Faculty of Business Economics

Master of Management

Master's thesis

integrating AI into the business

Anas Talhaoui

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :

Prof. dr. Koenraad VANHOOF

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Integrating Artificial Intelligence into the business

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Master of Management: Business Process Management

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Disclaimer

"*This master thesis was written during the COVID-19 crisis in 2020. This global health crisis might have had an impact on the (writing) process, the research activities and the research results that are at the basis of this thesis."*

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Before starting it, I would like to thank the personnel who were involved and helped me to complete this research project successfully. I would like to express my deep gratitude to my Educational Supervisor Mr. Koen Vanhoof, for guiding me in the right direction and for giving me the feedback that was really useful. Secondly, I would like to thank all my colleagues for being a support in the research and for advising me in certain difficult situations. In addition, special thanks to the University of Hasselt.

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I. Introduction

Nowadays, many people still don't have a clear understanding of Artificial Intelligence and still associating it with science fiction dystopias, but this conception is fading as artificial intelligence develops and becomes more common in daily life. However, AI is not a new concept. The modern domain of artificial intelligence saw light in 1956, but it took many years of work and research to make considerable progress to reach a developed artificial intelligence system and a technological reality.

In business, artificial intelligence has a broad range of uses. From the ordinary to the most complex, artificial intelligence is already used in different business process in multiple industries. As artificial intelligence technologies increase, they are becoming primordial for companies that want to obtain a competitive edge (Adam C. Uzialko, 2019).

The dominance of Artificial intelligence (AI) continues to spread into business and non-business environments among different criticisms owing to the fear that integrating AI technologies could limit the role of people within the organization and business operations (Hislop, D., Coombs, C., Taneva, S., & Barnard, S. 2017).

Moreover, the fast evolution of artificial intelligence technologies is pushing companies to rethink their business models. This is raising the integration of AI in the business processes but the consequences of this adoption are underexplored and needs more focus (Brynjolfsson, E, 2017).

The ambition to integrate AI in the business is high at most companies. Three quarters of executive think that AI could help their companies to move into new businesses. Approximately 85% believe that a competitive advantage is could be obtained from integrating AI. However, only few companies have incorporated Artificial Intelligence in processes. Large companies with more than 100,000 employees are the most likely to obtain an AI strategy in place (Sam Ransbotham, David Kiron, 2017).

This thesis provides the findings of the entire research carried out during last few months. It is divided into eight main chapters and several sub chapters. First chapter of this thesis includes brief introduction. The second chapter includes problem definition, research questions, and research methodology. The third chapter includes the literature review, which includes description of artificial intelligence and its components. The fourth chapter explains the strategies of implementing AI. The fifth chapter focuses on AI maturity levels within the business.

The sixth chapter of our thesis includes a practical part in the form of two case studies to assess the results of AI Maturity in the business. Moreover, the last two chapters of this thesis provide recommendations and conclusion based upon the entire research.

II. Research question & methodology

Integrating Artificial intelligence into the business is not an easy process. Many artificial intelligence solution in the market claim that competitive advantage can be obtained from implementing artificial intelligence by making the processes easier and faster and considerably reduce costs, errors and delivery times.

Thus, in this research we will shed light on the strategies of integrating AI in the business, and investigate the impact of this technological solution on companies' processes.

To do so, we will try to answer the following main question:

How to integrate Artificial Intelligence into the business?

In order to address our main question, we will try to answer the following

Sub-questions:

How does Artificial intelligence work?

What kind of artificial intelligence solutions are available on the market?

What is the optimal implementation strategy?

How to assess the AI maturity level of the company?

Different research methods can be utilized to answer our research sub-questions. For instance, qualitative research, quantitative research. For this thesis qualitative research methods will be used. Which includes interviews with experts, Desk research and literature study. However, this Research Methodology may be subjected to some changes depending on the circumstances.

III. Literature study:

1. Basic Concepts of Artificial Intelligence

The excitement around AI in recent years may make us think that we are facing a whole new technology. Yet the term artificial intelligence actually dates back to the 1950s. In 1956, John McCarthy first introduced the term during a summer seminar at the University of Dartmouth (United States National Research Council, 1999). In order to obtain grants to create a research group of ten scientists, McCarthy submitted a research proposal. He and the co-authors of the proposal explain the purpose of the research as follows: "to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy et al., 2006: 2). Thus, for two months the group would be dedicated to studying the potential of computers to learn and reproduce human intelligence processes. Many areas of study were derived from this, such as the use of language by the machine, its self-improvement, and its ability to solve problems previously reserved for humans (McCarthy et al., 2006). This variety of topics has become known as artificial intelligence in order to bring them all together and create a new independent field of study (Ezratty, 2017: 11). Nevertheless, the working group convened by John McCarthy did not achieve the expected results. Moreover, even today, no one has managed to achieve convincing results (Ezratty, 2017)! But this initiative will have had the effect of bringing more researchers and funding to artificial intelligence (United States National Research Council, 1999: 201). This was followed by some thirty years of innovation, including the appearance of the first chatbots, the establishment of the foundations of neural networks and expert systems, and the LISP programming language developed by John McCarthy and used for several decades (De Ganay and Gillot, 2017).

We will come back to neural networks and expert systems later on. According to the chronology presented by Claude De Ganay and Dominique Gillot, around 1973 the world of artificial intelligence experienced its first slowdown. Until 1980 there were far fewer innovations, mainly due to a reduction in funding. This period is called the first "winter" of AI. A second winter took place between 1987 and 1993. In between the two, there was a significant expansion of expert systems.

Expert systems were at that time the best known and most widely used type of artificial intelligence program. These systems are algorithms where the engineer codes rules into them, creating rule engines. These are for example in the form of "If... and... then...” which is often found in mathematics. In less than a decade, many companies have implemented them in their processes, but there was quickly a lack of computing power, which did not allow computers to run expert programs (De Ganay and Gillot, 2017: 38-42). Today we are in the last known phase, a phase where AI is booming (France et al., 2017). Mainly characterized by the advent of Machine Learning (ML) and neural networks characteristic of Deep Learning (DL).

Artificial Intelligence (AI) has existed over many years; nonetheless, where it can be used may involve conversation. With the technological advancements, right now there is a gigantic interest of extensive human learning in computational angles – fit for changing its own behavioral belief. Being able to choose, learn and decide dependent on the past occasions and follow up on it steadily. Artificial intelligence alludes to complex technologies and tools that can be consolidated in different manners to detect, recognize and perform with the capacity to learn from previous experiences and adapt with time. (De Ganay and Gillot, 2017).

In general, intelligence is considered as the ability to understand the objective reality and to find solutions to problems applying knowledge. Intelligence of an individual comprises of wide-going abilities, for example, capacity to see and comprehend objective things, the objective reality and oneself; ability to pick up understanding and obtain information through learning; capacity to understand information and apply knowledge and experience for problem solving and critical thinking; capacities of affiliation, discovery, thinking, decision making and invention; ability of phonetic reflection and speculation; abilities of revelation, development, imagination and advancement; ability to proper, quickly and sensibly adapt to the unpredictable situations; and capacity for forecasts of and bits of knowledge into the development and changes of things (Arel, I., Rose, D., & Coop, R. (2009).)

Artificial Intelligence is a modern concept – actually, it just over the past recent years that its theoretical and technological foundation has progressed. For the record, AI's authentic beginning is considered the "Dartmouth gathering" in 1956. Also, somewhat, the Turing test originates before even that and offered considerations on the most proficient method to perceive an "intelligent machine". In any case, the journey of AI has been very tempestuous. Thinking back, there has been generous advancement in practically all areas which were fundamentally viewed as a feature of AI. (Bengio, Y., Courville, A., & Vincent, P. (2013)).

Let us take a gander at a portion of the invigorating advancements in the field of AI. Knowledge based frameworks were maybe the best functional part of AI. There have been a few applications conveyed at organizations throughout the world. Many apparatuses, usually marked expert system shells, were created. These systems accomplished enough loftiness to turn into an independent discipline, to the degree of having separate the academic world courses. Alongside the practical triumphs, the field likewise added to development of AI itself. These areas that contributed to the academic growth are for example; rule based knowledge, reasoning with uncertainty, automatic knowledge acquisition, machine learning, ect.

Natural language processing is another field of progress, intelligent translation programs are now accessible for use in some specific contexts with a small human intervention in terms of guidance. (Bengio, Y., Courville, A., & Vincent, P. (2013).
For example, Systran, is a program that provides on-time language solutions in terms of, eDiscovery, collaboration, content management, e-commerce, ect. The field has likewise added to the improvement of the region of information retrieval. The World Wide Web is one of the significant purposes behind the enthusiasm for this area, with the accessible data far surpassing restrictions of human creative mind. Another area is speech processing that has generated some valuable tools. Nowadays, translating your voice text into a machine processable text word document has been possible. These do require some preparation and are not yet compelling in adjusting to various speakers. Such instruments are helpful for individuals who don't have great composing pace, and all the more critically those with handicaps to interface with PCs. (Hislop, D., Coombs, C., Taneva, S., & Barnard, S. (2017) robotics is likewise on a high energy way.

There is a significant Japanese activity, which expects to create humanoid robots to help the older in their normal work. This sort of activity is right now boosting mechanical technology work in Japan and the USA. Honda and Sony of Japan have fabricated robots that can walk, wave, do some simple move steps, and so on. Automated pets have arrived at business status with a few organizations promoting advanced pet canines. What we have noted down are only a piece of the achievements of AI. (Davenport, T. H., & Harris, J. G. (2007).

From the unobtrusive beginning about 50 years prior, AI has developed in numerous measurements. While a portion of the AI experts are seeking after the first objective of accomplishing machine insight, greater part of AI look into today is centered around taking care of complex viable issues. While AI has been a piece of our regular daily existences for quite a while, this innovation is at an emphasis point, primarily because of late key advances in profound learning applications. Deep learning uses systems which are fit for self-learning from information that is unstructured or unlabelled. The neural systems that support deep learning abilities are getting increasingly proficient and precise because of two noteworthy ongoing technological headways: a phenomenal access to large information and an expansion in computing power. The viability of neural systems connects to the measure of information accessible. (Hislop, D., Coombs, C., Taneva, S., & Barnard, S. (2017))

Machine learning (ML) is considered as one of the most interesting areas of AI, it automatically makes sense of data by developing computational ways. It gives the fact that this technology is a dynamic process by learning from experiences and examples. It can get get smarter over time like a human being. Differentiating a human, a machine isn't slanted to lack of sleep, interruptions, data another zone of progress has been characteristic language handling. Sensible interpretation frameworks are accessible today for use in limited setting, for the most part viable if a little human direction can be given to the framework. (Partanen, J., Jajaee, S. M., & Cavén, O. (2017).)

With applications in pretty much every industry, AI vows to fundamentally change existing plans of action while simultaneously making new ones. In finance sector, for instance, there are clear advantages from improved precision and speed in fraud detection AI-speed systems, estimated to be a $3B showcase the last quarter of 2020. What makes AI more advanced than human intelligence are its continuous improvement capabilities, adaptability and scalability. Such characteristics are foreseen to distinctively lower price, increase productivity and minimize human error. (Hislop, D., Coombs, C., Taneva, S., & Barnard, S. (2017))

Despite the fact that at a promising stage, AI technology is relied upon to present another standard for competitive advantage, economic growth and corporate productivity. AI uses the gigantic amount of collected data and minimize the limited usage if the usual instruments are applied. Posing the correct inquiries and associating the information such that fits to the inquiries may yield pertinent data. An entire assortment of techniques is currently within reach to do this, for instance, statistical methods, neural networks, data warehouse, machine learning. AI has made a considerable commitment to information technology which is commercially utilized since a couple of years and is habitually called data mining. (Rajbanshi, A., Bhimrajka, S., & Raina, C. K. (2017))

2. Three levels of intelligence

It is commonly considered in the literature that there are three levels of AI:

- Artificial Narrow Intelligence (ANI),
- Artificial General Intelligence (AGI),
- Artificial Super intelligence (ASI).

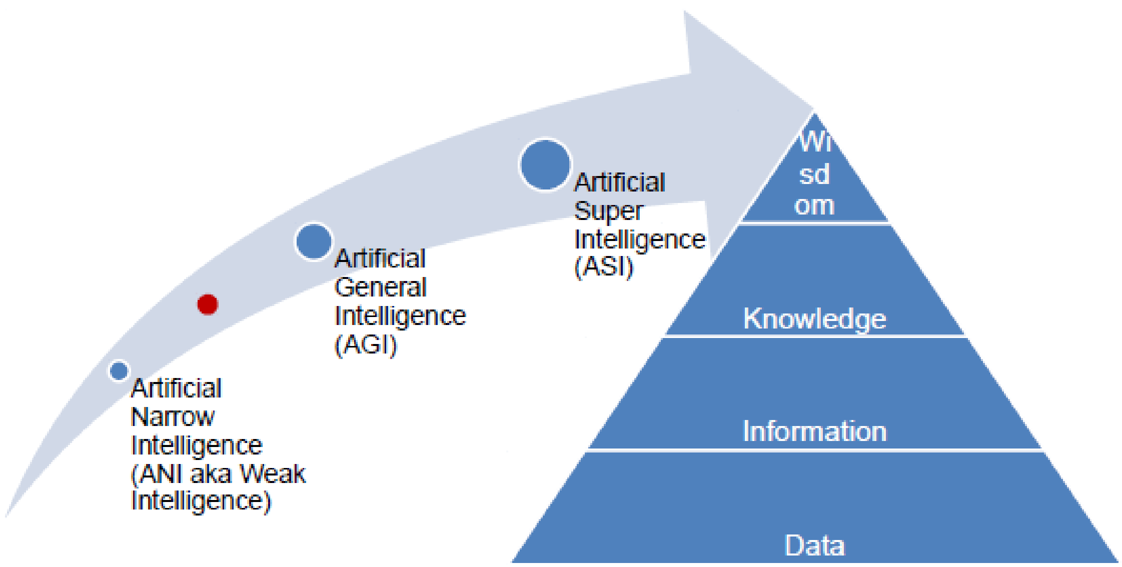

Figure 1: Artificial Intelligence levels

Will AI replace humans in their work? How to make Humans and robots cohabit? Is there a moral for artificial intelligence? Could robots become dangerous for humans? What is the place of a robot compared to a human in our society? If a robot is endowed with consciousness and emotions, is it slavery to use them? The list of questions that are currently being asked in newspapers, conferences, research centers, etc. is a long one. But all these questions are about a highly developed AI, an AI rising to the level of human intelligence. It is this level, the AGI, which is currently the goal of many researchers, companies and governments. Also called strong intelligence, it refers to a computer as intelligent as a human, meaning that it would be able to do everything as well as we do (Urban, 2015b). This, of course, leads to much debate about what human intelligence is and what characterizes it. Professor Linda Gottfredson (1997) proposes this definition: "a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience" Gottfredson (1997). Once AI has reached this level, some scientists based on the concept of "singularity" predict that it rapidly evolves to the level of superintelligence, ASI, far exceeding that of humans (Kurzweil, 2005), but always at the level of an intelligence where emotional intelligence is not considered, for example.

There are many questions about the impact of the IGA and the ASI, as no one can know how this evolution will take place. AI remains a machine created and coded by humans, that's why it is essential to think today about how we develop this new technology (Sullins, 2006). The bases that we give it now, will be the bases that can potentially create an AGI and then an ASI. These reflections are very present in literature and the media, as they are considered an important vector in the definition of our future. They are also complex because they are based on prognoses and hypotheses, as no one knows for certain what an IGA2 will look like. But we must not forget that questions are already being asked for our near future, because artificial intelligence is happening now: it is already present in our society, but in the form of an ANI, called weak artificial intelligence. The ANI already surpasses Man in some areas, such as chess, the game of go, reading comprehension... but unlike an AGI, it surpasses us only in one specific task. For example the Google DeepMind AlphaGo software, beat the world champions in the game of go in 2016 (DeepMind). This is considered a technological breakthrough, because unlike the game of chess where there is a finite number of possibilities that the computer can simulate before playing, the game is very complex. The game has 10,170 possibilities of board configurations, more than the number of atoms known in the universe! A second version, AlphaGo Zero, recently managed to beat the first one. The difference is that this time, instead of learning by playing games against humans, AlphaGo Zero had only the rules of the game written into its system and only played against itself. So he had no human data to train with. But ask the same software if there's a cat in a picture, it just won't be able to do it.

He is expert only in a very specific task and therefore still falls far short of human capabilities (Bostrom and Yudkowsky, 2014). The ANI is an interesting tool for Big Data analysis and will require a great deal of adaptation, especially in the workplace. But it will not result in a complete paradigm shift (Duranton et al., 2018; Frey and Osborne, 2013). It is closer to a new industrial revolution, but instead of creating a new physical force through machines, this time a cognitive force is created, allowing us to go beyond the limits of humans (Brynjolfsson and McAfee, 2014). The promises are many and it is therefore interesting to note that as early as the 1960s, many leading scientists were already making very ambitious predictions for the coming decades:

”Within our lifetime machines may surpass us in general intelligence”
(Marvin Minsky, 1961)
“Machines will be capable within twenty years of doing any work a man can do”
(Herbert Simon, 1965)
“In from three to eight years we will have a machine with the general intelligence of an average human being”
(Marvin Minsky, 1970)
“Within a decade, AIs will be replacing scientists and other thinking professions”
(John Hall, 2011)

As we now know, these predictions have not yet happened. Nevertheless, the effects of the ANI are real and are already influencing facets of our society. In the remainder of this thesis, we will try to discuss in the coming parts the subject of AI and its application in the business.

3. Data Pyramid

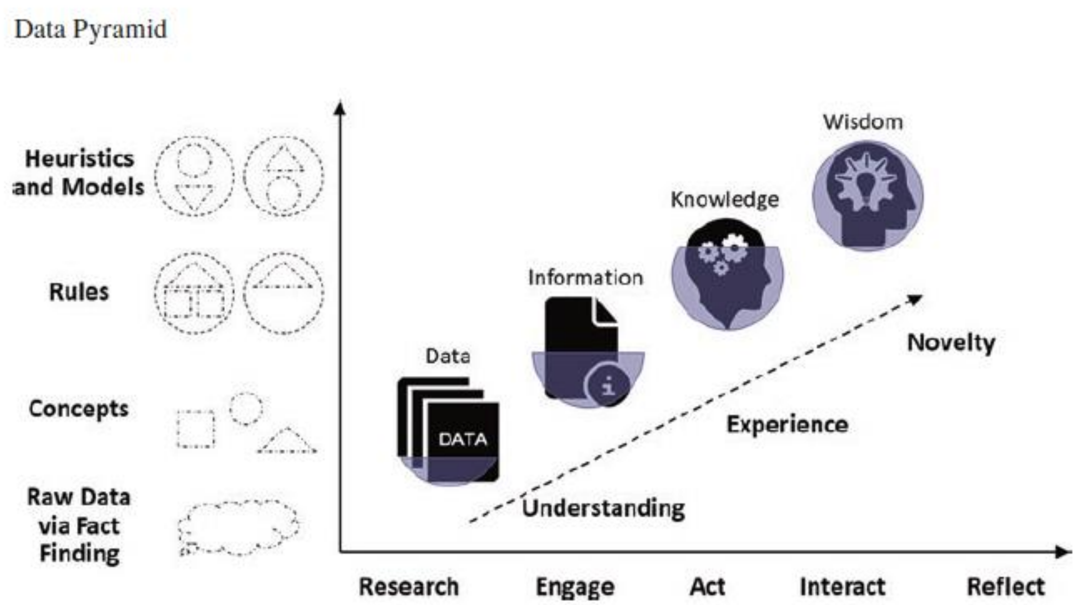

Figure 2: Convergence from Data and Intelligence (source: Forrester research inc.)

AI systems use AI techniques that allow them to acquire expertise in problem-solving in a given field. Systems that use one or more expert expertise to solve problems in a particular field are called information-based or expert systems. Traditional information systems are based on data and/or information.

Figures 2 and 3 reflect the data pyramid for the relationship between data, information, knowledge and intelligence. Figure 2 illustrates the integration of data with information by implementing activities such as analysis, communication, communication, interaction and reflection. Humans usually gain understanding and experience in this process and can come up with creative ideas.

Figure 3 displays the data pyramid from the management viewpoint. Operational level workers typically operate in a formal environment and use predefined processes to carry out daily business activities that are the core business operations. Operational workers use the Transaction Processing System (TPS) to conduct daily business transactions. Having a completely configured framework and collection of predefined procedures, the implementation and automation of these systems (TPS) is made easier. These TPS considers the raw field observations and processes them to produce useful information. This is the pyramid data point. Data produced by business transactions is analyzed in order to create routine and exceptional reports that allow managers and executives to make decisions. The program that does so is called the Information Management Program (MIS). TPS and MIS operate on a standardized system that works with data and/or knowledge. Management also needs to take a call on the cost-benefit ratio of the various potential options necessary to make efficient use of scarce resources and environmental constraints. The type of system used for this purpose is the Decision Support System (DSS). Unlike TPS, which only uses databases and operates in a structured environment, the DSS typically works on a structured to semi-structured environment and uses model base and database for optimum resource utilization. Systems such as TPS, MIS and DSS perform routine business transactions, offer valuable detailed analysis of the information obtained and support the business decision-making process. Such systems, however, neither make decisions themselves nor explain them with clear explanations and logic, because they do not have expertise. Management at a higher level requires knowledge and expertise in policy and strategy making, and thus the need for information-based and wisdom-based systems (KBS and WBS). Information can be distilled and translated into knowledge by applying ethics, values and decisions to the decision made only after a degree of maturity (experience).

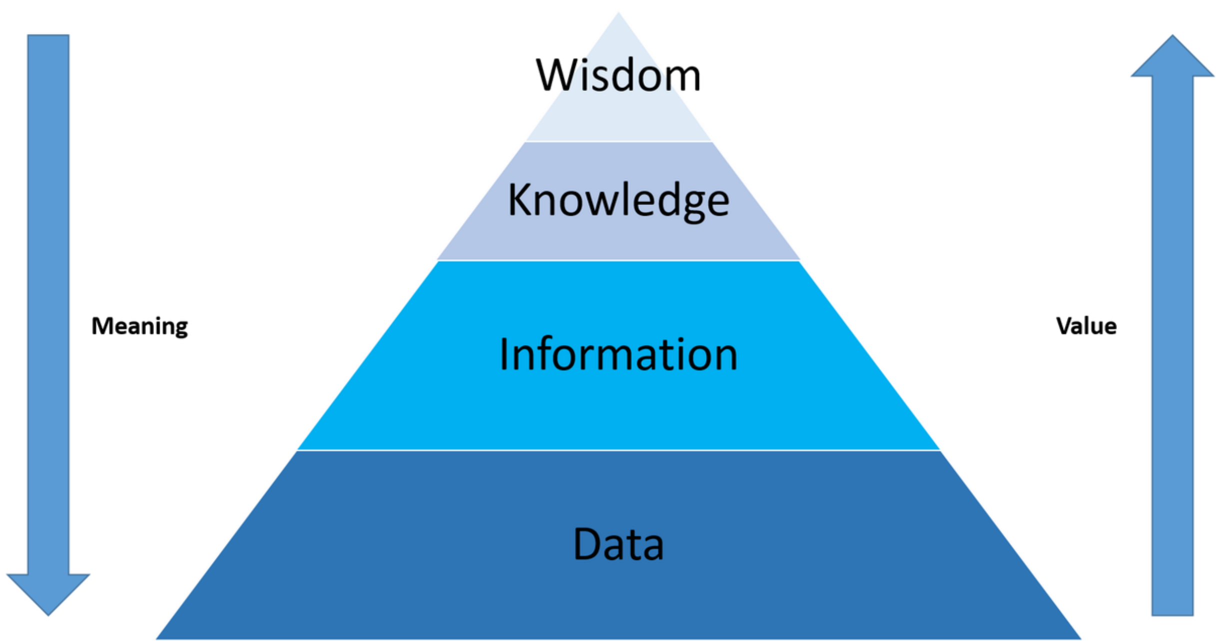

Figure 3: Data Pyramid, decision making perspective

4. Property of Autonomy

Distributed systems have been developed in Computer Science for many years and have shown to be an effective means to improve problem-solving efficiency but also to open new application domains for computer technology. In addition to designing new algorithms for these systems, AI's contribution to the area of distributed systems was to provide the components of distributed systems with some level of autonomy.

Until the last decade, computer systems were mainly regarded as computing devices and mass data storage, and used to assist decision making. Humans refused to embrace computer-system decisions. Nevertheless, computers already monitor vast installations in some technological environments, which in some way require decision-making while humans still serve as supervisors. Computer systems have therefore already begun being autonomous. Autonomy is a key problem in multi-agent systems which are the contribution of AI to distribution. Only if a part of a system has any degree of autonomy can be interpreted or modelled as an entity, then it is considered a passive component. Several characteristics may be indicative of autonomy. In a given case, it means the right to select any action from a collection of potential actions, including the choice between remaining inactive or being active when necessary. The capacity is called being constructive.

Another important aspect is the ability to hold deadlines. Not only is it important for an agent to have priorities that direct his preparation and operation, but it also needs to be able to adjust them, remove them or introduce new ones. A third function is the capability to connect and collaborate actively. Here the word "active" is significant, since the exchange of messages between passive components in the context of functional calls is usually often called communication, but this is not meant here. Co-operation and communication between agents is also a constructive behavior; an agent may initiate contact or seek co-operation whenever it is necessary. Autonomy property establishes a new relationship between agents-whether they are realized as robots or as software systems-and people with partnership efficiency. It is no longer possible to consider autonomous agents as pure machines that are started when needed, do their job and are stopped. They may be seen as servants, but servants have their own will and complex cognitive abilities, and these also have to be granted to the agents. In the future, we must expect to live in a much more complex society than we do today as just another "living" entities along with agents. As personal assistants in our connected computer system, as drivers of our car or as managers of our household, they will be present in our daily life for example. AI researchers will deal with the problems that could be created by this viewpoint along with sociologists.

5. Situation Awareness

Within a general sense, all computer systems are placed, but in very restricted well-defined cases, traditional systems exist that are absolutely decided by humans. Also with the advent of agents in multi-agent systems and adaptable mobile robots, locationness became an important subject of study.

Clearly, situatedness is strongly linked to the autonomy problem. Also autonomous systems need to locate themselves and align themselves, and behave in circumstances. Situation here means a collection of environmental stimuli which are at least partly unpredictable but of tremendous importance to the system, so that it has to respond accordingly. A situated system needs to address two key problems, mainly how to detect the situation and how to select a suitable answer. Detecting a situation in a well-defined setting may be a very simple task for a mere software agent. Yet if we think of agents working in the Web for example, things get even more complex as this world is extremely unstructured and complex. Robot sensing is much more complicated.

The very first physical signals are to be converted into data, a task that physicists and engineers may delegate to them. But then in the next step, it is important to put together the indications from different sources to provide a summary of the situation which helps the system to respond appropriately. This function is called sensor fusion, and the methods of AI come in here. Through Cognitive Science we discover that a very complicated method of interpreting a situation requires a lot of context information and a lot of nervous behavior. The brain builds the condition from various inputs. We really know nothing about the cycle and it's hard to recreate it for obvious reasons. Simulations using AI methods can be helpful in getting insight into it. If simulation is feasible, artificial situated systems may also be used to compile a situation summary for their own reasons.

The primary aim of creating explanations of situation for situated structures is to use them for their own activities. The essential functions of self-localization and orientation as well as the related task of acting could only be justified on the basis of explanations of the situation. At the other hand, this means that the development of a definition of a situation is often aimed at assisting the positioned structure in performing its functions; it is not an end. Criteria such as completeness or continuity have little priority, but instead a definition meets the needs of the program in place if it helps to choose the correct behavior. Situated knowledge bases are needed consisting of large context knowledge and pieces of specific knowledge that do not need to be compatible with one another or the background knowledge. In such pieces the information can also be expressed in various types and granularities. Strategies must be built for selecting the right chunk of information, integrating it, and converting information from one type to another. However, modern scenarios are not completely distinct from each other, but there are parallels between them in all rational contexts, and knowing, that is, identifying and classifying related instances, makes sense. Learning will strengthen a given system's behaviour. The existence, autonomy and location of knowledge can be considered as future focuses for AI research and development. Many single processes need to be merged into larger structures to address these challenges. Thus, the overall direction of AI R&D can be defined by the development of complex structures that incorporate various methods and meet the three requirements.

6. Machine Learning

We mentioned two artificial intelligence techniques: expert systems and machine learning. Both are based on the assumption that the human thought process can be mechanized. On the other hand, the two techniques differ in their conception of what this process is. They are respectively based on two schools of thought: symbolism and connexionnism (Smolensky, 1987).

In the case of symbolism, expert systems follow a formal logic: "Symbolism models concepts in the form of objects linked together by logical predicates" (Ezratty, 2017: 21). Expert systems are less well known today, even if they are more rigorous than other methods, thanks in part to their traceability. Their reasoning is easy to understand and we know why they have given us this or that answer. However, it is more difficult to create and takes much more time.

Unlike symbolism, connectedness is based on bio-mimicry, the attempt to reproduce the biological process of the brain (Larochelle, 2017). If AI is the ability to make a machine intelligent, ML is the ability to make the machine capable of learning without being explicitly programmed into it, a definition given by one of the pioneers in the field, Arthur Samuel in 1959. To do this, ML is based on many techniques, all of which have one thing in common: their ability to automatically refine their methods and improve their results as they receive more data (Brynjolfsson and McAfee, 2014). These techniques include regression, classification, clustering, and size reduction. However, the most widely known to the general public remains neural networks, the most advanced version of which is what is known as Deep Learning, loosely based on the real neural networks of the human brain (Larochelle, 2017). Two of the pioneers are Canadian researcher Geoffrey Hinton and French researcher Yann LeCun. There is also Canadian researcher Yoshua Bengio, internationally recognized as a leading expert.

The principle of software using Machine Learning is to recognize trends or make predictions or recommendations from a large database autonomously, without the need for a human to program instructions. In addition, the software is able to adapt and self-improve through experience and the addition of new data (Chui, Kamalnath and McCarthy, 2018). These software programs operate on the basis of algorithms. There is a first phase of training these algorithms when they are created to ensure that the mathematical functions used work. Then, the people using these algorithms will have to train them on their own data so that the software can adapt to them and meet their needs. Once this training is done on a specific database, the AI solution will be ready to be deployed to a larger database. This is a training called supervised training where the software uses human feedback to improve. There are also unsupervised trainings where the software by itself detects trends in a given database (Chui, Kamalnath and McCarthy, 2018).

In any case, the use of AI solutions requires a very large amount of data. They are what feeds the algorithms, their quality determines the efficiency of the AI software (Rogati, 2017). Without quality data, even the best algorithms will not give the desired result (Ezratty, 2017).

ML remains the tool with the greatest potential to teach machines cognitive skills, such as image, text and speech recognition. It is this technology that is behind Apple's virtual assistant, Siri. It is also the ML that is mainly used in the development of autonomous cars, making several programs communicate with each other, each with its own specialty.
It is only recently that researchers have had the technical capacity to develop ML-based solutions. Certain factors have been key in its evolution and will be equally key to further progress in this area of research. Canadian scientist Hugo Larochelle, a Google Brain researcher and former student of Yoshua Bengio, proposes a recipe of three ingredients that has enabled the major advances in ML and DL in recent years (Larochelle, 2017): computing power, data access and information sharing :

- By increasing the computing power, this allows complex systems requiring large amounts of data to run faster. This will continue to be a key factor in the development of artificial intelligence, as more power will always be needed to operate increasingly complex systems.
- The digitization of our societies has made it possible to increase the amount of public and private data. The creation of databases to train one's ML system is a tedious and often long step. The precreation of databases reduces the time needed to create an AI solution. Although quantity is a very important point, work will also have to be done on their quality and accessibility. Beyond the raw data, speed in scientific iterations has also been catalyzed by the creation of free "libraries", which contain banks of algorithms that have already been created and which facilitate the work of coders by directly retrieving these algorithms and inserting them into their codes.
- The idea of transparency and collaboration that has been brought about by open data projects and free libraries, are two values that also seem to prevail when it comes to research results. Thus, private or public research groups 8 publish and share their results regularly, allowing other groups to build on them. The pace of innovation is so fast that it is quite rare to see patented

projects, because no sooner is a new program developed than a new version or a new way of doing it can quickly render it obsolete.

Note that in these three ingredients, there may be some bias on the part of Hugo Larochelle (2017) since he is part of a large corporate group, Google. Computing power and resources as well as access to data are two elements on which there is consensus. On the other hand, it is easier for large groups to advocate information sharing knowing that certain results can be revealed, but keeping those with the most potential private.

Artificial intelligence is a domain of intelligent computer design and justifiable decision taking. This research also uses data and implements machine learning. Artificial intelligence is the area that is applied omnipresently in most other areas, and can apply to any domain. In addition to traditional intelligent models and algorithms, it has the ability to learn from a vast amount of data, the capacity to simulate nature-inspired behavior. This makes it uniformly applicable to artificial intelligence where traditional formal model fails. Perhaps the biggest change is the analytical capacity and the volume of data that we can obtain and analyze compared to decades ago.

Nowadays, a smartphone that fits comfortably in a palm can store and process more data than a 1960s mainframe computer that dominated many rooms. We can use massive and unorganized data with lots of conditions, instead of relying on carefully curated and small data sets, to train algorithms and draw predictions. It also differentiates current machine learning techniques from statistics is the quantity and quality of data. Although statistics typically rely on a few variables to identify a pattern, having thousands of data parameters, machine learning can be used efficiently. (Larochelle, 2017).

Machine learning is an integral element of computer science and an ICT-related area. Different algorithms and techniques are emphasized in the world of machine learning to render machine learning from the data automatically. These tests can be used later in the analysis and implementation of data to solve problems. But some statistical and mathematical methods are applied in the area of machine learning. (Rogati, 2017).

Back in the 1960's the word data science was created. As data science progresses and develops new "instruments" over time, the core business goal focuses primarily on discovering meaningful trends and extracting valuable insights from the data. Today, data science is used in a wide variety of sectors and deals with various analytical issues.
Exploring consumer age, gender, place, and actions in marketing, for example, allows highly targeted promotions to be made, determining how much consumers are susceptible to purchasing or leaving. The discovery of outlying client behavior in banking helps to detect fraud.

Examination of the medical history of patients in hospitals will reveal the probability of developing illnesses, etc.

Machine learning and AI are also closely related to ***data mining***. The word "data mining" is an imprecise word and does not sound like it stands for. The discipline is about developing algorithms to derive useful information from vast and probably unstructured data, instead of mining data itself. The fundamental issue with data mining is mapping existing data and translating it into comprehensible patterns. Data mining is seen as part of a wider method called Information Discovery in Databases (KDD) introduced by (Gregory Piatetsky-Shapiro in 1984). Many of the common methods, along with a few statistical models, include pattern recognition, grouping, partitioning and clustering. That is, the data mining also has some statistical overlap. Customer personalization is one of the key sources of competitive advantages for businesses selling their goods and services online in such an era dominated by social media. Market analytics tools and state-of-the-art recommendation engine AI apps are the key game breakers that make an efficient market personalization possible. Through business intelligence software and AI algorithms, data on consumer desires, interests, and real-time and previous habits could now be effectively captured, stored, and analysed. For instance, inputs from this data enable marketers to provide valuable content to website users, video game designers to change player game difficulties and features, or recommendation engines to recommend music, videos, or items that customers may like. Thus, data-driven personalization is a perfect tool for keeping customers and giving them the goods, services and apps they are really searching for.

7. Clustering or Segmentation

Clustering is the mechanism by which objects are grouped into groups whose members are in some way identical. Whereas consumer segmentation is the process of separating a customer base into groups of individuals which are similar in marketing-related unique ways, including age, gender, preferences, purchasing habits, etc. In several ways segmentation or clustering of customers is useful. This can be used in targeted marketing. Often clustering the data and creating a separate predictive model to each cluster is relatively efficient when creating predictive model.

Clustering is an understated strategy for data mining. Which implies it can be used to recognize secret trends and structures in the data without a clear theory being formulated. Clustering is without goal component. For illustration, at the beginning of the study, the grocery store did not consciously seek to locate the fresh food lovers. It was also trying to grasp the client base's various purchasing patterns.

Clustering is performed to classify correlations about particular habits or measurements. For example, we want to classify groups of customers who have similar purchasing behaviour. Therefore, the clustering was carried out using variables reflecting the trends of the consumer purchasing.

Cluster analysis may be used without offering a description or explanation to discover structures in the data. Study of clusters clearly uncovers trends in data without specifying why they exist. The corresponding clusters are in themselves irrelevant.

To order to establish their identity, therefore, to understand what they reflect, and how they vary from parent population, they need to be thoroughly profiled. Clustering is mainly used for segmentation, whether it is for the consumer, product or store. Items, for example, may be classified into hierarchical classes depending on their attributes such as usage, size, brand, taste, etc.

– Revenue, scale, customer base and so on – can be grouped together.

Clustering method may be hierarchical where clustering is defined by a hierarchy or tree-like structure forming.

• In a specific cluster, agglomerative clustering begins with each entity and clusters are created by grouping entities into larger and larger clusters.

• On the other direction, divisive clustering begins with all objects clustered into a specific cluster and clusters are either separated or divide until each object is in a different cluster;

• K-means clustering is considered as a non-hierarchical clustering method that first selects or defines a cluster center and then aggregate all objects working together from the center within a pre-specified threshold value. The number of clusters to be calculated is dependent on theoretical or practical considerations. The intervals at which clusters are grouped can be used as parameters in Hierarchical clustering. In non-hierarchical clustering it is possible to map the ratio of total inside group variance to within group variance against the number of clusters.

Interpreting and analyzing the clusters involves studying the centroids of the clusters. The centroids on each of the variables represent the average values of the items found within the cluster. One may designate the centroids with a name or sticker. In order to test reliability and accuracy one has to conduct cluster analysis on the very same data employing different distance measurements comparing the results to assess solution stability. One of the favorite ways is to divide the data randomly in halves and conduct clustering on each half independently, and compare cluster centroids between two sub-samples. In hierarchical clustering, the answer in the data set will rely on the ordering of the cases. Make several runs with different order of cases until the solution stabilizes, to obtain the optimal results. Clustering may also be used for identification of irregularities, for example to classify transactions involving fraud. On a sample consisting just valid transactions, cluster detection approaches may be utilized to assess the shape and size of the "natural" cluster. If a transaction comes along that for whatever reason falls outside the class, it is suspicious. In medicine, this technique was used to identify the presence of irregular cells in tissue samples also in telecommunications to identify fraud-indicative calling patterns. Clustering is also used to split large data sets into smaller classes more likely to use certain methods.

For instance, the findings of logistic regression can be enhanced by conducting it separately on minor clusters which act differently and can pursue slightly different distributions**.**
In conclusion, clustering is an efficient method for exploring trends inside data structures and has broad applications in business analytics. Clustering approaches are complex. An analyst must be familiar with various clustering algorithms, and also be able to implement the most applicable technique according to business needs.

8. Psychographic Personas

Psychographics are measures of one's desires, behavior, attitudes and opinions that help to explain why an individual might or might not buy a product. Once paired with demographic data, psychographic data can offer a nearly complete image of the consumer and help pick the kind of items that would relate to that person. A person's psychographic tracking parameters are characterized by a psychological propensity for a group of people to act or be drawn to similar items in a certain way. So the psychographic criteria for a young mother will include an ability to explore tools that offer her information on how to take care of her infant. On the online environment, the metrics for defining a person's psyche will include past browsing activity, website behavior, past purchasing history, reported social networking pages interests, and other such details. Psychographic data, then collected and stored, may provide a very good insight into what kind of products a person may be interested in or willing to purchase. (Akerkar, R. (Ed.). (2013).

Market segmentation is the process of dividing a market into categories or groups of consumers which are similar but separate from other groups of consumers. Segmentation splits a sector down into subgroups. Targeting is about determining which segments are most beneficial. Positioning also means developing a product identity that relates to a target market or multiple target markets. Psychographic segmentation helps to create or position goods in a way that makes them more appealing to competitors. Developing perceptual maps helps you recognize how your brand is perceived by customers and enables you to place your brand to optimal gain. AI gathers clients through audience pools focused on touchpoints and sentiment analysis that enable marketers comprehend how different segments of consumers may respond to a social post, billboard or blog. By looking at how consumers speak to each other, it can recommend phrases and moods that better align with each section of the audience. (Bengio, Y., Courville, A., & Vincent, P. (2013).

9. Business Innovation with Big Data and Artificial Intelligence

A slowdown in economic growth in advanced countries has been felt in recent years. One of the repercussions of this slowdown is lower growth in wages, directly affecting quality of life (Furman et al., 2016). In the report Artificial Intelligence, Automation, and the Economy, written by a research group commissioned to study the impact of the economic slowdown on the quality of life, Furman et al.

According to the White House, the authors present the opportunities and risks of artificial intelligence for the American economy and society in this context. The conclusions can be extended to some extent to other Western capitalist countries and offer a vision of the forecasts for the coming years.

Similar to previous industrial revolutions, economists predict increased productivity through the adoption of AI solutions in enterprises (Furman et al., 2016). Since the 1990s, technology has been one of the main drivers of economic growth, enabling steady productivity gains (Basu, Fernald and Shapiro, 2001). The report's researchers explain this phenomenon through the link between the number of hours worked and the output produced : "One of the main ways that technology increases productivity is by decreasing the number of labor hours needed to create a unit of output". (Furman et al., 2016: 10). This will allow firms to reduce their costs per unit of output, become more profitable and increase the country's GDP per capital.

For the authors, as long as AI is equated with higher profitability, it is likely that investment for its development will continue. Indeed, they explain that AI is a directed innovation that does not happen by chance; its development is the result of decisions made by governments, firms and individuals (Furman et al., 2016). They take the "directed technological change" argument of Daron Acemuglo, an economist at MIT, and explain it as follows: "Technological advancement is generated and adopted into the economy as the product of choices of entrepreneurs, workers, and firms looking to better serve a market or streamline a production process [...] In a process of directed technical change, incentives draw investment towards more potentially profitable innovations and so the types of technological change that are likely to occur, among those which are technologically feasible, are those which are most profitable" (Furman et al., 2016).

Historically, using the argument of the economist Joseph Schumpeter, many capitalists point out that our societies have already experienced periods of transformation due to innovations. Despite a disruptive effect on societies, including the loss of jobs, these "industrial changes" become beneficial, as they flow into periods of strong economic growth.

Schumpeter calls this phenomenon "creative destruction" (Schumpeter, 1942). Economists W. Michael Cox and Richard Alm summarize the argument as follows: "Schumpeter's enduring term reminds us that capitalism's pain and gain are inextricably linked. The process of creating new industries does not go forward whitout sweeping away the preexisting order" (Cox and Alm, 2007). Based on historical observations, several economic studies show that through the phenomenon of creative destruction, the net number of jobs created is greater than the number of jobs destroyed (Clark, 2017). Thus, for authors and thinkers relying on economic studies, society has always managed to adapt to changes, which are for them necessary and sources of economic growth.
This vision of the future is not shared by all and other points of view exist in this regard. Focusing on the impacts of an ANI, other researchers and professionals do not believe that AI will lead to a significant increase in productivity, especially in our context of social inequality, global warming and an aging population. For them, we should expect no more than stagnant economic growth (Knickrehm, 2018).

10. Applications in Business

Following our review of the literature on the subject of the adoption of AI solutions in companies, we only found reports issued by private companies or independent professionals. The topics addressed address the conditions necessary for the integration of AI solutions as well as their technological and human implications within companies.

We can note that the majority of the literature deals with the influence of AI in large and medium-size companies. We consider this trend due to the fact that the majority of reports are produced by consulting firms with the objective of informing their clients and future clients, which are mainly large and medium-size companies. We take into account that these reports also serve to prove the relevance of the services they wish to sell to their clients. We must therefore bear in mind that biases may exist, as companies have an economic interest in the information they publish.

Nevertheless, their research is based directly on the impressions of the directors and managers of several firms around the world and is addressed to the rest of the business community and researchers who can influence their decisions in this regard. It is therefore, in our view, relevant to report on the discourse promoted in the business world.

So in our view it is relevant to report on the discourse promoted in the professional world.

During several conferences on the impact of AI or in press articles, a discourse often put forward by speakers is the need for companies to adapt to this new technology at the risk of not "surviving" in the coming years in the face of competition using AI solutions.
Today, the effects of the integration of such systems on a company's competitiveness are still not very observable. Nevertheless, in 2017, the MIT Sloan Technology Review in collaboration with The Boston Consulting Group surveyed 3,000 executives, managers and analysts in 112 countries and 21 industries. Among the results, while 65% expect that the adoption of AI will have a significant effect on their organization five years from now, 61% believe that it is urgent for their company to develop a strategy to integrate AI now.

Indeed, approximately 85% of respondents believe that AI will enable their company to maintain or develop their competitive advantage (Ransbotham et al., 2017). According to the survey and the results of the report, it appears that the majority of companies see opportunities in the integration of AI solutions that should allow them to reduce costs, enter new markets and prepare for the entry of new players using this technology (Ransbotham et al., 2017). The three areas that are expected to be most affected within a company are information technology, operations and production, and customer interaction activities (Ransbotham et al., 2017). But one point that is reiterated in the literature is that changes due to AI solutions will require a global transformation of the enterprise, as these solutions will only work to their full potential by avoiding the creation of silos between departments and effective communication between them (Chui and Francisco, 2017; Ezratty, 2017; Plastino and Purdy, 2018; Ransbotham et al., 2017).

Thus, even if companies do not expect significant impacts on their business for another five years, they want to start planning for the integration of AI solutions into their processes today. The reports so far identify three main types of impacts: financial, technological and human. The financial impacts are due to the new investments required and the reallocation of resources within the company. They are directly related to the two other impacts that we will discuss in more detail below.

According to Olivier Ezratty (2017), the approach to using this technology requires three main points. First of all, the company must have a business case, i.e. a precise problem to which it wishes to respond. In the report published by MIT and BCG, the authors point out in their survey that building a good business case is the main issue facing companies beginning to think about adopting AI solutions, while for companies that are more advanced on the subject it is the issue of talent acquisition that stands out (Ransbotham et al., 2017). Secondly, companies must have the relevant data to address their issues (Ezratty, 2017). A significant amount of work must be done by the company to collect and "clean up" its data (Rogati, 2017).

A sufficient amount over a long period of time will allow the software to highlight the desired trends (Ransbotham et al., 2017). As highlighted in Figure 1, data is the foundation of any Machine Learning system. As seen earlier, Machine Learning systems require the training of mathematical algorithms, requiring a large database. The interdependence between data and AI algorithms would therefore be crucial (Ransbotham et al., 2017).

However, it is also possible to use other AI solutions, such as expert systems. This leads to the third important point to be able to start using AI, an understanding of the tools and their uses within the company. These solutions are powerful tools, but they are not necessarily the most suitable for all problems. It is therefore necessary to be able to understand the tools and determine which ones are appropriate for the problem and the data (Ezratty, 2017). The technical issues of data mining and algorithm training are therefore very important, but there are also managerial issues (Kolbjørnsrud, Amico and Thomas; Ransbotham et al., 2017).

From a managerial perspective, AI solutions are generally presented as an opportunity to allocate work time to value-added tasks and to delegate repetitive or less complex tasks to AI software (Duranton et al., 2018; Kolbjørnsrud, Amico and Thomas, 2016). The reports by BCG, in partnership with Malakoff Médéric (2018), and Accenture (2016) highlight several themes on managerial concerns: work transformation, skills development, the evolution of corporate culture, the human-machine relationship, and the development of an ethic in the use of AI. In our opinion, the first three themes can fall into the category of change management, the stakes of which remain close to what has already happened in the past with other technologies, unlike the scale that this time it could take in terms of the scale of transformation. This is not just happening in one department, but in the end throughout the entire company. The man-machine relationship and the development of ethical behaviours, such as transparency in algorithms, raise greater ethical questions for society in general.

Moreover, over the past few years the market for data has grown. Businesses race to accept in-house data warehouses and business intelligence tools and reach out to public and private repositories in pursuit of data to push their AI strategies forward. Data is becoming a coveted asset due to the rising demand and companies are beginning to compete for the most lucrative reserves. Until quite recently, corporations didn't realize they were sitting on a data treasure house and didn't know what to do about it. With the groundbreaking advancements in data mining and AI, companies can now make use of customer and user generated data.

For instance, Moz utilized AI to predict client churn through a deep learning neural network that analyzes user behavior and can predict user behaviour. Since activities customers are about to do inside the program are triggered by a variety of factors from the past, this makes it possible

to mine some useful market insights and decrease the turnover of current customers, which has a huge impact on the overall growth of the company. Lately, online user practices such as search requests, clicks, or transactions have become the primary data sources for big business.
However, as it turns out, in our physical environments and even in offline interactions, data is plentiful. Big corporations such as Amazon have developed plans for corporate regulation of grocery stores. Installed in shops, modern sensors and actuators will gather data on customer tastes and behaviours. Drones, AI personal assistants and even the Internet of Things (IoT) are devices that can transform useful data into every single moment of human life. This data is a driver of algorithms for price setting that respond to changes in market demand. Uber has started using this pattern in his system for rates. Some businesses on the verge of such disruption would have the greatest chance of generating profit from customer behaviour. One of the most interesting approaches is the study of feelings using NLP methods to understand the complexities of the emotions and input of users.
One can also recognize positive and negative feedback of their goods on e-commerce sites like Amazon using sentiment analysis. In fact, understanding the competitor's feelings will help businesses measure their own success and find ways to enhance it. One advantage of online reputation management sentiment analysis is automation, as it can be difficult to manually process loads of user reviews. Some of the most powerful solutions that can set you apart from the competition is converting reviews into data to be piped into the business intelligence applications. AI is becoming a major competitive advantage for companies, from chatbots and smart story developers to business intelligence tools, encouraging automation, cost reduction and smart decision taking.

Nevertheless, companies need high-quality data to build their AI strategies and train their machine-learning models. Indeed, Facebook and Google addressed this problem by exploiting the user-in-the-loop model in which users create data for them through messages, comments, or search queries. Some companies gain access to data by accessing public and commercial repositories, tools for gathering and classifying data from crowdsourcing, partnering with data-driven businesses, etc. Whatever approach best suits your business model, successful data acquisition strategies need to be implemented to leverage AI's strength.

For instance, we can observe the use of Artificial Intelligence in the following activities:

Customer Relationship Management (CRM) Use a combo of regression analysis and clustering techniques, CRM software may classify the company's clients into cronies focused on their profiles and where they are in the customer lifecycle, enabling to target your marketing strategies in aspects that are most likely to be efficient.

Detection of outliers and fraud where most predictive analytics systems try underlying patterns, detection of anomalies searches for things that stand out. This has been used for years by the financial industry to identify fraud, but the same statistical methods are also useful for other applications, including pharmaceutical and medical research.

Anticipating demand is a necessary yet complex activity is predicting demand for new products and services for any sector. Previously, these sorts of projections were generated utilizing data from time series to make broad forecasts, but now retailers can anonymize search data to estimate sales of a specific product moving down to the regional level.

Improving processes Predictive analytics can increase productivity by predicting what machines and parts are expected to need maintenance for manufacturers, energy producers and other industries that depend on complicated and critical machinery. Such predictive models can boost efficiency and decrease downtime when using historical performance data and real-time sensor data, while preventing the sorts of major work stoppages which can arise when large systems malfunction unexpectedly.

Building recommendation engines rely on streaming platforms, online stores, dating apps and more to improve user satisfaction and interaction. Collaborative filtering approaches use a blend of previous experience and similarities to other users to generate recommendations, whilst content-based filtering attributes features to objects and suggests the current items based on their similarities to previous items.

Improving time-to-hire and **retention Businesses** can use human resource systems data to automate their recruiting process and detect good applicants that human screeners may miss. A combination of performance data and personality assessments are often used by certain organizations to determine when workers are expected to leave or predict future disputes so they can be proactively dealt with.

IV. AI Implementation strategies:

In this part of our literature review, we are going narrow our focus and discuss AI implementation strategies. In his article on Data Science Central 2020, William Vorhies has suggested 6 strategies in order to implement Artificial Intelligence within a company.

1. Applied AI – Optimizing the Current Business Model

We mention this strategy seeing as that's where today the vast majority of companies are. Carrying out different projects where certain AI / ML components would be used to change the current business model. This is the growing approach to grease new technologies on old obsolete business models.

This isn't special or inherently even bad for big developed corporations. There are however many startups that literally grafted AI / ML on their existing products. This is not AI-first and is the source of the latest 'AI-Washing' term. Which rightfully means that there isn't enough AI / ML here to produce a breakthrough, just enough to justify putting it in the commercial.

2. Horizontal Strategy

The central idea is to make an AI system or platform that other companies will use to solve issues more efficiently than we might have before AI. Several businesses initially thought they could build cross-industry AI utilities. And if you're one of the advanced analytics systems or data preparation packages that survived you may have been right.

The monoliths like Google, Amazon, IBM and Microsoft easily ate up those resources. They rapidly dominated the opportunities such as advanced analytics and generalized image, video, voice, and text AI tools through their own work and strategic M&A.

None of these began being an AI-first enterprise. They grew up amid the AI / ML innovations and were able to follow it.

There is no unique prerequisite for profound business or process knowledge here. It is a commonly held belief among VCs that startups should maintain a maximum distance from these rivals to be defensible either.

And due to IA's open source ethic, in a 'proprietary ML or DL algo' there really is no defensible IP. Besides, they do not own the core problem of the client or train on data that is unique to that problem. Those are general purpose tools which need to be modified to become tailored solutions by industry or consultants.

3. Purpose Built Analytic Modules

There is a slight exception to the horizontal strategy which comprises of broadly defined, technologically difficult issues that are shared by many businesses. The poster children for this category are fraud detection and other unusual anomaly detection issues such as malware intrusion detection.

These are highly tuned specific purpose modules that in the industries and applications for which they are aimed are basically plug-and-play. They have often modified their UIs to allow non-data scientist analysts or even LOB managers to utilize their advanced DS techniques without having to run or customize them directly.

4. Vertical and Data Dominant Strategies

The strategies of vertical and data dominance have converged quickly, and still give potential for commercial success. They need deep industry and process experience, where the emphasis is on a single industry and the key training data typically require defensible ownership.

Apps in this category often aspire to be broad-based companies extending beyond their main specific AI / ML positioning to establish a full vertical solution to a particular industry problem.

BlueRiver in agriculture, Axon in police vest cam cam video and StitchFix in fashion are all strong examples of effectively implemented vertical / data dominated strategies. How effective will the businesses be in this strategic group? Deere had acquired Well BlueRiver. Axon (of Taser fame) is public and, by spreading to police footage, could have prevented a flame-out. Stitch Fix has gone public in late 2017 and is trading around $24 today where it has stood for much of its post-IPO existence.

5. Systems of Intelligence (SOI)

The strategy for Systems of Intelligence (SOI) originated from an article by VC, Jerry Chen of Greylock Partners, published in early 2017. Mr. Chen found that the main operational data had been locked in operating systems which are record systems. At the time, attempts to get data from SOR and combine it with other external sources were difficult and custom solutions were needed mainly from the new-at-the-time data lakes environment.

Chen envisioned a business environment where users can call on intelligence systems inserted between SORs and friendly UIs which would allow all users to access advanced analytics and modeling based on DS, thereby creating value.

The SOI approach does not actually include defensible data (which could only be appended to data from external sources) and aims to be as general and common as horizontal approaches, implying that they were not targeted to particular sectors or consumers.
One could, for example, build an SOI that would sit on top of a CRM SOR framework to provide useful analytics throughout the customer journey. It's not clear that there are still any businesses that use this technique. Generally speaking if your SOI was strong you easily became an M&A target for the underlying deep-pocket SOR (SalesForce, PeopleSoft, SAP, Oracle, and the like) or became an acqui-hire target.

6. Platform Strategy

CBInsights recently released a study on the "19 Business Moats That Helped Form the Most Massive Companies in the World." Six of these firms, Amazon, Google, Open Table, Uber, Apple, and Facebook, are AI-first firms and all achieved and built material barriers for rivals by implementing the Platform Strategy. Consider:

- 13 of the top 30 global brands are now platform companies and rising solid.

The Network companies trade between 4 and 11 X sales compared to 3-7X technology companies and 1-3X service companies. Remember that this is a multiple of sales, not profits! (Barry Libert, Professor of Digital Transformation, DeGroote School of Business, McMasters Univ., Toronto).

- Major platform businesses like Uber, Airbnb and Instagram have exceeded the market caps of their existing rivals in just 6 to 7 years relative to the decades that traditional businesses have taken to do this.

At the end, William Vorhies, affirms that the winner is Platform Strategy which is technically, defined as a two-sided market.

The cornerstone is an intermediary economic mechanism with two distinct consumer classes, usually buyers and sellers, which adds value to transactions by leveraging Metcalfe's law and shows that the value of the network increases with the number of users.

There are some main characteristics here. First, economies of scale allow the platforms to offer a growing degree of value to all parties. This may be economic in terms of sales volume or discounts. Yet they're just as likely to be intangible. Second, Knowledge is the source of value, the platform could customize the user experience in order to improve usability benefits for both users. It is here that AI / ML is becoming crucial. Finally, the resources being managed are not controlled by the platform organization, and even the network management is often provided by the participants (e.g. presenting profiles, preferences acquired, pricing, and supplier-customized product / services).

V. AI Maturity

In this last part of our research, we will try to discuss and answer the question of the level of AI maturity within the business, following with two case studies showing results of AI maturity in different countries and different industry sectors.

1. Maturity Model

Several maturity models (MMs) were developed and introduced as part of the hysteria surrounding industry 4.0 initiative (Lichtblau, 2015; Ganzarain and Errasti, 2016; Lanza et al., 2016). In a given state, the terms 'maturity' and 'immaturity' are generally used to continuously compare and assess a direction or roadmap (Andersen and Henriksen 2006). They were originally suggested by Gibson and Nolan (1974) during the 1970's. MMs are widely used as benchmarks for assessment and enhancement of organizational capacities (Schumacher et al., 2016).

Scientists and practitioners have extensively researched the evolution of the maturity term with respect to software creation, elearning and supply chain management (Schriek et al., 2016). Several various types of MMs were produced over the last four decades (Mettler and Rohner, 2009). For instance, MMs as classification systems, the Capability Maturity Model (CMM) developed by Carnegie Mellon University in the software industry (Paulk et al., 1993) to enhance organizational capabilities (Schumacher et al., 2016) and project maturity model (PMMM) (Ibbs and Kwak, 2000) and QMMG Crosby (1979). Academic research MMs are described in information systems (IS) as "a measuring tool for evaluating an organization's capabilities" (De Bruin et al., 2005).

Initially introduced in the 1970s (Mettler and Rohner 2009), over one hundred different IS maturity models were implemented in several different fields such as market intelligence (Raber et al., 2013), cloud computing (Weiss, 2013), and the ERP method (Holland and Light, 2001). Pöppelbuß and Röglinger (2011), describe three basic types of MMs; descriptive (an examination of capacity status by current characteristics); Prescriptive (giving recommendations and interventions) and comparative (providing a benchmarking tool for organizations). MMs have been shown to be an effective resource for guiding organizations in improving their ability and process orientation of the organization (Schriek et al., 2016). Although current models cover many aspects of IS domain importance, the AI facets are not yet addressed.

2. How to develop AI Maturity?

Step 1 - Problem recognition

The first step in the development of an MM starts with a preliminary problem description (Becker et al., 2009). (Hevner et al.2004) describes a problem in describing the concept of an MM as the difference between the current situation and the target system point. Although novel, AI has already had significant economic influence (Purdy & Daugherty, 2016). AI is going from science fiction to a corporate organization that is at the heart of keeping businesses competitive. (Vanson Bourne's 2017) study on 260 large organizations reveals that 80% are investing in AI, but AI is still in its early stages of commercialization.

In addition, a recent report by Gartner (2018) notes that in terms of its capacity, how to match AI with a business strategy is uncertain. Additionally, the concept of AI is unclear; organizations are struggling to define and implement AI applications. This brings us to an appreciation of the substantial differences between organizations already knowing and embracing AI and those lagging behind. Organizations must constantly develop their capacities and reshape their business models to accomplish this (De Bruin et al., 2005).

AI maturity demonstrates the degree of growth and the scope of the performance steps taken by the company to reduce risks that endanger its properties. They must therefore define the maturity level, so that they can exploit AI to give them a competitive advantage. Objective or creation plan helps a number of different artifacts to mature their model. An AIMM was designed to assess the maturity level of organizations which implemented or partially adopted AI. By pursuing a scientifically sound development model, AIMM's design approach for the AI field can be used as the basis for future research and app-specific maturity models.

Step 2 - Comparison of Existing Maturity Models

A systematic literature review was performed to compare existing AI maturity models and establish the initial MMs for this study. The theoretical history and analysis of literature was based on the Webster and Watson (2002) research. This analysis covered the computer science, information system / informatics, and business fields. The keywords used when searching for related papers included "Artificial Intelligence Model," "AI Maturity Model" and their combinations.

From 2011 to 2018 the emphasis was on IS MM literature. Only articles were selected which were written in English and published in leading peer-reviewed journals. A research database was used to perform the search, containing top-level IS journals / conferences and online professional AI papers. The findings of current AI maturity models (e.g. Gartner Target, Andrews et al. 2018; Ovum, 2017) showed that in most of the models examined, the absence of theoretical basis and lack of documentation were almost entirely ignored. So we decided to develop a completely new model because all of the established and accepted model has deficits according to the procedure model requirement.

Step 3 - Evaluating Development Strategy

According to Becker et al. (2009), one of the foregoing strategies will explain the implementation of MMs: developing a new model; enhancing an existing model; merging many existing models into a new model; moving systems or applying material from existing models to new fields. Developing a new model will transfer relevant structure and content from existing models while remaining conscious of what such models lack (De Bruin et al., 2005). Since empirical AIMM does not exist, however, a new MM will be built based on the construction approach suggested by Becker et al. (2009) and De Bruin et al. (2005).

Phase 4 - Design Iterative Maturity

The AIMM design model has undergone multiple iterations. Bacher et al. (2009) describe four sub-characteristic frameworks for the proposed new model of maturity: design stage, model method, model selection and evaluation. The degree of Design refers to the basic structure. For eg, the maturity definition theory, the level structure, single or multidimensional, and the maturity model sub-dimensions. The design method will usually follow either a top down methodology or a bottom-up approach (Bacher et al., 2009).

A bottom-up approach first describes maturity dimensions and attributes, then extracts definitions thereof. In the case of a top-down method, the rates and their definitions are defined first. Considering the characteristics of AI discussed above, it appears that a bottom-up strategy is most suitable for mature domains (De Bruin et al., 2005). The dimensions are used for structuring the topic of research in the sense of the maturity models (Hansmann, 2016). Two simple methods highlight the dimension: a one-dimensional series of discrete measures, and a multi-dimensional approach to the measures of maturity. This addresses the fundamental questions of "what must be calculated" and "how can it be calculated" (Becker et al., 2009).

The design stage measurements are calculated based on the complexity of the model defined from the literature. Several classifications or measurements have been suggested to conceptualize AI to classify specific AI technology (McCarthy, 1956; Nilsson, 2014; Millington, 2016; Corea, 2017). According to Hansmann (2016), basing on existing literature or expert information, the initial model element or scope can be justified. In the literature a number of AI dimensions are defined by marking main characteristics and related topics for each level (Chen et al., 2012); they can be argued to be highly important and applicable to the research context. In addition, we argued that organizational aspects are the problems raised by implementation of the AI. Thus AI dimensions can be organized into the following areas: AI functions, data structures, individuals, and organizational functions.

3. What are the AI Maturity Levels?

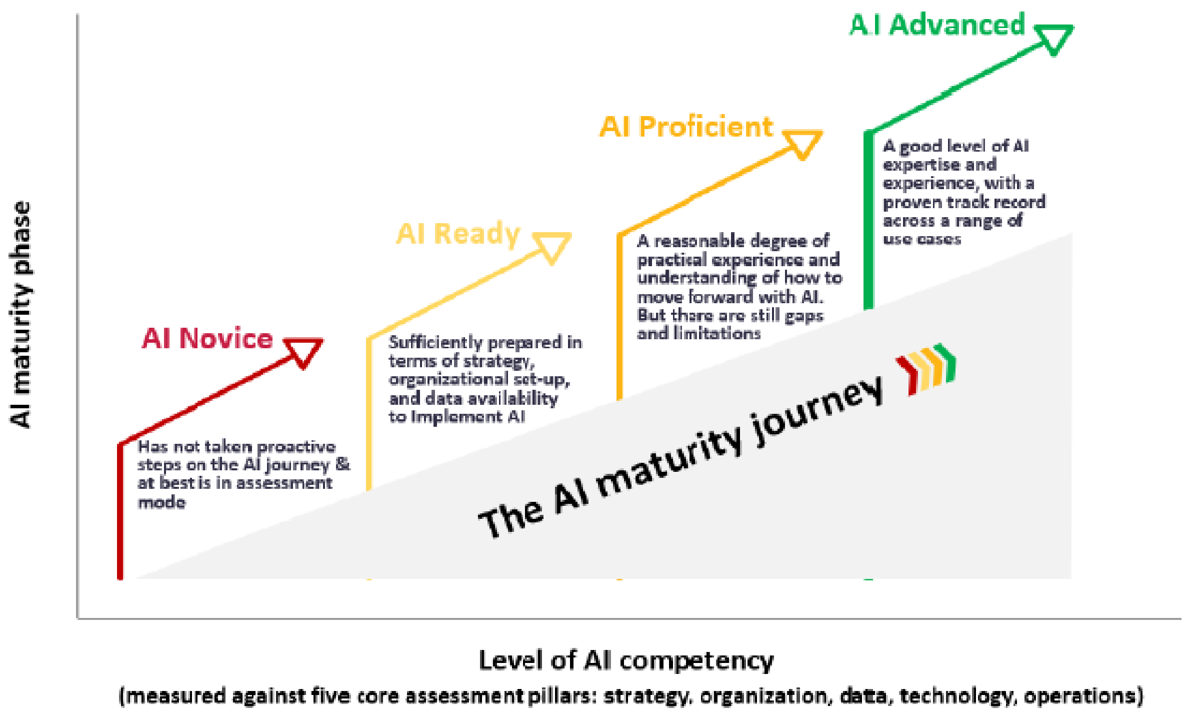

Figure 4: Stages of AI Maturity, Source: Ovum

AI Novice

Organizations associated with level one maturity-there is potential, but there is a lack of awareness of organization. Responsibilities for AI are decentralized and have no dedicated AI device. It is actually used by the role or team of the entity without the organization's specific knowledge of the actual use. Because there is a lack of organizational awareness about the usage, the organizational IT cannot adequately measure and control it. Thus, there is no AI-related governance or standard operating principles which users themselves apply to AI services.

AI Ready

Here the potential is well built and with some initial measures in that direction the company has agreed to shift towards AI. The AI substructure already operates centrally and offers essential capabilities such as ad hoc analyses. Organization's initial AI strategy; a value ratio is one of the key drivers of AI adoption for each AI application and specified. Decentralized approaches still exist, however, and the company faces issues of AI restrictions.

AI Proficient

The company is more aware of the potential threats and opportunities for AI, based on the experience acquired at this level. Organizations that achieve this degree provide a technology-focused AI strategy. The company has formal operating procedures addressing AI scenarios; management of the transition is made. The company, too, hires AI experts and offers services. This level has strong top management that affects the task of aligning the AI with organizational goals; it is possible to tackle IT capabilities.

AI Advanced

The capacity to coordinate is very well established. There is a well-defined interest to help in achieving the primary goal for this level, and full top management help. With regard to the data dimension, data rises with respect to the source and structure. In addition, sufficient data science occurs at the final stage of AI sophistication to make important business decisions using AI optimized organizations. We serve the full role; roles and responsibility within each AI project are clearly established. The data structure is versatile and constructive for having an impact on companies.

VI. Case studies:

After reviewing the literature and elaborating on the definition of AI maturity, we will attempt to examine 2 case studies, the first was performed by (Anna Paula, Tanajura Ellefsen, Joanna Oleśków-Szłapka, Grzegorz Pawłowski, Adrianna Toboła, 2019) in selected Polish and Norwegian firms to study specific developmental and maturity stages of AI. The second study was conducted by Vanson Bourne from Infosys in 2017 in order to investigate the approach and attitudes that senior decision-makers in large organizations have towards AI technology and how they see the future application and development of AI in their industries.

1. A preliminary research in Norway and Poland

The research centered on the use of technology in warehouse facilities and composed of questionnaires that middle-management practitioners replied. They were asked how much the company is launching new initiatives and the obstacles to this. It could be noted that bigger companies are more dedicated to creative ventures.

They will see more gains from these ventures than smaller business professionals. Both small and large businesses replied that more focus is paid to the manufacturing processes and process management fields than to human resource management or transportation. We both pointed to budget limitations as the reason why more research programs are not being introduced. The picking process, shipping process, internal transport processes, location of products in the warehouse, and inventory management were examined with respect to physical process flow. These processes were deemed partly automated, predict inventory optimization at the largest company investigated in Norway. That is not yet automated but will be so in the future. None of the responders use robots in the physical process flow but there is interest in potential usage of robots in areas including shipping as well as internal transport. The small companies have no automation in their operations and no ambitions to implement this in future ventures.

In Poland the situation is very close. Bigger businesses are investing in warehouse modernization and the automation of selected processes. More technologies are attracting globally capitalized businesses.
In the flow of knowledge cycle the situation is identical. The companies were asked about the use of real-time recognition technology, electronic document flow, real-time access to data and their method of analyzing data. Only bigger businesses were passionate about data

management and data processing in real-time. The respondents were asked whether the devices of their organization are capable of making autonomous decisions, learning during processes, and interacting with each other and with employees, but they could not answer that. In order to understand the degree of AI maturity and how the company is prepared to progress towards AI, these questions are critical. The respondents either didn't know about this issue or were unable to provide particular examples of AI applications.
All the firms studied in this preliminary study may be categorized as AI Novices: firms that have not taken constructive measures on the AI journey and are in evaluation mode at best.

Also bigger firms with more digital systems can't see the advantages AI can offer. Despite the amount of research showing the benefits of using smart sensors, data analysis tools, tracking systems, and machine learning, the industry is still in a novice phase with respect to AI apps. Authors hope to increase the number of respondents for further inquiries, expanding the research to various client places, and environments for innovation. Connection to more companies as well as different employees in the same organization will be needed. It'll be important to see the employees' different perspectives on innovation and AI solutions.

2. A Market research about AI maturity

Infosys appointed an independent market research expert in technology, Vanson Bourne, to conduct the research underpinning this study. In November 2016, 1,600 IT and business decision-makers were interviewed. All came from companies of more than 1,000 workers, of annual sales of $500 million or more, and from a number of industries. The study was carried out with interviews divided evenly across seven countries:

Country	Number of interviews
US	400
UK	200
France	200
Germany	200
Australia	200
China	200
India	200

Table1: Number of interviews in 7 different countries

Most interviews were conducted with a limited number of telephone interviews, using online interviews. All were conducted using a stringent multi-level screening procedure to ensure that the opportunity to participate was granted only to qualified applicants. The findings mentioned shall be based on the total sample, unless otherwise stated.

2.1. General Results:

Organizations have been using AI on average for two years but for at least another three years, they don't plan to reach "mature" adoption. Meanwhile, only 25 per cent say they have completely implemented and operating AI technologies as predicted. Just 10 per cent of those who use it believe they are completely leveraging AI's existing available benefits.

However, more than six out of 10 (64 per cent) believe their organization's potential growth depends on adoption of large-scale AI. More than half (53 per cent) claim that ethical issues are preventing AI from being as successful as possible. The vast majority agree that staff (90 per cent) and consumers (88 per cent) face AI implementation issues.

Nonetheless, most respondents (71 per cent) agree that AI is "inevitable" and would be disruptive. Given this apparent inevitability, it is important that just over one-third (36 percent) believe their organizations have fully addressed the ethical concerns related to the use of AI.

2.2. AI Maturity results

In an ever-changing, rapidly digital environment, whether the organizations of respondents concentrate on strategies to enhance the consumer experience (46 percent) or to create new products and services (43 percent), the vast majority (76 percent) agree that AI is central to the success of the strategy of their organization.

Just one quarter (25 per cent) have completely deployed AI technology that fulfills expectations. Approximately four out of 10 respondents agree that deployment time, ease of use and interoperability with other systems and technologies are areas of AI that need the greatest development until they can be successful in their companies. There is a long journey ahead for many, with most of them en route somewhere. The bad news for the minority (9 percent) that does not plan to deploy AI is that they risk being left behind.

What are the big AI technologies planned for deployment, either now or in the future, in respondent organizations? Around (65%) report big data automation, and more than half aim at predictive analytics (54%) or machine learning (51%). Expert systems (44 percent) or neural networks (31 percent) already have or are expected to be implemented by large numbers.

There are multiple forces which encourage deployment. Of those whose organizations have implemented AI, they are usually motivated by a desire to take advantage of competitive advantage (28%) or are directed by an executive level (25%)

2.3. Maturity index:

A maturity index was developed to bring greater meaning to the analysis of the opportunities and challenges faced by organizations when implementing AI. This index identifies five main maturity groups and highlights the stages of the journey towards a more effective use of AI technologies.

A series of questions were built to assess and rate organizational maturity right at the very beginning of developing the research on which this study is based. Scores were allocated to the answers to those questions, and each respondent earned a cumulative score in all areas.

Depending on the score achieved, participants were put in one of five groups that represented the maturity of the AI of their organizations:

Skeptics (Maturity score: 0–19 percent)

This represents a small but important study party. With no existing implementation of these technologies and no intentions to do so in the immediate future, these organizations are least experienced when it comes to AI. Such organizations continue to lack AI-related expertise and do not see a clear correlation between the acceptance of AI and the performance of its strategy.

Watchers (Maturity score: 20–39 percent)

Comprised of about one-fifth of the organizations of the respondents. Partial deployment of AI has started here, but things stay in the very early phases of its use in learning. AI abilities are smaller, and as such several long-term preparatory or supporting AI activities are planned. Nonetheless, there is recognition of the correlation between AI and effective strategy.

Explorers (Maturity score: 40–59 percent)

They are the most prevalent group. Their partial AI implementations prove their worth and there is a need to grow further. AI-related ability levels are on the rise and further AI-support programs are on the horizon in the coming 12 months.

Rising Stars (Maturity score: 60–79 percent)

These are organizations which are taking the leap to a more widespread AI deployment across the sector. There is further work to be done to optimize the benefits but initial successes are supported by a broader presence of AI-related skills and a increasing number of supporting activities. AI is seen as a cornerstone to the strategic performance of the organisation.

Visionaries (Maturity score: 80–100 percent)

Are the real leaders of AI. The growing number of companies have already applied AI effectively in their enterprise and are reaping the benefits. AI-related skill rates are high and open doors to more innovations and opportunities for AIs. AI is crucial to the success of the plans for the future.

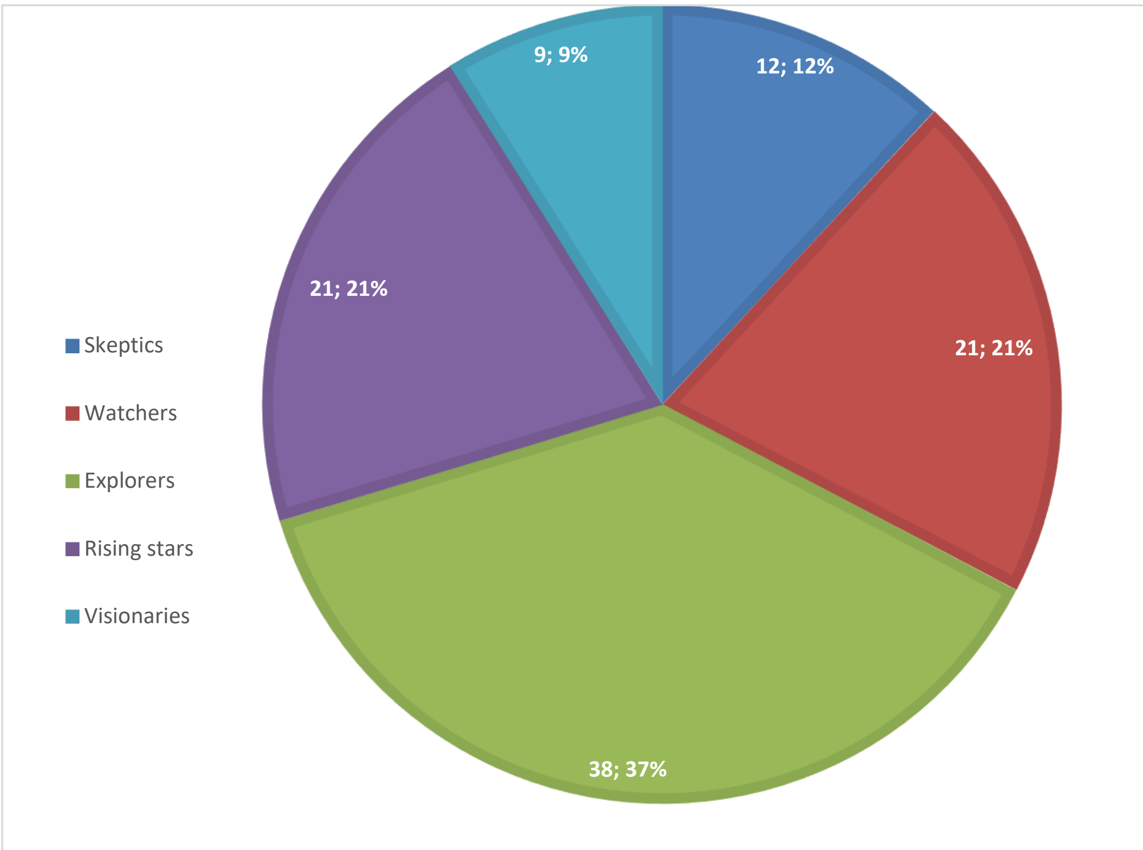

FIGURE 5: PERCENT OF RESPONDENTS IN EACH MATURITY GROUP, ALL 1600 RESPONDENTS

2.4. A deeper look at AI maturity levels by sector:

The maturity index tells us that the evaluation and partial implementation stages dominate the AI process for all organizations. Organizations continue to analyze AI across all verticals, as well as looking inwardly at their own workflows and employee processes to better understand how and where AI could suit. Present investment will be partly on appraisal, proof of concept, prototypes, international support and resources to assist businesses on their way.

We also note, however, that a quarter of the organizations are actively investing in and implementing AI technologies. In the infancy of modern AI technology, these "rising stars" represent the trailblazers, eventually setting themselves up for better results as AI becomes more broadly embraced and developed.

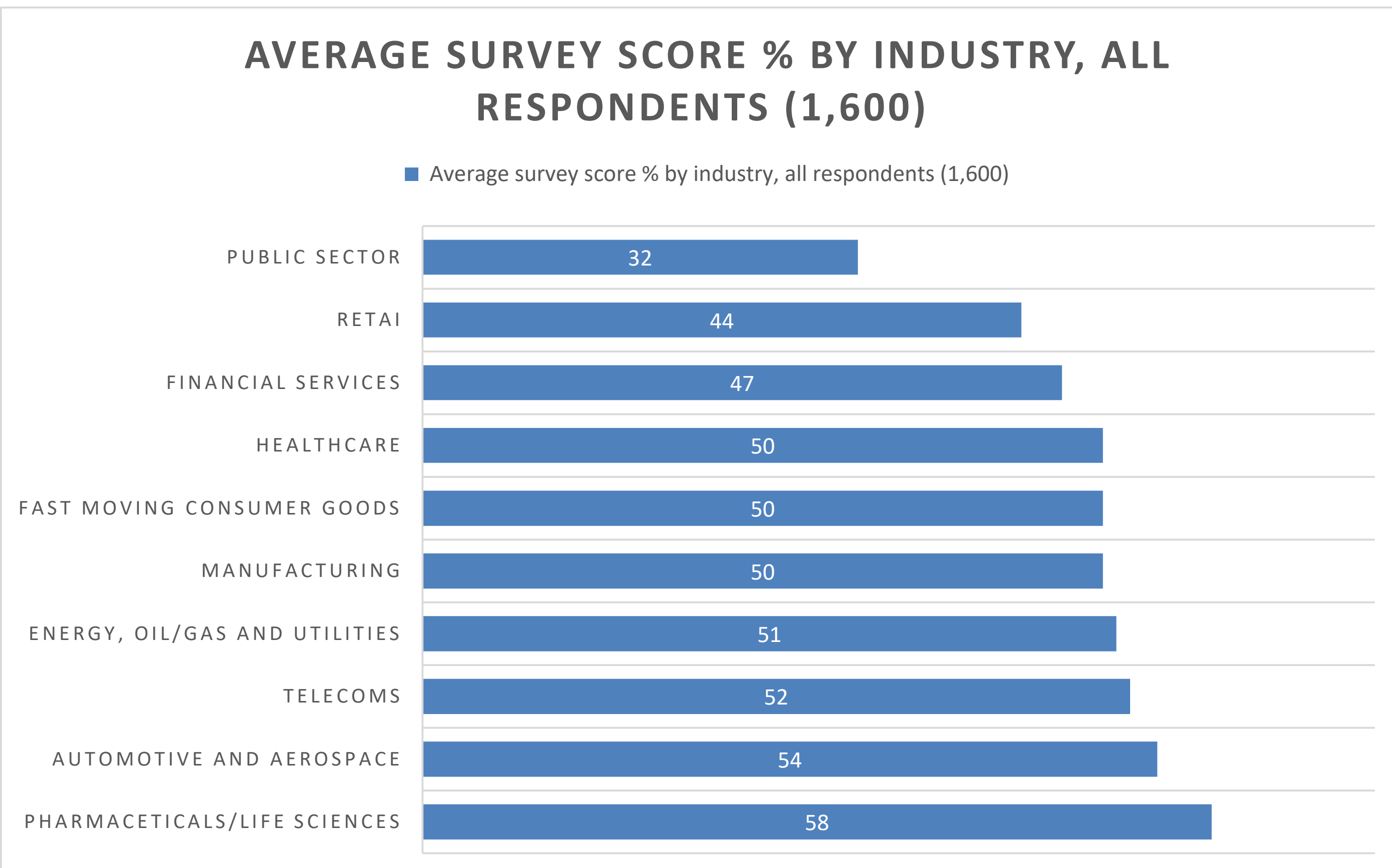

Figure 6: Average survey score by industry

VII. Recommendations:

Without leadership support, AI transition cannot be successful.

Efficient AI adopters have strong support from corporate leadership for the new technology. Survey respondents from firms that have successfully introduced a scale-based AI technology continue to score C-suite support as nearly twice as high as those firms that have not implemented any AI technology. We note that good support comes from not just CEOs and IT managers, but all other C-level members and the board of directors as well.

Resist the urge to put AI projects exclusively in charge of the technology teams.

Compartimentalizing AI transparency for functional IT, digital, or innovation leaders will lead to a hammer-in-search-of-a-nail outcome: innovations being deployed without convincing use cases. AI projects should be analyzed and co-led by both business and technical leaders to maintain a focus on the most important use cases, a strategy that has proven popular in the adoption of other emerging technologies.

Technological capabilities come before AI.

We noticed that industries leading in AI deployment — like high-tech, telecom, and automotive — are also the most digitized ones. Similarly, the businesses that are early AI adopters have already invested in digital technologies within the sector, including cloud computing and big data. Yes, it seems that businesses can't quickly leapfrog to AI without the experience of digital transformation. In businesses that have good digitization expertise, the chances of producing income from using AI are substantially higher.

Focus on people and processes.

In certain cases, the complexities of change-management including AI in organizational processes and decision-making far outweigh the complexities of technological implementation of AI. As leaders decide the tasks to be performed by machines, versus those performed by humans, both modern and traditional, it will be crucial to introduce programs that allow the workforce to be continuously retrained. And as AI continues to merge with advanced visualization, teamwork, and design thinking, companies will need to move from focusing solely on process performance to focusing on effectiveness in decision-management, further requiring leaders to build a culture of continuous improvement and learning.

Put simply: There's the next new frontier, and it's AI. Although some businesses still reel from previous digital transformations, a new one is taking shape. It is early days, however. AI still has time to become a strategic advantage.

Finally, we came to these non-exhaustive list of recommendations based on the findings of our research that shows and explains the importance of integrating Artificial Intelligence into the business.

VIII. Conclusion

The focus of this research was mainly related to the impact of integrating AI into the business. First, a concept definition and literature review of AI was provided followed by elements affecting integrating AI into the business. Then the integration strategies and the levels of AI maturity were thoroughly discussed. Based on previous researches, there are different implementation strategies and maturity modules that identify the state and the capacities of companies in integrating artificial intelligence in their processes. This thesis was designed to clarify the importance of artificial intelligence and to discuss the level of AI maturity in order for companies to obtain a competitive advantage.

Additionally, as the vast majority of decision-makers believe, based on our research experience, AI is unavoidable. Some organizations, though others remain focused on preparing their strategy, are already actively researching how the technology will work for them. However, what is evident is that good use of AI requires balance: greater efficiency versus employee involvement and customer satisfaction against evolving business models. The goal is to leverage the wide range of possible benefits while reducing the many potential dangers as well.

Driven by the importance of future benefits, AI implementation begins to spread more broadly across companies and starts reaching and affecting more workers and customers. But ethics is an important consideration. The main obligations and obstacles for organizations here are managing ethical issues appropriately, as they seek to optimize efficiency. Not only for AI technologies but also as they aim to improve the human workforce's capacity. This is not a simple job, yet it stays one that provides major advantages for the company, with AI and the workers working side-by-side, as AI encourages the organization's people to do better, be more innovative, and generate greater market value.

So, with several companies still a few years away from achieving AI maturity, what should they learn from those pioneering AI visionaries? The key factor in companies that are more advanced in using AI is that employee resources are being used efficiently for the purpose of applying AI and not simply sidelined by technology. Organizations that can retrain or redeploy employee resources rather than only make redundancies stand to benefit from improved skills and improved enthusiasm to help further explore what AI can offer.

Overall, the implementation and use of AI technology provides many companies an interesting leap ahead, but due consideration needs to be given to the effect of doing so to ensure that workers and consumers are actively involved along the path.

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