solution (Casier, personal communication, April 15th, 2020). Also, companies themselves are working on it to have rules on a company-level. For example, Microsoft set 6 principles to be followed by its employees when developing this technology (Ongena, personal communication, April 21st, 2020). Some respondents claim that even though some efforts are put forward, these ethical rules seem to be lagging behind and should be a priority.

The last barrier from the literature review that was agreed on by the interviewees is the cultural barrier. As discussed in the review this can be on an individual, team or organizational level. On an individual level, it can be fear of change and job loss, but also non-awareness or understanding of the technology. For the same reason, it is best to have the management understanding and supporting the artificial intelligence implementation otherwise the project will slowly vanish. According to Professor Proserpio, hundreds of projects died because of a bottom-up approach without managerial support. Therefore, an AI project should be driven top-down (Proserpio, personal communication, May 4th, 2020).

Some barriers discussed by the interviewees did not find common ground with the literature review or with the other respondents.

A first debatable barrier is the required skills. Whereas in this literature review was supported that companies will require people with a new set of skills to accompany AI, and some interviewees agreed on this, other mentioned that skills are not a priority as companies should focus on their core activities as they can find a lot of other companies offering this service of taking care of the technical implementation and maintenance of the system. Therefore, it depends on the application of AI and the sensitivity of its outputs. Besides, Sebastien Deletaille argued that people developing AI solutions should not be regular statisticians, but people that learned this particular technology and know how to use the tools to correctly and efficiently implement it. Lastly, a focus was set on hiring or training people that could work as “bridgers”

to close the gap between business and technical implementation. These “bridgers” should have a business background with a good understanding of the technology in order to translate the business needs to the data scientists (Proserpio, personal communication, May 4th, 2020).

A second argument is concerning the scale of the project. This barrier was not discussed in the literature review but was mentioned several times by different interviewees. Whereas Ferdinand Casier suggested that companies should start by experimenting with small projects to collect the “low-hanging fruit” and to get accustomed to the technology before scaling it up, Thierry Geerts and Luigi Proserpio advocated that companies should directly go “big” by having first projects with a big impact on the company. The rationale here is that if they do not start big enough, the project will never get scaled up because the management will not see the added value of the technology.

The last barrier that was not universal is the requirement of hardware for computational power. The first chapters suggest that this technology requires a lot of computational power to handle the pool of data and the running of the algorithm. However, this computational power could be internal or outsourced. Therefore, some interviewees said that, because of cloud services, computational power is not a real barrier as companies can pay for their usage. It was even suggested by Mihailo Backović that in a decade cloud could probably become a standard. However, not all companies will be willing to send their data on the cloud. Even though cloud infrastructure ensures to encrypt and secure the data, the sensitivity of the data might be a restraint to send the company’s data on those platforms as a service.

7.3.4. Some advantages and disadvantages of AI

Some advantages and disadvantages of using AI in companies being highlighted from literature, the main reaction from the interviewees is that it depends on the business application of AI. This foster the idea, as was segmented in the literature research part, that there can be general and business specific advantages and disadvantages of using AI in companies. Concerning the advantages of AI, as mentioned by Professor Proserpio, those that are highlighted in this literature review are right for most new technologies and not particularly for AI. In fact, AI has some intrinsic advantages as being a new technology that is being adopted by companies. Therefore, general advantages of applying new technologies into a business are increase in efficiency and quality of outcome.

Some more business specific advantages for new technologies are that it has the potential to decrease long-term costs, it can be a digital assistant and it offers opportunities for differentiation. All of these were also mentioned by the interviewees.

Consequently, the AI specific advantages that were mentioned by Professor Proserpio would be that it has the capability to transform non-structured knowledge into structured knowledge and analyse connections between data.

Also, interviewees shared their opinion on the fact that it would help make their work “more human” by automating repetitive cognitive tasks and letting people do more creative and stimulating tasks.

Concerning the disadvantages of AI, most of the interviewees did not see real disadvantages of using AI at first, but confirmed the ones shared in the chapter 5 and putted an emphasis on biases, the “black box” aspect and the decision power trade-off dilemma. On the contrary, Thibault Helleputte mitigated the fact that black box, responsibility shift and decision power trade-offs are disadvantages. Is it truly an issue to work with a black box if it works well or even better than humans? And for the same reasons should it not be given some decision credit? Also, according to him, the responsibility should be given to the person developing the AI solution as he fed the algorithm with data, parameters and constraints.

7.3.5. Some recommendations

Regarding the few recommendations for AI implementation and adoption from chapter 6 and the interviews, the structure is similar.

To start, the company and the management need to be aware of the artificial intelligence possibilities and foster realistic expectations. Then, the quality of the requirements (data, people, hardware) needs to be assessed and finally the adoption plan needs to be supported by pushing efforts towards an AI-accepting company culture. However, per recommendation step, some recommendations were added by the interviewees. Following are the recommendations from chapter 6 enhanced and nuanced by those given by the interviewees.

Firstly, before defining a clear goal it is even more fundamental for a manager to get a clear understanding of what the technology is, what it is capable of and what it cannot do, because the AI concept remains vague for some managers. Then only, can managers define a clear business goal that needs to be solved and that can be done with AI. By getting informed and comparing his objective with use cases from similar projects from similar companies, a manager can weight his expectations to have them more realistic and feasible. Additionally, it seems important that at this stage the manager fixes quantitative objectives and a threshold for satisfaction. The purpose of having quantitative objectives is to define at which point the project will be judged as good enough. Having a satisfaction level is equally crucial if the company

wants to outsource the development of the AI system to a third-party company, so that both companies know where they are heading to. Besides, it was also suggested that the results must be valuable and actionable, because having good outputs with which cannot be done anything, is of no use. Therefore, the company should ask itself, if they have the output, what will they do with it? So what?

Secondly, concerning the requirements, checking if a company has qualitative data was a key point as well in the literature as in the field research. The saying “Garbage in, garbage out” was mentioned a plurality of times and therefore working on having well-structured and useful data was shared to be the most time-consuming activity in an AI implementation project. Hence, this issue should be tackled up front. Then, defining what is the extent of the required level of skills and computational power seems more difficult. With cloud services and companies focusing on B2B-services for the development of AI solutions, the development of the AI solution could be outsourced. However, Mihailo Backović shared that outsourcing should not always be considered as it should also depend on the sensitivity of the data. Moreover, not only skills, as data scientists, are required, but also AI “bridgers” who will bridge the gap between business needs and data scientists’ understanding.

Thirdly, the culture of the company should be accepting and encouraging change. This was highlighted in the literature review, but particularly emphasized in the field research as all the respondents mentioned the importance to get the team early on in the process. As mentioned, the company should deal with its employees’ fear for change and for the unknown through trainings. Furthermore, an interesting insight that was brought during the interviews is about the scale of the initial AI project. Whereas, one interviewee suggested to experiment with a small project and scale it up, two other interviewees were in favour of starting with a big and impactful project claiming that otherwise the project would never be adopted and scaled up. The idea is that it must be shown that AI has the potential to add substantial value to the current processes. This is also the rationale behind the suggestion that the project should be led top-down by the managing team in order to make sure that the project is supported.

A last recommendation that was added and emphasized during the field research is to make sure that the ethical questions that might be relevant with the development of the AI solutions are correctly answered and managed, during the whole process of AI adoption, by the company and in line with the company’s values.

Conclusion

Contributions and implications

This paper aims to clarify the “artificial intelligence” concept, provide some key attention points for managerial consideration and to suggest some recommendations for managers willing to implement and adopt an AI solution in their business activities. This topic is relevant nowadays as artificial intelligence knows fame and excitement for its possibilities. It is therefore critical for managers to understand the implications of this technology by getting a down-to-earth explanation of what AI is, where it is applicable, what the barriers that could alter its implementation are and why it can be relevant for a company to use this technology. This structure is also the one followed in this paper in order to end with a few recommendations for managers envious to start an AI journey.

In order to first understand what artificial intelligence is, the concept was explained and confronted to different related concepts. This chapter of the literature review discusses the fact that artificial intelligence can be seen as a buzzword that brings a lot of discussion about how to define the concept and what it includes. Thanks to the literature and the field research, it is understandable that this confusion comes from different sources including a lack of understanding of the concept, an amalgam with its subsets (machine learning and deep learning), a long history of continuous evolution, over-expectations and a more fundamental misalignment on the notion of “intelligence”. Whereas, theoretically speaking, AI is broad and could include expert systems, depending on the way we define “intelligence”, in reality it was observed through the interviews that people tend to have more recent concepts in mind as machine and deep learning. This is because of recent events in 2016, when AlphaGo beat the world champion at Go using deep learning and therefore showed great potential for different applications. This created an important hype around AI and its often-extrapolated future. However, discussion with experts showed that over-expectations from AI are slowly decreasing and tend towards more realistic objectives and this is mainly due to people getting more informed about the technology and its potential.

In short, artificial intelligence is defined, for this paper, as the computer-based techniques that improve the speed, reliability or accuracy of processes that would require intelligence when

done by humans, to help a company in its business activities by automating processes, supporting analyses through gains in insights or engaging with employees and customers.

Then, in an attempt to understand and highlight the domains of application and exclusion of AI, it was analyzed that it is actually impossible to limit oneself to a few industries where this technology can be applied. Actually, artificial intelligence matches the characteristics of a General-Purpose Technology (GPT). This technology is therefore not limited to a certain group of industries but finds opportunities in each industry to some extent. By confronting the analysis that maps some industries according to two axes: data generation capabilities and digital maturity (including hardware and skills), that was done in order to understand which industries seem to be technologically advanced to implement AI solutions, with the bibliometric research on the Harvard Business Review (HBR), we observed that the data generation capability axis seemed to be the biggest driver out of the two axes for AI opportunities. This must be due to the intrinsic characteristic of AI to leverage on big amounts of data and, as highlighted by some interviewed experts, hardware and skills can be outsourced to cloud services and third-party companies if the data isn't too sensitive.

From the research and interviews done in this thesis could potentially be assumed that manufacturing is one of the industries with the biggest technological potential to implement AI solutions as this industry generates substantially more data than the other industries that were mapped and had also the most articles about AI published in the bibliometric research made on HBR. Besides, when the interviewees were asked what would be their top three of industries with AI potential, 3 out of the 4 answers topped manufacturing. Potential explanations shared by interviewees for manufacturing topping, besides the data generation capabilities, are both the characteristic that the generated data is often non-sensitive and the potential to automate, even more, patterned activities performed in factories which can now benefit from AI applications as, for example, predictive modelling and image recognition. Interestingly, healthcare was topping in terms of published articles in bibliometric researches made in the scientific journals IEEE Computational Intelligence Magazine, Research Policy and Technological Forecasting and Social Change and was also mentioned by some interviewees. However, healthcare was lowly mapped on the matrix of technological potential which could indicate that technological potential to implement AI solutions is not the only driver, but that the potential financial and non-financial return on investment could also play a key role in the decision to adopt AI or not as was mentioned by most of the interviewed experts. Supporting this idea is the fact that AI is seen as an opportunity in healthcare for medical imagery diagnosis

resting on image recognition. With deep learning, we can now leverage on images as we couldn't before. It opened doors to new opportunities with potential substantial financial and non-financial returns on investment. This is not only to be seen in healthcare, but also in mobility, for example, with autonomous cars and many other industries as manufacturing, security, etc. Hence, as acknowledged by Mihailo Backović, all the industries that can benefit from image recognition, might profit a lot from this technology.

As discussed in chapter 3 and through the interviews, AI could be defended as being a General-Purpose Technology, meaning that it can be applied, in many industries, to different ends.

Therefore, the next natural question could be to understand what the barriers that can refrain a company from implementing and using this technology are. From research and interviews, it was deduced that potential barrier can appear at 3 stages of an AI adoption project: prior implementation, for the implementation itself and during the usage of the AI solution.

It is interesting to highlight that barriers can come even before the project starts. Some companies might directly start to think about the data and the required skills and hardware without paying attention to potential prior barriers as artificial intelligence awareness, problem definition and expectations.

However, interviewees recommend that companies understand first the technology that they are going to use, define correctly a problem that can be solved by AI and have the right expectations that they should form based on similar use cases from similar companies for similar projects and on potential return on investment (ROI). This could help companies understand the added value of the technology for their process as well as remain down-to-earth. From the research and the interviews, it can also be deduced that the main barriers during the implementation process of an AI solution are the data and the company culture, whereas the extent of skills and hardware as barriers seems debateable as it can be outsourced to third-party companies if the data is not sensitive. It was shown that data is one of the biggest barriers as it needs to be of quality, accessible, complete, codifiable, sufficient, non-biased and structured. Respondents defended that data management takes therefore a considerable amount of time in an AI project and should hence be an attention point. Next to data, cultural barriers were said to be also one of the biggest barriers to be taken into account. They occur under the form of neglect and fear from managers and employees for the unknown and for change.

Thus, some experts proposed that information and training sessions should be done in order to keep everyone on board from scratch and said that the organizational structure might have to be adapted in order to incorporate effectively the AI application.

Lastly, with the usage of AI comes ethical barriers. As shared in the literature review, a company willing to use artificial intelligence should set ethical goals as impartiality, transparency and robustness and answer to ethical questions as responsibility and decision-power trade off. This is important as with the emergence of AI came new possibilities and therefore also new responsibilities. As a result, ethical guidelines should be set at an institutional level, but also at a company level and especially because research and interviews support that advances in the technology and its adoption are going faster than the setting of its legislation and ethical guidelines. Consequently, there is, even more, an emphasis to be put on setting ethical principles on a company level.

The what, the where and the potential barriers being discussed, a final question that needs to be answered is the why it is interesting for a manager to use artificial intelligence in its business activities? To answer this question, the advantages and disadvantages of AI were discussed and found to be divisible into general and application-specific ones. The general advantages of using AI are mostly similar to the ones of using a new technology in a company. The reason is that gains in efficiency, efficacy and quality of outputs are similar for most of new technologies and are often the main reasons why companies adopt a new technology. Therefore, the only two highlighted general advantages more specific to artificial intelligence are: being able to turn a pool of unstructured knowledge into structured knowledge and to generate links between pieces of information. Concerning the disadvantages, more can be highlighted as being specific to artificial intelligence. From all the mentioned disadvantages in this paper, the ones that got the most attention are biases, black box, responsibility shift and decision-power trade off. For this reason, it was suggested in the literature and by the interviewees that managers should try to tackle these issues up front by checking the data, defining whether the black box aspect could be an issue or not in the particular application, setting up front the responsibility rules and deciding on the decision-power extent of the AI solution (full autonomy or support function).

The insights gathered and some conclusions drawn through this whole paper by discussing the AI concept, its domains of application, its barriers and its advantages and disadvantages led to the setting up of a list of a few recommendations and “lessons learned” to support managers to some extent in their AI journey. These recommendations are general and applicable to all the industries as artificial intelligence was categorized as being a general-purpose technology and the scope of this paper was therefore not to focus on one particular industry. In addition to the few mentioned advices in the previous paragraphs, following are a few recommendations, for

managers willing to implement and adopt AI solutions in their business, summed up and synthesized in a chronological order. All these recommendations come from chapter 6 and are revised, nuanced and enhanced by the answers and comments made by the interviewees.

The first one would be to foster artificial intelligence awareness and understanding among the employees and managers that will be in contact with this technology.

Secondly, the company should define a goal or a business problem that can be solved through an AI solution, determine how it can help and make sure that the output is actionable.

Thirdly, the manager should forge oneself realistic expectations from the AI project. Besides getting more informed about the potential of AI itself, the manager should also compare its AI project to comparable projects done by comparable companies and get an idea of the potential ROI. Additionally, the satisfaction threshold to judge if the AI system is good enough should be quantitatively defined and tested for feasibility.

Fourthly, the right data matching the problem to be solved should be gathered, structured, managed and controlled for bias while keeping in mind that this step, even though important, can be time-consuming.

Fifthly, the manager should check whether they have the right skills and hardware to develop and run the AI application or check whether outsourcing would be an option.

Lastly, the potential impacts on the stakeholders, internal or external, should be highlighted and dealt with. On the one hand, internally, information and training sessions could be given to employees in order to get them on board directly, “AI bridgers” might have to be hired in order to translate the business problems to data scientists and the organizational structure might have to be adapted to incorporate the AI tool in the business activities. On the other hand, externally, but also sometimes for internal reasons, potential ethical concerns should be highlighted, and ethical guidelines should be set in order to operate morally and according to the company’s values.

Answering to these recommendations and following the points discussed in this paper for a company’s specific situation might help managers to implement and adopt artificial intelligence solutions in their business.

Limits of the paper

It is also important to define what were the limits of this paper. This work was confronted to some restrictions due to the scope of this thesis, the limited access to some resources and the led interviews. Following are the main limits to be considered for this work.

As segmented in the definition chapter, this thesis discusses only weak AI and not strong artificial intelligence. In fact, the paper also tends to put an emphasis on machine learning and deep learning, rather than expert systems, as these are more recent systems and are at the origin of the current extensive publicity of artificial intelligence.

Besides, the insights and conclusions provided by this paper are up until the latest publications of this continuously evolving technology of April 2020.

In addition, weak AI is then only analysed in a business context for its implementation and adoption. Hence, other contexts, as for example, legal, political, social and ecological ones are not the main focus of this thesis.

Additionally, the application field analysis showed that artificial intelligence is a general-purpose technology, hence the rest of the paper is made on a cross-industry level and do not focus on a particular industry neither on a particular application but takes a more generic approach. Because of this generic approach, some points discussed will be more relevant for some industries or applications than for others.

Also, during the industry analysis, a ROI axis couldn't be added because of a lack of resources and means to reach out the information to create such an axis. Thus, the application field analysis indicates the industries that are technologically advanced to perform AI, but this does not fully translate into which industries could benefit the most from artificial intelligence as there is no axis reflecting the potential return on investment.

Moreover, the interviews were conducted only with Belgians, meaning that the extent of some claims might not reflect the reality of the AI culture in some other countries. As a concrete example, the importance of fostering artificial intelligence awareness in companies can vary depending on the current AI knowledge and culture in different societies.

Furthermore, not all the 7 interviewees did an actual implementation of an AI application themselves. Hence, the thesis might lack sometimes of proper implementation experience.

Lastly, due to limited time and access to resources, this thesis remains a general synthesis and is a first glimpse to contribute to the clarification of the concept, the application fields, potential barriers and (dis)advantages and provides some recommendations based on these.

Further research

Along the way of scoping down this thesis, it also left room for further research outside of the scope. Therefore, a first further research that could be done is concerning strong AI for firms. Weak AI has been analysed here, but implications and key issues to address could probably

vary with strong AI. However, this concept is still futuristic as we aren't close to strong AI yet. So, it might be too soon to write a paper about this subject, or it could be done to provide food for thoughts to predict how companies might have to adapt to incorporate strong AI if it was to exist. A second further research, as this thesis focuses more on the business adoption of AI, could be to take a more legal, political, social or ecological point of view. As discussed in this paper, setting up legal rules for AI seems to be lacking behind. Hence, it could be interesting to dig deeper into potential legal frameworks and regulations for developing and using AI and analyse which scenarios the current legislation covers or not yet.

Further research could also be done to complement this research. So, a further research could be to take a more technical approach to the implementation of AI solutions in companies as this research was done out of a managerial perspective. This would be more practical recommendations of what is required in order to implement and run an AI solution in companies and could also gather all the best-in-class methods. Also, to complement this research, an industry analysis could be made to understand the potential ROI of adopting AI solutions for particular industries. This could then be added to the matrix in this paper to get a sense of "Does the industry have the technological capabilities to use AI?" and "Will it bring financial or non-financial value?". This could be interesting as healthcare and mobility, for example, show potential and interest for AI, but do not show signs of already-acquired technological advantages in comparison to other industries. Thus, a hypothesis could be that the main driver for these industries is the potential financial or non-financial return on investment and this could be analysed by adding an axis of potential ROI to the current matrix.

Lastly, further research could be done resulting from this paper to deepen some insights. First, the industries, manufacturing and healthcare, shows some particular interest and potential in this thesis. Hence, an in-depth analysis of the potential of AI in these sectors could be done. Similarly, concerning the applications of AI, image recognition seems to be one of the applications with the most potential. So, a similar methodology could be adopted to analyse more specifically the AI application, image recognition. Last but not least, ethics is confronted to new challenges with AI and some are already working on potential ways to work morally with AI as the MIT moral machine. Consequently, a research could be done to have companies work morally with AI by providing them with guidelines to set proper ethical rules. This research would then also explain the new environment created by artificial intelligence for companies as it does not only automate manual tasks anymore, but also cognitive ones.

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Appendix

Appendix A: Examples of AI applications in each industry as defined by the International Labour Organization (ILO)

A1 Agriculture & plantations

As labour force is decreasing in agriculture, farmers need to find new ways for the daily work that has to be done on their fields. Robots that use AI and more specifically image recognition are a solution. This technology helps to harvest crops, for example, faster and in higher volumes that humans would be able to achieve. It can also identify weed and get rid of it (Walch, 2019).

A2 Basic metal production

Casting of metal into a definite shape involves identifying the Ultimate Tensile Strength (UTS), which can only be measured by testing the metal out with destructive methods leading to incremental costs. By modelling the foundry process and using machine-learning algorithms, the predictions were shown to be better than other forecasts methods meaning that with machine learning a metal casting company would achieve reasonable results with lower costs than physical trials (Santos, Nieves, Penya, & Bringas, 2009).

A3 Chemical industries

The pharmaceutical industry requires high investments in research & development. Using artificial intelligence, drugs researchers can leverage from their big set of data for prediction of bioactivities and molecular characteristics with high precision to reach their objectives (Ekins et al., 2019). As an example, GlaxoSmithKline (GSK) is partnering with Exscientia Ltd., an AI-based research company for developing new drugs, to optimize its productivity of R&D (Paton, 2019).

A4 Commerce

Commerce and E-commerce more particularly can benefit from the different artificial intelligence applications. E-commerce can use machine learning for assistants under the form of chatbots, better customer targeting and recommendations, intelligent logistics and optimal

pricing strategy (Song, Yang, Huang, & Huang, 2019). Through user's profile, click rate and interest in certain type of products E-commerce has a lot of data to work with from which it could leverage. Sephora, for example is one of the first companies in retail using a chatbot on messenger to recommend styles to users or to answer specific questions. Even if it is not completely independent yet, it can take over part of the customer service freeing employees or reducing headcount. According to Vodaphone, a bot could do the work of up to 3 employees, but in a fraction of time a human would take and error free. Hence, improving the quality of the customer service and this for a cost of €6,000/year (Kerr & Moloney, 2018). Recommendation is also used in e-commerce to suggest products similar to what they clicked on or that are characterized by the same style. Amazon is using that technology to suggest other products based on a customer's researches and clicking behaviour. E-commerce is confronted to complex logistics networks and customer's short delivery time requirements and customer's variability in demand. Machine learning could intervene here in order to make data-based recommendations of ordering and inventory quantities leading to anticipation of the bullwhip effect²³ (Prakash & Pandey, 2014). Lastly, optimizing pricing based on customer clicking behaviour, which is a proxy for showing interest and making the final purchasing decision, could help companies in defining an optimal pricing strategy.

A5 Construction

In the construction sector accidents due to work happen daily. Increasing efficiency while fostering workers' health and security is an improvement made possible by AI. By using image recognition, for example, to automatically stop a machine when a human is in danger is a potential application of the technology. Bobcat, the compact construction company, is partnering with SafeAI, a Silicon Valley start-up developing AI algorithms for safety issues. Together, they will develop algorithms to be implemented in the equipment that will be able to analyse a complex environment around the equipment to assure an automated control (Fargo, 2018).

²³ The bullwhip effect is a concept that demonstrates the increasing variability in demand when going upwards in the supply chain.

A6 Education

While learning is currently standardized by being exactly the same for group of students, it can become more personalized thanks to artificial intelligence. Using this technology can help to track the progress of each student and understand his weaknesses in order to train them by personalizing the learning. AI will not only slow down the pace for students that have difficulties somewhere but could also speed up the pace or complexify the learning path for students that need to be more intellectually challenged. Therefore, AI could be a solution against the “one-size-fit-all” standards that schools and universities are based on (Pedro, Subosa, Rivas, & Valverde, 2019; Rouhiainen, 2019).

A7 Financial and Professional services

Artificial intelligence is a good opportunity to reshape part of the workflow in financial services. To review their current services, companies can rely on the automation of certain repetitive tasks and the usage of machine learning to take the most out of the tons of data they have for predictive analysis. From detecting fraudulent practices to making AI-driven investment suggestions, there are plenty of new opportunities created by this technology. As an example, Simudyne is a company that simulates a lot of different future scenarios based on a client’s information and measure their impact in order to provide financial services with the possibility to anticipate and prepare contingency plans (Simudyne, 2020).

A8 Food, drinks and tobacco

Image recognition can also enhance current sorting processes to ensure the alignment with health and safety policies. Tomra sorting machine is an example of a machine that was designed to scan food and sort out the perished vegetables. This enables a company in the food industry to be more efficient, as it checks the products than a human would, while taking out unwanted vegetables. This also prevents other vegetables to perish (Tomra, 2019).

A9 Forestry, wood and paper

Since the 1900s quality of trees have been analysed the same way by humans going into the forest to check the woods by looking for different criteria as volume of wood, height of trees, type of wood, health of trees, etc. With deep learning and the usage of satellite images, this can be done through algorithms in order to help forestry management define which sections should

be cut, treated, etc. 20tree.ai is a company that has recently developed such a service to deliver forest intelligence (20tree.ai, 2020; Taillon, 2019).

A10 Health services

Using image recognition to detect skin cancer, tumours and other diseases has been one of the most successful AI applications in the health sector yet. Through the usage of convolutional neural networks (CNN) the AI algorithm have succeeded to classify correctly 92.4% of the tumours images that it had to analyse, while an experimented pathologist was only successful 73.2% of the time. Such achievements promise to be helpful in the health sector (Konno & Ishii, 2019).

A11 Hotel, tourism, catering

Hotel client services can be answered by chatbots or voice assistants. This technology is being used by some hotels in order to help out their concierge service to handle client's questions and queries. According to Oracle, 70% of client's queries are handled by AI-supported response technologies in hotels where the technology has been implemented (Oracle, 2018).

A12 Mining

Mining is a cost intensive activity that faces uncertainty about where to dig. In order to minimize initial investment, a mining company should accurately understand where to dig as an error could costs millions or even billions. Artificial intelligence can be applied here as to better map out the terrain and predict where the digging should be done. By this application of AI, it could potentially reduce uncertainty and its according costs (Schmelzer, 2019).

A13 Mechanical and electrical engineering

In mechanical engineering, applications of artificial intelligence get more technical. Applications of AI in this field are plural. It can be used as a method to control the output as it can analyse surfaces and texture of products by image processing in order to assure the quality of it. It can also intervene in complex machines themselves by analysing data from the sensors of these machines in order to analyse, understand and predict where an issue can occur to intervene rapidly and prevent it in the future (Glatz & Peters, 2018).

A14 Media, culture and graphical

In the media sector, Netflix is a known example of a company whose success is based on a recommender system which enhance customer's retention and engagement. This recommender system uses customer's profile, historic data of streaming and clicking behaviour in order to predict what the customer will potentially like to watch and links a percentage of "taste match" to movies to better suggest a basket of watching options that will increase the customer's experience (Gomez-Urbe & Hunt, 2016).

A15 Oil and gas production and refining

Similarly, to the mining industry, the oil and gas industry finds huge costs to drill for these resources while facing considerable uncertainty and efficiency criteria. Neudax found this issue as an opportunity to develop a new service which support oil and gas companies in their decision-making by leveraging on deep learning to assess more than 10 000 field development scenarios and evaluate what is the best field development plan. By this decision supportive function, they claim to help oil and gas companies to be more efficient and more accurate (Neudax, 2020).

A16 Postal and telecommunication services

Telecommunication services has a lot of different potential AI applications. It can enhance its customer services, support decision making through analysing the big pool of data they have, recommend for their investment in capital expenditure, etc. Vodafone, for example, introduced TOBi which is a chatbot. This chatbot deals with most of the customer's requests online. As this chatbot is able to solve 70% of all inquiries, it cuts substantial costs in customer service (Brady, 2019).

A17 Public services

Numerous governmental organizations have adopted artificial intelligence to automate tasks. According to the European Commission, object recognition is already used to analyse digital media, natural language processing is used to review audio and text with the possibility of interaction, and they use the technology also to detect anomalies. All these applications benefit to the public services be reducing the bureaucratic processes and enhancing efficiency of employees (EC, 2020).

A18 Shipping, ports and fisheries

The Orient Overseas Container Line Limited (OOCL) company has partnered with Microsoft the 23th of April 2018 in order to use artificial intelligence to review their shipping network operations to reach higher degrees of efficiencies. With this collaboration with Microsoft Research Asia (MRSA) they expected to save 10 million USD annually on operating costs (OOCL, 2018).

A19 Textiles, clothing, leather and footwear

In the clothing industry AI applications can help companies, among other things, in their designing process. As an example, Tommy Hilfiger has invested in deep learning in order to analyse fast a lot of images and videos to provide designers with better insights of the current trends and to create the right product at the right time for the right people. Thanks to AI that was feeding on social media feeds, Tommy Hilfiger prototyped a jacket that is eco-friendly with changing colour fibre and with different patterns (Baker, 2018).

A20 Transport

Autonomous transport is an AI application that has known big investments from several transport companies. According to Morgan Stanley, the autonomous cars could lead to global savings of \$5.6 trillion worldwide annually (MorganStanley, 2015). This new technology could reduce congestions, make traffic easier, let the driver do something else and reduce car crashes (Niestadt, Debyser, Scordamaglia, & Pape, 2019). It can also disrupt the taxi services. Therefore, Uber has partnered with Volvo to develop autonomous cars with deep learning techniques. These autonomous cars are currently driving in specific areas of the United States to train and get better at driving in all circumstances (Uber, 2020).

A21 Transport equipment manufacturing

In the transport equipment manufacturing industry, an important driver is the efficiency of manufacturing and the potential economies of scale. Through the years, manufacturing evolutions and efficiencies have been shown the way by automotive companies, as the Fordism introduced by Henry Ford in the 1920s (Scott & Storper, 1992) and the Toyota Production System (TPS) that laid down the lean manufacturing concept as was introduced by Taiichi Ohno in the late 1980s (Ohno, 1988). Nowadays, AI brings opportunities to develop even further this lean concept in the automotive manufacturing by having an impact in the 6 following ways:

less equipment failure, robot-human collaboration, less quality problems, leaner supply chain, better project management and support functions (Breunig, Kässer, Klein, & Stein, 2017).

A22 Utilities (water, gas and electricity)

Electricity distribution from power plants to customer preferences is difficult to handle as it involves changes that need to be predicted and answered. Hence, artificial intelligence can come in handy to regulate the electricity delivery and stocking to reach minimum power losses (Soliman Qudaih & Mitani, 2011). Besides serving the market appropriately in electricity, AI can diminish the electricity shortages and also analyse and prevent electricity theft (Schenker, 2019).

From this analysis, it is clear that artificial intelligence is not a technology that is predetermined to be used in a few single industries. Its applications are widespread across all the industry and presents value for all the industries. However, the impacts and potential value of adopting AI might reach different degrees depending on the industry.

Appendix B: OECD stats for digitalization of industry

B1 Businesses purchasing computational power

Dataset: ICT Access and Usage by Businesses			Indicator	G3: Businesses purchasing cloud computing		
			Time	2014: 2014	2016: 2016	2018: 2018
Country	Breakdowns					
EU28	INDUSTRY: Businesses by industry	MAN: Manufacturing		17,25	17,49	21,99
		CON: Construction		14,33	15,67	20,58
		WHO: Wholesale trade, except of motor vehicles and motorcycles		20,33	21,88	29,82
		RET: Retail trade, except of motor vehicles and motorcycles		13,64	16,60	19,92
		TRA: Transportation and storage		15,30	17,05	21,02
		ACC: Accommodation and Food and beverage service activities		13,92	16,23	16,85
		INF: Information and communication		44,51	53,45	63,99
		REA: Real estate activities		20,06	24,14	32,89
		PRO: Professional, scientific and technical activities		27,32	35,38	43,73
		ADM: Administrative and support service activities		19,94	22,10	29,03

Data extracted on 28 Mar 2020 09:40 UTC (GMT) from OECD.Stat

Figure 9: Reprinted from OECD. (2018b). Businesses purchasing cloud computing services (%). Retrieved from <https://stats.oecd.org/>

B2 Businesses employing ICT specialists

Dataset: ICT Access and Usage by Businesses			Indicator	H1: Businesses that employ ICT specialists, within the last 12 months (%)						
			Time	2012	2014	2015	2016	2017	2018	2019
Country	Breakdowns									
EU28	Businesses by industry	Manufacturing		21,10	20,44	20,99	21,04	20,04	19,99	21,35
		Construction		11,48	9,23	8,79	8,70	8,70	8,24	10,05
		Wholesale trade, except of motor vehicles and motorcycles		27,02	24,64	25,46	25,68	24,97	24,63	25,68
		Retail trade, except of motor vehicles and motorcycles		14,20	13,32	12,38	15,76	12,65	13,29	14,66
		Transportation and storage		15,60	14,05	14,84	13,49	14,23	13,10	13,07
		Accommodation and Food and beverage service activities		9,87	8,09	7,53	8,08	7,02	7,94	7,47
		Information and communication		69,79	72,77	74,82	74,02	72,51	73,51	72,77
		Real estate activities		28,02	20,52	21,84	20,28	22,36	22,23	24,18
		Professional, scientific and technical activities		34,08	32,24	31,00	33,78	30,06	31,45	29,84
		Administrative and support service activities		18,61	16,87	18,01	17,65	17,48	18,26	18,72

Data extracted on 28 Mar 2020 10:17 UTC (GMT) from OECD.Stat

Figure 10: Reprinted from OECD. (2018c). Businesses that employ ICT specialists, within the last 12 months (%). Retrieved from <https://stats.oecd.org/>

B3 Businesses performing big data analysis

Dataset: ICT Access and Usage by Businesses		Indicator		G7: Businesses having performed Big data analysis (%)	
		Time		2016	2018
Country	Breakdowns				
EU28	Businesses by Industry	Manufacturing		7,20	8,89
		Construction		7,81	10,54
		Wholesale trade, except of motor vehicles and motorcycles		10,23	12,43
		Retail trade, except of motor vehicles and motorcycles		8,91	11,53
		Transportation and storage		14,51	18,78
		Accommodation and Food and beverage service activities		9,79	9,89
		Information and communication		24,28	27,01
		Real estate activities		9,38	9,12
		Professional, scientific and technical activities		10,84	14,45
		Administrative and support service activities		10,83	13,31

Data extracted on 28 Mar 2020 10:21 UTC (GMT) from OECD.Stat

Figure 11: Reprinted from OECD. (2018a). Businesses having performed big data analysis (%). Retrieved from <https://stats.oecd.org/>

B4 Ranking of industries based on Tables B1, B2, B3, values of 2018

Industries	Purchasing cloud computing		Employing ICT specialists		Performing big data analysis		percentage (%)		Ranking		
	2018										
	Manufacturing	Percentage (%)	Ranking	19,99	5	8,89	10	Average	Ranking	Average	Ranking
	Construction	20,58	8	8,24	9	10,54	7	16,96	7	7,0	7
	Wholesale trade, except of motor vehicles and motorcycles	29,82	4	24,63	3	12,43	5	13,12	9	8,0	9
	Retail trade, except of motor vehicles and motorcycles	19,92	9	13,29	7	11,53	6	22,29	3	4,0	3
	Transportation and storage	21,02	7	13,10	8	18,78	2	14,91	8	7,3	8
	Accommodation and Food and beverage service activities	16,85	10	7,94	10	9,89	8	17,63	6	5,7	6
	Information and communication	63,99	1	73,51	1	27,01	1	11,56	10	9,3	10
	Real estate activities	32,89	3	22,23	4	9,12	9	54,84	1	1,0	1
	Professional, scientific and technical activities	43,73	2	31,45	2	14,45	3	21,41	4	5,3	5
	Administrative and support service activities	29,03	5	18,26	6	13,31	4	29,88	2	2,3	2
								20,20	5	5,0	4

Figure 12: Ranking of industries based on OECD's stats for purchasing cloud computation, employing ICT specialists and performing big data analytics in 2018

Appendix C: Bibliometric research for published scientific articles in AI per industry

C1 Harvard Business Review

Date of analysis	21/03/2020	
Filters	artificial intelligence; machine learning; deep learning	
Number of articles	11017	
Number of results assigned to an industry	5899	
Industry from HBR	Number of articles in that industry	Percentage
Administrative & support services	75	1,27%
Advertising, marketing & public relations	39	0,66%
Aerospace & defense	125	2,12%
Agriculture	209	3,54%
Arts & culture	192	3,25%
Educational institutions	228	3,87%
Energy & natural resources	176	2,98%
Engineering, construction & infrastructure	112	1,90%
Financial services	506	8,58%
Food & beverage	354	6,00%
Government	171	2,90%
Healthcare	389	6,59%
Hospitality	154	2,61%
Manufacturing	584	9,90%
Media	262	4,44%
Pharmaceuticals	179	3,03%
Professional services	404	6,85%
Real estate	40	0,68%
Retail & Consumer goods	877	14,87%
Sports	53	0,90%
Technology	413	7,00%
Telecommunications	175	2,97%
Transportation	145	2,46%
Travel	37	0,63%
SUM	5899	100%
Average	245,79	4,17%

C2 IEEE computational intelligence magazine

Date of analysis	04/04/2020		
Filters	artificial intelligence; machine learning; deep learning		
Number of articles	302		
Number of articles assigned to an industry	72		
Industry from HBR	Number of articles in that industry	percentage	For the top 10 industries: What was the most discussed topic?
Administrative & support services	3	4,17%	
Advertising, marketing & public relations	1	1,39%	
Aerospace & defense	8	11,11%	Space planning; improve rover missions
Agriculture	2	2,78%	
Arts & culture	2	2,78%	
Educational institutions	5	6,94%	Learn about AI & thanks to AI
Energy & natural resources	2	2,78%	
Engineering, construction & infrastructure	0	0,00%	
Financial services	5	6,94%	Stock market prediction
Food & beverage	0	0,00%	
Governement	1	1,39%	
Healthcare	12	16,67%	medical images analysis & recognition (cancer, cells,...); btter understanding of complexity of human body (e.g. genes))
Hospitality	0	0,00%	
Manufacturing	4	5,56%	Automation for speed and reduction of errors
Media	5	6,94%	Social media analysis for interaction
Pharmaceuticals	4	5,56%	Drug discovery
Professional services	1	1,39%	
Real estate	1	1,39%	
Retail & Consumer goods	1	1,39%	
Sports	1	1,39%	
Technology	4	5,56%	Biometric technologies
Telecommunications	5	6,94%	Enhance and analyse wireless systems
Transportation	4	5,56%	Automation of navigation
Travel	1	1,39%	
SUM	72	100%	
Average	3,00	4,17%	

C3 Technological Forecasting & Change and Research Policy

Date of analysis	14/04/2020	
Filters	artificial intelligence; machine learning and deep learning were researched as keywords in both journals: "Technological forecasting & change" and "Research policy"	
Number of articles	664	
Number of articles assigned to an industry	184	
Industry	Number of articles	Percentage
Administrative & support services	3	2%
Advertising, marketing & public relations	2	1%
Aerospace & defense	6	3%
Agriculture	2	1%
Arts & culture	2	1%
Educational institutions	9	5%
Energy & natural resources	13	7%
Engineering, construction & infrastructure	17	9%
Financial services	10	5%
Food & bevarage	0	0%
Governement	10	5%
Healthcare	29	16%
Hospitality	0	0%
Manufacturing	13	7%
Media	11	6%
Pharmaceuticals	5	3%
Professional services	4	2%
Real estate	2	1%
Retail & Consumer goods	4	2%
Sports	0	0%
Technology	8	4%
Telecommunications	12	7%
Transportation	18	10%
Travel	4	2%

C4 Scopus analysis for AI articles published in healthcare over time

Healthcare		
Year	Number of articles about AI & ML in healthcare on scopus	Yearly increase (%)
2010	5484	
2011	6006	10%
2012	7071	18%
2013	8235	16%
2014	8933	8%
2015	10835	21%
2016	12452	15%
2017	15232	22%
2018	18784	23%
2019	25698	37%
2020	Uncomplete	

Appendix D: Gartner's hype curve (2019)

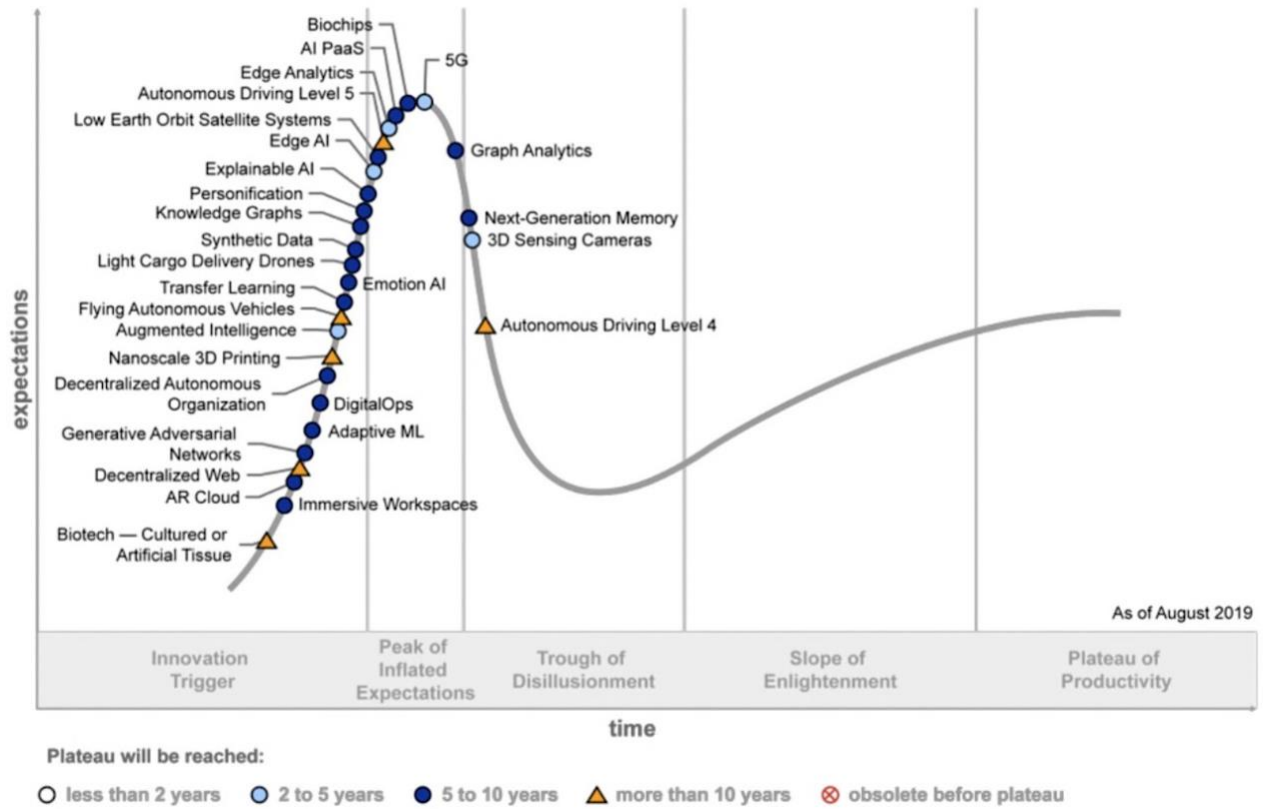


Figure 13: Hype cycle for emerging technologies, 2019 - Reprinted from Gartner. (2020). Hype Cycle for Emerging Technologies, 2019. Gartner website: Gartner.

Appendix E: Interpreting facial expressions

E1 Facial expressions without context



Figure 15: The difficulty to interpret facial expressions - Reprinted from Heaven, D. (2020).
Expression of doubt. *Nature*, 578, 502-504. doi:10.1038/d41586-020-00507-5

E2 Facial expressions with context



Figure 14: Adding background-context to facial expressions - Reprinted from Heaven, D. (2020).
Expression of doubt. *Nature*, 578, 502-504. doi:10.1038/d41586-020-00507-5

Appendix F: Questionnaire

- 1) As artificial intelligence often means and includes different things for different people, how would you define AI?
- 2) According to you, what are the most relevant application fields of AI? Is it a general-purpose technology? (//Internet)
- 3) According to you, what would be the top 3 industries for the application of AI?
- 4) According to you, what are the main barriers to implement AI in companies?
 - a. How would you describe the digital maturity of your industry?
 - b. How would you describe the data generation capabilities of your industry? In terms of quantity, quality and “usability”?
- 5) According to you, what are the main advantages and disadvantages of using AI in a company?
- 6) How do you see AI evolve in companies? Which role will it play?
- 7) What would be your main recommendations for someone willing to implement AI in his business?

Appendix G: interview transcripts

G1 Didier Ongena, Country Manager Microsoft Belux, April 21st 2020

Alexandre Verdoodt

[...] « Alors j'ai 6 questions que je vous avais envoyé par mail hier soir, je ne sais pas si vous avez eu le temps de les parcourir, mais j'aimerais passer les deux premières questions dans un premier temps et revenir dessus à la fin si nous avons encore le temps. Alors du coup ma première question pour vous serait : Quelles sont les barrières à l'implémentation de L'IA au sein des entreprises selon vous ? »

Didier Ongena

« Alors, j'en vois 3, in fine. Le premier élément c'est que quand on discute d'intelligence artificielle, il faut toujours combiner 3 éléments. C'est la partie computing power, la partie algorithme et la partie données. La première barrière, elle est plutôt au niveau des données. C'est-à-dire qu'aujourd'hui il y a énormément d'entreprises qui disposent de beaucoup de données, mais qui n'ont pas un data lake ou un environnement qui est assez clean au niveau de leur data. Non, seulement un environnement clean, mais aussi un environnement qui reprend aussi les datas des différents processus. Donc ce qu'on voit c'est que comme l'intelligence artificielle par essence n'est pas déterministique, mais probabilistique, l'erreur qu'il ne faut pas faire au niveau des données c'est de dire je veux résoudre un problème X et pour résoudre ce problème je vais mettre à disposition un certain data set. Ce qu'on voit c'est que les résultats ne sont pas très bons, donc il faut vraiment être large dans ces data. Il faut prendre des data de ses clients, de sa production, de ses produits et mélangé ça et c'est là qu'il y a de la richesse. Donc 1, avoir un environnement data qui est très holistique très large et assez propre. Je pense que ça c'est une première barrière donc c'est pour ça que souvent quand on fait des projets d'intelligence artificielle, on amène les clients par un cycle de maturité. Ce cycle c'est d'abord data warehouse, puis c'est la partie big data puis c'est seulement l'intelligence artificielle. Si on n'a pas les deux premières alors ça ne va pas. Une deuxième difficulté, c'est qu'aujourd'hui on voit beaucoup d'entreprises qui font des projets pilotes, mais qui ont du mal à amener l'intelligence artificielle à travers l'entièreté de leur procès. Aujourd'hui en Belgique je vois que quelques entreprises qui ont des centaines de use cases, une banque comme KBC, un operateur telco comme Voo a des centaines de use cases et donc la partie scalability est un

deuxième gros défi pour beaucoup d'entreprises. Le troisième défi est l'aspect data gouvernance et éthique. Aujourd'hui quand on est dans des applications un peu plus avancé de l'IA il est quand même important d'assez rapidement former ses équipes sur certains principes éthiques. Microsoft a un conseil éthique pour l'IA, on a édicté 6 principes. Par exemple un principe c'est un principe de transparence, équité, etc. mais donc avoir une compréhension de ces principes éthiques parce qu'ou sinon on peut se retrouver assez rapidement dans des situations compliquées. Il faut des gens qui y réfléchissent à ces principes et c'est même, par exemple, pour des applications assez banales, mais si on utilise l'IA pour faire un screening de CVs et utiliser ça pour faciliter un peu le système de recrutement, il faut s'assurer que l'IA ne soit pas biaisé. On crée par exemple un modèle qui est basé sur le modèle existant mais si aujourd'hui tu as une boîte d'engineering et 80% de tes ingénieurs sont des hommes blancs de la quarantaine, forcément ton modèle va probablement screener des CVs d'hommes blancs. Donc même pour es applications qui ont l'air assez banale, avoir une réflexion éthique est assez important. Donc ça c'est les trois éléments, en tous cas les trois éléments sur lesquels nous on travaille beaucoup avec les clients. »

Alexandre Verdoodt

« Oui tout à fait, c'est aussi les barrières que j'ai identifiées, donc avoir des bonnes attentes, donc ne pas sous-estimé, mais ne pas surestimé aussi les capacités de l'IA, donc avoir des use cases pour se former de bonnes attentes. Comme vous avez dit aussi un bon travail au niveau des données donc qu'elles soient disponibles, accessibles, suffisantes, codifiables et non biaisées et puis avoir aussi une bonne culture d'entreprise qui accepte le changement et puis enfin aussi le point de gouvernance et éthique. Ok, parfait, ma deuxième question pour vous est quel serait pour vous les principaux avantages et inconvénients d'utiliser l'IA au sein d'une entreprise. »

Didier Ongena

« Honnêtement je ne sais pas trop s'il y a des inconvénients à son utilisation. Je pense que l'IA pose un certain nombre de questions sur lesquelles on n'a pas vraiment de réponses et à nouveau je ne sais pas s'il y a vraiment des inconvénients. Par contre les avantages sont assez clairs. Je pense que le plus gros avantage de l'IA permet à certains secteurs (ceux de la pharmacie, biotechnologie, médecine, etc.) de résoudre un certain nombre de problèmes qu'on n'arrivait pas à résoudre jusqu'à présent. C'est clair qu'une fois qu'on aura des plateformes d'IA dans ce genre de secteurs, on verra apparaître des nouvelles familles de traitements, de médicaments et

d'autres choses qu'on ne savait pas faire. De la même manière, de façon générale, je pense que l'IA en combinaison avec des modèles d'IoT ou de smart city, etc. pourra permettre de prendre des décisions qui sont beaucoup plus basées sur des données. Moi, j'habite *** et à un moment il y avait des discussions pour fermer la rue devant les écoles entre 8h et 9h pour réduire les émissions CO2. Aujourd'hui on n'a pas de modèles pour modéliser et avoir du data, donc je pense que l'IA permet cela. Ce qu'on voit aussi c'est que l'IA permet aussi l'évolution des activités humaines. Nous avons une vision de l'IA qui est vraiment en partenariat avec l'activité humaine. À travers l'activité humaine on peut quand même automatiser toute une série de tâches qui sont plus répétitives et donc permettre aux gens d'avoir des activités qui sont de plus forte valeur ajoutée, donc c'est ça un petit peu un certain nombre de domaines où on voit les bienfaits de l'IA à conditions bien évidemment que toute nouvelle technologie on fasse attention au côté éthique et aux dérives potentielles. »

Alexandre Verdoodt

« Ok, parfait. Ensuite, comment est-ce que vous voyez l'intelligence artificielle évoluer aux seins des entreprises, donc quel rôle va-t-elle jouer au sein des entreprises ? »

Didier Ongena

« Alors je pense que d'abord il faut d'une manière ou d'une autre revenir sur la première question sur la définition même de l'IA, mais peut-être quand même sous-catégoriser quand même les sous-domaines. Je pense que quand on réfléchit à l'intelligence artificielle on a tendance à réfléchir en 3 grandes catégories. Il y a la première catégorie qui est le cœur de l'IA, c'est le machine learning, c'est le deep learning. C'est ce que font les spécialistes des data scientists et c'est vraiment les gens qui utilisent des masses de données et créent des algorithmes, des modèles d'analyse qui sont très profonds et ça c'est une catégorie à part dont on parle le plus. La deuxième catégorie est une catégorie d'intelligence artificielle, mais qui est liée à des modèles préformés et qu'on va utiliser dans des applications de tous les jours. Ce sont des modèles de speech to text, de traduction, de bot et donc chez nous chez Microsoft, on a toute une série de micro-services qui sont sur Azure et donc quand on a un développeur implicatif on utilise ces Microsoft services. L'exemple que je donne souvent c'est Uber qui avait son application et certifie les chauffeurs Uber mais avait un problème à résoudre qui était qu'ils n'arrivaient pas à montrer que le chauffeur certifié était bien celui qui conduisait le véhicule et qui utilisait un micro-service qui est basé sur l'intelligence artificielle, c'est-à-dire la reconnaissance faciale pour dire toutes les 30 minutes le chauffeur doit s'identifier et puis les

coordonnées de la voiture et du téléphone sont comparé et si c'est bien le chauffeur qui conduit alors c'est accepté. Donc ça c'est une deuxième catégorie de l'IA qui est pré-packagé. La troisième catégorie d'IA, c'est celle qui est déjà pré-packagé dans les outils de tous les jours. Par exemple, Teams, quand on reçoit un chat qui n'est pas dans la langue usuelle, il reconnaît la langue usuelle et va traduire si le chat est dans une autre langue et ça on ne s'en rend même plus compte. Moi, j'utilise ici dans Teams le background blur et bien ça utilise aussi de l'IA. Donc je pense qu'on a ces trois catégories. La troisième catégorie, elle va commencer à être infusé de plus en plus. Quand le demande aux gens s'ils utilisent de l'IA et qu'ils disent non, alors je donne un certain nombre d'exemples comme les recommandations Netflix, la manière dont on fait du fishing sur les mails, fin les gens utilisent déjà sans le savoir de l'IA. Je pense que quelque part au niveau des entreprises, la catégorie qui aura le plus grand impact à long-terme c'est cette catégorie du milieu. Pourquoi, parce que cette catégorie du milieu c'est une combinaison de l'IA avec une autre tendance qui est le low code, no code. C'est-à-dire, toutes ces applications qu'on commence à construire à travers des power plateforme où c'est l'utilisateur lui-même qui va commencer à utiliser son propre environnement de travail. Un petit peu de la même manière que y a 10 ans il fallait être un super IT expert pour développer un site web et maintenant si tu as quelques connaissances tu peux développer ton propre site web, parce que les outils ont évolué et au niveau de l'IA il va y avoir le même phénomène. C'est un peu pareil qu'on fait chez Microsoft, c'est qu'il y aura toujours une catégorie de spécialistes, de data scientifiques qui font des choses très pointues, mais où l'IA va avoir son extension très large c'est quand les individus vont eux-mêmes commencer à utiliser l'IA comme ils utilisent PowerPoint, Excel et Tableur. Parce que c'est quelque part l'utilisateur final qui a le plus de connaissance de son propre métier, de son propre processus c'est lui qui est au contact du client final. Donc au plus on peut amener cette technologie vers ces gens-là au plus on aura de l'impact. Je pense que à long-terme ça c'est notre grand pari. Donc nous on voit vraiment la communication de trois pôles. C'est la communication et collaboration avec Office 365, Teams, la partie power apps, Power BI donc la partie automatisation et puis la partie intelligence artificielle qui amène l'intelligence et en fait c'est ces trois qui vont transformer. Aujourd'hui une entreprise intelligente, c'est une entreprise qui a beaucoup de data qui crée de l'intelligence, mais qui crée aussi des nouveaux procès d'intelligence en d'automatisation sur base de cette intelligence, mais en real-time. Les processus d'aujourd'hui doivent être différents de ceux de hier et ceux de demain seront encore différents. D'ailleurs c'est un peu ce qu'on voit nous chez Microsoft, c'est qu'on a nous des centaines et des centaines d'applications et les gens commencent à utiliser des composantes de l'IA pour améliorer et changer leur quotidien. »

Alexandre Verdoodt

« Donc plus d'interactions avec l'IA, mais au niveau individuel aussi, donc chacun dans l'entreprise. »

Didier Ongena

« Oui et je pense qu'aujourd'hui il y a quelque part cette notion que l'IA c'est assez nouveau, c'est très compliqué, y a des data scientists, la data gouvernance, mais c'est le top de l'iceberg. Le grand va se faire à travers de choses extrêmement simple dans les applications que les gens utilisent. Donc aujourd'hui quand on voit une entreprise du top 500 en Belgique a en moyenne entre 500 et 1000 applications qu'ils utilisent et donc c'est cette opportunité là qui a de moderniser ces applications et d'infuser des éléments d'intelligence artificielle dans ces applications et donc ces chiffres donnent un sens de l'opportunité, mais dans son sens large qu'on peut avoir et par exemple quelque chose que moi je ferais ou que je recommande quand on discute avec des clients c'est quand on regarde l'entièreté des processus de l'entreprise ou d'ailleurs du secteur public et l'entièreté des applications combien de ces processus et applications ont déjà été infusé d'éléments d'intelligence artificielle ? Parfois très simple, tout ne doit pas être compliqué.

Alexandre Verdoodt

« Ok, vous m'en amenez à ma dernière question qui est quelles seraient vos recommandations pour quelqu'un qui voudrait utiliser l'IA au sein de son entreprise ? »

Didier Ongena

« Comme je pense que quelque part le cœur du problème, comme souvent avec des nouvelles technologies, c'est un problème culturel. C'est un problème de change. Je pense qu'il faut inclure dès le début les utilisateurs finaux dans les projets. Pour qu'ils comprennent que certes leur métier va changer, mais que quelque part dans relativement peu de cas le métier va disparaître et qu'on les inclut dans ce processus et qu'on les inclut dans le use case afin de construire cette confiance qui est non seulement une confiance dans l'aspect technologie et capacité technologique de déployer et de faire des choses, mais aussi la confiance dans le côté et éthique et transformationnel de l'IA. Donc si je prends un exemple chez Microsoft, nous par exemple on utilise l'IA pour faire des forecasts donc on ne fait plus de forecasts manuels, donc on n'a plus ce processus où avant je demandais aux accounts exécutifs de me donner les deals

qu'ils pensent close ce quarter-là, il y avait le sales manager qui avait un jugement puis ça venait chez moi et puis ça montait jusqu'en haut. On n'a plus ce processus, alors c'est clair que pour la finance ça a été une transformation assez forte parce que les financiers passaient plus ou moins 4 à 5 jours plein temps tous les quarter pour ne faire que du forecasting processes et donc à l'échelle d'une boîte comme Microsoft, c'est potentiellement des centaines de personnes en équivalent temps plein qui font ça et donc comment on peut les amener à réfléchir sur ce type de problématique et réinventer leur propre métier et aujourd'hui on n'a pas réduit le nombre de financier chez Microsoft, mais ils ont des jobs beaucoup plus à valeur ajoutée où ils utilisent les données pour de l'intelligence pour nous aider plus sur notre business et donc on les a vraiment inclus dans ce processus de changement. Je pense que ça c'est pour moi l'essentiel. Parce qu'en fine dans la technologie, le côté technologique même s'il a l'air impressionnant aujourd'hui, ce n'est pas ça qu'il y a de plus compliqué, c'est le côté transformation, changement et humain.

Alexandre Verdoodt

« Ok, donc accepter le changement et encourager les gens à aller dans ce sens-là aussi. »

Didier Ongena

« Accepter, encourager, absolument. Et on se rend compte qu'une fois que les gens, une fois qu'ils comprennent que beaucoup de choses arrivent aussi bottom-up quand les gens sont assez intéressés. »

Alexandre Verdoodt

« Ok, un tout grand merci, c'était les seules questions que j'avais pour vous. Je vous remercie énormément pour votre temps. »

Didier Ongena

« Parfait ! »

G2 Ferdinand Casier, AI Business Group Leader at Agoria, April 15th 2020

Alexandre Verdoodt

« Alors ma première question pour vous, comme il y a énormément de désaccord sur ce que l'IA est et ce que cela comprend, qu'est qu'est-ce que l'IA d'après vous ? »

Ferdinand Casier

« Au niveau européen, il y a tout un exercice en cours qui a déjà été fait, mais qui va être fait pour déterminer c'est quoi l'intelligence artificielle. Et là encore, ils ont beaucoup de mal à mettre tout le monde d'accord sur ce que c'est exactement. Donc, tout dépend comment est-ce qu'on veut définir l'intelligence artificielle. Moi, j'ai plutôt tendance, mais je sais que ce n'est pas complet comme définition, loin de là. Mais, moi j'appelle ça des systèmes auto-apprenant. C'est assez basique comme définition. Les systèmes auto-apprenants permettent déjà de mieux définir ou en tout cas de faire la différence entre l'IA et tout ce qui est data analytics. Il y a quand même une différence entre les deux et pour des raisons marketing, parfois, les boîtes aiment bien parfois mélanger les deux, mais partons du principe que c'est tout système auto apprenant. En Allemagne, Ils ont une plateforme sur l'intelligence artificielle, qui n'utilise pas le terme intelligence artificielle mais qui s'appelle "selbstlernendes System". Voilà, ça dit ce que c'est. Maintenant, je suis bien conscient c'est certainement incomplet comme définition. Il y a bien plus que ça et je vous invite aussi si vous avez le temps. Et c'est gratuit. Agoria a mis en place un cours en ligne sur l'intelligence artificielle. Je ne sais pas si vous avez vu ça. »

Alexandre Verdoodt

« J'ai vu que vous aviez un cours mais je ne l'ai pas encore fait, non. »

Ferdinand Casier

« Eh bien il faut le faire parce qu'il est franchement sympa. Il est en anglais avec une intro en français par Alain Gerlache. Et il reprend des témoignages d'entreprises aussi en Belgique. Le premier chapitre, c'est justement "Qu'est ce que c'est l'IA?" Et on se base sur la définition que donne l'Union Européenne, qui est aussi assez large, je trouve. Je trouve qu'à partir du moment où on parle de systèmes auto apprenants qui vont chaque fois les systèmes perfectionner par rapport aux données récoltées précédemment, c'est à partir de ce moment là, on peut vraiment parler d'intelligence artificielle. En tout cas, c'est une des facettes qui évolue le plus en intelligence artificielle ces dernières années, mais y a encore d'autres facettes dans l'intelligence

artificielle. Mais bon, je crois que c'est celle qui est le plus visible et qui va emmener plus de plus d'avancées, je dirais, au sein des entreprises déjà aujourd'hui et puis dans les années qui viennent. Donc très simple en fait. je ne complique pas, je pourrais venir avec des définitions très complexes. Alors là, je vous invite peut être d'abord à chaque chapitre de cours en ligne. Ça donne vraiment une bonne définition complète. Je dirais de l'intelligence artificielle parce que ça va reprendre la définition de l'Europe. Parce que l'Europe, définie comme l'intelligence artificielle. »

Alexandre Verdoodt

« Juste je fais une petite interruption, je ne vous ai pas demandé si ça vous dérange si j'enregistre la discussion, c'est juste pour retranscrire quelques parties. »

Ferdinand Casier

« pas de problèmes. »

Alexandre Verdoodt

« Donc, vous vous concentrer sur la partie de machine learning, mais pas spécialement sur tout ce qui est les systèmes d'experts. »

Ferdinand Casier

« ça reste une partie importante de l'IA. Mais les systèmes experts existent depuis très longtemps. Le terme a été utilisé pour la première fois en '56 à la conférences de Dartmouth. Donc, ça fait déjà pas mal d'années que le terme est utilisé. C'est parti sur un gros malentendu. Malheureusement, l'objectif de cette conférence en 56 était de recréer l'intelligence artificielle et de l'intelligence humaine. Il ont royalement raté leur objectif. Mais le terme est resté. C'est comme ça. On est là avec un terme qui va amener plus de mythes et qui risque d'emmener plus de mythes que d'apports réels et réalistes. Surtout, puisqu'il faut rester très réaliste dans cette approche de l'intelligence artificielle et ne pas trop vite partir dans les mythes. Maintenant, je remarque bien que depuis 2 ans dans les médias, on devient bien plus réaliste par rapport à l'intelligence artificielle. Il faut dire qu'il y a 2 - 3 ans et avant quand les médias en parlaient, c'était chaque fois pour sortir des scénarios de science fiction. Depuis 2 ans les médias ont quitté cette tendance là pour chaque fois mettre l'accent sur l'apport de l'IA de façon très concrète, très réaliste au quotidien, dans les entreprises ou pour les citoyens ou pour le gouvernement. Donc ça c'est une évolution déjà très positive qu'on a eu depuis deux ans. Au niveau de l'IA, les

systèmes experts existent et sont intéressants pour plein de choses. Mais pour le commun des mortels quand on parle de l'IA, Je crois qu'on pense plus aux systèmes auto-apprenant. »

Alexandre Verdoodt

« Je pense aussi. C'est ce qui est plus récent en tout cas. Selon vous, quels sont les principaux champs d'application? »

Ferdinand Casier

« Justement, je crois que c'est très, très large. Ça peut aller dans toutes les directions. Les champs d'application, on peut les classer de deux façons, soit par secteur (vertical). On peut dire c'est pour la santé, pour le secteur manufacturier et pour tout ce qui est tech. Bon on peut vraiment partir en vertical ou on peut partir par technologie. C'est plutôt le computer vision, c'est le NLP, c'est tout ce qui est robotique. Ce sont deux axes. Je dirais un peu différent pour voir toutes les applications possibles. »

Alexandre Verdoodt

« Donc, vous pensez aussi que l'IA peut être une general purpose technology, donc une technologie qui, un peu comme l'électricité ou l'IT, s'applique partout. »

Ferdinand Casier

« Elle l'est ce n'est pas qu'elle peut l'être c'est quelle l'est, c'est tout. Toute entreprise devrait se poser la question qu'est ce que l'IA peut apporter? Je sais qu'il y en a qui le comparent à l'électricité. C'est une comparaison assez forte. Je préfère le comparer à l'arrivée d'Internet dans les années nonante. Internet est arrivé et au début beaucoup de gens se sont demandé si c'était pour eux cette technologie. Ça va passer. Et puis, on se rend compte que l'Internet a vraiment intégré notre quotidien, aussi bien au niveau des entreprises qu'au niveau individuel. On peut pousser la comparaison plus loin en comparant à l'arrivée de l'électricité. Mais ça, je crois que pour beaucoup de gens, ça reste encore un peu difficile à sentir. La comparaison avec l'arrivée d'Internet est déjà très facile à comprendre. »

Alexandre Verdoodt

« Sur base de ce que vous avez dit, on en arrive à la prochaine question, qui serait de dire, selon vous, quel serait le top 3 des industries qui peuvent bénéficier de cette technologie, de l'intelligence artificielle ? »

Ferdinand Casier

« Il y a plusieurs études. Tout dépend aussi par rapport à quoi? Est-ce qu'on va utiliser l'intelligence artificielle pour optimiser les process? Ou est-ce qu'on va utiliser l'intelligence artificielle pour améliorer l'offre que l'entreprise met sur le marché? Je crois que c'est déjà important de faire la différence entre ces deux points là. Soit on va utiliser l'IA pour améliorer les process et donc surtout dans le secteur manufacturier. Prenons Audi, par exemple. Ils ont leur usine de production et peuvent, et ils le font d'ailleurs, améliorer la chaîne de production en mettant des caméras extrêmement pointues qui savent détecter toutes les anomalies, ces anomalies detection et ainsi optimiser tout ce qui est service qualité et surtout contrôle de qualité dans la chaîne de production. Là, on va améliorer un process, mais on vend toujours des voitures. Par contre, si je regarde au niveau de l'offre, donc l'offre d'Audi, c'est mettre des voitures sur le marché, en tout cas à ce moment là, c'est toujours des voitures. On peut se dire oui, on va améliorer l'offre et donc rendre les voitures plus intelligentes c'est ce qu'ils font déjà maintenant, avec le freinage automatique, avec la voiture autonome qui le devient de plus en plus, mais on va à chaque fois utiliser l'IA pour améliorer son offre. Par contre, dans ce deuxième cas de figure, on est toujours avec comme un produit, une voiture. Il y a un troisième cas de figure où l'IA a un impact très fort sur le business model. Et pour reprendre le cas d'Audi, à ce moment là Audi ne vend plus des voitures mais vend de la mobilité. C'est une tout autre approche. Ça veut dire qu'en créant une voiture autonome, on ne va plus être propriétaire de sa voiture, mais on va plutôt les partager dans un système et utiliser des voitures "on demand". C'est un business model qui est tout à fait différent que la vente de voitures. Pour que quelqu'un puisse être propriétaire de sa voiture, il faut à chaque fois avoir ces trois aspects bien différents ou en tout cas évolutif. Bien que pas toujours évolutif, on peut faire des trois ensemble si on veut améliorer l'organisation, c'est à dire des process au sein d'une entreprise grâce à l'IA, entre autres grâce à l'IA (car il n'y pas que l'IA) et on va améliorer le produit ou le service, les rendre plus intelligents, mais ça reste toujours sur les produits. Et puis après, on a un impact sur le business model. Grâce à cela, on arrive à proposer quelque chose de tout à fait différent. L'exemple d'Audi, qui va arrêter de vendre des voitures, mais vendre de la mobilité. Je crois que ça parle assez bien et ça montre assez bien vers quoi ça évolue. C'est ce qu'on appelle la

servetization. Ce sont des modèles qu'on voit de plus en plus. On vend de moins en moins de produits, mais de plus en plus de services qui se trouvent derrière. Quand on voit bien ces trois aspects différents, on peut se dire que l'IA va jouer un rôle important. D'ailleurs il y a une étude qui démontre bien que, idéalement, il faut investir de façon équilibrée dans ces 3 parties. Ce sont des projets qui investissent de façon équilibrée dans ces trois parties qui vont bien mieux réussir. Des sociétés qui vont investir uniquement dans l'optimisation des process organisation, c'est bien, mais ce n'est pas aussi bien que l'entreprise qui fera un bon équilibre entre les trois, qui fera en partie l'optimisation des process, en partie l'amélioration de ces produits en les rendant plus intelligents et en travaillant sur son business model. C'est un équilibre entre ces trois pôles permettra aux entreprises d'avancer dans les secteurs. Pour revenir à votre question, c'est tellement large que j'ai peur de dire un secteur, mais je crois que le secteur manufacturier est un secteur connu là dedans. Les use case de la maintenance prédictive par exemple sont largement, fin, de plus en plus utilisés. Donc là, on voit très bien qu'on va optimiser tout ce qui est maintenance. On utilise aussi très fort dans ce secteur et même dans d'autres secteurs, ce qu'on appelle le asset monitoring. Asset monitoring, c'est à dire qu'un produit qui est sur le marché est rempli de capteurs et donc on pourra mieux étudier le comportement du produit qu'on aura mis sur le marché en temps réel. Quand est ce que mon produit est vraiment utilisé par le client final? De quelle façon? Quels sont les facteurs qui vont détériorer mon produit? Tout ça sont des données qui vont être captées par le produit en temps réel et qui vont permettre à l'entreprise d'abord, d'avoir déjà un meilleur contact avec le client final et ça permettra aussi d'améliorer au niveau recherche et développement, le développement de ses produits puisqu'elle aura une meilleure connaissance du comportement de son produit sur le marché dans son contexte d'utilisation. Donc ça c'est ce qu'on appelle asset monitoring. Bon, ça, c'est pas que le secteur manufacturier, mais on le voit quand même très fort dans le secteur manufacturier. Car ils ont des machines de production qui sont équipées de ce genre de capteurs, mais il y a aussi plein d'autres secteurs où c'est utilisé. Mais je crois que le secteur manufacturier est un secteur important. »

Alexandre Verdoodt

« C'est effectivement aussi celui que moi même j'ai trouvé comme étant celui qui a énormément de potentiel. Ce moi ce que j'avais fait aussi, c'est une matrice avec un axe étant la digitalisation de chaque industrie et l'autre axe étant la capacité de générer un nombre de données utilisables et donc à ce niveau là. C'est aussi le secteur manufacturing qui ressortait. »

Ferdinand Casier

« Le grand avantage du secteur manufacturier, c'est que le moment où on va équiper les machines de capteurs on est avec des données qui ne sont pas des données personnelles. Et donc je dirais que c'est un frein en moins, je dirais en moins que d'autres secteurs comme le secteur de la santé, par exemple, seraient naturellement freinés par l'aspect des données privées à caractère personnel. »

Alexandre Verdoodt

« Oui, la santé est justement un secteur qui est beaucoup plus bas en terme de digitalisation et dégénération de données. Mais pourtant, il y a énormément et un nombre croissant de recherches scientifiques qui sont publiées sur l'IA au sein de la santé. »

Ferdinand Casier

« Mais il y a beaucoup de recherches. Mais moi, je regarde surtout au niveau adoption. Alors, des recherches autant qu'on en veut. Mais ici ce qui nous intéresse, c'est qui l'adopte vraiment. Je suis curieux de voir, par exemple maintenant dans le confinement avec l'application de tracking qui va se mettre en place, probablement. On voit déjà les débats naturellement au sein de l'Europe par rapport à ça, alors que c'est utilisé en Corée par exemple, sans savoir en plein débat. Et donc il faut voir qui va l'adopter. Voilà un débat qui est très important et qui doit être suivi et pour lequel on doit trouver des solutions pour revenir à la question. Le secteur manufacturier est important. Le secteur des médias est un secteur fortement utilisé. Tout ce qui est reconnaissance d'images, naturellement pour pouvoir classifier et retrouver un bagage d'images par tout ce qui est supervised ou unsupervised learning sur des images et donc pour pouvoir retrouver très facilement des personnes, par exemple dans des vidéos. C'est vraiment utilisé pour pas mal d'aspects dans le milieu des médias. Et là, ils ont aussi beaucoup de données télécoms aussi. On va d'abord prendre en fait les secteurs où il y a beaucoup de données, donc télécom, secteur bancaire aussi, qui étudie ça énormément avec tous ces domaines là. C'est vraiment une approche verticale. »

Alexandre Verdoodt

« D'après vous, quelles sont les principales barrières pour l'implémentation de l'IA? »

Ferdinand Casier

« Oui, pendant longtemps, j'ai entendu que la principale barrière, c'était les compétences. Mais j'en suis pas convaincu de ce que j'entends et sent auprès des entreprises, moi j'en vois deux qui sont plus importantes que ça. La première, pour le principe de l'adoption, c'est de bien pouvoir démontrer les ROI d'un projet IA. Et ça, ça reste quand même une grosse barrière, c'est de pouvoir montrer et rendre beaucoup plus palpable et c'est pas évident des projets de rendre le ROI vraiment palpable, mais c'est pourtant ça qui va inciter une entreprise à l'adopter ou pas. Si le ROI est clair et net, le projet va démarrer. Or, dans un projet AI, il y a beaucoup d'essais et erreurs. On est vraiment plutôt. Un des facteurs les plus bloquants, c'est de bien pouvoir démontrer le ROI et de là aussi l'importance de mettre en avant des use cases. D'ailleurs, dans le cours en ligne qu'on donc mis en ligne au mois de novembre. Dans le cinquième chapitre, il y a déjà plus d'une trentaine de use case belges. Parce que c'est ça aussi important de montrer des use cases qui sont proches de la réalité des entreprises. Si on vient toujours avec des use cases genre Amazon aux États-Unis ou Alibaba en Chine, ou je sais quel autre use case d'ailleurs, ça ne va pas trop inspirer, je crois, nos entreprises en Belgique. Par contre, des uses cases d'entreprises locales, ça, ça va inspirer. L'entreprise aura aussi traversé ce processus de essais et erreurs d'expérimentation pour finalement arriver à quelque chose qui va vraiment avoir un grand ROI, mais qui n'aurait jamais pu être défini clairement au début du projet. Et donc, il nous faut aussi ces ambassadeurs quelque part, ces cas inspirants qui vont permettre aussi d'adopter l'IA. D'ailleurs, ça rejoint très fort la courbe d'innovation. Je ne sais pas si vous connaissez la courbe d'innovation avec les early adopters, les innovators, et tou ca. Ça vous dit quelque chose? »

Alexandre Verdoodt

« Oui oui tout à fait je vois très bien »

Ferdinand Casier

« Et bien là, on voit très bien que pour les innovators, c'est plus ou moins 15% et que ceux là sont déjà bien occupés et que maintenant, le grand objectif, c'est de plutôt bien atteindre ce qu'on appelle la majorité des 34% qui suivent dans cette courbe. Et la majorité, c'est typiquement les entreprises s'inspire des use cases et des innovateurs et des autres. Tous ça, pour moi, c'est le premier facteur bloquant. Je crois que c'est pour démontrer à l'entreprise un deuxième facteur bloquant, celle de la qualité des données dont dispose l'entreprise. Et souvent, dans un projet, on passe 80 du temps à mettre ces données en ordre. Faire en sorte que

les données soient de qualité et surtout qu'il soit pertinent. "Est ce que j'ai bien les bonnes données pour vos projets?" Et "est-ce qu'elles sont de qualité parce qu'elles sont pertinentes?" Ça, ça prend 80 - 90% du job. Et finalement, le projet IA ce n'est que la cerise sur le gâteau. Mais. Pour revenir à votre question, je crois que les freins principaux, c'est le manque de clairvoyance dans le ROI et la qualité et la pertinence des données. Et après ça, seulement après ça vient et compétences. Je crois que les compétences viennent souvent qu'en troisième position. Bon, ça reste important, mais ce qu'il faut mieux démontrer par rapport aux compétences, c'est qu'il y a aussi bien d'autres compétences en externe. Il ne faut pas tout réinventer, mais c'est toujours nécessaire de développer quelques compétences. Mais il ne faut pas avoir des idées simplistes. Dans chaque entreprise, ce n'est pas nécessaire. On a plein de sociétés en Belgique, des start-up, des même des boîtes déjà bien établies qui sont des experts en la matière qui savent soutenir des entreprises dans ce processus. Et puis après, il faudra former en interne être deux ou trois personnes ou des personnes capables de faire le lien entre ces expériences là et le business de cette entreprise. Mais on n'a absolument pas besoin de data scientists dans toutes les entreprises. Ce n'est pas nécessaire. Quand on est accompagné par un bon acteur externe qui s'occupe aussi à former en interne de la bonne façon des personnes qui pourront compléter l'équipe dans ce projet. Ben voilà, c'est ça, c'est la meilleure chose. Et comment trouver ce bon équilibre entre les deux? C'est ça qui est important pour les entreprises, c'est de trouver ce bon équilibre entre les deux. C'est tout à fait jouable. Il faut être épaulé par un bon acteur et on en a des bons en Belgique, aussi bien des Belges que des boîtes américaines. Chacun selon ses envies et sa stratégie de choisir le bon acteur. On a aussi des mélanges entre les deux. Naturellement, on a des bonnes boîtes belges qui travaillent avec des plateformes américaines, donc restant toujours Google, Azure, Microsoft et Amazon qui reste la plus grosse plateforme utilisée, mais il y a aussi moyen de trouver, en fonction des cas, d'autres formules où cela peut être pas aller dans le cloud ou en partie dans le cloud. Parce que là aussi, il faut être entouré des experts pour déterminer quelle est la partie qui devra interagir avec le cloud et quel est la partie qu'on va plus mettre dans ce qu'on appelle le edge ou même ce qu'on appelle le embedded AI, vraiment dans le produit. On appelle ça aussi distributed AI qui est de descendre l'intelligence le plus bas possible, c'est à dire le plus près possible du produit. Et parfois, c'est dans le chip aussi. Les chips qui peuvent déjà runner certaines parties de l'intelligence dans des middleware, je dirais qu'on appelle le edge alors avoir pas mal de calculs. Déjà, à ce niveau là, et seulement après, on est arrivé là où il y a vraiment différents niveaux, où la puissance de calcul peut être utilisée. Et là, il faut s'entourer d'experts pour bien déterminer qu'est ce qu'on va faire dans le cloud et qu'est ce qu'on va faire dans le edge? Au niveau du

produit, il faut vraiment être bien entouré et bon. Il y a plein de projets qui peuvent se faire uniquement dans le cloud. Seulement certains projets doivent être plus équilibrés à ce niveau là. Donc, voilà pour moi les trois les plus importants. Quand on regarde un peu les autres barrières qu'on entend au niveau éthique, par exemple chez Agoria, on s'occupe beaucoup de ça, on a tout un groupe qui travaille sur l'étiquette. On travaille également avec le high-level experts group au niveau européen et donc déjà depuis le mois de janvier de l'année passée. Ça fait plus d'un an et trois mois. On connecté l'avis de nos membres qu'on a renvoyé au niveau Européen qui a alors émis son draft des ethical guidelines qui sont maintenant tester. On regarde qu'est ce qui est utilisable? Qu'est ce qui n'est pas utilisable. Il faut savoir qu'au niveau européen, les guidelines reprennent 149 questions, 149 questions qu'une entreprise devrait se poser quand elle met en place un projet? On sait bien que 149 questions, c'est tout simplement impossible. Et donc, on essaie de réduire ça de devoir par secteur vertical. Quelles sont les questions les plus pertinentes? Y a pas mal de choses qui se font au niveau des entreprises par rapport à ça, pour faire en sorte qu'on arrive à des projets, ce qu'on ethical by design. Ça veut dire où on prend en compte des questions éthiques dès le début ou dès la conception du projet, en se posant les bonnes questions. Et on sent bien au niveau des entreprises que ça leur tient à cœur. Ça reste quand même quelque chose d'important. Bon, c'est vrai que pour une question, par exemple, de notoriété et de réputation qui pourrait être remis en cause si un algorithmes partait quelque part vers les résultats n'est pas souhaitable, on a bien vu un certain algorithme. C'était, je crois, celui de Microsoft à mon avis, qui ont l'arrêter assez rapidement parce qu'il mettait en avant un certain racisme. Toujours très prudent par rapport à ça et donc le mieux est de commencer dès le début du projet se poser les bonnes questions au niveau éthique, mais je ne crois pas que c'est un facteur très bloquant. Je crois que beaucoup d'entreprises en sont conscientes et intègrent ça comme une gestion de risque. Un autre facteur qui peut être un peu bloquant aussi. Bon un peu moins, mais c'est que parfois il y a de solutions sur le marché que parfois des boîtes ne savent plus. Les entreprises disent oui, mais à qui est-ce que je dois m'adresser? il y a tellement de solutions. Et moi, je les connais pas. Et qu'est ce que je dois faire? Je dirais que en Belgique, à nouveau, on met en place plein de trajet pour accompagner les entreprises à ce niveau là. Donc, c'est normal que une entreprise qui n'a jamais fait de l'IA. Comprenne qui fait quoi. Mais il existe des trajets pour accompagner les entreprises dans ce cas. Il faut les connaître naturellement, mais ça peut être un facteur bloquant pour certaines entreprises. Je dirais que ça, c'est le facteur 5. Donc 1, ROI, 2 data 3, c'est tout ce qui est talent, 4 ethics et 5, peut être, La complexité de l'écosystème AI. »

Alexandre Verdoodt

« Ok, moi même j'avais aussi souligné les mêmes, donc avoir des bonnes attentes. Je pense que ça fait référence à ce que vous appeler aussi le ROI, que les données sont accessibles, suffisantes, codifiable, structurée. Donc voilà, il y a vraiment un travail au niveau de la donnée qui est importante aussi. Avoir une entreprise qui soit suffisamment digital, donc avoir le hardware et le computational power, avoir des personnes compétentes. »

Ferdinand Casier

« Mais ça, je ne crois pas que c'est un problème à la base parce que de tout ça, tout dépend du projet, mais il y a beaucoup qui peut se faire dans le cloud et on utilise à ce moment-là la puissance de calcul à un moment précis. Par exemple, quand on est dans les phases d'entraînement des données, on peut utiliser à ce moment là une capacité. moi, je ne crois pas que c'est un soucis. Cette capacité de calcul n'est pas un souci puisqu'il se trouve facilement dans le cloud. »

Alexandre Verdoodt

« Oui, ça dépend vraiment du projet et de l'importance aussi du projet. Et puis, un dernier c'était aussi la culture d'entreprise qu'elle accepte en fait le changement, tout simplement. »

Ferdinand Casier

« Oui mais là, c'est ça le point. C'est d'abord arriver, à commencer avec un petit projet. Il faut prendre le low hanging fruit et donc prendre un projet qui va donner au début en tout cas de plus vite un retour sur investissement, aussi petit soit il. Et souvent, on va regarder alors plutôt quand je parlais de mes trois boules. On va regarder dans la première boule l'optimisation des process. C'est plutôt là qu'on va regarder pour trouver un premier projet. En tout cas, plutôt facile à aborder. Et la dans, par exemple, on va plutôt se focaliser typiquement sur l'aspect sales parce que c'est ce qui parle le plus, je dirais aux entreprises à niveau vente. OK, on va utiliser l'IA pour dans le marketing, pour la segmentation ou pour faire des offres plus ciblées. Ça peut être ça, mais le tout est de commencer avec des petits projets pas trop ambitieux, mais qui démontrent rapidement un ROI. Ca va permettre de déjà pendant ce petit projet qui va démontrer rapidement un ROI de construire cette capacité et cette culture en interne. Et grâce à cette première marche qui aura été franchie, le restant pourra passer la seconde marche avec un projet peut être un peu plus grand, qui va demander encore un peu plus de capacités en

interne. Mais il ne faut pas viser. Il faut commencer dans la petite profondeur avant de se lancer dans la grande. »

Alexandre Verdoodt

« La prochaine question, c'est plus quels sont les avantages et les inconvénients de l'intelligence artificielle, selon vous? Pour son utilisation au sein des entreprises. »

Ferdinand Casier

« C'est comme si vous me posez la question c'est quoi l'avantage d'Internet? C'est tellement large. C'est quoi? C'est quoi l'avantage? Moi, je crois que si on peut résumer. Et rester à un niveau un peu plus haut, c'est à dire mais rendons notre job plus humain où nous éliminons tout ce qui est répétitif, éliminons tout ce qui, tout ce qui n'épanouit finalement pas trop l'être humains et gardons l'êtres humains pour des parties plus créatives. Pour des parties où on a besoin de créativité et de soft skills. Je crois que l'avantage est là. On aura à mon avis, à terme, on devrait quand même être. Dans des jobs où on va travailler avec des outils d'intelligence artificielle, ce n'est pas que ça va remplacer, mais on va travailler avec eux nous laisser focaliser sur l'aspect créatif. Mais il faut rester vigilant dans des projets, bien que ce ne sont pas des algorithmes qui se mordent la queue. Je dirais, mais qu'on arrive toujours à injecter des données nouvelles, des données différentes qui permettent de voir d'autres choses. Qu'est-ce que ça va apporter? Qu'est ce que l'intelligence apporte? Je crois que je résume, comme je l'ai dit, je crois que je vais rester là parce qu'après on peut partir à plein de niveaux différents. Mais je crois que ça peut libérer quand même. Il y en a d'autres qui parlent de augmented AI. J'aime pas trop ce terme là. Mais quelque part, cela devrait nous permettre de nous libérer des tâches plus répétitives. Oui, moi je suis encore fort partisan de ce qu'on appelle le narrow AI. Et je ne crois pas trop au general AI. Je suppose que dans vos recherches vous avez vu la différence entre les deux? »

Alexandre Verdoodt

« Oui, tout à fait. C'est même comme ça, quelque part que moi, je définis l'intelligence artificielle ou en tout cas l'approche que je prends pour mon mémoire et je ne pars pas dans tout ce qui est strong AI. »

Ferdinand Casier

« Oui, il faut rester dans le narrow AI parce que c'est ça qu'on peut faire aujourd'hui, c'est à dire qu'on va aussi se focaliser sur des tâches bien spécifiques. Pour ma part, il y a plein de projets qui vont un peu plus loin déjà, mais actuellement c'est vraiment ça. »

Alexandre Verdoodt

« Alors ma dernière question, qu'est-ce que vous recommanderiez si quelqu'un aimerait utiliser une intelligence artificielle au sein de son business? Quels seraient les quelques recommandations que vous lui donneriez? »

Ferdinand Casier

« Pour moi, la première, ce serait d'aller suivre...je vais être très concret, pragmatique. Suivre notre cours en ligne, il est gratuit, donc on n'a rien à gagner en soi, mais vraiment, ça peut être très inspirant. Et de se dire tiens, oui, je crois que je vois plus ou moins ce que c'est et j'ai peut être quelques idées pour mon entreprise. 2, C'est après ce cours en ligne, suivre un petit workshop qu'on appelle chez nous, les discover sessions. Bon on devait démarrer ça normalement au mois de mars. Maintenant, ce sera postposée au mois de septembre. Ce sont des petits workshops d'une matinée où les premières idées qui ont émergé pendant le cours en ligne pourront être testées avec des experts IA. Voilà, c'est juste tout à fait une confrontation qui permet de dire j'ai une idée est-ce qu'elle est bonne ou pas. Où est-ce que ça peut aller? C'est une session collective avec quatre ou cinq autres sociétés que chacun peut enrichir un peu de l'idée des autres, on fait, en sorte que ce soit des sociétés qui soient en compétition. Mais ça doit commencer avec ça. Faire ce travail de reconnaissance qui peut se faire en suivant ce cours en ligne, en allant vers une session découverte. Et puis, petit à petit, comme c'est arrivé à déterminer un premier petit use case qui peut emmener à un ROI rapidement. Voilà, tout simplement, c'est rien de très compliqué. Il faut pas se dire que c'est un truc inatteignable, il ne faut pas se dire je ne suis pas un Facebook, Google donc c'est pas pour moi, même pour la petite PME. Même si on a peu de données, il y a moyen de faire des choses. C'est ce qu'on appelle le smart data ou le small data. On sera peut être plus dans machine learning et peut être plus dans tout ce qui est experts systems. Mais bon, c'est aussi de l'IA, on est bien d'accord. mais il faut commencer avec des petits projets. Il y a moyen de faire des petits projets avec aussi très peu de données, surtout quand maintenant on a des systèmes de transfer learning. je ne sais pas si ça vous dit quelque chose? »

Alexandre Verdoodt

« Transfer learning, c'est donc utiliser un modèle à une autre fin. »

Ferdinand Casier

« Oui, on va créer des données pour une boîte qui n'a peut être pas assez de données en faisant des transfer learning on peut créer des données en plus. Ça ne peut pas être un facteur bloquant. Ce que nous reprend généralement dans notre discours envers nos entreprises, on dit que voilà, il y a quatre phases dans un projet IA. On appelle ça un AI journey. C'est un trajet et la première partie, c'est tout ce qui est awareness donc conscientisation. Alors ça peut être aller à des événements qui vont sur l'IA, à des séminaires. Déjà commencer ce cours en ligne. C'est un peu se renseigner déjà. Lors de la deuxième partie, c'est ce qu'on appelle exploration. C'est la phase d'exploration. C'est aussi un peu ce cours en ligne de cours en ligne. Mais c'est aussi ce workshop d'une matinée, par exemple, qui va permettre de tester son idée avec d'autres expert AI. C'est ce qu'on appelle vraiment déjà plus concrètement l'exploration. On va essayer de déterminer quel serait le premier use case à implémenter au sein de l'entreprise. On est dans la phase d'exploration, déjà plus loin que la conscientisation. Une fois que là on a déterminé un premier use case qui semble intéressant. Là, on peut se lancer dans la troisième phase d'expérimentation. Ça peut durer assez longtemps, un peu en fonction de la maturité numérique de l'entreprise, mais c'est dans cette phase là qu'on va faire trois choses. On va faire du design thinking approfondi. Je ne sais pas si vous voyez ce que c'est, le design thinking? »

Alexandre Verdoodt

« Non ça ne me dit rien ça »

Ferdinand Casier

« Le design thinking, c'est vraiment voir quelles sont tous les impacts possibles de mon projet au sein de mon entreprise. Là, ce sont des exercices en profondeur qui peuvent durer trois, quatre jours complets, avec des personnes qui devront aussi dans l'entreprise travailler avec cet outil. c'est une phase importante. faire du design thinking approfondis pendant trois jours, 4 jours, c'est vraiment conseillé en même temps. On va déjà travailler à la gouvernance des données. C'est la deuxième partie de cette troisième phase, c'est améliorer ses données et en même temps, on va mieux définir encore le use case en décrivant le proof of concept (POC). C'est pas évident d'écrire un bon POC (Proof of concept). Ce terme là vous est familier? »

Alexandre Verdoodt

« Oui proof of concept oui »

Ferdinand Casier

« Si ces trois blocs. Design Thinking, data governance and proof of concept. On va les retravailler plein de fois de façon très agile. Ce sont vraiment des loops qui vont revenir plusieurs fois. Ce n'est pas quelque chose qui est uniquement linéaire. C'est vraiment plusieurs fois plusieurs, plusieurs itérations qui devront être traversées pour arriver finalement. A avoir un POC ultra bien défini et avoir une bonne idée des données qui seront utilisées dans ce POC. Ca c'est la phase d'expérimentation pour cette phase d'expérimentation là, il faut s'associer à un partenaire externe qui peut accompagner l'entreprise dans cette phase d'expérimentation. Il existe en Belgique à nouveau des très bons partenaires à ce niveau là, au niveau d'Agoria, ce qu'on fait, c'est que après le cours en ligne, on va organiser des workshop d'Exploration, qui donnera déjà la possibilité aux entreprises de tester certains partenariats. Si, après ce workshop, le courant passe pas avec le partenaire, alors ils pourront peut être aller vers un autre partenaire. Cette troisième phase très importante se veut vraiment mettre en place ces POC, mais de façon très agile, en faisant data gouvernance en même temps et en faisant du design thinking. C'est aussi la phase où on peut se faire aider par des pouvoirs publics, c'est à dire par des subsides d'innovation. Et en Wallonie, par exemple, c'est l'Agence du numérique qui fait ça, avec deux projets qui s'appelle Start IA et l'autre qui s'appelle Tremplin IA. Ces projets sont en cours. start IA correspond plus au design thinking de 3-4 jours. Donc, il y a des subsides pour les entreprises pour qu'elles puissent faire ça et le projet Tremplin IA et plus là pour mettre en place des POC. Et là, il y a des subsides pour aider les entreprises aussi à être dans dans ces phases. Ce troisième grosse partie d'expérimentations qui comprend ces trois blocs de façon très agile. Ensuite, on arrive à la quatrième phase. Plus classique, je dirais qui est vraiment la phase du projet où on va mettre son POC en production. Le mettre en production, c'est à dire que le POC sera vraiment implémenté au sein de l'entreprise, c'est important de garder ça en ligne de mire parce qu'on voit beaucoup de POC qui ne passent pas en produit et c'est dommage. Donc, il faut vraiment arriver et garder en ligne de mire cette quatrième phase qui est la mise en production, l'implémentation du POC. Et si tous ces quatre blocs, donc je reprends conscientisation, exploration, expérimentation et implémentation sont bien suivies, on a quand même beaucoup de chance d'avoir un beau projet. Et là Agoria est là pour soutenir les entreprises à ce niveau là, donc un conseil que je donnerai à ce niveau là c'est aller voir chez Agoria. »

Alexandre Verdoodt

« [Rire] C'est une bonne réponse. Ok, ba Je vous remercie énormément. c'est toutes les questions que j'avais pour vous. »

Ferdinand Casier

« Si vous avez encore besoin d'aide par rapport à d'autres personnes que vous souhaitez contacter moi j'en connais pas mal en Belgique, donc n'hésitez pas. »

Alexandre Verdoodt

« C'est très gentil ! »

Ferdinand Casier

« Bien ! Bonne continuation. Que tout se passe bien, c'est en tout cas un projet passionnant et un sujet passionnant qui est important pour notre économie. »

G3 Mihailo Backović, Project Manager at B12 Consulting, April 16th 2020**Mihailo Backović**

“[...] Certain processes are to extract value from data. But what people call AI in different sectors and these differences for different applications is vastly different. The problem with the AI and data science is that it's a very loosely defined field. It can be many different things that can mean many different things. But the common kind of thread, I think, is that it's always about either automating something or about having the tool that will allow you to take some raw product, which is the data, and essentially turn that into information or value and to do so.”

Alexandre Verdoodt

“Ok, so whereas some of the interviewees really scoped it more into the learning aspect, so more I would a machine learning. You would rather keep it broader and include as well as some expert system?”

Mihailo Backović

“Yes, I mean to me machine learning is a different set of tools that we use in artificial intelligence. Artificial intelligence, to me is more of a general approach on how to attack certain problems. OK. So, you see what I mean?”

Alexandre Verdoodt

“Yes, definitely! Thank you. So, then what would be the most relevant application fields for you?”

Mihailo Backović

“It's again, I don't know if I can single only one. But I would say that let's say that the fields where data science and A.I. has definitely made the kind of transformative changes are anything that has to do with computer vision. So, things like, you know, like the companies that need to read the street signs or to read the license plates and things like that. I mean, for them I have been completely transformative. Identifying, features on images of people, different kinds of objects and stuff like that. These kinds of things have been revolutionized in the last 10 years with AI. But then, you know, to a smaller degree, what you see is that most companies that have data are benefiting greatly from a smaller project where machine learning and A.I. and data science and things simply trying to extract insights. So, things like, you know, maybe you

don't want to build a product that will automate this aspect of your operations. But maybe all you need to know is certain inside that will guide your decision-making process. So, in a way, what actually what I would say is one of the most important changes and value that their life has brought is to essentially advance data driven decision making.”

Alexandre Verdoodt

“So, people say it's also like a general-purpose technology and compared often to electricity, would that be something you would think of? Or Internet more the electricity.”

Mihailo Backović

“I think it's probably a bit extrapolated because. I'm not sure, it remains to be seen. I mean, it's true that the impact of all the AI applications will be huge, but I'm not sure I would weight it compared to the invention of the Internet and the electricity especially.”

Alexandre Verdoodt

“What would be the top three of industries you think could benefit from AI?”

Mihailo Backović

“Oh, tough really. I mean, if everybody ever most of the industrial and business sectors will benefit. That's for sure. Who will benefit the most from my opinion? I would say that that companies that run essentially automated production lines, they have a lot of room now to do things like automate the defect detection on the product. Automate some decision-making processes. Doing the production that was before done by humans. There is a lot of potential there. I think actually that the applications and benefits and companies that deal with products of human behavior. I think that they're the A.I. effects have been hyped up, but the actual returns on investment have probably been lower than expected. So, things like predicting what people are going to buy and for big things want, you know, how consumers will behave and so on. I think that there are the limitations. Human behavior is very difficult. Everything that has to do with essentially machines and kind of analysing data produced by processes which are either stationary or are not very, you know, influenced by differences in human thinking and so on. Those are the areas that can probably benefit the most from AI at the moment. So, one, as I said, is a kind of industrial sector of world production, automated production, lines of sight. What else? I mean, as I've said. You know, my impression is that the greatest advances have been made in the field of kind of image recognition. So basically, any kind of industry that can

benefit or relies on this kind of technology, then they will reap enormous benefits from this kind technology. So, basically, any business that can benefit from analysing image data. For sure, they will they will gain a lot of value. But other than that, you know, everybody will. Everybody will gain something. As long as there is data there is need for science, there is insight in that data, and you can you can extract that.”

Alexandre Verdoodt

“Ok, what would be then the barriers basically for the implementation of AI? What are the main barriers you see?”

Mihailo Backović

“So, you have you had quite a few. One is essentially that people are intrinsically conservative and they tend to have, to a degree, resistance towards change the other one is that the implementing A.I. solutions is not the same as adopting other technologies, because when you start the project, there is no guarantee of return on investment. If I come to you and I tell you that you and all your company could benefit if we developed an algorithm that will read street signs or something like that. OK. And they asked me. OK. But can you guarantee that it's going to work? I cannot give that guarantee before we start. And so, there was this big barrier then that people are hesitant to sometimes invest in these technologies because they don't have a guarantee on the return. But this is a huge barrier. The third barrier of fees is the raw material that data. So, what's the what's the. In my experience, what we're finding a lot of things. And this is the case across the board. Small companies, big companies. It doesn't matter. Is that the data infrastructure and the way data is stored and managed is usually quite bad? And just to obtain the data that you need of the quality that is necessary is probably the biggest challenge in any data science budget. The last might be, in certain industries, there is a very rational and reasonable kind of backlash against the AI because he will he will essentially lead to automation of some jobs that humans are currently occupying. So, you know, there is this sense of the technology because it will lead to loss of jobs. I mean, if you automate the factory lining you have to fire a lot of people and, you know, they end up without work. Then then that's clearly a problem. So, there's probably a bit of a barrier in some relation with this regard. There are some very reasonable ethical barriers which we don't actually are not clearly established yet, but there probably will be in the near future and these very laws are actually necessary. It's sad that it's a bad thing that there's a barrier, but we are dealing with technology, which is potentially very powerful and as such can be appropriated for, you know, unfortunately, bad things, and we

need to make sure that that doesn't happen. I mean, for example, deep fakes and things like that. You know, you can manipulate people, you can manipulate the whatever public opinion. These are things that, you know, should not be probably very legal. The other thing is, during my talk, I think I mentioned this thing of kind of we're developing AI without really thinking about the consequences too much. Okay. I mean, it sounds like killer robots are going to rise tomorrow and kill us all. But things like, you know, people have claimed that they have developed an algorithm that can recognize gay people and this basically at the same period of time when some governments were announcing that there were going to state death penalty on everybody who's gay. I mean, you know, what's the worst that can happen? So, these kinds of barriers that need to be considered then established and we need to think about this, the consequences of these kind of technologies have on society and enough them on everything, on industry and so on. But the summary, yes, for implementation I think that this kind of intrinsic conservatism and the sign of hesitance to invest in something that is not as certain as traditional foreign investment and the overall unavailability of the necessary data to make these algorithms work. Those are the three biggest obstacles I know.”

Alexandre Verdoodt

“Ok thank you! So, the ones I highlighted are having the right expectations, meaning having some use cases for expected return on investment to show that it is going to be successful, having data availability, access, needs to have sufficiently data, needs to be codifiable and not biased. Then, being digital enough, so having skilled people to do it, or at least having some experts that can help with that, having computational power and hardware and then having also a change accepting environment as you mentioned also.”

Mihailo Backović

“Yes. So, I can tell you that computer infrastructure, computing, research is less and less a problem, especially with the appearance of these cloud computing services. It used to be that if you wanted to, you know, to have a lot of computing power, you have to spend a lot of money to wait for this equipment to arrive. Somebody had to install it. Then you have an entire department to manage it and stuff like that. Now, I can start the cluster of a thousand computers in 15 minutes on either way and then just run on it. So, I don't foresee that as a big problem. but maybe the way I should have framed my answer, like what you said was actually correct. It is this gap between expectations and what's possible with the data they have. A lot of times you talk to a client and they say we know that you are able to do several things that you can

recognize people, recognize brands, etc. And then you ask them how much money and labeled images do you have? Do you have them? 10, well, no, you can't do that. So, yeah, these kinds of things. What's good about implementing AI is that, at least out in the West, most companies now are aware of A.I. They're becoming aware of what it can do and so on. But the problem is this. There are over expectations. A lot of times you have to sit down, have to explain to people that they should not expect hundred percent accuracy. They should not expect the tool to completely automate something better. But in the end of the day, you usually manage to convince them that even if they automate, 50 percent of the process is still a huge saving, even if the accuracy is 95 percent. It's still a lot of save money and things like that. So at the end, the value is there. I'm now doing some business development in the Balkans, for instance, and there is a completely different story. Like people have heard of the AI, but even the way that they think about it and the approach and everything is fundamentally different from, let's say, Belgium or Germany.”

Alexandre Verdoodt

“Do you do work for a specific industry or more of them?”

Mihailo Backović

“So B12 consulting we are now not domain specific. So, we serve clients from many different sectors. So public transportation, pharmaceutical industry, medical sector, automotive, aerospace. I mean, we are really covering a very, very wide fields, though.”

Alexandre Verdoodt

“Ok, I will go to the next question then, because the coming one was more about the maturity of digitization and the digital and data generation capabilities of specific industries.”

Mihailo Backović

“Maturity of digitalization is an ill-defined question in my point, because it's not something I mean, one thing that people make is that they see digitalization as something with a clear beginning and a clear end so that you can define the maturity. I mean, this is not the case. You will never end your digitalization process. It's a perpetual thing that you just need to constantly change and change and change and change. And that's because technology is simply evolving at such a fast rate. The fact that you put everything on the clouds today, I guarantee you in 10 years will be an obsolete fact. The fact that you implemented a state-of-the-art mature algorithm

today in five years will be obsolete. The fact that you built the data infrastructure to source something, well in a certain way in 10 years, you're got to do something different. So, this is why I don't like this concept. I don't I don't like the question of like the maturity of something, I don't like it. I just it's not for me, it's not a well-defined substance. It's something that will keep going on and on and on. And that's just like we need to accept it as it is. And that's something that is a one-time investment. And you do it and then it's done. You need to continually follow the digitalization.”

Alexandre Verdoodt

“Don't you think that companies might be a bit scared if they have to put some sensitive data in the clouds?”

Mihailo Backović

“Absolutely. But there are ways to protect the data, there are encrypted data. There are ways to manage data in a safe way. I mean, maybe not all data should be on the cloud. I don't know, maybe I don't know if, for instance, medical records should be stored in the cloud or not. Some ethical discussion that we should have if it is stored in the cloud and then we are forced to make sure that the privacy is protected, and those data is protected and so on. But sure, some companies are afraid to store data in the cloud for various reasons, and that's fine. The cloud is not a necessity, cloud is a technology of convenience, cloud simply allows you to share data, better store it and back it up in a way that's more secure to access it easier and across your organization. But that doesn't mean that you cannot achieve these kinds of things without the cloud. You know, that's another thing. I mean, everybody's talking about the, you know, everything needs to live in the cloud and so on. Sure, for some companies, this makes perfect sense. But for others, I'm not sure. It depends on what they're trying to do with their business model is with what their needs are and so on. When you look at the cost of putting this and maintaining the data on the cloud versus the benefit that it actually brings you, sometimes it doesn't pay off. I mean, a trivial example, as you should probably not. If all your business can fit into a single excel sheet, you should probably not be implementing the solution to it.”

Alexandre Verdoodt

“My next question is what are the major advantages and disadvantages of using AI for the companies.”

Mihailo Backović

“So, I mean, AI makes the operations more efficient. OK. So, either through automation or through essentially gaining insight about the operational processes, how to improve them, how to make them more efficient, etcetera. So that's the main kind of purpose of AI. The risk is always that you'll become over reliant on this technology without actually understanding what it's doing. Let's say I'm making. I don't know, glass sheets or something like that. And I need to detect whether there is a defect. There is a crack or something on it during the production process. This is a process that can be successfully automated. We go to a degree which is. Comparable or probably even better than a would a human worker. However, if you're trying to do something like find key factors which are driving the production levels of some chemical, you're making. There you will almost always need a human to interpret the results before you make a conclusion. In these kinds of cases, you cannot blindly rely on AI. So, to me that the biggest risk is really this over reliance on this kind of attitude that, you know, a, I will simply take care of things. That's not the case. I mean, you cannot. You know, we have not found a replacement for a human being when it comes to critical thinking. To me, that's the biggest one.”

Alexandre Verdoodt

“Just to give you some of what I highlighted, though, there are a lot of different ways in some merger into the same. So, as general as advantage just to increase efficiency and productivity, as you mentioned, increase quality of outcomes, sometimes if it's a supportive function, decrease long term costs, which also refers actually to efficiency or digital assistance and differentiation opportunities. Then there are disadvantages: high investments, one task oriented so is good at doing one thing, implementation time, biases, black box. So, what you refer to, we don't really know always how it's working, jobs turnovers can happen as well. Lacking out of the box thinking and responsibilities shift. Here we also have an issue. What do we do with responsibility?”

Mihailo Backović

“Yes, you can. You cannot automate critical, critical decision-making systems. I mean, this is a point that, I don't see any time in any foreseeable future that, you know, banks will turn stock trading to do an AI algorithm. Some people are trying to replace radiologists with A.I. that will diagnose people from scans. I don't think that this will happen any time soon. I don't think it

should happen because you don't have accountability. You're limiting your decision on a simple scan. There're all kinds of meta data that a doctor takes into account that AI could not possibly do. There's a intuition. There is experience of the doctor that comes into play. You know, these kinds of things all matter and you're not saying that in a field like medicine saying like "oh but it's going to be okay, 98% percent of the time". Yes, but the point is these 2 percent, that's the whole point in medicine. What are you going to do about this 2 percent that diagnose wrong? I mean who is the person going to sue if they make some mistakes.”

Alexandre Verdoodt

“But does this also refer to what you mentioned before with ethics. When you implement AI, you should think also before with this will imply.”

Mihailo Backović

“You see the big problem in aid today, I would say, is not really technological. It's about the data. I mean, with technology you can do in principle very interesting things. Very successfully applied to solve an enormous number of problems. But most of these solutions. They are essentially the data is not good kind of junk in, junk out. That's what it's called. And the big problem is that your data, without an exception, will contain certain biases that you a priority might not understand. So I don't know if I showed you this example where Google published the image recognition algorithm that was classifying all different animals and objects and then somebody fed in a picture of a black person and it came out classified as a gorilla. That's the thing. I mean, there is an intrinsic bias in the algorithm, which is essentially manifesting as racism. But to understand these biases, a priori is incredibly difficult because your algorithm is very unlikely to be able to learn what's not in the data. This technology is bad at extrapolating things. And the thing is that once we started feeding into the algorithm things that weren't in the data. Who knows what can happen? And this is super difficult to quantify, super difficult to predict, will be difficult to understand. And I would say that the number one challenge right now for AI is precisely this to understand these data bias.”

Alexandre Verdoodt

“So, my next question would be how do you see AI evolving then in companies? What's your outlook?”

Mihailo Backović

“Every single company above 100 people is undergoing a digital transformation right now. Some of them think it's going to stop, but it will not. So, what you will see is that businesses will start relying more and more and more on AI technology. But what you will also see probably is that that it will not be to a degree to which they expect it to be at the moment. OK, so what they will find out is stuff like what Tesla found out the hard way. Tesla tried to automate their production line completely and then they found out that they cannot and then they ended up with a huge backlog of orders. This is going to happen to a lot of companies. Then we'll find out that AI will not magically make all their problems go away. It won't fix some problems completely. You will fix some problems 60 percent of the way. But nevertheless, compared to today, we'll see that more and more businesses will rely on A.I. as a tool. What percentage? I can't tell you. But. But I mean, I expect to like most people in my field, the market and demand for A.I. services and so on to grow.”

Alexandre Verdoodt

“OK, cool. Thank you. Then my last question would actually be what would be your main recommendations for someone willing to use an AI solution in it's business?”

Mihailo Backović

“I would recommend them to essentially apply to choose problems where AI can actually help not to blindly say we will throw AI in and it will work. It doesn't work that way. You should apply AI where AI has a profit, where we have data, where data can actually help you solve the problem. I would advise them also to manage their expectations. It's not a magical wand, it's a mathematical tool. It's very useful but it might not revolutionize the way you do business. You might also have to understand that a lot of times especially with big operations, 1% improvement in operational processes can be of huge value and experience has shown that AI is very good at delivering small corrections to processes. Altogether, I would recommend companies to explore AI as a way to improve their operations, their business. As soon as you have data you can do something with that data and AI is a tool to do it. But not to jump into it without thinking what it's for. Another thing that I have noticed is, sometimes with clients, what they do is when they start their digitalization process their emphasis is on constructing data infrastructure and collecting data and what they end up is ok we have end up spending millions of euros in this cloud solution and we have all this data now, so ok what do we do now? This process of collecting and storing data, building data infrastructure should go step in

step with the operational problems that your client told you about and not just build data for the sake of storing data, it should always be connected to some problem that you're solving. That's something that I see a lot and I think it's kind of a problem in this digitalization tragedy."

Alexandre Verdoodt

"So if I could rephrase that, you say that companies are willing to use AI and they are thinking about how can we use AI instead of first defining a goal of how it could help and then see how they could use the technology?"

Mihailo Backović

"Yes, what they should do is they should say we would like to solve these problems, then they should say, can we solve these problems using data. The answer is yes then they could see what kind of data do we need, where can we store it and in parallel what do we want to do with it? What is the technological solution? You should start with a particular set of problems. In the end of the day, what you're trying to do is to optimize your operational processes and so it should start from there and not ok we should link everything together and build this infrastructure, but then ok what if you spend all this time and then you realize your data is not very good and then you store 100 of gigabytes of data that is bad or that you cannot use to solve the problems that you want to solve. The connection between the actual operational problem and what you're doing needs to be much more explicit."

Alexandre Verdoodt

"Well thank you so much, these were actually all my questions. Thank you so much for your help and your insight. I love this subject and every time I discuss it, I learn something more."

Mihailo Backović

"Yes of course! If you need anything else let me know. Good luck!"

Alexandre Verdoodt

"Thank you, have a nice day!"

G4 Thibault Helleputte, CEO and founder of DNaalytics, April 16th 2020

Alexandre Verdoodt

« [...] Ma première question pour vous est que, il y a énormément de définitions différentes de ce que c'est que l'IA, donc je voulais avoir votre avis sur ce qu'est l'IA. »

Thibault Helleputte

« En fait, l'intelligence artificielle c'est très mal défini. Les frontières de l'IA sont mal définies. Il y a plein de définitions effectivement. Pour moi, fin ce n'est pas moi qui aie inventé cette définition là, mais pour moi c'est un ensemble de techniques qui permettent à une machine de réaliser des tâches dont pour les réaliser on qualifierait qu'il faudrait une certaine intelligence. Traditionnellement, dans le champ de l'intelligence artificielle, il y a des choses de nature très différente qui ne sont pas non plus unifiées d'un point de vue scientifique. Beaucoup de choses très différentes. Ce qui compte finalement pour que ce soit qualifié d'intelligence artificielle, c'est que ça réalise une tâche qui, a priori, n'est pas triviale. »

Alexandre Verdoodt

« OK Très bien, donc, j'ai eu plusieurs personnes qui allaient directement sur l'aspect de learning, mais learning ne fait pas spécialement directement référence à l'intelligence artificielle. Les systèmes d'experts en font aussi partie. »

Thibault Helleputte

« On entend beaucoup de buzzwords, régulièrement pour le moment on entend beaucoup data science, intelligence artificielle, machine learning et deep learning et en fait pour moi, chacun est un sous ensemble de la précédente c'est-à-dire, Data science, c'est toute la science des données, mais ça inclut aussi la gestion traditionnelle de bases de données, le data management, data engineering et tout ça, donc la mise en place des systèmes et la plomberie des données, donc mettre les bonnes données au bon droit dans le bon format. Cela comprend aussi l'intelligence artificielle et au sein de l'intelligence artificielle, vous avez une sous catégorie qui est le fait de permettre à des machines d'apprendre par elles mêmes. Sur base d'exemples. Ça c'est le machine learning et à l'intérieur du machine learning. vous avez encore un sous ensemble de techniques de machine learning qui sont du deep learning. C'est une technique bien particulière de machine learning. Voilà comment moi je vois le tout. Si vous voulez je peux vous envoyer un petit schéma. »

Alexandre Verdoodt

« Ok, c'est gentil. Oui tout à fait, mais c'est aussi comme ça que j'ai défini. J'ai aussi commencé par scoper en disant que les IA est un ensemble et qu'il ya des sous ensembles. Donc voilà. Ma deuxième question pour vous est quels sont les principaux champs d'application pour l'IA? »

Thibault Helleputte

« En général, là où il faut prendre des décisions, très souvent. C'est quand même des outils d'aide à la décision ou d'automatisation de tâches. Voilà, je ne crois pas qu'on puisse être plus spécifique. En général, c'est des outils d'aide à la décision quand même. »

Alexandre Verdoodt

« Ok, parce que souvent, on parle aussi d'intelligence artificielle comme une general purpose technologie, une technologie qui s'applique un peu dans différents scénarios et on le compare à l'internet. Qu'est-ce que vous en pensez? Est-ce que vous pensez aussi que c'est General Purpose Technology l'IA? »

Thibault Helleputte

« Que ce n'est pas restreint à un domaine économique particulier, par exemple c'est ça que vous voulez dire? »

Alexandre Verdoodt

« Oui »

Thibault Helleputte

« Oui, oui c'est sûr que c'est ouvert à plusieurs domaines économiques. »

Alexandre Verdoodt

« OK, mais du coup j'en vient à la prochaine question : quel serait le top 3 des industries qui pourraient bénéficier de cette technologie, d'après vous? »

Thibault Helleputte

« C'est difficile à dire. Moi, je trouve qu'il y a plutôt un scénario type d'utilisation plutôt qu'une industrie type d'utilisation parce qu'après, je pourrais vous dire le secteur des soins de santé qui

est celui dans lequel je travaille. Mais si vous regardez le type d'application qu'on fait. Parfois, c'est pour de la recherche et développement. Parfois, c'est pour l'optimisation de la production et parfois, cela peut même être à des fins de marketing, de politique, de gestion de fonds de santé. Donc c'est très différent. Pour moi ce qu'il faut, c'est qu'il ait une tâche répétitive qui doit être faite, mais qui est pas simple et il faut qu'il y ait des données et il faut que le résultat soit actionnable, c'est à dire que si vous, pour reprendre le cas de la santé, si vous arriver à mettre au point une solution d'intelligence artificielle qui fait du diagnostic de patients Alzheimer. Ça n'a aucun intérêt industriellement parlant, parce que vous ne savez rien, Ce n'est pas actionnable. Il n'y a pas de traitement. vous ne savez rien y faire. L'information est peut-être vraie, mais n'est pas utile. Pour moi, il faut que ce soit des choses répétitives et qu'il faille faire souvent, que beaucoup de données soient disponibles et que le résultat soit actionnable. Alors là, c'est un bon scénario d'application de techniques d'intelligence artificielle. »

Alexandre Verdoodt

« OK, merci. Quelles sont, d'après vous, les principales barrières pour l'implémentation de l'intelligence artificielle au sein des entreprises? »

Thibault Helleputte

« Il pourrait y en avoir plusieurs et vraiment de nature très différente. Parfois, c'est le manque ou la désorganisation des données. Dans l'industrie pharma, mais je pense que ça doit être la même chose dans d'autres types d'industries contrôlées ou réglementées, l'agro alimentaire par exemple, ou même l'automobile à mon avis, la plupart des grosses entreprises qui génèrent beaucoup de données elles le font pas comme un moteur de croissance, mais simplement comme une contrainte réglementaire, c'est à dire, voilà vous devez faire des moteurs qui ont telle ou telle émission de CO₂, par exemple pour reprendre un cas connu ou vous produisez des médicaments et vous devez respecter certaines normes de qualité. Toutes ces données sont stockées, mais simplement dans le but de pouvoir répondre à un audit externe, par exemple, ou un contrôle externe ou pouvoir gérer une crise ponctuelle. Si on constate qu'un lot est rapportée sur le marché comme étant défectueux, etc. Ce n'est pas utilisé à l'heure actuelle vraiment pour faire une boucle de rétroaction vers la recherche et développement ou vers l'optimisation de la production et les données ne sont pas structurées comme ça parce qu'elles n'ont pas été pensés à cette fin là. Donc, ça je pense que c'est un des gros freins, c'est de voir les données comme une opportunité de croissance et pas simplement comme quelque chose qu'on stocke pour du backup ou pour des audits possibles ou simplement parce qu'il faut, parce qu'il y a une

réglementation comme quoi il faut stocker des données. Donc ça c'est un premier point, un premier frein. Un autre, c'est qu'il faut quand même. En tout cas, dans l'installation, le design, la conception et l'installation de ce système n'est pas gratuit, c'est un certain coût et donc il faut que ça se fasse, en tout cas dans un premier temps, sur des produits ou services à haute valeur ajoutée. Parfois, il vaut mieux mettre trois personnes faiblement qualifiées pour faire de l'inspection de flacons à la sortie d'une chaîne de production parce qu'à court terme, c'est moins cher que de mettre au point un système qui va repérer des défauts dans les produits en analyse d'images. Donc, là il faut qu'il y ait une grande valeur ajoutée aux produits ou services qui seraient visés par de l'innovation de l'intelligence artificielle. Un autre frein aussi, c'est la méconnaissance dans le chef des top managers d'entreprises qui auraient des données, qui auraient les moyens d'y avoir recours, parfois simplement ils ne perçoivent pas ce que ça peut leur apporter et en quoi ça consiste. C'est trop vague et donc ça, c'est un problème de culture. C'est pour ça c'est très bien quand on voit des initiatives d'initiation à l'intelligence artificielle pour des non-scientifiques et donc pour des managers. Je ne sais pas si vous avez vu le programme AI Black Belt, par exemple? »

Alexandre Verdoodt

« Oui tout à fait je vois ce dont vous parlez. »

Thibault Helleputte

« Très bien. Il y en a d'autres, mais donc c'est des choses qui s'adressent à des managers non scientifiques pour finalement expliquer en quoi cela consiste, mais sans rentrer dans les aspects trop techniques. Ça je pense que c'est des bonnes initiatives parce que ça vise, justement, à faire prendre conscience à des décideurs quelles sont leurs options et en quoi ça peut, ou pas être approprié pour eux, pour leur business. Voilà quoi d'autres? La perception du public parfois, qui peut parfois soulever des problèmes éthiques. Là aussi, il y a plein d'exemples possibles. En santé, évidemment, c'est assez évident qu'on se pose des questions éthiques par rapport à l'application de l'intelligence artificielle, par exemple pour du diagnostique, mais il y a un autre exemple récent qui était intéressant. L'agence pôle emploi en Flandre a mis au point un système basé sur le deep learning pour faire du matchmaking entre des demandeurs d'emploi et des offres d'emploi, avec des critères de métriques à optimiser, le taux d'emploi, la satisfaction de l'employeur après embauche, etc. Et au bout d'un certain temps, assez rapidement la solution, c'est mis à ne recommander que des candidats masculins. Ce qui n'est évidemment pas le résultat attendu. En fait, c'est simplement un dérives du système qui a appris que voilà

probablement que les femmes ont parfois des enfants ou demandent des temps partiels pour s'occuper de leur famille. Le système a appris que c'était plus efficace selon les métriques qu'on lui avait donné optimiser de ne recommander que des hommes pour les emplois. Mais après même dans ce cas-là, le problème n'est pas un problème de la technologie. Le problème, c'est de bien spécifier finalement ce qu'on qualifie comme étant un bon état des choses à obtenir, à optimiser. »

Alexandre Verdoodt

« Oui, tout à fait, mais donc moi aussi ce que j'ai trouvé dans la littérature, c'était de dire aussi qu'il faut avoir d'un des bonnes attentes, ne pas sur- ou sous-estimer la technologie, avoir des données qui sont accessibles, en avoir suffisamment qui soient codifiables, non biaisées, structurées et d'autres critères, ensuite à être digital, donc avoir des personnes qui s'y connaissent ou alors engager des experts. Ensuite, avoir aussi une culture d'entreprise qui accepte le changement et je pense que ça fait aussi référence à ce que vous mentionnez sur les chefs d'entreprise qui n'ont pas toujours la connaissance de la technologie. Ensuite, j'ai peut-être une question plus par rapport à la santé. Quelle est la maturité de la digitalisation, je dirais, dans cette industrie ? »

Thibault Helleputte

« Je pense que si on compare maintenant par rapport à 5 ou 10 ans, il y a une vraie prise de conscience de ce que cette technique peut amener parfois à l'extrême inverse. C'est-à-dire, qu'il y a 5 ou 10 ans, ça n'intéressait pas les gens, ou marginalement. Maintenant, certains pensent que ça va résoudre tous leurs problèmes, que ce serait un peu comme une formule magique qui va résoudre tous les problèmes de l'entreprise. Ce qui n'est pas le cas non plus, évidemment. Mais voilà, on voit quand même que dans les différents cas, que ce soit pour optimiser le côté opérationnel de l'entreprise, mais aussi pour la conception de nouveaux produits de santé, pour l'optimisation des chaînes de production ou pour la conception de chemins de traitement adapté à chaque patient. On voit quand même des choses qui évoluent fortement ces derniers temps oui. »

Alexandre Verdoodt

« Et en termes de génération de données, dans le sens de la quantité de données et leur qualité, sont l'utilisabilité en général ? »

Thibault Helleputte

« Là c'est un peu un cas particulier, mais qui est récurrent. C'est qu'en santé, pratiquement toujours, on va se retrouver avec des données qui pour chaque objet qu'on veut mesurer, les données vont être énormes en termes de nombre de variables qu'on va être capable de mesurer sur un objet. Si c'est un patient dans une étude clinique, on va mesurer possiblement tout son ADN, c'est déjà 3 milliards d'information. Plus aussi ces symptômes, son historique médical, donc on va se retrouver avec des millions, des milliards de variables. Mais, le contexte fait que dans la recherche clinique, on va pouvoir recruter dans une étude clinique, par exemple, entre quelques dizaines et quelques milliers de patients au grand maximum, mais souvent, ce sera plutôt quelques centaines. Et donc, on se retrouve, en fait pas avec du big data, mais avec ce que moi j'appelle du fat data, c'est à dire qu'on a énormément de colonnes dans la base de données, mais pas beaucoup de lignes. Ce qui est l'inverse de ce que Google ou Amazon font quand ils essayent de faire du ciblage publicitaire, parce qu'ils ont des millions ou des milliards d'utilisateurs et ils ne mesurent pas tellement de choses que ça sur chaque personne. Et donc ça c'est vrai pour la recherche clinique en santé, mais c'est aussi vrai pour le manufacturing par exemple. Si on regarde pour produire un vaccin ou une thérapie ou une thérapie à base de grosses molécules de protéines. Tout au long de la chaîne, on peut aussi collecter des dizaines de milliers ou des millions de paramètres de caractérisation des matières premières. La durée de chaque opération qui a fait chaque opération, sur quel matériel, avec quel réactif, etc. Il y a des capteurs dans les bioréacteurs qui vont mesurer en continu la température, la pression, la disponibilité d'oxygène, le poids des réactifs qu'on est en train d'introduire progressivement, etc. Mais même de très grandes entreprises pharmaceutiques comme celles qu'on a en Belgique, qui sont pourtant parmi les plus grandes du monde y a Janssen, GSK, UCB, même sur leurs produits qui font des blockbusters, ils vont faire quelques dizaines ou quelques centaines de lots par an seulement et donc, on se retrouve de nouveau dans une situation où on a des bases de données qui sont très, très large en termes de nombre de variables mesurées, mais avec un nombre d'observations qui est assez faible. Et ça, c'est une difficulté supplémentaire parce que si on doit adresser ça avec des statistiques traditionnelles, on ouvre un bouquin de statistiques, on lit "à chaque variable que vous ajoutez, vous devriez ajouter 10 exemples observés en plus, si vous voulez faire des déductions statistiques fiables". Et bon, voilà il y a des techniques d'intelligence artificielle, de machine learning qui aident à contrebalancer ça, mais ce n'est pas magique non plus et donc ça c'est une caractéristique de ce secteur. »

Alexandre Verdoodt

« Ok, d'accord, merci beaucoup, je ne savais pas du tout que ce secteur est confronté au fat data comme vous appelez ça. Ma prochaine question, ce serait qu'est-ce que vous pensez sont les avantages et désavantages de l'utilisation de l'AI au sein des entreprises ? »

Thibault Helleputte

« C'est difficile de répondre comme ça de façon générale. Ça dépend. Oui, ça dépend. »

Alexandre Verdoodt

« Ok, ce que moi j'avais souligné comme avantages, évidemment, comme vous dites, ça dépend, il y en a énormément. Les principaux que j'ai trouvé sont que ça permet d'être plus efficace et parfois d'avoir une meilleure qualité de résultats, décroître les coûts à long terme, avoir une assistance plutôt digitale et cela permet de différencier aussi parfois certains produits. En termes de désavantages: C'est un gros investissement, focus sur une seule tâche, donc l'intelligence artificielle est fort pour faire une chose, mais ne va pas faire ce qu'on appelle super-intelligent AI, donc voilà; le temps d'implémentation; Les biais; que ce soit une black box, donc on ne sait pas toujours comment ça pris une décision; Parfois aussi, ça manque de out of the box thinking, de créativité; Bon, ça dépend son application; Puis shift de responsabilité aussi. Si maintenant l'intelligence artificielle doit faire certaines choses qui est responsable pour les résultats et ce genre de cas d'éthique. Enfin, aussi une compétition qui peut venir plus disruptive et donc on doit regarder à droite à gauche ce qui peut arriver en termes de compétition. C'est un peu un ensemble de ce que moi j'avais sélectionné. »

Thibault Helleputte

« C'est une question intéressante, en fait à mon avis, la réponse est simple. C'est-à-dire que la responsabilité de la décision est prise par un système AI. C'est la responsabilité de celui qui l'a conçu, celui ou ceux qui l'ont conçu. Qu'est-ce qu'on a donné comme métrique à optimiser à ces systèmes? Qu'est ce qu'on lui a donné comme objectif? Et qu'est ce qu'on lui donne comme information? Pour moi, c'est assez clair. Si on se fait déplacer dans des voitures complètement automatisées, je ne vois pas pourquoi le passager serait responsable de la conduite de la voiture? Ce serait Tesla qui sera responsable ou Audi, parce que c'est eux qui ont mis en place le système et ça devrait être la même chose dans le domaine médical. Soit on donne une recommandation aux médecins avec l'explication de pourquoi on fait cette recommandation et on laisse le médecin juge, de façon informée, de savoir s'il la suit ou pas. Alors là, la responsabilité peut

rester chez le médecin. Si on dit à partir de maintenant, les appendicites seront opérés par un robot qui embarque le système d'intelligence artificielle pour analyser les images qu'on lui donne et le médecin n'a plus rien à faire, alors il n'a pas de raison que ce soit le médecin qui reste responsable. Ce sera le système. Donc, ma réponse est assez claire. Une autre question que vous avez soulignée aussi, c'est que parfois, ce sont des systèmes Black Box. Parfois, ça peut être problématique. En même temps, on ne se rend pas compte que tout le monde utilise un smartphone, mais qui sait comment ça fonctionne ? Est-ce que ça pose problème ? Pas forcément. Et même dans le domaine médical, c'est la même chose. On dit voilà, ce serait insupportable qu'on ait des solutions de diagnostic qui ne justifient pas leur décision. Mais je vous mets au défi de demander à un médecin de vous expliquer comment le Dafalgan fonctionne. Pourtant, tout le monde en prescrit. En fait, le mécanisme d'action ne sont pas vraiment connus. Simplement, on a fait suffisamment de tests pour montrer que c'était sûr et efficace. Et en fait, c'est ce qu'il faudrait faire aussi avec des systèmes, s'ils sont plus black box, c'est de les tester dans des études cliniques au même titre qu'on test un médicament. Voilà, on a testé sur des milliers de patients et on montre que c'est sûr et efficace. C'est ça qu'il faudrait faire, parce que y a certains systèmes, si on les force à être transparent et à expliquer comment ils prennent leur décision. En fait, on limite aussi leur puissance. Par exemple, on peut faire le parallèle avec des systèmes qui ont été mis en place pour battre Garry Kasparov aux échecs à la fin des années nonante, et le système AlphaGo, qui a gagné contre le champion du jeu de go. Dans le cadre du jeu d'échecs. C'est en fait une technique d'intelligence artificielle qui se base sur des arbres de recherche, donc le système peut projeter tous les mouvements possibles que son adversaire va faire et que lui va faire et simplement, comme on lui a expliqué les règles du jeu d'échecs. Il peut calculer plus de coups à l'avance que son adversaire et il trouve la bonne solution, celle qui l'amène vers un gain plus probable. Et ça, on peut expliquer à chaque étape pourquoi il prend cette décision-là. C'est parce que s'il fait ça, son adversaire n'a le choix que de faire ceci ou cela, etc. Si on applique ce genre de raisonnement compréhensible au jeu de go, il n'y a aucun système qui arrive à battre l'humain, alors que le système qui a réussi à battre l'humain au jeu de go. C'est un système dont on comprend pas du tout pourquoi il fait tel ou tel mouvement. La seule chose qu'on sait, c'est que maintenant, il n'y a plus aucun humain qui peut battre ce système au jeu de go. Ça fonctionne très bien, mais on ne comprend pas comment la prise de décision se fait et techniquement ce n'est pas du tout le même genre d'approche. Ici, c'est une approche de deep learning. Donc, le système a atteint des millions de paramètres qui sont optimisés pour gagner à ce jeu-là. Ça marche, mais on ne comprend pas. Alors, est-ce que

parce qu'on ne comprend pas, ce pas une bonne solution ? Bien, si elle fonctionne. Donc voilà, il faut voir le pour et le contre. »

Alexandre Verdoodt

« Oui, tout à fait. C'est mon point de vue. C'est vrai que dans la littérature. J'ai tendance à voir qu'une black box, c'est un désavantage, mais, c'est vrai qu'au final vous avez un bon point de vue aussi qui est intéressant aussi. Donc, j'avais une prochaine question : Quelles seraient vos recommandations pour quelqu'un qui devrait utiliser l'intelligence artificielle dans son business ? Pour son implémentation et pour son utilisation ? »

Thibault Helleputte

« De très bien spécifier ces besoins, donc de faire abstraction une seconde du défi technique et de dire OK, j'imagine justement cette black box. A la limite, on la rendra moins black box après. Avant de démarrer le projet, j'imagine que ce système fonctionne parfaitement. Qu'est ce qu'il doit pouvoir me rendre comme service? Et comment je vais juger, moi, si c'est un bon système ou un mauvais système? Qu'est ce que j'attends de lui comme comportement idéal? C'est seulement si on explicite à fond ces attentes là qu'on peut alors développer un système pertinent. On a ça très souvent dans des études, justement sur du diagnostic ou du pronostic médical où on nous demande de développer des outils d'aide à la décision. Mais, en fait, la métrique d'évaluation du système in fine n'est pas claire pour les médecins. Qu'est ce qu'ils attendent? Je prends le cas du dépistage du cancer colorectal. Première discussion avec les médecins, ils vont nous dire: "Oui, il faudrait absolument optimiser le taux de classification correcte d'un système automatisé de diagnostic. OK, c'est facile. Je classe tout le monde sans exception comme étant un cas négatif, donc pas atteints de cancer colorectal. C'est super. Juste en faisant ça, je vais avoir une accuracy de 99,99%, parce qu'il y a un cas positif sur 140.000 personnes, ou 40 000 je ne sais plus. En tout cas, les cas positifs sont rares et donc la métrique initialement pressentie, comme celle qu'on souhaite, n'est pas la bonne. Alors vous commencez à entrer dans plus de considérations. En fait, ce que vous voulez, c'est un certain niveau de sensibilité, de spécificité, mais est-ce que vous pouvez me donner des chiffres. Qu'est-ce que vous jugerez bien? Et à ce moment-là on n'a toujours pas commencé à taper une ligne de code ou à entraîner le moindre modèle. C'est juste la définition des attentes. Et souvent, ça c'est compliqué. Voilà donc, je dirais que c'est ça le principal point. C'est qu'il faut pouvoir vraiment formuler ce qu'on jugerait être un bon système, si on arrivait à développer avant de commencer à le développer et puis de voir si ce système va effectivement pouvoir être utile, c'est à dire

qu'on va pouvoir l'utiliser souvent et que les recommandations qu'il va fournir sont actionnables. Sur base de l'analyse de la situation par le système, est-ce que je peux prendre des décisions qui ont de la valeur? Et alors, le dernier point évidemment, c'est de s'assurer qu'on a déjà des données structurées ou qu'on peut les obtenir. »

Alexandre Verdoodt

« Ok, parfait, un tout grand merci. C'était toutes mes questions. Donc un tout grand merci pour votre aide et pour votre insights. Mais, en tout cas c'est un sujet très intéressant et j'en apprend tous les jours plus aussi qu'en interview des intervenants, donc c'est vraiment super intéressant. »

**G5 Professor Luigi Proserpio, Professor of Digital Business Transformation at Università
L. Bocconi, May 4th 2020**

CONFIDENTIAL

G6 Sebastien Deletaille, Co-founder and CEO at Rosa, April 11th 2020

1. What does AI mean for you?
 - a. People vulgarize the term and amalgam it with other concepts as big data, etc. Hence, it became a buzzword.
 - b. It is a continuous evolution of what already exist, so a natural evolution.
 - c. People have in mind machine learning nowadays when talking about AI
2. What are the application fields for AI?
 - a. /
3. What about AI in healthcare?
 - a. The healthcare is a sector in which there is an issue with the potential usage of data. In this sector, data is secured, not structured, difficult to access, not standardized, etc. So, there is an issue with the data and its accessibility and this does not help for the application of a technology as AI.
4. What are the main barriers for AI implementation and adoption?
 - a. It is important to understand that AI is a method and people tend to use it as a goal in itself. However, the nuance is that it should be a tool to achieve a goal.
 - b. Data quality is as well a barrier, as mentioned previously
 - c. Having sufficient hardware to utilize this resource and having people that have the skills to work the data and this technology. However, a manager should be careful, as some statisticians think to be able to use this technology, but there is a need for people with specific knowledge and competences for this technology and that can use the proper tools. So, people knowledgeable about machine and deep learning specifically.
 - d. It is important to have supporting leaders who know and understand what the added value of the technology is, because he experienced often that CEO don't understand the added value of new technologies and find it therefore pointless to adopt this technology.
5. How do you see the maturity of the digitalization of the healthcare industry?

- a. Healthcare is a catastrophe. The top three of the worst digitalized industries in Belgium would be healthcare, government and education.
6. What about the capacity to generate data in the healthcare industry?
 - a. It is a sector that generates substantial amounts of data, but the main issue is the quality of the data generated. In the way this data is collected, standardized, codified, etc. so that we could leverage from this data.
7. What are the advantages of AI?
 - a. It can be used in different fields
 - b. It is a digital assistant, so it makes recommendations and these recommendations can be followed or not, so there is still a liberty of choice.
 - c. It is a continuity of what exists in statistics, so it becomes an advantage if you're an early adopter and then it becomes generalized and standardized across industries.
8. What are the disadvantages of AI?
 - a. AI can present some biases
 - b. If you leave the technology in the hands of incompetent people, you will have unusable outputs.
9. What is the evolution of AI in companies according to you? Which role will it play?
 - a. It will be more generalized and standardized. Hence, it will be used across a variety of processes as other technologies did as well.
10. What would be your recommendations?
 - a. Someone willing to implement AI must make sure to have a clear goal in mind and have correct expectations.
 - b. One of the main steps is to work on the database in order to have well-structured data.
 - c. Also, make sure to have hardware and competent people to work with the data.

G7 Email from Thierry Geerts, Country Manager of Google Belgium, May 4th 2020

Thierry Geerts 

Re: Mémoire sur l'IA au sein des entreprises et ses impacts managériaux

To: Mr. Alexandre Laurent M Verdoodt

Voici qq's réponses comme promis:

1) L'IA connaît beaucoup de désaccord quant à ce qu'elle inclût et n'inclût pas, donc comment définiriez-vous brièvement l'IA?

Il faut surtout démystifier l'IA (en fait, c'est du 'machine learning')

Bref, la possibilité de faire fonctionner l'informatique (et donc aussi les objets connectés) de façon plus intuitive et "intelligente".

Le meilleur exemple est : la possibilité de passer du 'clavier' pour interagir avec l'ordinateur, vers l'utilisation de la voix (avec toutes ses imprécisions) ou des gestes

Ne plus devoir apprendre par coeur des instructions pour l'ordinateur ('format C/'), mais l'ordinateur qui comprend ce qu'on veut dire et faire en fonction du contexte.

2) Quel serait votre top 3 des industries qui peuvent bénéficier de l'IA?

1/ Santé

2/ Vie de tous les jours ("ambient computing") - du smartphone au frigo

3/ Mobilité (véhicules autonomes, ...)

3) Quelles sont les principales barrières pour l'implémentation de l'IA au sein des entreprises d'après vous?

1/ compréhensions stratégiques des possibilités

2/ attraction de talent

3/ impact sur le business modèle

4) Quels sont les principaux avantages et inconvénients de l'utilisation de l'IA au sein des entreprises?

1/ possibilité de réinventer son business modèle (plus sustainable)

2/ meilleur service client

3/ meilleure rentabilité

5) Comment voyez-vous l'IA évoluer au sein des entreprises? Quel rôle jouera-t-elle?

Un fameux bouleversement, plus important que l'arrivée de l'informatique dans les années 1960-1980

Il faut 'réinventer' son entreprise en fonction de l'IA (voir 'Digitalis, comment réinventer notre monde')

6) Quelles seraient vos recommandations pour quelqu'un qui voudrait implémenter une solution d'IA au sein de son entreprise?

1/ bien comprendre de quoi il s'agit, quelles en sont les possibilités

2/ attirer du talent

3/ démystifier, expliquer, rassurer si nécessaire pour éviter la résistance au changement

4/ expérimenter, mais sur des éléments avec un impact important sur le business (pas sur un détail)

En espérant que cela vous aide,

Thierry

Appendix H: Tables of interviews' summaries per question

H1 AI consultants, Ferdinand Casier & Mihailo Backović

Table 1 – AI Consultants	Ferdinand Casier , AI digital group leader Agoria	Mihailo Backović , B12 consultant in AI
<i>Date of interview</i>	<i>April 15th 2020</i>	<i>April 16th 2020</i>
How would you define AI?	- Auto-learning systems - Definition from the EU	- Very loosely defined field - Common thread: it's always about either automating something or about having the tool that will allow you to take some raw product, data, and essentially turn that into information or value.
What are the most relevant application fields?	- Wide and varied - Can be analyzed through 2 axes: Per industry and per application (NLP, computer vision) - AI is clearly a General-Purpose Technology (//Internet)	- “Where AI has made the most transformative changes are anything that has to do with computer vision” - You don't always want to automate, but sometimes you want to advance data-driven decision making - Purpose is wide and varied, but not sure how to weight it against the internet
What would be the top 3 industries for the application of AI?	- Is constantly evolving - There are 3 points of view: process automation, enhancing product itself and disrupting business model (going towards “servitization”)	- Every industry and business will benefit from it - Especially companies that run automated production lines for defect detection, automate decision-making processes

	- Healthcare is limited due to sensitivity of personal data, so low AI adoption - Importance for manufacturing and 1. Manufacturing 2. Media 3. Telecommunication	- Any industry that will benefit from analysing image data
What are the main barriers to implement AI in companies?	- Often hear skills, but is not convinced - Importance is to show potential ROI through use cases that are comparable to company - Quality of data (80% of the time they spend on a project is to check if the data is structured, of quality and relevant) - Ethics is important to take into account but is not a blocking factor. They are currently working with the EU, to define a set of ethical questions for companies to ask themselves when using AI - Perceived complexity of the AI ecosystem - Hardware and computational power are NOT a barrier as cloud can be used - Change management and culture of company, this is	- People are intrinsically conservative and have resistance to change - No guarantee of ROI as a developer cannot give the guarantee that the project will work which makes companies hesitant - Data is an issue for small as well as for big companies. Data is often badly stored and managed. "To obtain the data that you need of the quality that is necessary is probably the biggest challenge in any data science or AI project" - Backlash in companies were people fear it will take over jobs - Ethical barriers, these barriers are not yet clearly established and are necessary - Computing infrastructure is less and less an issue due to cloud;

	why companies should start with the low hanging fruit	In 10 years, the cloud is going to be obsolete - Strongly approved, my saying “there is a gap between expectations and what is realistically feasible with the data they have” - Awareness about AI is at different stages in different countries
What is the maturity of your industry?		- It’s an ongoing process, so you can’t define it as if it would have a beginning and an end, because technology is evolving so fast
How are the data generation capabilities of your industry? In terms of quantity, quality and usability?		
What are the main advantages of using AI in companies?	- “Make our work more human” by deleting repetitive tasks, working with AI and do more creative aspects	- Make operations more efficient - Outcome can be of better quality than when done by humans
And the main disadvantages?		- Become over reliant on the technology without understanding what’s it is doing: There is still a need of humans to take conclusions as AI cannot replace critical thinking

		- Biases: “junk in, junk out”, data without exception contains bias which is difficult to understand a priori and this technology is bad at extrapolating things - “once we start feeding into the algorithm things that weren’t in the data... who knows what can happen”
How would you see AI evolve in companies?		- Every company above 100 employees is undergoing a digital transformation right now - They will find out that AI won’t make their issues magically go away - But even if you can fix part of it, it’s already a huge deal
What would be your main recommendations for someone willing to implement and use AI in its business?	- 4 main phases : 1. Awareness: Get informed about AI 2. Exploration: Try out your idea by confronting it with experts 3. Experimentation: Make a design thinking to understand the potential impacts of the project on the company; Handle governance of data; Make a proof of concept to show that the project is feasible 4. Implementation	1. Choose the right problems where AI applies - Companies should manage their expectations it’s not a magical wand - Even though it is possible to automate less than expected it can already be important - Explore AI as a way to improve operations Understand how it works, do not use it blindly Clearly define a problem to solve, then define what is needed to solve it rather than starting the digitalization

		process without a clear goal of where you're heading: 1) we want to solve this issue, 2) can we solve it through data?, 3) we need to collect data (rather than starting with point 3)
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H2 CEOs & founders of digital start-ups, Sebastien Deletaille & Thibault Helleputte

<i>Table 2 – Founders of digital start-ups</i>	Sebastien Deletaille, CEO & founder of Rosa	Thibault Helleputte, CEO and founder of DNAalytics
<i>Date of interview</i>	<i>April 11th 2020</i>	<i>April 16th 2020</i>
How would you define AI?	- People vulgarize the term AI and amalgam it with big data and other concepts. - It's a constant evolution of what already exists	- AI and its boundaries are not well-defined - AI is a set of techniques that allow a machine to achieve tasks that would require intelligence when done by humans - Applied to non-trivial tasks
What are the most relevant application fields?		- Generally speaking, where decisions need to be taken - Tools for automation and to help in the decision-making - AI can be applied to different economic domains
What would be the top 3 industries for the application of AI?	- It is not his field of expertise. So, I explained the literature research, mentioning the seemingly growing potential of AI in healthcare, to which he answered that healthcare is an unconventional sector as data are secured, unstructured, not standardized, hard to access as not always shared which doesn't help for this technology	- There is more a typical scenario of application rather than a typical industry of application - E.g. in healthcare it is used for R&D, product optimisation, marketing, politics, healthcare funds management, etc. - It requires repetitive tasks that needs to be done,

		needs data and that the result is actionable (e.g. detecting Alzheimer has no value as nothing can be done)
What are the main barriers to implement AI in companies?	- AI is a method to arrive at a goal and not a goal in itself. - Data as a barrier was given in prior question - Make sure that companies have enough hardware to use this resource - Need of skilled people to work with this technology and with data. Careful, as there are statisticians who believe can use this technology, but AI, in terms of machine learning lately, uses new tools, so we need people knowledgeable about machine learning more specifically. - Leaders must support the project and understand the added value of AI, because often CEOs don't understand the added value of new technologies and therefore don't put efforts to adopt and implement it.	- Lack of data or its unstructured characteristic - Today, companies produce data for regulation to answer to audit criteria, but not leverage value out of it, so data is not structured in order to leverage value as it wasn't always the purpose. - AI systems are expensive, so need to be done on projects with high added value. - Cultural issue: Lack of understanding of executives that have data, but don't know what the technology is and how it works. - Ethics can be an issue in adopting AI solutions
What is the maturity of your industry?	- Healthcare is in the top 3 of the worst industries in terms of digitalization in Belgium. This top 3 would be education, healthcare and government	- Compared to 5 to 10 years there is an increase in consciousness about the importance of getting more digital, even to the

		extreme inverse, now some believe it is a magical formula that will resolve everything. - This evolve rapidly nowadays.
How are the data generation capabilities of your industry? In terms of quantity, quality and usability?	- Healthcare is an industry that generates a lot of data, but the issue is the quality of this data, how it is encoded, standardized, structured, etc. - There is quantity, but need of quality and accessibility	- Healthcare knows “fat data”: a lot of different variables, but low amount of observations, which makes it statistically difficult for inference
What are the main advantages of using AI in companies?	- Technology that can be used everywhere, but that is above all a digital assistance, it makes recommendations and these can be followed or not (free to choose) - It's the continuity of what exists in statistics. It becomes an advantage when used as early adopters, then it is generalized and standardized	
And the main disadvantages?	- Bias, to use AI, you need competent people, otherwise people might do things badly and then you get useless results; “garbage in, garbage out”	- The responsibility of AI goes to the one who conceived it. What kind of metrics were given to optimise the system? What's the objective? What was given as information?

		- About black box, there is a trade-off between transparency and efficiency - The black box aspect is not especially an issue in itself if it works well. E.g. like medicines if by testing it is proven to work well, then it's fine (e.g. Ask a doctor how an aspirin works, e.g.2 AlphaGo is unbeatable at Go, but we don't know how it takes decisions)
How would you see AI evolve in companies?	- With time, it will get standardized and used among several processes as a lot of other technologies did.	
What would be your main recommendations for someone willing to implement and use AI in its business?	- If someone wants to use AI, he needs to have a good idea of what he wants to obtain from AI to achieve his goals and have good expectations. - First you need to work on your data, you need good data and have a phased approach. First, one must be sure to have a good database, standardized. Second, we're sure to be equipped with hardware and competent people to handle data before working with this technology.	- To define well what is the objective of using this technology and how to judge if the AI solution is performing well or not; What do I expect from it as ideal behaviour? - The recommendations provided by the AI should be actionable

H3 Country Managers of digital corporates, Didier Ongena & Thierry Geerts

<i>Table 3 – CEOs of corporates</i>	Didier ongena, CEO of Microsoft Belux	Thierry Geerts, CEO of Google Belgium
<i>Date of interview</i>	<i>April 21st 2020</i>	<i>May 4th 2020</i>
How would you define AI?		- Machine learning - The ability to make computer science, and hence also IoT, work more intuitively and in a more “intelligent” way - Example: possibility to go from a keyboard to voice, gestures, etc. to communicate with a computer; No need of special instructions for the computer (format C/), but it understands based on context
What are the most relevant application fields?		
What would be the top 3 industries for the application of AI?		1. Health 2. Everyday life (from smartphone to fridge) 3. Mobility (automotive, ...)
What are the main barriers to implement AI in companies?	- Data, need of a data lake that is clean and comes from different processes (varied and holistic) - Therefore, they lead their clients through the maturity cycle: 1) Data warehouse, 2) big data, 3) AI	- Clear strategic comprehension of what can be achieved with artificial intelligence - The attraction of talents - Impact on the business model

	- Scalability: need of use cases to show the potential - Data governance and ethics data needs to be not biased, and ethics need to be taken into consideration	
What is the maturity of your industry?		
How are the data generation capabilities of your industry? In terms of quantity, quality and usability?		
What are the main advantages of using AI in companies?	- We will achieve things we weren't able before to achieve. - Make decisions that rely much more on data thanks to AI and IoT, smart cities, etc. - AI will make us able to model things we weren't able to model before. - Makes people able to have activities that bring more added value by automating repetitive work	- Possibility to reinvent your business model (and make it more sustainable) - Better client services - Better profitability
And the main disadvantages?	- There are a lot of questions ethics-wise, but I don't know	

	if there are really inconveniences	
How would you see AI evolve in companies? Which role will it play?	- 3 categories of AI 1) ML, DL as done by data scientists 2) Pre-packed AI for defined usage (NLP, NLG, image recognition) 3) Pre-packed AI in tools (e.g. blurred background in MS Teams) - 3th category will be used more and more - In companies, I believe that the companies will use the most the second category. Because of the combination of 2 trends: AI and low code, no code - “People will be able to create their own working environment” - “The real expansion of AI will be when people will use AI themselves as they use other tools (PowerPoint, Excel, etc.) [...] Because in the end, it’s the final user who knows best about his own job, processes and is in contact with the final clients. So, the more we can bring this technology to them, the	- A serious upset, more important than the arrival of computer science in the 1960’s – 1980’s. - Companies must reinvent their way of working in light of artificial intelligence

	more we can have impact. This is our long-term bet.” - An intelligent company is a company that has data, create intelligence and new processes of intelligence and can do it real-time - So, next to global use of AI for a company, focus on individual usage of AI in companies for employees’ daily work	
What would be your main recommendations for someone willing to implement and use AI in its business?	- Issue is not technical, but cultural - Include the users early in the change process as they need to be aware that this change is not going to change them, but how they work in a more effective way. You need to build trust. They have to trust the technology and the change (trust in the transformation and in the ethics). They have to “reinvent their own work”. - Accept and encourage for change	- Have a good understanding of what we’re talking about and what are its capabilities - Attract talents - Demystify, explain and reassure to avoid resistance to change - Experiment, but on elements with an important impact on the business (not on a detail)

H4 Professor in digital business transformation

Table 4 – Professor in digital business transformation	Professor Luigi Proserpio , <i>Professor of digital business transformation at Università L. Bocconi</i>
<i>Date of interview</i>	<i>May 4th 2020</i>
How would you define AI?	- Capability to turn non-formalised knowledge into something that can be processed, so AI makes semi-structured knowledge (e.g. pictures, videos, etc. processable by a lot of interesting analysis techniques - Given the vast amount of data, AI is a processor able to give meaning to build arrays of data
What are the most relevant application fields?	- Making non-structured knowledge into something structured - Being able to process automatically some data - (abstract terms) An interesting field that hasn't emerged yet is the ability to track and understand people's behaviours and turn it into predictable patterns. - (Concrete terms) You choose, it can be camera for surveillance, understanding what's happening in the environment, etc. - Yes, AI is a general-purpose technology, and, in the future, it might have an impact similar to the Internet.

	- It is about the possibility to process or pre-process data through AI and try to see whether some patterns emerge or not. - The solution to the data abundance around us is to use AI
What would be the top 3 industries for the application of AI?	1. Controlling people's behaviour. However, he's not saying that this should be legal or encouraged. It could be invasive or not, depending on how you implement it. 2. Education. You can understand how students are learning and adapt the material to their needs and progression. 3. Production, maintenance and logistics to make processes more efficient. Especially as it can be combined with IoT.
What are the main barriers to implement AI in companies?	- A first barrier is organizational, need to make sure to have the right competencies. - If you hire data analysts or scientists you have to be careful of where you put them in your organizations, because it happens a lot in companies, he knows that they get it wrong. To him data analysts and scientists are IT guys, they are not business guys as they don't know the business nature of the data. So, there is a need to design an

	“interface” between IT guys and business guys, by hiring people able to breach between the data proficiency and the business provisions (“AI breach guys”). - Level of investments, these needs to be high as he has seen a lot of companies trying out their first AI projects with small projects which don’t bring the companies anywhere and these projects are bottom up driven. - The magnitude of the project, when a project is bottom-up, you don’t have any chance to make this project bigger. Therefore, it is better to adopt a top down approach. - Once you start with small projects you will never go big because it’s too steep, because then you often delegate it to low level which will just show top management that you’re doing something. It’s so small that it does not integrate existing datasets, so these projects do not impact the whole organization. - You don’t have to push AI, you have to push a set of projects that will give you a competitive advantage. Because when there is a new technology, companies want to try it out, but who cares about the technology. It is a commodity. The
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	point is whether you are able to do something with this technology for business or not. (“So, the company starts to say, well, I mean, that there is a new technology around. Why don't we try it? OK. But this is not the way to go. I mean, technology is sort of a commodity, right? Who cares about technology? The point is whether you are able to do something with this technology for business or not.”) - Companies that want to try AI for the sake of trying AI fail using the technology.
What is the maturity of your industry?	
How are the data generation capabilities of your industry? In terms of quantity, quality and usability?	
What are the main advantages of using AI in companies?	- You can transform non structured data into structured data. - Advantages really depends on the business needs. - To him there are no intrinsic advantages. - When the author gave his findings, he didn't agree with the approach, because these advantages are very

	broad, you can say it for every technology. It's broad and depends on the usage of the machine. - The only two advantages are to turn non-structured knowledge into structured knowledge and to analyse connections between formalized pieces of knowledge. All the other advantages really depends on the case
And the main disadvantages?	- There are no real disadvantages. The only real one is the fact that you have to structure your dataset. Companies datasets are not clean enough to use them for AI yet. - We don't have the competences required in a company to put up something decent. - If you start small, you will never be able to scale up. - Yes, it's a black box, you don't know if using AI is better than tossing a coin. - Level of reliability is quite a problem, because you don't have a lot of cases to determine an efficiency threshold - He's not sure whether investments are always that big, it depends on the approach of implementation (top down or down up), for sure it is more expensive top-down but has more

	chances to be a successful implementation.
How would you see AI evolve in companies? Which role will it play?	- Automation is the best candidate - “we’re still in a sort of fascination phase. So, we’re fascinated by the endless possibilities of AI. Soon we will discover that AI is good at doing a specific task” - Supporting people in decisions - “AI is a different way to compute equations [...] to in the end understand relationships” - So, the best algorithms will win in terms of efficiency, etc. - Some algorithms will be embedded in machines or in information systems. - “if you’re able to locate problems that cannot be solved by traditional algorithms, then AI is a good candidate to help you.”
What would be your main recommendations for someone willing to implement and use AI in its business?	- Need of an enthusiast person willing to explore for possible AI solutions in business terms. - Then, go for small independent consultants, not big companies, that can code and understand what AI is and can give you the state-of-the-art project. - Then, I would put up some methodologies to find overlaps between business ideas and AI possibilities.

	- Then, generate a set of cases and rank them and develop an adoption map with sponsors with a decent amount of money - Then, develop a sort of strategic perspective to show the company that we're not experimenting, but have a consistent plan to incorporate AI in the company. - Have a clear business need and use AI as a technology to make it possible. Don't use AI for the pure sake of using AI. "I saw hundreds, not just tens, of projects abandoned, just because they were experiments of AI adoption. So that's dangerous. The companies that started small never scaled up and they abandoned AI as a tool because they didn't see any advantage, they see only costs, they didn't see anything good." - Two approaches to adopt AI: First, you have antennas and detect new technologies, so you can answer before business problems were raised. Second, you have business problems and you can use AI to better answer those.
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