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"Decision-making Transformation: How AI is Rewriting the Rules at Ernst & Young"

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Chapter 1: Introduction

Nowadays, in a world characterized by incessant information flow and increasing complexity, it is more and more difficult for organizations to make informed and timely decisions. We are constantly bombarded with data that grows exponentially, making it difficult for humans to distinguish what is relevant information from what is not. In addition, the decision-making process sees the influence of numerous factors such as technology trends, which are advancing at an unprecedented pace, market variables, customer needs etc. Under these circumstances, human beings may turn out to be "decision makers" who are not entirely correct, or rather rational, as their judgments may be biased by emotions, past experiences, beliefs, current mood and so on. There is a need for tools that enable decision makers to take into consideration all the factors involved, all the necessary information, and this is where artificial intelligence has come in.

In recent years, rapid technological progress has led to the steady development and growing importance of AI in various sectors, including consulting. The latter is considered the number one strategic technology for organizations, and it is being progressively integrated into the decision-making process, leading to a radical change in how business realities approach strategic management. It is true that AI-based tools have already existed for more than 50 years, but it is only in the last few years that the development of new algorithms, advances in computer power, and the availability of huge amounts of data have allowed this technology to make such enormous strides that it has become one of the priorities of the European Union. Consultants, who have always been considered "knowledge workers'" capable of solving complex problems through the use of their experience, knowledge and creativity, must come to terms with these new tools. In such a dynamic environment, analytical and technical skills alone are no longer sufficient, but they must possess a thorough understanding of AI and its applications in order to enjoy its immeasurable benefits. Jeff Boss has stated that "C*ompanies don't fail because of changes in the environment, they fail because their leaders are either unwilling or incapable of dealing with said change*" (2016), and this statement proves particularly true in the current context, where adaptability and the ability to take advantage of new technologies have become indispensable competencies. However, the integration of AI into the decision-making process and the consulting industry more generally is not without its challenges. This will bring about decisive organizational change, and consultants, despite their justified concerns, must develop an open mindset ready to accept change in order to allow this AI-enabled transformation to be completed successfully and to great benefit.

1.1. Problem statement

As seen earlier, organizations and more specifically consultants, are facing the challenge of making decisions in an environment increasingly saturated with data and characterized by rapid technological advances. If we combine these aspects with human bounded rationality, we might imply that the old way of decision making is close to change. In fact, the theory of bounded rationality introduced by Herbert Simon brings to light that, faced with the complexity of decision-making situations, humans are subject to limitations both in their ability to process all available information and in the time it takes to make optimal decisions, departing from the idea of perfect, error-free rationality. Artificial Intelligence is proposed as a tool that can extend human decision-making capabilities, addressing the challenge of limited rationality through advanced algorithms and powerful computational capabilities.

The changes generated by AI lead to the question of what future decision-making will look like. Undoubtedly there will be a greater presence of these technologies in the various stages of decision making, but how far will they go? Will they go alongside humans in the early stages, in the final stages, or in the entire decision-making process? And will they go alongside or even replace the consultant? These questions open the debate on how artificial intelligence can be effectively integrated into the consulting industry. It will require a holistic approach that on the one hand considers the potential of AI, but also keeps in mind its implications for the role of consultants and client relationships.

1.2. Research question

The advent of AI marked a turning point in the evolution of decision making within organizations, so the intended knowledge contribution of this thesis is to explore its role in refining decisions in consulting firms and thus to answer the following research question:

"*How can the use of artificial intelligence improve the decision-making process within consulting firms?*"

1.3. Purpose

The primary purpose of this thesis is to examine the different ways in which artificial intelligence can be used to improve decision-making in the consulting industry, with a particular focus on practices adopted by E.Y. Specifically, this research aims to initially identify the areas where AI has had the greatest impact, as well as to assess the challenges and opportunities arising from it. Subsequently it will also explore what are the implications for consultants who are experiencing this paradigm firsthand.

Accordingly, this thesis proposes to contribute to the ongoing debate on balancing human and artificial intelligence by investigating how consultants can leverage artificial intelligence to amplify their analytical capabilities without compromising the essential human element in the client relationship. Through case study analysis and the use of qualitative methodology, an attempt will be made to paint a clear picture of how AI is redefining the consulting industry, and specifically the decision-making withing it.

1.4. Limitation of the study

The main limitation of this thesis concerns the territory of analysis and the sample.

It has been seen that the aim of the study is to highlight what impacts artificial intelligence is having on decision-making process, however, it focuses specifically on the case of E.Y. and, therefore, the conclusions may not be generalizable to all consulting firms. In addition, geographically speaking, E.Y Italy was studied, which means that the results obtained are based on the practices, culture and market trends present in Italy. It could be that the integration of AI is happening differently in other nations or in case one was to study EY. Global in its entirety as different cultural, economic, and regulatory factors would come into play. A further limitation concerns the sample size since the research is based on interviews conducted within E.Y., but only within two service lines - Business and Technology Consulting. This limitation was due on the one hand for reasons of time and on the other hand for reasons of knowledge, since being a newcomer to this company I had the opportunity to interact with these two teams mainly. Although these teams can provide detailed insights into their experiences with AI and its impact on decision making, the results may not reflect the variety of perspectives and practices that exist throughout the organization.

For these reasons just mentioned, future research could expand this work by including a wider range of participants from various fields within E.Y., or by conducting comparative analyses with other consulting firms. Such efforts would improve the generalizability of the results and provide a more comprehensive understanding of the role of artificial intelligence in the consulting industry.

Chapter 2: Literature Review

This chapter presents the theoretical background on which this thesis is based. It is structured into three main sections and provides an in-depth overview of the existing literature. The first part introduces the concept of Artificial Intelligence, tracing its evolutionary path in general and then falling specifically into what has been its development in the consulting world. In the second section, the focus shifts to decision making as formulated by Herbert Simon, a mainstay in the field of decision theory. It will look at what are the different stages of the decision-making process - from intelligence to implementation - and then discuss the main challenges that consultants face in each of these stages. Finally, the third section focuses on the integration of artificial intelligence into the decision-making process, outlining a new paradigm. The benefits and potential pitfalls of adopting AI in decision-making practices are then assessed.

2.1. Artificial Intelligence

2.1.1. Definition of Artificial Intelligence

Throughout the years, numerous definitions of artificial intelligence (AI) have been put forward; yet there is currently no universally recognized definition for this concept (McKinsey, 2023). This might be attributed, in part, to the fact that AI is a very broad term that encompasses a wide range of technologies and domains, making it difficult to define in a clear and concise manner.

Figure 1 illustrates a collection of cardinal definitions, totaling eight in number, organized along two distinct dimensions (S. J. Russell and P. Norvig, 2016). This classification serves to capture the diverse perspectives and nuances associated with the multifaceted concept of artificial intelligence.

Figure 1: Four groups of definitions of artificial intelligence

Thinking Humanly	**Thinking Rationally**
"The exciting new effort to make computers think ... machines with minds, in the full and literal sense." (Haugeland, 1985) "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning ..." (Bellman, 1978)	"The study of mental faculties through the use of computational models." (Charniak and McDermott, 1985) "The study of the computations that make it possible to perceive, reason, and act." (Winston, 1992)
Acting Humanly	**Acting Rationally**
"The art of creating machines that perform functions that require intelligence when performed by people." (Kurzweil, 1990) "The study of how to make computers do things at which, at the moment, people are better." (Rich and Knight, 1991)	"Computational Intelligence is the study of the design of intelligent agents." (Poole et al., 1998) "AI . . . is concerned with intelligent behavior in artifacts." (Nilsson, 1998)

Source: Russell and Norvig 2016

The first dimension, or vertical axis, contrasts the definitions on the top side of the table, which focus on the internal processes and reasoning capabilities of AI, with those on the bottom side, which place more emphasis on external behavior. The second dimension, or horizontal axis, distinguishes between two criteria by which AI's success is evaluated. The definitions located on the left side evaluate the degree to which AI systems imitate or reproduce human performance. This standard is called "fidelity to human performance". Definitions on the right side, measure success in relation to an idealistic performance metric, called "rationality"[1] (S. J. Russell and P. Norvig, 2016).

From this set of definitions, it is evident that two foundational concepts underlie artificial intelligence: first, it is a system that can behave in a way similar to that of human beings, and second, it is a system that is capable of rational thought. Therefore, in this thesis, to answer the question "What is Artificial Intelligence?", we will refer to the following definition: "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages" (Oxford Dictionary, 2020).

[1] Cambridge Dictionary: Rationality is defined as "The quality of being based on clear thought and reason, or of making decisions based on clear thought and reason".

2.1.2. The History of Artificial Intelligence

It is hard to say exactly when the long historical process that has led to the development of AI began. Nonetheless, the roots can be dated back to 1942, when the American author Isaac Asimov published his story Runaround. The latter outlines 3 laws of robotics:

1. "A robot may not injure a human being or, through inaction, allow a human being to come to harm" (I. Asimov, 1942).
2. "A robot must obey the orders given to it by human beings except where such orders would conflict with the First Law" (I. Asimov, 1942).
3. "A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws" (I. Asimov, 1942).

Over the years, generations of scientists working in the fields of robotics, artificial intelligence, and computer science have been affected by this work, which is considered a masterpiece.

A year later, in 1943, the neurologist Warren McCulloch and mathematician Walter Pitts set the basis for artificial neural networks (ANNs). In "A Logical Calculus of Ideas Immanent in Nervous Activity", they put forth a model of artificial neurons in which every neuron is classified as either "on" or "off", and it is only activated when a significant number of its adjacent neurons stimulate it. Neurons were thought to be "*factually equivalent to a proposition which proposed its adequate stimulus*". For instance, they demonstrated that any computable function could be calculated by a network of interconnected neurons and that simple net architectures could be used to express all logical connectives (and, or, not, etc.). Their study demonstrated that machines could start to mimic the extraordinary powers of the human mind, which made their work a turning point in the history of artificial intelligence.

Another milestone is marked by 1950 as two crucial events take place: the publication of the first article discussing the development of computer programs along with the advancement of the Turing Test. In "Programming a Computer for Playing Chess", Claude Shannon explains the "methods of making man-machine games", and it was from this work that the theoretical study of computer chess began (C. E. Shannon, 1950). In "Computing Machinery and Intelligence", Alan Turing examined the idea of generating intelligent machines and suggested a technique for determining their level of intelligence - the Turing Test. More accurately, Turing proposed a theoretical situation in which a human judge converses with both a person and a machine, not being able to discern which is which. The computer is said to have passed the Turing Test and proven to have an equivalent degree of intelligence to a person if the judge is unable to consistently distinguish between the machine's and the human's responses (A. Turing, 1950).

Moving forward, six years later, in 1956, Marvin Minsky[2] and John McCarthy[3] organized the eight-week-long Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI), which is when the term "Artificial Intelligence" was first used in a formal context. As we can read from the proposal state "*We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is 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. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer"* (J. McCarthy, M. L. Minsky, N. Rochester and C.E. Shannon, 1950), the major goal of this workshop was to bring together scientists from many fields and define a new area of study centered on the creation of machines that can imitate human intelligence. Arthur Samuel from IBM, Allen Newell and Herbert Simon from Carnegie Tech, Oliver Selfridge and Ray Solomonoff from MIT[4], Trenchard More from Princeton were among the ten participants and are those who will be later considered as the founding fathers of AI.

After the Dartmouth Conference, the field of Artificial Intelligence experienced substantial advancements for almost two decades. The 1960s marked the beginning of AI's first major breakthrough, with the introduction of symbolic logic (Uhr and Vossler, 1961), the resolution of a number of everyday issues, and early signals of natural language processing (NLP) and human-computer communication. To give a few instances, between 1964 and 1966, MIT computer scientist Joseph Weizenbaum wrote the first computer program - ELIZA. It represented a natural language processing tool proficient in emulating a conversation with a human and was among the first programs to attempt to pass the above-mentioned Turing Test

[2] American cognitive and computer scientist primarily focused on artificial intelligence research.

[3] Influential American computer scientist and one of the founders of the discipline of artificial intelligence.

[4] Massachusetts Institute of Technology (MIT).

(J. Weizenbaum, 1966). Following this, MIT initiated the creation of the MACSYMA[5] system, which proved capable of handling more than 600 mathematical problems (Martin & Fateman, 1971).

Researchers in Artificial Intelligence have always been highly optimistic and have not shied away from forecasting the field's future successes. For instance, in 1957 Herbert Simon said: "*It is not my aim to surprise or shock you—but the simplest way I can summarize is to say that there are now in the world machines that think, that learn and that create. Moreover, their ability to do these things is going to increase rapidly until—in a visible future—the range of problems they can handle will be coextensive with the range to which the human mind has been applied"* (H. Simon, 1957). However, due to high expectations, unmet promises, and financial challenges, the first AI winter began in the 1970s. Simultaneously, AI encountered unsurmountable technological obstacles, mainly due to constraints in processing speed, memory capacity, and computing power. As a result, in 1973, the U.S. Congress began to question the allocation of funds towards AI research, expressing concerns about the projected outcomes put forth by researchers. The Lighthill report observed that "*In no part of the field have the discoveries made so far produced the major impact that was then promised*" (J. Lighthill, 1973) Consequently, both the British and U.S. governments discontinued financial support for AI projects.

In the 1980s, AI reached its second peak. A historic moment occurred when Hans Berliner's computer triumph over the world champion in backgammon (H. J. Berliner, 1980). An innovative viewpoint on intelligence —different from the symbol-based AI approach— was presented by Rodney Brooks in 1986. This marked the beginning of behavioral robotics, destined to become an essential area of AI research and development (R. Brooks, 1986). These instances represent only a few of the notable achievements during this period.

In the 1990s, with the advent of Deep Learning[6], which greatly speeds up societal development and advancement, the third wave of AI emerged. A number of noteworthy phenomena

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[5] MACSYMA is an acronym for "Project MAC's SYmbolic MAnipulator".

[6] Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain—albeit far from matching its ability—allowing it to "learn" from large amounts of data (IBM).

demonstrate the prosperity of the latter: firstly, the constant emergence of new deep and non-deep learning algorithms, like Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) (I. J. Goodfellow, 2014), VAE Federated Learning (McMahan, Moore, Ramage, Hampson, & y Arcas, 2017), etc.; secondly, AI applications and associated topics have become deeply embedded in people's daily routines, encompassing areas such as self-driving cars, robots like those developed by Boston Dynamics, entities like Sophia, IBM Watson, AlphaGo Master, and more; thirdly, notably in the field of computer vision and natural language processing, AI has solved numerous issues that humans were unable to. From this moment on, the availability of scientific publications, frameworks, datasets, code, and general knowledge sharing sped up the development of AI.

Nowadays, AI has a pervasive impact on nearly every industry such as manufacturing, healthcare, education, and consulting emerging as the main engine of cutting-edge technologies like big data, robotics, and Internet of Things (IoT). The presence of generative AI tools such as ChatGPT and AI art generators has already caught the public's attention and AI will continue to drive technological innovation in the coming years (McKinsey, 2023).

2.1.3. Evolution of Artificial Intelligence in the Consulting Industry

The introduction of Artificial Intelligence into the Consulting Sector is a relatively new phenomenon for two primary reasons. The first one is that the consulting[7] profession itself finds its origins in the late 19th and early 20th centuries, when someone with excellent observational skills who could appropriately analyze and arrange people, projects and problems was required. As a matter of fact, in 1886 the first management consulting firm - Arthur D. Little[8] - was established. The second motive is that only in the early 21st century data analysis and machine learning began to gain prominence (Davenport and Ronanki, 2018).

The early adoption phase saw the exploration of AI's potential to automate repetitive tasks, handle large data sets, and derive actionable business insights. Nonetheless, consulting firms

[7] According to the Cambridge dictionary, consulting is described as *"engaged in the activity or business of giving expert advices about a particular subject"*.

[8] Arthur Dehon Little was the first person to propose methods for boosting a project's or company's efficiency by identifying and addressing the problem's core cause. This methodology became known as "Scientific Management."

choose to focus on pilot projects and concept test demonstrations because of the nascent nature of the technology and the possibility of cultural opposition. Because of this, this period was mostly characterized by trials and small-scale implementation (McKinsey, 2017). On the contrary, consultants concentrated on comprehending the technology and its implications rather than on its actual use. During this time, internal skill development through training programs and workshops was essential (J. Bughin, E. Hazan and S Ramaswamy, 2017).

The relationship between AI and the consulting sector saw a significant change in the mid-2010s. This was the period that saw a surge in the integration of AI into various consulting services, moving away from the cautious experimentation of the preceding decade (E. Brynjolfsson and A. McAfee, 2014). It wasn't just about automating work; it was also about using AI's analytical abilities to gain deeper insights and provide clients with greater value. Moreover, having recognized the great potential of AI, leading consulting firms began creating their proprietary AI tools and solutions (Bughin and Hazan, 2017). Platforms like Macky AI by Kinetic Consulting and QuantumBlack by McKinsey are examples of how AI can complement human analysis by making the consulting process more efficient and comprehensive. These are based on advanced algorithms that are capable of executing a vast range of business tasks, from completing simple operational functions to formulating structured strategies (Integem, 2022).

From the late 2010s until today, there has been a remarkable development of Artificial Intelligence in the consulting industry. Two important variables have influenced this evolution: the growing accessibility of AI technology and the pervasive corporate digitalization movement. These days, real-time analytics, predictive modeling, and task automation are all made possible by the enormous potential of artificial intelligence (A. Agrawal, J.S. Gans and A.Goldfarb, 2018). Furthermore, the biggest consulting firms claim that generative AI, a new disruptive force, is the direction this business will go in. In order to gain a decisive edge, forward-thinking companies are already planning to leverage generative AI through all aspects of their business, from customer relations (front office) through administrative processes (middle office) to financial management (back office). The benefits are multiple: they will not only gain a competitive advantage over competitors, but they will also increase operational efficiency and accelerate innovation. To put it briefly, generative AI will be a real growth engine for companies that know how to make the most of it (Ernst & Young, 2023).

2.2. Decision-Making in the Consulting Field

2.2.1. Definition of Decision-Making

The decision-making process is a phenomenon that over time has interested many scholars given its complexity and multidimensionality. As a result, several different definitions of it can be read from the literature: "*Decision making is the optimum rational choice between alternative courses of action*" (Herbert A. Simon, 1948); "*Decision making is the process of identifying and choosing an alternative course of action in a manner appropriate to the demands of the situation*" (R. Kreitner, 1966) and "*Decision making is a management technique used to reach decisions by analyzing information, evaluating alternatives and, in each case, choosing the best policy or line of action*" (W. Fox and Ivan H. Meyer, 1995).

Despite the multiple definitions, three main characteristics can be outlined. First, decision-making is not a one-time event but rather a "process", which is a series of actions a person takes to arrive at a conclusion. Second, the idea of "alternatives" appears in every definition since making choices entails having more possibilities. As such, the decision-making process involves weighing the various options available to oneself and ultimately choosing only one. Ultimately, "achieve the desired result" is what drives decision-making. The alternative chosen, therefore, should align with the goal that the decision maker has set himself previously.

However, since the consulting sector is this thesis's main focus, let's examine how decision-making is described in this field. Here it is no longer simply just a matter of weighing the available options, but concepts such as "strategic thinking*"* and "problem-solving" come into play. According to H. Mintzberg, "*strategic thinking is about synthesis, about using intuition and creativity to formulate an integrated perspective, a vision, of where the organization should be heading"* (H. Mintzberg, 1994). In making decisions, consultants need to adopt a proactive and forward-looking approach. They have the ability to integrate different data and information with each other in order to have a clear vision of what is the current and future landscape. Moreover, consultants are able to solve problems even in situations when data is lacking or insufficient because of their inventiveness and intuition, which enable them to generate new ideas (W. H. Agor, 1986).

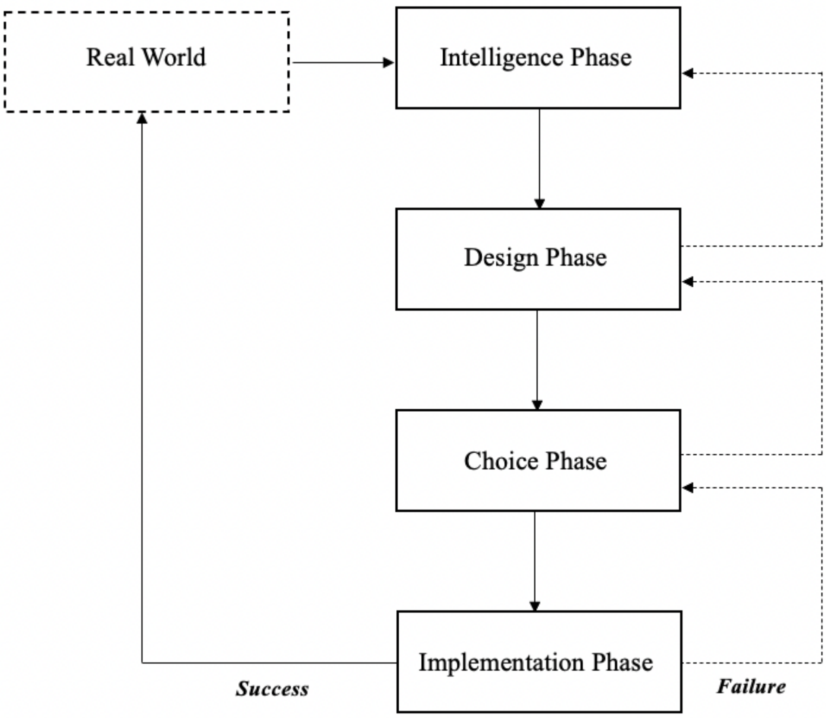
We have previously seen how the ultimate goal of the decision-making process is to achieve the "desired outcome", in the consulting field the desired result consists precisely in overcoming or eliminating obstacles to the objectives of clients - that is, problem-solving. As stated by J. R. Hayes (1980) "*whenever there is a gap between where you are now and where* *you want to be, and you don't know how to find a way to cross that gap, you have a problem*", this is exactly where consultants come in. In fact, clients turn to them when they have problems that need to be solved, and consultants' jobs frequently involve recognizing and resolving issues that have not yet arisen.

2.2.2. Decision-Making Process

As was previously mentioned, Herbert Simon was a prominent person in the fields of cognitive psychology and organizational behavior; we owe him the first theoretical understanding of the decision-making process and its phases. In his work "Administrative Behavior" (1947), he introduced concepts such as *bounded rationality*[9] and a methodical *framework for decision-making stages*, which is what we will concentrate on in this chapter.

According to H. Simon, such a methodical procedure consists of three main stages: intelligence, design, and choice. Later, he included the implementation phase as a fourth stage.

Figure 2: Stages of the Decision-Making Process



Source: Herbert Simon - Administrative Behavior

[9] According to the theory of bounded rationality, people's ability to make rational decisions is constrained, and as a result, they will choose a satisfying course of action over an ideal one..

Intelligence Phase

The decision-making process starts with the intelligence phase, which involves observing and analyzing reality in order to identify possible problems or opportunities. This means that there is either a discrepancy between the situation in which you are and the objectives you want to achieve or an opportunity to improve the initial situation (H. Simon, 1960). However, it is important to note that in the early stages of problem/opportunity identification, the problem/opportunity itself is still unclear, therefore, the intelligence phase also includes information collection to fully comprehend it. To be more precise, there are four strategies that can be applied to simplify the issue and properly phrase it (MacCrimmon and Taylor, 1976). First, the problem must be classified, that is put into a category that can be defined, and its boundaries must then be established. This entails stating not only the item's significance to the organization but also its level of structure. Concerning the latter, a number of issues fall into two categories: fully structured or programmed problems and wholly unstructured, or unprogrammed problems (H. Simon, 1960). The second strategy is to identify the changes that led to the problem. Tracing the root causes of the problem can help decision makers understand the origins. It is therefore a retrospective analysis useful to formulate solutions to address the underlying causes. Going forward, the third strategy is to break the problem down into many small sub-problems. By concentrating on these smaller, more manageable tasks, decision makers can approach the challenge of solving a complex problem. Furthermore, it can sometimes turn out that apparently unstructured problems have highly structured sub-problems, facilitating resolution. Finally, the last is to focus on the controllable elements. This strategy aims to prevent the feeling of being overwhelmed by factors beyond one’s control, in fact it consists in identifying and prioritizing the elements within the problem domain that are susceptible to intervention, those elements that decision-makers can influence or control.

The intelligence phase ends with a formal problem statement.

Design Phase

The second stage, referred to as the design phase, is crucial in determining how decisions turn out. Its important stems from the fact that it is essential in shaping and choosing the optimal course of action to solve an issue or seize an opportunity. It entails coming up with a number of different alternatives, assessing their viability and possible results, and honing them in light of facts and available information.

If we go back to Simon's words, he stated that it consists in "*inventing, developing, and analyzing possible courses of action*" (1977); three distinct but highly correlated activities, since each one informs and shapes the others.
Therefore, it all starts with "inventing", a dynamic and creative process that involves decision-makers exploring several options and solutions to address the problem/opportunity that has been identified. It is "*the part of decision-making where we can get away from the constraints of the real world and think about alternatives that we could not really implement*" (Herbert A. Simon, 1977). In fact, at this point in time, decision-makers are not in possession of all the knowledge they require, which forces them to move away from conventional thinking and, on the contrary, to embrace unconventional approaches. The design phase is characterized by "*uncertainty and the need to invent new solutions*" (James G. March and Herbert A. Simon, 1958). Going ahead, with the term "developing", Simon wants to mark the transition from the more abstract and inventive phase of the process to the more concrete one. In fact, we are witnessing the transformation of the initial ideas into more tangible, detailed and well-structured actions. To do this, decision makers need to consider the practical aspects and real-world implications of each alternative. Therefore, the result of this phase is to move from a pool of possible alternatives to a set of feasible solutions in the real world. Finally, Simon speaks of *analyzing*: this has as its ultimate goal the refining of the multitude of alternatives generated and developed during the previous phases, arriving at a more rigorous selection of solutions. A thorough monitoring procedure is carried out by decision-makers, who assess each potential course of action in light of predetermined criteria. Furthermore, each alternative's benefits and drawbacks are compared, and its alignment with the recognized opportunity or problem is taken into account.

To summarize what has been discussed thus far, the design phase represents a crucial transition from understanding the problem to generating and evaluating solutions.

Choice Phase

As the name suggests, the crucial step in decision-making is making a choice. Numerous theoretical stances have been proposed to explain this phase; *Rational Choice Theory* was among the earliest. This is based on the idea that decision-makers maximize their expected utility and act in a perfectly rational manner, that is to say, individuals weigh the benefits and downsides of every single option before selecting the one they believe would result in the best outcomes (A. Smith, 1776). However, the idea of perfect rationality in decision-making is called into question by the *Bounded Rationality Theory*. The idea behind this theory is that decision-makers are limited by time constraints, incomplete information, and limited cognitive capacity (H. Simon, 1947). Therefore, to make decision-making easier, decision-makers frequently use heuristics or mental shortcuts. Simon actually talked about "satisfaction" rather than choice optimization, which was the norm before to then. In his landmark book "Administrative Behavior" (1947), he makes the case that because of cognitive limitations, individuals frequently seek out satisfactory solutions rather than ideal and comprehensive ones. He argued that the choice phase consists in *"selecting a particular course of action from those available*". There are numerous ways to accomplish this, and weighing and comparing the potential outcomes of these alternatives is one of them. To perform a thorough analysis, one must consider four key factors: risk, limitation of resources, timing, and economy of effort (Peter F. Drucker, 1973). Starting with the first element, Drucker stressed the importance of considering the risk associated with each alternative since there is always some risk involved in any solution. He defined the risk by referring to the uncertainty or to the probability of negative outcomes associated with a choice. Decision makers will therefore have to assess the likelihood of various outcomes and their possible impact on the success of the selected course of action. Another crucial element is time since the decision's outcome is not just based on the option selected, but it is also closely related to the moment in which the choice is made. Drucker stated that "*Whenever managers must change their vision to accomplish something new, it is best to be ambitious, to present to them the big view, the completed program, the ultimate aim. Whenever they have to change their habits it may be best to take one step at a time, to start slowly and modestly, to do no more at first than is absolutely necessary*" (Peter F. Drucker, 1973). This means that in a situation of urgency, the best course of action would be to inform immediately and effectively all members of the organization about the importance of current events. Conversely, in a circumstance where there is less urgency, using a more methodical and cautious approach to decision-making is optimal. Decision-makers can therefore increase their odds of reaching desired outcomes by considering the timing of each alternative. Moving forward with the third factor, effective decision-making often results in trying to achieve the desired result as efficiently as possible. We refer to "economy of effort" because through the evaluation of the relative effort that each alternative requires, decision makers can understand and consequently adopt the solution that at the same time maximizes results and minimizes effort, time, and energy. Lastly, "limitation of resources". In this case the decision-makers need to be aware that there are several limitations, including those related to money, time and physical resources. But when it comes to making decisions, Drucker says that people are the most crucial resource to take into account. Those who will execute the decision must have the vision, competence, and skill to take the required action. Thus, at this stage a fundamental question to ask is "Does the organization have the right people and the means to realize the solution?". Optimal decision-making entails choosing alternatives in line with the resources at hand, avoiding options that can overcome these limitations. A key concept is that you don't have to select the wrong solution because you don't have the right resources; "*It is not solving a problem to find a solution that works on paper but fails in practice because the human resources to carry it out are not available or are not in the place where they are needed*" (Peter F. Drucker, 1973).

In summary, the choice phase is when the real decision is made, along with the commitment to pursue a particular path of action. However, the delimitation between the design and choice stages is very subtle: for instance, the decision-maker can regularly return from choice activities to design activities by coming up with new alternatives while evaluating current ones.

Implementation Phase

The implementation phase was not originally included, it was subsequently added by Simon to the model. As the last phase of the decision-making process, it is frequently the most complex and critical as well; it is the point at which the selected alternative is implemented and transformed into reality. N. Machiavelli once said, "*nothing more difficult to carry out, nor more doubtful of success, nor more dangerous to handle, than to initiate a new order of things*" (1514), demonstrating how this stage's complicatedness has long been acknowledged.

Since it denotes a long, and elaborate process with blurred boundaries, describing this phase is frequently difficult. However, to put it simply, it can be described as the process of implementing a decision, turning plans into action steps, and making sure that the selected course of action is executed successfully. Hence, it involves allocating tasks and resources, communicating clearly, and getting beyond challenges.

When considering the business context, there are eight typical flaws that might cause implementation efforts to fail: lack of a sense of urgency, not creating a guiding coalition, failing to develop a vision and a strategy to implement it, under-communicating the vision, failing to remove powerful individuals who resist to changes, not celebrating short term wins, declaring victory too soon, failing to establish agreed values and new social norms in line with the changes. (J. Kotter, 1996). By giving careful thought to these insights, organizations can improve their chances of effective implementation; in fact, this stage is crucial to guaranteeing that the decision's goals are met, and the organization experiences the desired results.

To sum up, we have observed that the intelligence phase comes before design, which comes before choice, which comes before implementation. The phase cycle is, however, significantly more intricate than we have managed to convey thus far. According to Simon, "*there are wheels within wheels: each phase in making a particular decision is itself a complex decision-making process*" (1977). For example, new intelligent activities may be required during the design phase. At every single level, problems give rise to subproblems, which have their own intelligence, design, choice, implementation phase. However, Simon has decided to not define this monitoring activity as a fifth phase, as it is not a single stage, but rather an iterative process that continues throughout the decision-making process. As illustrated in Figure 2, the feedback flow allows you to go back to any stage at any time.

2.2.3. Challenges in Decision Making for Consultants

When making decisions, leaders frequently face intriguing challenges. In organizational contexts, these obstacles are known as "barriers", and there are six different ones to go through.

Bounded Rationality

Even while it would be ideal to make every decision rationally, managers frequently face complex problems that make this unfeasible. The concept of "bounded rationality", which was introduced by Herbert A. Simon in 1957, refers to the notion that "*the world is large and complex, while human brains and their information-processing capacities are highly limited in comparison. Decision making thus becomes not so much rational as a vain effort to be rational*" (H. Simon, 1957). Thus, it is reasonable to state that there are three major constraints on human rationality: the amount of information available to them, the cognitive capacities of their minds, and the limited amount of time they have to make decisions. Consultants are awaited to assess several factors at once, and this crucial aspect frequently influences their decision-making process. Furthermore, the use of standard solutions has become less successful due to the increasing complexity of business problems, which raises the demand for consultants' judgment skills (K. M. Eisenhardt and M. J Zbaracki, 1992).

Uncertainty

Decisions are often made under conditions of uncertainty, which can be defined as the discrepancy between the knowledge at hand and the knowledge required to determine the optimal course of action. In the consulting sector uncertainty occurs from a variety of sources, including shifting market conditions, technology advancements, socioeconomic considerations, and legislative changes, adding complexity to decision making. The recent emergence of the global pandemic of COVID-19 is a tangible example of this uncertainty, which has created unprecedented situations, thus increasing the ambiguity and complexity of decision-making processes for consultants (S. Hadjisotiriou, V. Marchau, W. Walker, and M. O. Rikkert, 2023).

Time Constraint

Time restrictions are a common problem for managers, which can make it challenging to make effective decisions. When we talk about time constraints we refer to "*the difference between the amount of available time and the amount of time required to resolve a decision task*" (Benson & Beach, 1996). From this definition it is clear that it involves more than just time management. It is possible that despite the executives' excellent time management, an urgent decision was needed due to unforeseen circumstances. When faced with time constraints, decision makers have demonstrated a tendency to either revert to more basic tactics, stick with the same strategy if changing would require cognitive effort, or just go back to their previous behaviors (L. Ordóñez and L. Benson, 1997).

Escalation of Commitment

The escalation of commitment can be defined as the propensity for decision-makers to stick with the incorrect course of action, even when it produces progressively worse outcomes (J. Brockner, 1992). There are two main categories in which most explanations for this propensity fall in, and they both have to do with complimentary facets of human nature. First, the expectancy theory suggests that decision makers assess the possibility that further investment of resources will lead to the achievement of desired goals (V. H. Vroom, 1964). Second, the theory of cognitive dissonance holds that decision makers remain tied to a previous course of action to avoid admitting, to themselves or to others, that the resources previously invested have been allocated without success. This resistance to admitting past mistakes can lead to further effort in the initial course of action, even when it may not be the most rational choice. (L. Festinger, 1957).

Biases

Our personal biases also have an impact on the decisions we make and according to two pioneer researchers in cognitive biases - Amos Tversky and Daniel Kahneman - they frequently result in judgmental errors. In this context, the term "cognitive biases" refers to the tendency of people to rely on systematic but presumably inaccurate patterns of responses to problems of judgment and decision making (A. Tversky and D. Kahneman, 1970). Among the most common there are the "confirmation bias" (propensity to ignore or minimize contradicting facts in favor of seeking out, interpreting, and prioritizing information that support our pre-existing beliefs), the "anchoring bias" (inclination to overly rely on the initial piece of information, inhibiting adjustments when encountering new information), and the "in-group bias" (tendency to favor people perceived to be part of their own group over others).

Conflict

Conflicts are a natural part of life and are intrinsic to human interactions; they arise not only on a one-on-one level, but also within group dynamics (J. A. Schellenberg, 1996). According to James. A. Wall and Ronda R. Callister conflict can be defined as a situation where one party feels offended or annoyed by another (1995) and this dissatisfaction often results from opposing interests, especially when resources are limited, or objectives diverge. To narrow it down, it is possible to distinguish 3 types of conflict: task, relational, and process conflict. The former refers to different opinions about the content and could result, for example, from different interpretations or simply from different points of view on a given fact. The second category is about "interpersonal incompatibility" and this refers for example to differences in values and styles. Finally, process conflict includes how activities should be carried out, and some examples might be disagreements on who should do what or how responsibilities should be delegated (K. A. Jehn, 1995).

2.3. Artificial Intelligence and Decision Making

2.3.1. The Impact of AI on Human Decision-Making

Artificial intelligence has significantly transformed the decision-making process in the consulting industry. Where consultants once relied primarily on personal expertise, instinct, and traditional analytical tools, AI's ability to process and interpret massive amounts of data has enabled a shift toward more informed, data-driven decisions. According to Yash R. Shrestha, Shiko M. Ben-Menahem, and Georg von Krogh, three distinct forms of decision making can be distinguished based on the use of AI: "full human to AI delegation", "hybrid[10] sequential decision-making", and "aggregated human-AI decision-making" (2019).

In the first category, all decision-making is delegated to AI-based algorithms, meaning that human intervention is not necessary. This is especially helpful in situations where decision speed is crucial, there is a narrow and specific choice search space, a high number of alternatives, and interpretability of the conclusion is less important than prediction accuracy. It is clear that this form of decision-making in the consulting industry is still very limited. Examples of applications might include real-time product recommendation systems, such as the one used by Amazon, and dynamic pricing (Shrestha, Ben-Menahem and Krogh, 2019).
In "hybrid" decision-making structures, decisions are made successively by humans and AI-based algorithms, with the output from one being used as the input for the other. Within this category, two distinct sub-categories emerge. The first one sees algorithmic decisions as input to human decisions, and here artificial intelligence makes the initial decision. It acts as a filter, eliminating unnecessary or inappropriate options and sending a subset of acceptable options to a second stage, where a human decision maker makes a choice. When AI-based decisions are made early on, humans can handle scenarios with many options in an efficient manner. The opposite occurs in the second situation, where human decisions are used as inputs to algorithmic ones. Here, a smaller subset of options is initially chosen by human decision makers from a larger pool, and they are then passed to AI algorithms for the assessment and selection of the optimal option. This structure works well in situations where human decision makers have a high degree of confidence in a small number of alternatives, but in order to evaluate them effectively they must process a lot of data and carefully consider them over extended periods of time. When people are unsure about the optimal choice made, this approach can be used to efficiently take advantage of algorithms' predictive power (Shrestha, Ben-Menahem and Krogh, 2019).

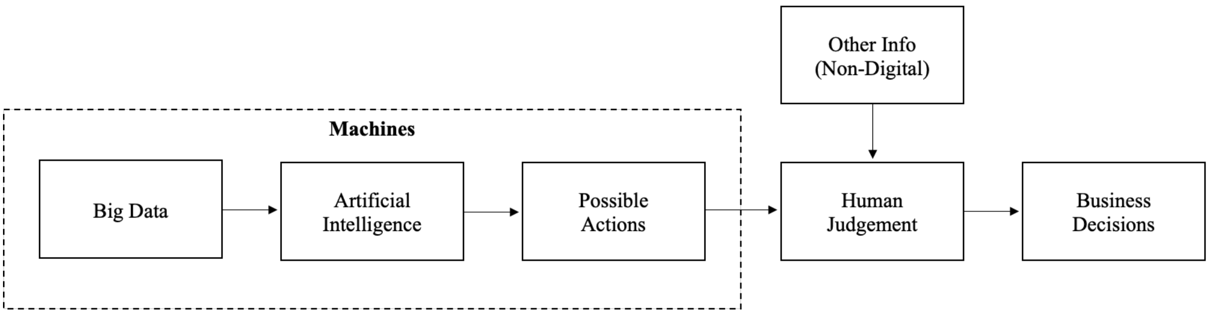
Finally, there are the "aggregated human-AI decision-making structures". This paradigm leverages the unique skills of humans and AI algorithms by first assigning tasks within decisions to one or the other. This results in a division of focus where each entity addresses distinct or overlapping aspects of the decision process according to their respective strengths. In contrast to hybrid decision-making structures where there is a significant degree of

[10] The term "hybrid" refers either to human-to-AI sequential decision-making or to AI-to-human one.

interaction between the human and AI-based decision maker, this type of decision making permits the independent combination of the two (Shrestha, Ben-Menahem and Krogh, 2019).

In the consulting industry, the most widely used decision-making style between the three that were just examined is the hybrid style - and more specifically "algorithmic decisions as input to human decisions" - as this allows both human and AI-based capabilities to be leveraged complementarily. Indeed, in complex contexts where a wide variety of skills and in-depth assessment is required, the hybrid approach allows consultants to integrate AI analysis with their own experience and intuition. Figure 3 illustrates the process just described: a typical decision flow where AI is initially employed to skim alternatives, followed by human intervention to make the final decision.

Figure 3: A Decision-Making Model that combines the power of AI and Human Judgement



Source: Eric Colson - Harvard Business Review

2.3.2. Improvements provided by AI in the Decisional Making process

The Consulting sector benefits from AI developments as it can harness its immense potential to optimize decision making.

One of the main advantages is improved data analysis. Because of the limits of human processing capacity (which we discussed earlier), the examination and interpretation of massive volumes of data has always been a great challenge. This limitation is even more evident today, in the era of "Big Data", where companies are accumulating ever-increasing amounts of data on a daily basis (B. Peters, 2012). On the contrary, AI is capable of handling and processing data with a speed and accuracy that far exceeds human capabilities. This allows consultants not only to expedite data analysis processes, but also to extrapolate information that might remain unnoticed by the human eye, helping to create more complete and accurate views (T. Davenport and J. Fitts, 2021). Through the lens of these deeper and more comprehensive analyses, consultants can provide data-driven recommendations and more sophisticated strategies designed around clients' specific goals. Thus, the end result is a more informed decision-making process (E. Brynjolfsson and A. McAfee, 2014).

The second major vantage is in the area of predictive analytics. Historically, the main method of making predictions was regression, a statistical technique based on the average of past events. But being exactly right on average could imply being incorrect all the time. On the other hand, while machine learning predictions may have lower accuracy overall, their errors are typically minimal. Advances in machine learning techniques are increasingly enabling the efficient transformation of available data into precise predictions, in fact, today regression and other methods are definitely being replaced by machine learning (A. Agrawal, J. Gans and A. Goldfarb, 2018). For consultants, this AI capability is crucial since it enables them to develop forward-looking strategies, identify potential risks, and consequently be able to take preventive measures and elaborate mitigation strategies.

Furthermore, consultants might use AI to automate repetitive or time-consuming tasks like trend identification, market research, and data analysis. This enables them to concentrate more on difficult, significant decisions (E. Brynjolfsson and A. McAfee, 2014). GenAI, for instance, allows consulting firms to speed up their clients' innovation cycles: by saving time, they can focus on higher-value tasks like strategic thinking and creative problem solving, resulting in faster and more efficient innovation (Ernst & Young, 2023).

These are just a few of the numerous advantages that artificial intelligence provides for decision making. As AI advances, its applications - and associated benefits - in the consulting industry are expected to broaden and deepen.

2.3.3 Drawbacks of utilizing AI for making decisions

Despite the numerous benefits discussed above, it is crucial to acknowledge that there are several limitations involved with applying artificial intelligence in consulting decision making.

When addressing AI, the first concerns that come up are trust and privacy. Advanced AI programs are so proficient at identifying data trends that they may unintentionally violate users' privacy (K. L. Siau and Y. Yang, 2017). According to Cameron F. Kerry "*As artificial intelligence evolves, it magnifies the ability to use personal information in ways that can intrude on privacy interests by raising analysis of personal information to new levels of power and speed*" (2020). This issue is particularly critical in the consulting profession, a field in which the management of confidential, sensitive, and sometimes exclusive client information is an important aspect of daily business.

Moving forward, the second significant challenge lies in quality control and monitoring of AI systems. Although the latter can provide many advanced insights, verifying its accuracy can be difficult due to its complex and often opaque nature. Indeed, while in traditional approaches consultants are able to clearly justify and explain their reasoning, GenAI, for example, often operates as a "black box". This means that it produces results without providing detailed explanations of the process that led to those conclusions. This creates a challenge for consultants trying to fully understand or justify the reasoning behind the recommendations. Moreover, this enigmatic component can further complicate attempts to build trust with the client, since it may be difficult for the latter to accept suggestions when he or she does not fully understand the logic or process behind such advice (T. Hafke, 2023). Related to this is there is the crucial importance of educating employees in the use of AI: in these days it is critical, and will be increasingly so as AI advances, that employees not only know how to use it, but also understand the logic behind its decisions. Proper training can provide them with the tools to make the most of AI's potential and to use this technology safely and ethically (Ernst & Young, 2023).

Finally, when it comes to the use of AI, another clear issue is information overload. While it is true that AI systems are capable of handling huge volumes of data, this may also result in information overwhelm and analytical paralysis, which makes it challenging to make wise decisions. Actually, this overabundance could divert attention from important issues, compromising the overall effectiveness and efficiency of decision making (Ernst & Young, 2023).

Going to draw conclusions, it is possible to understand how AI represents an indispensable tool for consultants today given the many advantages it offers in terms of accuracy, effectiveness, and data-driven insights. Indeed, three Vs can be used to summarize the current influence of AI: variety, volume, and velocity (T. Hafke, 2023). But it is important to point out that in order for consultants to fully benefit from this powerful instrument, it is imperative that they, as well as everyone else, have a thorough understanding of all facets of AI, both advantages and disadvantages.

Chapter 3: Case Study

This chapter will present a specific case study, exploring the adoption of artificial intelligence within Ernst & Young (EY), a leading global consulting firm. The first section of the chapter will introduce EY, its history, culture, and its innovative approach to AI. The second section will describe the methodology adopted for the study, detailing the data collection procedure and the conduct of interviews. Subsequently, the sampling strategy used to select the study population and the analysis techniques employed to interpret the collected data will be discussed.

3.1. Introduction to Ernst & Young (EY)

Ernst & Young's roots go back well over 100 years when the audit business was formed, and the generally accepted accounting practices developed. It found its origins in two large firms, Ernst & Whinney (founded in 1906, in Cleveland, Ohio), and Arthur Young (founded in 1895, in Kansas City). In 1989 these two large entities merged to form Ernst & Young, an international powerhouse of 70,000 employees in more than 100 countries. The goal was to create an organization that could compete more effectively with the other major accounting firms of the time (EY Past & Present, 2020).

Following several mergers[11] and strategic decisions, today Ernst & Young, commonly known as EY, represents one of the "Big Four" accounting firms along with Deloitte, PWC, and KPMG. It provides management, strategic, legal, tax, technology, organizational, and audit consulting; to date it has more than 365 million people and has over 700 offices in more than 150 countries (EY - About Us, 2024).

3.1.1. EY's approach to Artificial Intelligence

As we saw earlier, AI is transforming every business, and it has done so with EY as well. According to Chris Mazzei (EY Global Vice Chair, Strategy), AI is critical to the future of the firm because so much of what people do over time can be enhanced and complemented through the use of AI models. It is going to change the way they do everything; therefore, it is crucial to integrate AI across the entire practice to take advantage of its huge potential.

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[11] To cite an example, in 1995, EY expanded its range of services even more when it merged with Kenneth Leventhal & Co., the leading provider of professional services to the real estate investment and development community.

At EY, the approach to AI is different; instead of focusing on automation, they focus on augmentation. Then, the goal is to use AI to make employees more productive, more effective, and happier. In fact, if more mundane and repetitive tasks are automated, they are free to focus more on higher-level cognitive tasks. In addition, they have the opportunity to spend more time engaging in dialogue with customers and colleagues, asking new and better questions, generating new insights and increasing their knowledge (Ernst & Young, 2021).

Everything that is done in EY is anchored first by the goal of "building a better working world" and second by core values - integrity, respect, and ethics. Even if AI transforms some aspects of what is done within the company or changes entirely the way to operate, these values remain at the core of the business. Indeed, at this time of AI-enabled transformation, the intangible values that govern actions become more important than ever. This is the result of a responsible, people-centered approach to its design, implementation, and governance. The beauty of this approach is that there is a bidirectional relationship - that is, as AI is incorporated to augment people, AI itself can learn from them (EY.ai, 2024).

The fateful question is whether the ambition of the company lies in addressing some use cases and proofs of concept or is it a real transformation? EY's answer is undoubtedly the second - a true transformation. No doubt there is still a long way to go, but EY is acting in the right direction: to date, it has established more than 10 centers of excellence around the world with hundreds of AI scientists, engineers, and product developers creating and acquiring AI products and solutions. Moreover, it has established deep collaborations across the AI ecosystem with academia, technology companies, startups, and thought leaders. In 2021 it developed and deployed more than 20 new AI tools that are functional in every situation, from compliance to marketing, to back to the office. To mention some specific examples, two major solutions have been developed in the area of predictive analytics and data analysis (EY's AI journey, 2021). The first is "EY Intelligent Predictor", a solution that harnesses the power of deep learning to meet current and future demand forecasting needs. It differs from traditional forecasting methods which are based on a single source of historical data, combining internal and external data to produce highly accurate forecasts. The benefits are many: to start, a major decrease in manual labor enables the company to focus on other high-priority projects. In fact, traditional forecasting techniques require manual adjustments 90 percent of the time. Second, blind spots are reduced as a result of using multiple data sources to inform important business choices. In addition, there is improved alignment and transparency for reaching both financial and strategic objectives, and finally an increase in execution speed (by about 90%). To sum up, through this tool, more informed decisions can be made based on deep insights (EY Intelligent Predictor, 2022). Turning to the second example, EY analyzes hundreds of billions of transactions annually, which makes artificial intelligence crucial for this type of information. In fact, it can be leveraged to find anomalies, improve data quality, and classify transactions. During an interview with Nigel Duffy, EY Global AI Leader, he affirmed, "*For example, we use AI to analyze indirect tax transactions. Previously this was a very labor-intensive, very manual process, but by using AI to augment our people, we can process millions of transactions with much less effort and with higher quality*". While humans continue to handle the more complicated transactions, artificial intelligence has demonstrated the ability to learn rapidly enough to complete 95% of them successfully (EY's AI journey, 2021).

Certainly, the implementation and integration of AI is not easy, especially in a 170-year-old organization like EY, but according to the latter, the key to release sustained value over time is building trust. In order to establish confidence in AI, trust must be incorporated from the start; this means that in addition to performance, social and ethical factors must also be addressed. To do so, EY has created a program with three pillars:

1. "Trusted AI": provide examples that support the application of AI both inside and outside of EY in order to increase stakeholder acceptance of EY's capacity to produce positive outcomes and manage AI risks.
2. "AI in risk management": to promote the adoption of AI by enhancing existing services related to risk management and gaining competitive advantage through improving quality and efficiency in all their operations.
3. "Long-term value": to accelerate the use of AI to identify, assess and monitor the value generated for companies in terms of human, social and environmental resources.

In summary, it is incredibly important to build AI responsibly in ways that reflect the values of EY and of the societies in which we live in order to take full advantage of the potential that AI promises (Ernst & Young, 2021).

3.1.2. Introduction to Business Consulting: Business Design Unit

This thesis focuses on the analysis of two sectors within Ernst & Young: Business Consulting and Technology Consulting. The motivation for this choice stems in part from my personal work experience within the Business Consulting team; working closely with the latter made it easier for me to observe their behavior and especially the use made of AI. On the other hand, I felt it was important to investigate the Technology Consulting team as, considering the central importance of AI within the scope of this research, I thought that their technological expertise could offer more meaningful insights and deeper knowledge on the topic at hand. We will start by introducing Business Consulting and then move on to the Technology field.

Business Consulting represents a key aspect of EY's offering, which aims to provide companies with innovative strategies and specific solutions to address the complex challenges of the contemporary business world. In particular, EY's Business Consulting team supports its clients in major transformation processes by acting on business and operational models and sales/client management models for maximizing value creation and strengthening corporate sustainability. From this brief description it is possible to understand how EY's Business Consulting is more than just consulting; it is a synergistic set of specialized services that combine technological, strategic, operational, and organizational aspects to guide companies toward a complete transformation (EY - Business Consulting, 2024). Furthermore, in order to assist organizations in the changes brought about by the "digital age" and help them solve the complex challenges generated by it, EY provides a wide range of multidisciplinary expertise in Business Design, Enterprise Risk, Experience Design, Finance, Public, Supply chain and Technology Risk. In addition, it acts as a long-term strategic partner in the implementation of client transformation. Within this broad area of Business Consulting, our research focus is on a more specific team – the Business Design one, which works specifically within the Transportation market. The latter is defined by EY as *"the movement of people and goods by air, land and sea and help companies chart their course in today's disruptive landscape*" (EY - Transportation, 2024). The speed at which change is occurring, mostly because of digitization, is pushing transportation and logistics companies to innovate and evolve within their ecosystem, presenting many opportunities for growth. From aviation, to railways, to shipping, the EY team provides targeted services to help to improve the movement of people and goods around the world.

3.1.3. Introduction to Technology Consulting

Technology is becoming the key for innovation and expansion in today's quickly evolving business environment. Organizations require strategic direction along with strong technological know-how to continue operating profitably. In light of this, EY's Technology Consulting provides companies with an extensive range of services aimed at helping them realize the full potential of technology, promote digital transformation, and find long-term success in the digital era. But each organization has its specific needs and objectives, therefore EY's team of professionals collaborates closely with its customers to create customized solutions. As a strategic partner in achieving transformation, EY combines technical know-how, in-depth industry knowledge, and creative thinking in technology consulting with competence in strategy, business, tax, legal, and assurance (EY - Technology Consulting, 2024).

To be more precise, EY's technology consulting portfolio includes solutions in Technology Transformation, Data & Analytics, Technology Solution Delivery, Digital & Emerging Technology, and Cyber Security and Digital Protection. When it comes to technology transformation, EY guides clients in defining winning strategies and optimizing processes through leading solutions such as ServiceNow, ensuring efficiency, security, and scalability. Strategy, creativity, and knowledge set EY solutions apart (EY - Technology Transformation, 2024). On the other side, the EY Data & Analytics team helps clients become data-driven companies by making data and artificial intelligence indispensable tools for decision-making and problem-solving in business. The end-to-end approach, innovation practices integrated with other service lines and industry expertise, a comprehensive innovation offering, and a business model that empowers executives to meet future challenges and create new business models are key differentiators of EY Data & Analytics' offerings (EY - Data & Analytics, 2024). Moving on to EY's “Technology Solution Delivery” section, it discusses the difficulties associated with digital transformation and how to use technology to enhance organizations and processes. Using the newest software platforms, they develop, implement, and manage end-to-end IT solutions for key business functions. The goal is to oversee the development of Core Enterprise Applications and oversee their whole lifecycle, from ideation to maintenance (EY - Technology Solution Delivery, 2024). With regard to “Digital & Emerging Technology” solutions, EY employs a combination of enabling and transformative technologies, including Mixed Reality, Blockchain, Cloud, Metaverse, and Quantum Computing, to help clients identify the best options for them and develop transformation business plans. The result is that these technologies provide competitive advantages (EY - Digital & Emerging Technology, 2024). Finally, the Cyber Security and Digital Protection practice consists of 150 experts who increase the digital confidence of companies by facilitating the adoption of innovative technologies and managing cyber risks. The team supports clients from cyber security strategy to security operations management and its integral approach is based on the principle of

Security by Design, applied to the areas of people, processes and technology (EY - Cyber Security and Digital Protection, 2024).

By analyzing these two areas within Ernst & Young, we aim to gain a clearer view of how major consulting firms like EY are leveraging artificial intelligence in their decision-making processes.

3.2. Methodology

The objective of this study is to answer the following research question: "*How can the use of artificial intelligence improve the decision-making process within consulting firms?*". Thus, what this thesis sought to do is to understand what respondents think about using artificial intelligence to make business decisions, and how they perceive its impact on the quality and effectiveness of their decisions. Additionally, this chapter describes the underlying reasons for choosing to use a qualitative rather than quantitative research methodology to answer this question. The following table (Figure 4) illustrates the main differences between the two methodologies in terms of objectives, sample, data collection methods and analysis, giving us a deeper understanding of why qualitative methodology is particularly well suited to answer our research question.

Figure 4: Quantitative vs Qualitative Analysis

	Quantitative	**Qualitative**
Research Question	Specific, narrow focusing on testing hypotheses ("*what*" questions)	Broad and flexible, focusing on generating hypotheses ("*how*" or "*why*" questions)
Purpose	Measure and statistically analyze data to reveal underlying patterns and relationships	Understand and interpret social interaction
Nature of data	Words, Image, Objects	Numbers and Statistics
Sample	Larger, selected randomly	Small, selected intentionally
Collection Methods	Surveys, Experiments	Interviews, Observations, Documents
Study Design	Pre-structured	Flexible
Outcome	Results can be generalized to a larger population, often representing averages	Results, representing participants' views and experiences, are not generalizable to the population

Source: Social Research Methods - Oxford University

Qualitative research makes it possible to investigate complex phenomena for which it would not be possible to use standardized measures (M. Q. Patton, 2002). A perfect example of such a phenomenon is artificial intelligence that, with its comprehensive influence on various facets of the decision-making process within the consulting industry, makes the qualitative approach pertinent. The latter is particularly appropriate when a research question requires an in-depth understanding of the problem under investigation. Since the goal of our study was to learn about the experiences and perceptions of people who deal with AI on a daily basis in their work, a quantitative approach might have proved unable to capture the nuances and complexity of such interaction. Finally, another reason underlying the choice is that quantitative research tends to depend on pre-existing tools, making it difficult to conduct analysis in under-researched or under-developed areas such as this (J. A. Maxwell, 2012).

In light of these considerations, the research methodology chosen does not only align with the study's objectives, but also contributes to the broader discourse on AI's integration into businesses by filling a research gap with in-depth, first-hand knowledge and insights.

3.2.1. Data Collection Procedure

Documents, interviews, and observations are the primary data gathering methods used in qualitative research: according to the purpose of this thesis, conducting interviews was the most suitable method, therefore I decided to move forward with it.

Similar to a simple conversation, an interview involves drawing out the experiences of the interviewees and explaining how those experiences have impacted their life, or in this case, their job. The aim of the interview, in fact, consists of "*entering into the other person's perspective*" (M. Q. Patton, 2002). However, "qualitative interview" is a broad term that brings together structured, semi-structured and unstructured interviews. These three types all have their advantages and disadvantages and are suitable for different contexts. Starting with structured interviews, the researcher follows a rigid set of predefined questions, consequently not being able to change the order or content of the questions during the interview. This type is commonly used when it is desired to collect standardized data from a wide range of participants (J. W. Creswell, 2009). In semi-structured interviews, on the other hand, the interviewer yes has a set of predefined questions, but also has the flexibility to explore topics in more detail. The order of questions can change, and new questions can be inserted in response to what the interviewee has said. Finally, in unstructured interviews, interviewers only have a general topic to discuss with participants and do not follow a predefined set of questions. This category is most effective when you want to get an in-depth comprehension of a certain phenomenon within a specific cultural context; however, it is not useful when you already have a basic understanding of a phenomenon and want to focus on specific parts of it (K. F. Punch, 1998).

As can be understood from this description, semi-structured interviews proved to be the most appropriate category to study our research question. In fact, conducting structured interviews with predefined and rigid questions could have limited the possibility of exploring participants' experiences and perceptions in depth. Capturing details and nuances in participants' responses would have been complicated. Unstructured interviews would also have had their limitations: lacking a defined guide would not have made it possible to compare participants' responses (J. W. Creswell, 2009). In conclusion, semi-structured interviews are generally preferred for addressing complex and specific research questions such as the one investigated in this thesis because they provide a balance of flexibility and structure, allowing participants' experiences to be explored in a detailed and focused manner.

3.2.1.1. Interview Guide

As stated in the previous paragraph, the methodology chosen for data collection is the semi-structured interview, so it was necessary to structure an interview guide. The interview guide has multiple purposes, but among the main ones identified, there are two. First, it acts as a memory aid to ensure that the interviewer covers all the intended topics. Second, the interview guide facilitates data analysis; in fact, by making interviews more uniform, responses can be easily compared and categorized (Cambridge University Press, 2015).

In order to write good interview questions, they must have two crucial features. First, they must obtain full, rich, and personalized narratives from participants, encouraging them to share their reflections on their experiences. Indeed, they are referred to as open-ended questions and only rarely as questions about specific facts or questions that simply require agreement or disagreement (i.e., yes/no questions). The second characteristic is that they must provide content that is directly related to the interview topics. With this in mind, I went on to structure the interview guide.

Before starting each interview, consent was sought to have it recorded and later transcribed. Then, the interview[12] itself was divided into six sections, each consisting of two questions, except the last one of only one, for a total of eleven questions. The first part focuses on the participant's current position within the company and the type of decisions he or she makes. After that, we focused on the use of AI in the participant's daily work, trying to understand the frequency with which he or she uses AI-based tools and the impact they have had on his or her decision-making process. Next, there are some more specific questions regarding the impact of AI on decision-making: investigating what types of decisions the participant feels most comfortable delegating to AI-based tools and whether he or she has noticed improvements in the way he makes decisions since he started using them. In the fourth part, the main challenges and advantages in using AI in decision making are discussed. An attempt was then made to understand what obstacles or concerns the participant may have encountered using these tools and what benefits he or she has gained from them. Training was another key aspect of the discussion: the participant was asked whether he or she received sufficient training to effectively use AI-based tools and whether he or she sought out opportunities for independent learning. Finally, the interview concluded with a reflection on the future, seeking to understand the participant's expectations for the role of AI in decision making within EY.

3.2.1.2. Pilot-testing the Interview Guide

Once the preliminary interview guide was constructed, a key phase of my research was the pilot testing of it. The first step was to ask one of my colleagues if she would be willing to do this test interview, and she gave me her full willingness.

The pilot testing has two different but both fundamental objectives. The first is that it allowed me to refine my interview guide by reviewing the questions formulated, their order, and consequently make the necessary changes. Through this rehearsal I was able to make sure that the questions were correctly phrased, with simple terms and not technicalities that perhaps not everyone knows. In addition, I could see if participants understood the questions in the way I intended. This was a crucial step because if they did not, the answers obtained to my questions might not have been relevant to the objective of my research. Finally, I was able to check whether I had covered all the topics I was interested in.

[12] To see the entire interview guide, go to section “Appendix”

In practice I went to rephrase three questions: the first was question number four: "*in which specific areas do you think AI had the most impact in decision making*" as it was causing confusion in the respondent not understanding "*in which areas*" for what it stood for. Therefore, I realized that the one was not worded well, so it was replaced with the following "*At what stage of the decision-making process do you think AI had the greatest impact? (ex: information search, choice, implementation...)*". The other two questions to which changes were made related to the "Benefits and Challenges in Using AI" section, and specifically were number seven and eight. They would have been too broad, so I went to add specific examples at the end of the question to give participants help in structuring their response.

The second objective of the pilot testing is more about practice, in fact the testing gave me the opportunity to perform the interview and become familiar with it. Knowing how to do an interview is a skill one acquires with experience, but without a doubt this practice interview helped me greatly. At the end of it, I asked the participant first of all whether or not I had succeeded in putting her at ease. Next, I asked her how she had felt about the way I had asked and handled the questions and my ways of soliciting further responses. Finally, I then went on to ask if she had handled some topics differently or added others.

The last step I took was to listen again to the recording of the test interview to understand firsthand what my style and behavior had been like as well. This allowed me to analyze my pace, voice volume, the speed with which I spoke as well as my approach with the interviewee. As a result, not only was I able to refine my interviewing guidance through the pilot tests, but I also took the opportunity to develop greater self-awareness and competence as an interviewer, aspects that I believe are critical to conducting effective interviews.

3.2.1.3. Conducting Interviews

Of the different ways in which interviews can be conducted, doing them face-to-face is considered the oldest and preferred method. Because of its advantages and the results I wished to obtain, I selected this type to conduct the interviews.

One of the first advantages that led me to select this type is direct human contact. In fact, by doing the interviews in person I was able to personally meet, see, and talk with the interviewee, perhaps catching something that I would not have been able to do at distance (W. L. Neuman, 2012). By this I refer to the so-called "non-verbal language" that I have been able to capture, such as body language, gesticulation, and facial expressions. These clues often offer strong insight into the interviewee's emotional state and sincerity, adding considerable depth to their responses and providing valuable context to the information they share (J. A. Hall, T. G. Horgan,and N. A. Murphy, 2018). In addition, the interviewer's first task is to put the participant at ease from the beginning of the interview, and conducting interviews in person allowed me to do just that: it fostered a more open, two-way dialogue. In addition, being present in the same physical space often made it easier to establish rapport and bond with the interviewee (Cambridge University Press, 2015). This fosters a feeling of trust and improved relationship that encourage respondents to provide honest answers and share information. Not surprisingly, participants indicate a higher level of satisfaction when interviewed in person rather than via phone or web (Hoolbork et al. 2003). Finally, face-to-face interviews allowed me to adapt on the spot based on the respondent's answers, allowing me to elaborate on their answers with immediate follow-up questions. Unlike online or telephone interviews, where technical difficulties or delays can interrupt the flow of the conversation, face-to-face interviews are free of such interruptions. In sum, although they may require more time and effort, the unique advantages of face-to-face interviews - in terms of obtaining richer and more nuanced data - made them the clear choice for data collection.

However, it is always good to emphasize the fact that "*the quality of information obtained during an interview depends largely on the interviewer*" (M. Q. Patton, 2015). For this reason, the following ten interviewing principles were always kept in mind to ensure the quality of interviews and data obtained.

1. Use open-ended inquiries that create an environment for the interviewee to provide comprehensive answers.
2. Pose questions that are direct, comprehensible, and concentrated on the topic at hand, allowing for responses that are insightful and relevant.
3. Ensure the interviewee feels heard by actively and attentively listening, then respond accordingly.
4. Request more information or clarity when responses are not complete, to ensure a well-rounded understanding of the interviewee's perspective.
5. Treat each interview as an opportunity for observation to better direct the course of conversation.
6. Display empathy while maintaining neutrality, providing non-judgmental support and showing genuineness in your interest.

7. Smoothly guide the conversation from one topic to another to maintain the flow of the interview.
8. Know when to use different types of questions, like interpretive, descriptive, behavioral, knowledge-based, or those that address feelings or attitudes.
9. Be adaptable and ready to handle unexpected turns in the conversation for maintaining its effectiveness.
10. Stay committed and attentive through the entire interview process, ensuring the interviewee that their responses are valued, and keeping distractions to a minimum.

Ended the interview questions, I thanked each interviewee and left room for any questions they might have.

3.2.2. Population and Sampling Procedure

One of the biggest debates and most frequent questions regarding qualitative research is “How large should the sample size be?”. There are different views on the types of sampling techniques in qualitative research. If we were to take Morse (1991) as a reference, he identified four types of sampling: the purposeful or theoretical sampling, the nominated sample, the volunteer sample, and the sample that includes the whole population. Nevertheless, one thing that is agreed upon is that all types of sampling techniques in qualitative research can be included in a broader term, namely “purposeful sampling” (M. Shaheen, S. Pradhan, and R. Ranajee, 2021). This refers to the fact that qualitative research typically focuses on “*relatively small samples, even single cases, selected intentionally*” (M. Q. Patton, 1990). This is due to the fact that qualitative research methods frequently aim to gain an in-depth understanding of a phenomenon, with a focus on the how and why of a particular issue, procedure, or group of social interactions. Since the purpose of my research is to understand whether EY employees use artificial intelligence when making decisions and its impact on them, I went to select consultants in the Business Consulting and Technology Consulting area of the Rome office. They belong to different positions, starting from interns up to Senior managers, and this gives me the possibility to have an all-inclusive understanding of the phenomenon. This precise selection, rather than a broader sample across the organization, is designed to provide a detailed and relevant overview of the use of artificial intelligence in the context of two specific teams. Furthermore, the choice to include individuals from the entire hierarchy of job positions in the membership is motivated by the desire to understand how AI can influence decisions at various levels of responsibility. The purpose of interviewing is not so much to make generalizations to a larger population of interest, much less to rely on hypothesis testing, but is more inductive and emergent in its process. Accordingly, the goal of them is to create categories from the data and then analyze the relationships between the categories, paying attention to how the "lived experience" of research participants can be understood.

So far, we have seen that there are various discussions about what is the right sample size for this type of research. However, most scholars argue that two concepts - that of "saturation" and "data sufficiency" - are the most important factors to consider in determining this (M. Mason, 2010). Saturation can be defined as "*the point at which the data collection process no longer offers new or relevant data*" (K. Charmaz, 2006). If, on the other hand, we were to consider the conceptual categories of a research project, they are defined as saturated when "*the collection of new data no longer elicits new theoretical insights or reveals new properties of your main theoretical categories*" (K. Charmaz, 2006). On the other hand, "data sufficiency" refers to having enough data to adequately answer the research question. However, "*the logic of data sufficiency is driven by the researcher's perception of what constitutes sufficient evidence to achieve the purpose of the synthesis*" (H. Suri, 2011).
Saturation depends on many factors and not all of them are within the control of the researcher. Some of these include the scope and nature of the study, the quality of the data received, the amount of useful information obtained from each respondent, and the use of shadowed data. Regarding the "scope" of the study, the broader the scope of the research, the longer it will take to reach data saturation. If it is necessary to narrow the topic of the study it should be done at an early stage, however, it should not be done at the expense of losing important aspects of the topic under study (M. Shaheen, S. Pradhan, and R. Ranajee, 2021). When I went to formulate my research question, the first thing I did was to select a specific industry and a specific company, in order not to make the study too broad. In fact, I was aware that narrowing the scope would allow me to conduct a much more meticulous, and comprehensive, analysis. Moreover, this focus provided a well-defined contextual framework, simplifying the process of data collection through targeted interviews. When we talk about the "nature" of the topic we refer to whether it is familiar and clear or not and whether the information is easily accessible and available or not. In this case fewer respondents will be needed. Therefore, as we saw earlier, what I went to do was to make the topic as clear as possible and define it correctly so that the respondents could understand it easily and provide clearer information. The third factor to consider is "data quality", which is crucial in determining the number of respondents needed for the study. The quality depends on the respondents' familiarity with the phenomenon under study, their experiences or, for example, their understanding of the researcher's objectives and

the amount of time spent. Consequently, care must be taken to select the right informants. Indeed, my choice of interviewees was guided by the knowledge that they were familiar with the phenomenon and had related to AI previously. Finally, there is the so-called “shadowed data” that is, information reported by respondents about the experiences of others. Sometimes participants discuss how their own experience differs or resembles others, and why (M. Morse, 2000). However, in my study this was not asked because what we were interested in was how each employee related to AI in his or her daily work, consequently going to ask about others' experiences would not add value to the research.

Downstream of all these considerations, in my opinion, data saturation and sufficiency were achieved with a sample size of 10 people. The table below (Figure 5) is intended to offer a clearer understanding of the people interviewed, starting with age, gender, current position, and years of experience in the field.

Figure 5: Interview Respondents

Respondent	**Gender**	**Age**	**Current Position**	**# of years of experience as a consultant**	**# of interview minutes**	**Business Line**
1	Female	23	Intern Consultant	0,6	8:51	Business Consulting
2	Female	25	Intern Consultant	0,6	9:48	Business Consulting
3	Female	26	Senior 1	3	6:54	Technology Consulting
4	Male	22	Intern Consultant	0,6	8:22	Technology Consulting
5	Female	25	Staff 2	2	7:26	Technology Consulting
6	Female	25	Staff 2	1,6	9:28	Business Consulting
7	Male	26	Senior 1	2,6	8:37	Business Consulting
8	Male	25	Staff 1	1	6:57	Business Consulting
9	Female	47	Manager 3	3,6	16:19	Technology Consulting
10	Male	36	Senior Manager 1	5,6	14:12	Business Consulting

Demographic information (gender and age) allows the reader to better understand the different personal perspectives of each respondent, and how more or less teams within EY are composed. Our specific sample consists of 10 employees of whom 6 are female (60%) and 4 are male (40%). As far as age is concerned, the average age is 28 years, with a minimum age of 22 and a maximum of 47. However, if we divide the sample into age groups 20-29; 30-39; 40-49; we can see that the majority (80%) belong to the first group. In contrast, the 30-39 and 40-49 age groups are represented by only one participant each, constituting only 10% of the sample for each age group. In addition, it is well known that when the so-called "outliers" are present in a data set, that are those that deviate significantly from the other data and thus represent very high or low values, the average can be distorted. In our case, in fact, there is one value (47) that deviates significantly from the other data, making the average value higher. If, on the contrary, we were to consider the median, this would be 25. Sometimes, when there are outliers, it is preferable to refer to the median[13] as it is not influenced by the latter and may better represent the "center" of the data.

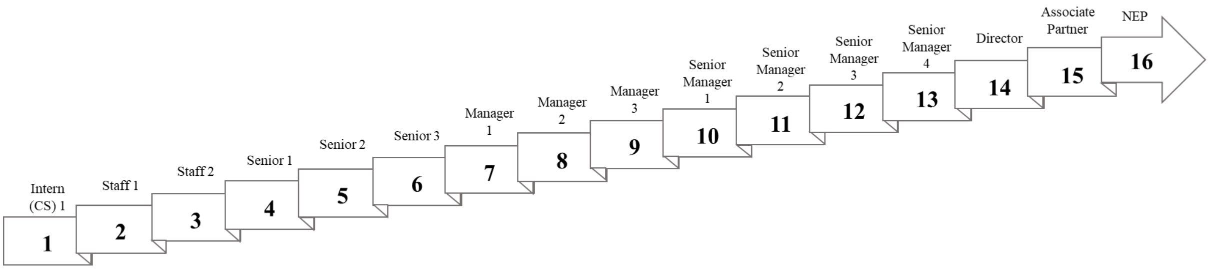
The respondents' current position in the industry adds another layer of enrichment to the data collected. This in fact, along with their years of experience in the industry, gives us an overview of the different levels of power and responsibility within the EY team and their respective expertise. Usually, those with more experience can provide insights that come from time and familiarity with industry trends and changes. They may also have differences in perception from those who are relatively new to the field, which may offer fresh and perhaps even disruptive perspectives. If we look at the distribution of positions in our sample of 10 respondents, it is varied. There is a prevalence of entry-level and staff figures, with three "Intern Consultants" and three "Staff", together accounting for 60% of the sample. The Interns have less than a year's experience each, but as stated earlier they bring value to our analysis as what differentiates them most is their curiosity, innovation, and freshness of approach. Staff, on the other hand, present different years of experience ranging from 1 (Respondent 8) and 2 (Respondent 5). This is followed by two respondents in Senior Consultant positions, representing 20% of the population and having an average of 2.8 years of experience. Finally, the picture of positions in our sample is completed by more experienced and senior figures. We have a "Manager 3" (10% of the sample) who has 3.6 years of experience in this sector and a

[13] In an ordered data set, the median is the value that lies exactly in the middle of it. Consequently, it is a measure of the central tendency separating the lowest 50% from the highest 50% of values.

“Senior Manager 1” who, with the most years spent in the industry, provides an essential perspective on the evolutionary impact artificial intelligence is having on EY's consulting strategies (also representing 10% of the population).

To get a better understanding of the different positions within EY, I have shown the hierarchical scale of the company in Figure 6. This visual representation will help to illustrate the sequential progression of positions, plus it is useful in assessing the perspectives and experiences of the respondents in the context of their specific position within the hierarchy.

Figure 6: Consulting Rank



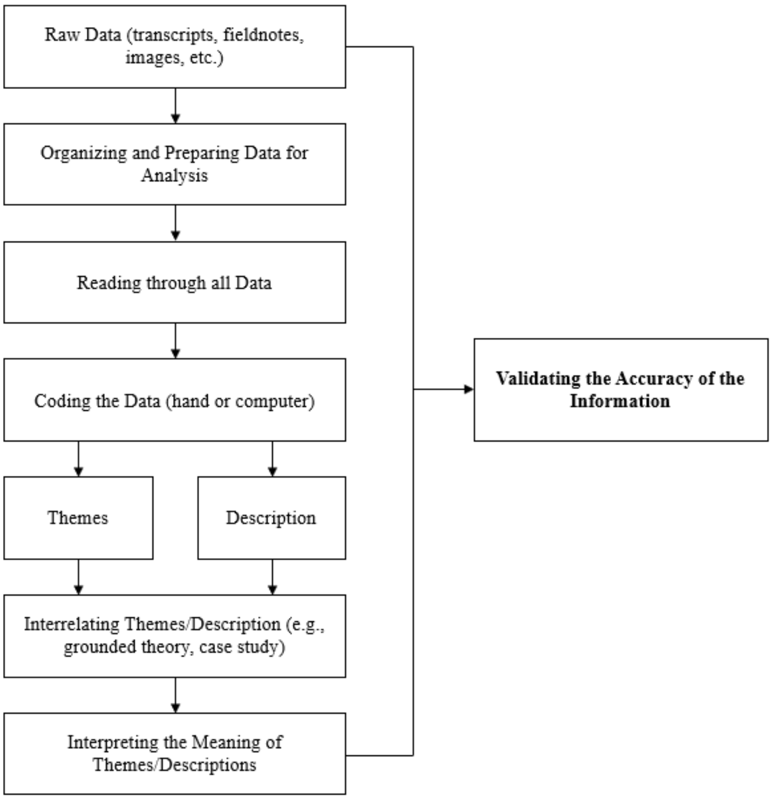
Source: Ernst & Young

The diversity of the sample in terms of roles and experience with artificial intelligence ensures that the results discussed in the thesis are based on a comprehensive understanding of the use of AI in EY. This approach provided a deeper insight into the applicability, benefits, and limitations of AI as a decision-making tool in the consulting industry.

3.2.3. Data Analysis Techniques

Unlike quantitative research in which there are specific and consecutive steps i.e., data collection, information analysis and finally report writing, data analysis in qualitative research will proceed hand in hand with the other parts of the study development (J. W. Creswell, 2013). In this research, data analysis was divided into 7 steps, which are those that are generally carried out in a qualitative study, and which are illustrated in Figure 7.

Figure 7: Data Analysis in Qualitative Research



Source: John W. Creswell

The first phase - "raw data" - consists of the literal transcription of the recorded interviews and note-taking during them. Personally, after every single interview, the first thing I did was to listen to the recordings again and transcribe them manually. As for the notes, however, rather than jotting down cues about what the interviewee was saying, I preferred to focus more on body expressions. This is because I knew that they were recorded only vocally, so what was said I could retrieve while what was done was not. Digitization of this data was another crucial step in this process: the notes about each interviewee were transcribed to the same document in which his or her interview was written. For me, this was a key step in making the collected data more manageable and was essential to facilitate the next stages of analysis.

In most cases, data are not completely ready for analysis at the time they are collected. This is where the second stage of "organizing and preparing the data" begins. First, as soon as data are collected, appropriate and well-developed physical and/or digital storage systems are needed to ensure that data are stored securely and well organized (M. M. L. Arthur, 2021). In my case, I opted for digital archiving: I created a single folder with the different files inside with the name "NumberResponse_Position_Data". In addition, in a different document I went to create a tabular record showing the number of the respondent, the location and the corresponding duration of the interview to keep track of the number and the time spent. Then, researchers need to address data formatting and layout. Developing a consistent template for data and documents is helpful for the next steps in the process (J. W. Creswell, 2013). Once a consistent template is created, all data can be structured to fit this template. This facilitates the quick identification of specific information, making comparison between different data sets easier and more systematic. In addition, uniformity also helps to recognize any patterns, correlations or even errors[14] that might be present among the information collected.

Once organized and transcribed, researchers need to familiarize themselves with the data they have collected. The phase of "reading through all the data" can be thought of as an initial analysis, in which notes are taken of initial reflections or any emerging interpretations. These notes are as a "*conversation with ourselves about our data*" (A. E. Clarke, 2005). In fact, as I went through the various interviews again, I was already trying to grasp possible similarities or differences from one another, providing possible insights for further reflection. In addition, familiarization with the first interviews also allowed me to guide subsequent ones, to dwell on points of particular interest or to seek clarification on certain aspects in particular. However, it is important that these notes "*be suggestive and not conclusive*" (I. Dey, 1993).

With the fourth stage - coding - we come to the central part of the analysis process being the moment when meaning is given to the collected data. As can be understood from the name, coding consists of using "codes", that is, words or short phrases representing a category to organize the data (G. B. Rossman and S. F. Rallis, 2012). In practice this involves taking data, segmenting the phrases into categories, and then labeling those categories with a term, usually based on the participant's actual language - called an "*in vivo"* term. To be more specific, 3 consecutive sub-steps can be identified. In the first stage, the researcher associates generic codes with the complete data set with the aim of reducing its size. These are descriptive tags that identify interesting experiences and cues but raise a relatively low level of inference (J. N. Lester, Y. Cho, and C. R. Lochmiller, 2020). Subsequently, the interviewers revisit the sentences or paragraphs to which they assigned codes in the first phase in order to review them and assign further codes, arriving at a higher level of inference. In fact, here, the researcher

[14] Since the data were collected and transcribed manually, there could be typos or duplicates or whatever, so it is always good to do a second verification.

starts looking at the data more closely; he or she continues coding but trying to be more specific and detailed in the codes assigned. The purpose of this second sub-phase is to start linking the statements and experiences of the interviewees with the objective of the research. Finally, with the third stage the highest level of interference is generally reached: the codes are grouped into broader categories, and this helps to see patterns in the data, beginning to form a more complete picture of what data are saying (J. N. Lester, Y. Cho, and C. R. Lochmiller, 2020). In fact, the codes themselves do not convey the whole story. To do so, it is necessary to comprehend how codes interrelate and counter with each other, which means how they are encompassed in categories.

Personally, I began the coding process by carefully reading and re-reading each transcribed interview with the aim of fully understanding the data and then extracting meaningful words or phrases. I then went on to associate 'codes' with particular segments of the interviews. In my study, five main codes emerged - Organizational Context (OC), Decision Making (DM), Artificial Intelligence (AI), Training and Support (TS) and Future of Artificial Intelligence (FAI). Each of these codes also included specific sub-codes (Figure 8).

Figure 8: Transcription codes

Codes	Description of Codes	Sub-Codes	Description of Sub-Codes
OC	Organizational Context	OC-CP	Current Position
		OC-R	Responsibilities
DM	Decision Making	DM-TD	Type of Decisions
		DM-ID	Impact of Decisions
		DM-DATAI	Decisions Attribute To AI
		DM-DATH	Decisions Attribute To Human
AI	Artificial Intelligence	AI-FU	Frequency and Usage
		AI-IP	AI Impact Phase
		AI-IB	Improvements and Benefits
		AI-TL	Trust and Limits
TS	Training and Support	TS-AT	AI Training
		TS-SL	Self-Learning
FAI	Future of Artificial Intelligence	FAI-E	Expectations on future usage of AI
		FAI-EY	Future role of AI in EY

With the code "Organizational Context (OC)" I wanted to encapsulate all the information concerning the context in which I went to carry out the interviews, i.e., the context of EY. Within this more general code, two more specific sub-codes were identified: the first is the "Current Position (OC-CP)", which refers to the role that the interviewee held at the time of the interview within EY; the second is “Responsibilities (OC-R)”, which refers to the tasks and consequently the associated responsibilities that each employee is called upon to perform as a result of the position held.

The second main code is “Decision Making (DM)”, which describes the decision-making process followed by employees. This in turn has also been broken down into sub-codes and this time four have been identified, namely: “Type of Decisions (DM-TD)”, to better understand what types of decisions people at EY have to make every day, and thanks to this code we could see how these differ according to the role they hold. Then we have “Decision Impact (DM-ID)”, to understand what the result of the decisions made is and what kind of impact they may have on everyday work or even on the project as a whole. Finally, the last two sub-codes are “Decisions attributed to AI (DM-DATAI)” and “Decisions attributed to humans (DM-DATH)”, to identify which types of decisions employees prefer to make themselves, and which ones they entrust to AI.

Moving on, there is the “Artificial Intelligence (AI)” code that encompasses all the various aspects of AI within EY, from its use to its limitations. As with the “Decision Making” code, four sub-codes were identified here, and this stems from the fact that decision making and artificial intelligence are the two variables that this research focuses on, consequently an attempt was made to gather as much information as possible around them. The higher number and specificity of these sub-codes comes from wanting to analyze and understand in more detail the information obtained around the two main variables. The “Frequency and Usage (AI-FU)” sub-code encompasses everything around the time, number, and manner in which AI-based tools are used within the company. “AI Impact Phase (AI-IP)”, to understand which stage of the decision-making process was most impacted by the introduction of AI; “Improvements and Benefits (AI-IB)”, to outline what were the greatest benefits of using AI found by the respondents; and finally, “Trust and Limits (AI-TL)”, to understand what limitations and concerns the respondents have about such tools.

The fourth main code is “Training and Support (TS)”, and this includes all the study that was done by the participants to learn how to properly use these AI tools. Here the two sub-codes “AI training (S-AT)” and “Self-Learning (TS-SL)” aim to distinguish what was the part of the study that was done independently by the participant and what is owed to EY instead. In addition to this, they also aim to understand what ongoing support EY provides to its employees in terms of AI.

To conclude, the last main code "Future of Artificial Intelligence (FAI)" focuses on what the future of this technology will be according to the participants, and this is divided into what will be the future of AI in general, i.e., regardless of the work context, and what will be its use within EY, included in the sub-codes "Expectations on future usage of AI (FAI-E)" and "Future role of AI in EY (FAI-EY)" respectively.

As mentioned earlier, once coding is finished, a higher level of interference is reached. The generated codes and sub-codes are analyzed to understand whether there are similarities and connections between them so that they can be grouped in turn into larger categories, known as "themes". In addition, this stage also includes deciding how the themes and description will be represented in the qualitative storytelling moment (J. W. Creswell, 2013). In most cases a narrative is opted for in order to convey the results of the analysis, and this was also the choice in my case.

Having reached this point, the last remaining step is the interpretation of the collected data; here the researcher tries to create a comprehensive picture of the results obtained. To explain simply what this stage consists of, Y. S. Lincoln and E. G. Guba stated that it is all about being able to answer the question "What were the lessons learned?" (Y.S. Lincoln and E. G. Guba, 1985). In my case, what was done was to compare on the one hand what I learned from the experiences of my colleagues, parallel to my internship experience in EY, with previous knowledge drawn from the literature. Through this step I was able to understand whether my results were in line and thus confirmed what had been stated so far or not, also raising new aspects of interest and future studies. All this will be covered in more detail in the next phase of "Results and Discussion".

Chapter 4: Results and Discussion

This chapter delves into the results obtained, by opening a discussion on the perception of artificial intelligence among EY employees. Initially, it will explore the decision-making model within the organization, and then understand the current use of this technology and its impact throughout the decision-making stages. It will investigate whether and how AI can truly enhance decision-making processes and finally it will conclude by exploring future expectations regulated to the use of AI at EY.

4.1. EY's Decision Making Dynamics

In this first section, we will look at the dynamics of decision-making within EY. Thanks to the interviews carried out, it was possible to understand how, depending on the different positions held, the decisions taken vary and, consequently, also the impacts associated with them.

Starting with the analysis of the initial positions, i.e., the trainees (respondents 1, 2 and 4), it emerged that their decision-making perimeter is quite narrow, and this is justified by their lack of seniority in the field. Indeed, these are purely operational decisions; actually, all three respondents emphasized the fact that rather than making decisions, they execute them. In fact, the statements were very similar for both the Business and Technology Consulting service lines. For example, Respondent 1, from the Business Design area stated "*I can maybe give hints for improvement, ideas or maybe if there is something to be done and implemented I do it, but let's say I don't have decision-making power*"; from this brief declaration it can be seen that although she can help in generating ideas, the strategic choices and the overall project performance remain outside her sphere of influence. If we were also to analyze what Respondent 4, from the area of Technology Design, said: "*Let's say that for now the responsibility I am given is quite limited, so I would say that my decisions mostly affect the tasks I am assigned, I don't have a responsibility that impacts on the progress of the group project. I have mostly personal, self-management responsibilities for time and work".* Here, too, it emerges that the responsibilities relate more to his personal work rather than to the whole team. The tasks entrusted in the first months in the company are very precise tasks, which are functional for wider company processes, consequently also the impact is relatively low. While it is true that the interviewees in entry-level positions perform very practical and simple tasks and their impact does not seem to be far-reaching or decisive, their small insights and suggestions can positively influence the entire team.

Moving to the immediately higher level, that of Staff (taking into account both levels 1 and 2), there is a shift from the mere execution of assigned tasks and the conception of possible inputs to a more active participation in the creation of the final project. In fact, those at this level often act as a crucial link between EY's senior management and the clients themselves. As a result, it is possible to say that with this role comes a greater level of responsibility: in this case, the decisions made can influence the work of the entire team, and the project timelines. Respondents 5, 6, and 8 have reported that they experience more autonomy compared to interns, but it is still within the boundaries of the parameters set by their supervisors. The following is precisely what was said by interviewees 5 and 8 respectively: "I *deal with the redesign of business processes in a digital key. In this area, I mainly interface with the client, and I am responsible for drafting documents and acting as a liaison between the more senior part and the client itself*" (Respondent 5); "*The decisions we make are decisions that concern the coordination of the activities that the client is in charge of, so the level of decision-making is operational: we choose how to manage documents (when and how to send documents, how to set them up, what type of messages to send, the timing, the type of communication to have with the different actors involved in the project and with whom the client is dealing). With regard to impact, these types of decisions are reviewed both on an internal team level and with the client"* (Respondent 8). It is immediately clear how we have moved to a much higher level of responsibility: both respondents emphasized their role in client relationship management. They are the ones who have to understand how best to represent the company and build lasting relationships of trust with their clients. They have had to learn to adapt their way of communicating to the different people they interface with, to manage their clients' requests and to manage time. However, as pointed out by respondent 8, we are still in the realm of "operational" and not yet strategic decisions.

Proceeding with the analysis of the responses of Senior Consultants (Respondent 3 and Respondent 7), we see a further leap in terms of responsibility and decision-making autonomy compared to the levels of Staff 1 and Staff 2. Within the position of Senior Consultant, tree levels can be identified: Senior 1, Senior 2 and Senior 3. The two interviewees are both Senior 1 and although there is only 1 year difference from the Staff level, the gap is significant. Respondent 3 carries out the operation of a project of considerable importance - a transformation of the customer journey for a large Italian parastatal company. Her testimony suggests a broad influence not only in the execution of tasks but also in their definition: "*I define in broad terms a direction in the production of deliverables, an approach for solving the client's problem* [...]." It is the first time that we talk about strategic decisions and no longer just operational ones. However, it should be noted that her decisions are not yet final, but always remain open to adjustments and inputs from higher management levels. This highlights an iterative decision-making process, where her expertise contributes to the creation of an initial strategy that is later refined. On the other hand, Respondent 7 mainly deals with Project Management Office (PMO) activities, a key role that includes overseeing documentation for top management and managing entire projects. He also makes the distinction between those decisions that he can make autonomously and those that are instead taken in collaboration with others "*There is a perimeter of decisions that I can make autonomously, therefore we are talking about those decisions that have to do with the day- to-day of the type of project I'm on. I frequently have to manage documents or situations that have to do with the top management of the company where I am the PM, so there are roles higher up than me who then do further checks on the work*". In conclusion, the role of the Senior Consultant is characterized by greater influence on the course of projects and the development of operational actions.

The role of Manager can also be divided into Manager 1, Manager 2 and Manager 3 and this time I went to interview an employee covering the role of Manager 3. Having reached this level, two different areas of decisions and responsibilities can be identified: on one side there is project management, but on the other the managerial role takes over with respect to human resources. Starting from the project management and therefore from the client side, the main decisions are linked to the resolution of the problem presented by the client himself. Setting and meeting project deadlines emerges as a crucial part of her work and the impact of this commitment is directly linked to the performance of the team and the success of the projects themselves. She gave me a concrete example that happened shortly before the interview: "*the most important decisions on the client side are linked to the project deadlines. This morning with the third company we went on for 10 minutes saying 'no, you're not moving my deadline'*"; this underlines the importance of the comparisons necessary to maintain the established times and the quality of the prescribed deliverables, which are crucial for customer satisfaction. Subsequently, the second managerial role is linked to resources, as well as the management of orders. Here, her influence is even more personal and decisive, in fact she declared: "*in this case the main decisions are those related to the promotions or progressions of the person I* *work with in the group*"; hence she is entrusted with decisions on the future of EY people, on the path they should follow. Furthermore, another aspect she mentioned is that of the figure of the "counselor"; as soon as a new resource joins EY, he/she is assigned to a counselor, a person who can always be relied on, a sort of guide. Indeed, she stated: "*I am also a counselor for various people, so let's say I also take care of the more psychological and educational aspects, therefore, the more human side as well as the professional one".* The interesting point here that I want to underline is that she confessed to me that she considers these decisions "*almost more important than the others*", as they involve both the personal and professional sides on the same level. Before client satisfaction, the well-being and satisfaction of the employee always comes first; in her words I found much of EY's mission to "build a better working world". The role of the manager thus reflects a more complex facet, which requires a balance between technical abilities and interpersonal skills. One must be able to effectively manage the workflow and, at the same time, develop talent within the team by paying the right attention to each individual resource. The decisions made in this role have resonances that go beyond the success of a single project, touching on aspects deeply rooted in the company culture and investment in human capital. It is this dual aspect that highlights the diversity of the manager's role compared to previous levels.

Finally, there is the role of the Senior Manager which is divided into 4 subcategories: Senior Manager 1, 2, 3, and 4, reflecting different levels of responsibility. In particular we will focus on the role of Senior Manager 1, having had the opportunity to interview the latter. As we have seen for the manager role, decisions here can be traced to two types: on the one hand, decisions concerning project management and on the other hand, decisions concerning human resources. Always starting with the first area, the senior manager in EY plays a crucial role in project management, taking responsibility for coordinating and leading high-level initiatives. A unique contribution that he makes is the ability to anticipate client needs through his long-standing experience, and consequently to direct the project in a way that solves problems even before they emerge. It stated that one of the main tasks is to be able to ensure that the various deliverables are achieved on time and in the agreed manner, and to do this constant monitoring is required in order to intervene promptly in case of deviations from the established paths. However, what he believes is important is the climate in which one works, so within a project his intent is not to issue orders to then be carried out, but rather to get resources thinking from the earliest intern figures so that they can begin to understand how to efficiently structure the progress. Despite its high figure in fact, it is wont to place itself at the same level as the people it works with so that they are encouraged to actively contribute to the decision-making process and the project as a whole. Through open dialogue on his side and a listening attitude on the employee side, he manages to create the climate to realize the best possible contribution. Human resource management is another key pillar of the Senior Manager's role, and unlike the role of the manager analyzed above, it holds a broader decision-making power that also includes hiring; in a nutshell, it is in charge of their journey from start to finish, from the selection phase to their advancement within the company. Typically, entry into EY is through a 3-step process, the last of which is handled entirely by the Senior Manager. This additional responsibility underscores the importance of the Senior Manager's role in building EY's human capital. Once in, resources are assigned to projects, and this, too, falls within the decision-making area of the senior manager; it is he/she who, by analyzing employee profiles and associating them with project needs, assigns a "job order" to each individual person.

Through the analysis of the different figures within EY, we were able to understand how the decision-making process is highly articulated and that sometimes a decision before being the final one has to go through several roles and even through the client. This "multi-level" approach ensures that each decision is the result of careful evaluation and constructive dialogue among the various stakeholders, ensuring effective and customized solutions.

4.2. Current applications of AI in Decision Making

Nowadays, we are witnessing an ever-deeper integration of artificial intelligence into business workflows, supporting, and complementing the human factor; this is a significant evolution, especially in the consulting sector. However, this transition is not without its doubts and questions; the balance between automated efficiency and human judgment remains a critical point of reflection, so much so that we are still seeing employee perplexity about which tasks to entrust to AI and which not. The interviews conducted provide an incisive insight into the current adoption and perception of artificial intelligence by professionals in different roles and experience levels within EY. By examining the frequency of use of AI-based tools, practical applications, and the level of trust in these tools, we can paint a picture of emerging trends and present resistance within this company.

From an analysis of the responses to the question "How often do you find yourself using AI-based tools or systems in your daily work?", it is evident that the use of AI-based tools is an integral part of the respondents' daily workflow. The frequency of use ranges from "3 to 4 days a week[15]" to "practically every day". What is even more remarkable is that not only do the majority of respondents use AI tools every day, but one respondent, reflecting a sentiment shared by several others, has stated that "*Essentially, every task I perform involves the use of AI tools, even if only for decision support purposes. So, we can say that not only do I use it every day, I practically use it all the time*". Based on these first statements, it is evident how AI is evolving from being an occasional assistant into a constant companion for employees, and this applies not only to younger new entrants, but also to those with more seniority who are recognizing the immense value that these tools can provide. This indicates a paradigm shift in the way work is done.

In addition to the frequency of use, my aim was to find out which AI-based tools are used the most and how they are able to support and thus facilitate employees in their daily work. The analysis revealed a clear preference for generative AI tools and in particular for EY-Q, the version of ChatGPT provided by the company. In fact, thanks to this customized version, employees can be comfortable about providing information or even uploading entire documents containing sensitive information about their clients as it is an open version for EY employees only, so all uploaded data will remain for the exclusive use of EY consultants. Among the main reasons why EY-Q is the most used tool is its ease of use and speed of response. In fact, respondents said that thanks to the platform's intuitive interface and its smooth but above all-natural interaction, they are all able to integrate it seamlessly into their work activities, maximizing the productive impact from the very first use. We have seen that 100% of the respondents named EY-Q as the main tool used, but another large part of the sample (40%) also named another tool, namely Power-BI. But how does this tool help employees? This business intelligence tool from Microsoft supports consultants in another critical area, that of data analysis. In fact, through facilitated and interactive visualizations, Power BI transforms complex data into intuitive insights that consultants can use as a basis for subsequent strategy formulation or to guide their own projects. Instant information sharing and interactive reports and dashboards appear to be the underlying reasons for use that were mentioned by respondents.

[15] To remember that by 'week' we refer to the five-day working week. So when the respondent answered "3 to 4 days a week", it means that the AI utilization rate falls between 60% to 80% of his/her workdays.

Finally, a further question I went on to ask the interviewees was ‘What types of decisions do you feel more confident in entrusting to AI-based tools than those made by you personally?’; in this way, I was able to understand how employees make use of these tools in their decision-making process. In fact, this approach allowed me to probe not only the extent of adoption of AI tools in the workplace, but also to assess the degree of reliance and autonomy granted to such intelligent systems. With regard to the type of decisions that employees feel safe to delegate to AI-based tools, there is a tendency to reserve tasks that require objective information processing, such as translation, or even requests for the meaning of terms or entire concepts. To cite some examples, Respondent 1 stated: “*I prefer to entrust AI with objective queries instead the ones I take are the ones that have more impact and also need critical thinking behind them*”, while Respondent 6 said “*When there is a need to translate or clarify concepts. I often have to deal with technical issues and so in order to get into the content and to be able to help the client operationally I need to understand and so I really ask for explanations*”. Other decisions that interviewees tend to delegate to AI are those concerning data. They mentioned both the collection and preliminary organization of information and the analysis of large datasets or the generation of statistical reports. These are activities that require fast and accurate data processing, an area in which AI can outperform humans in terms of speed and accuracy. According to Respondent 9 “*The one I feel most confident about is definitely the world of analysis because let's say it is difficult for AI to make mistakes, if I set it right it cannot make mistakes”*. Artificial intelligence is seen as a reliable support tool when information is well structured and can be processed from hard data. Finally, respondent 10 brought up an additional type of decision that no one else mentioned - namely, those concerning e-mail. He increasingly relies on AI-based tools both to write emails and to filter and prioritize them. Holding one of the highest positions, it is obvious that the inbox can often be full, and managing such a high volume of communications can become a very time-consuming task. If on one hand he receives a large number of emails, on the other he also has to respond, and this is where he after seeing a positive result decided to completely delegate this function to AI. Through the use of this technology, he has noticed how it is able to adapt to the recipient's style, correct grammatical errors that might have happened before, consequently improving the quality and effectiveness of communication. However, caution is observed when relying on AI systems for decisions concerning critical aspects or those with a greater impact, such as strategic decisions or those related to career progression within the company. The human component remains central especially in those contexts where subjective sensitivities and considerations are required. Again interviewee 9 said “*I'm certainly never going to give AI the decision over* *progression, even if EY is counting on it. There is an algorithm that follows and directs towards progression or regression, then there are the round tables where managers and senior managers (it depends on the role of the people to make decisions on) read the results of the algorithm and say yes/no. I would never entrust these decisions to these systems, but not in the future either, otherwise we would lose the human part which is very important to me*". From these words we perceive the conviction that despite all the technological advances experienced to date, there are aspects of the decision-making process that cannot be delegated and in which the human factor therefore remains irreplaceable.

To conclude, we can say that we have seen how AI-based tools are widely used in EY, marking a paradigm shift in the consulting industry. Despite this, employees want to see AI as a complement to their work, as a tool to enhance efficiency and effectiveness and consequently the final result. The underlying implication is that, while human decision-making capabilities remain crucial for strategic guidance and ultimate supervision of the output, an increasing number of operational and analytical decisions are moving towards AI. This new balance between human and machine will establish the basis for an innovative working environment.

4.2.1. Impact of AI on Decision Making

In this section, we are going to understand how AI is intervening to modify the decision-making process in the consulting reality. Through the analysis of the answers provided with respect to the question 'In which phase of the decision-making process do you think AI has had the greatest impact (intelligence, design, choice, and/or implementation...)?', I intend to highlight the role of this technology in the different phases: from the search for information to the implementation and execution of the actions derived from the decisions taken. However, the interviews reveal a plurality of viewpoints that point out an uneven impact of AI, probably due to the different roles played by the interviewees, and the different decisions they have to make every day. This analysis allows us to understand which phases are most impacted and to outline a scenario where AI accompanies, modifies, and sometimes revolutionizes human work, requiring a reconsideration of the skills and methodologies adopted by consultants.

To be more precise, when discussing the "phases" of the decision-making process, I will refer to the subdivision made by H. Simon that we discussed earlier, i.e., Intelligence, Design, Choice and Implementation. The phase that was most frequently mentioned by respondents is the first, the intelligence phase, which is the preliminary stage of gathering information to fully understand the problem or opportunity, but above all to comprehend the context in which one finds oneself. In this context, the use of AI is varied, ranging from assisting in understanding the context to identifying key information. In particular, AI is seen as a key facilitator in the acquisition and management of information to the extent that respondents pointed out that it allows them to access in a very short time a quantity of data that would otherwise not be possible, giving them a solid basis for making more informed decisions. Respondent 1 said "*From my point of view, the phase where AI has had the greatest impact is undoubtedly in the phase of gathering all the information, in fact before making any decision if I don't know something, I first go and ask EY-Q for clarification about it*", just as respondent 5 said "*Mainly we use it to give us additional information, to research material. In my opinion it is very useful in the initial phase of the work so to set up the work, to give a structure*". For consultants, having a tool that accelerates and simplifies data collection can be a significant competitive advantage: on the one hand, the ability to respond quickly to client requests with accurate and up-to-date information can significantly improve client trust and satisfaction, enhancing the reputation and reliability of the consultant, and on the other hand, the time saved from information research can be devoted to more in-depth analyses. As the manager of the technology consulting team stated: "*Certainly AI is useful in the search for information, but especially in the analysis phase. In-depth analysis without AI, I would do it, but it would take months compared to a minute'*". Here, the respondent emphasizes how AI not only speeds up the information gathering process, but also how it amplifies the capacity for analysis, allowing for the exploration of scenarios and variables that would otherwise be too onerous to consider manually. This is where AI can help differentiate the offering and also become a distinctive element in the value offered to clients. During the Design phase, on the other hand, AI seems to play a less direct role, but is still used to support the creation of alternatives. The design phase refers to the moment when possible solution alternatives to the identified problem/opportunity are developed and the pros and cons of each alternative are evaluated in order to have a picture with possible decision-making scenarios and here only one respondent referred to the fact that "*the most correct use of AI is not in competition but rather to give you suggestions and inspiration. In fact, after generating ideas, I am able to generate others with the help of AI*". Although the other respondents did not explicitly mention AI as a design tool, it is reasonable to assume that the use of data and information gathered in the intelligence phase can influence the generation of innovative solutions and the evaluation of options as pointed out by respondent 10. Moving on to the third phase, the Choice one where the selection of the best possible alternative takes place, here it seems that AI has had no significant impact. This is a very delicate passage that respondents still prefer not to rely on AI, but rather to use their own personal judgment. For example, respondent 7 stated that "*at this point in my career, I don't use AI as a facilitator in making decisions, but it has a whole other impact on my work, but not to make me make the decisions*", while respondent 3 "*as far as making the decision, I rely more on my own expertise, because after gathering all the necessary information, I think I can work it out*". Therefore, the final decision remains a highly human domain, where experience and personal evaluation play an essential role. This is consistent with what emerged earlier from the analysis of the decisions that are entrusted to AI and those that advisors still prefer to make themselves: in fact, we had seen how while more operational decisions were delegated to AI tools, strategic ones were not yet. This stems from the fact that great responsibility is associated with individual decisions; this is what drives the consultants to maintain direct control over this critical phase, wanting to ensure that every decision made is aligned with EY's strategy and objectives. Finally, the last phase of the decision-making process concerns the implementation of the decision taken: in a few words, the execution is planned, the necessary resources are allocated, the chosen solution is implemented, and the results are monitored to ensure that the objectives are achieved. At this stage, the contributions seem to suggest a limited use of AI; indeed, the latter was not mentioned as assisting or supporting the implementation of decisions, but more as facilitating the operational processes that follow the choice. Both respondents 6 and 7 described it as an "*operational support*" in terms of document drafting and editing. This may indicate that while AI assists in the preliminary processes, its function in the practical implementation of decisions is less prevalent, probably due to the complexity and interactivity required in this phase, which often demands a direct contact with the client.

To sum up, then, what emerges from the respondents is a reality in which AI has a relevant impact above all in the initial phases of the decision-making process, where its ability to analyze large volumes of data proves particularly useful. Less immediately appears its contribution in the implementation phase of choices, where interpersonal dynamics may play a more decisive role than AI assistance. However, if on the one hand it is true that all respondents dwelt on the first intelligence phase, recognizing the great positive impact that AI has had, on the other hand it is possible to affirm that this impact is also indirectly reflected on all the other phases of the decision-making process insofar as better choices and implementations derive from more accurate and in-depth information gathering. Specifically, the choice phase benefits by being able to make more informed decisions while the implementation phase is indirectly influenced by the quality of the previous steps, since a well-informed decision is typically easier to execute and more likely to succeed.

4.3. Benefits and Challenges in the use of AI

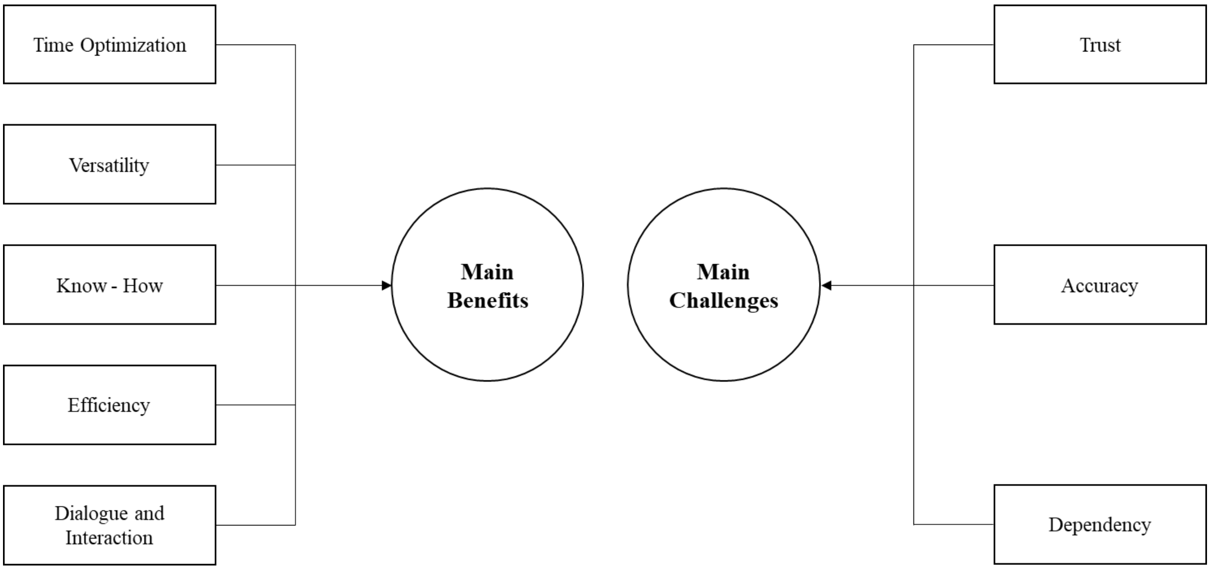
The integration of Artificial Intelligence into Ernst & Young's decision-making process has provoked significant reflections among employees; the interviews conducted revealed a diverse range of advantages, benefits, but also challenges related to the use of AI, and in this section we will explore just that.

Starting with the advantages, the first one that was mentioned is the reduction of time. Thanks to artificial intelligence and, in particular, to generative AI, consultants have on the one hand the possibility to access huge data sets in a short period, and on the other hand the possibility to receive information, analysis or insights in real time, which translates into significant time savings. In fact, all respondents claimed to have noticed a significant improvement in the speed with which they complete tasks or make decisions. For example, respondent 9 stated: "*For me, the number one advantage is time and certainly in many ways, both because she answers me quickly and because it would take me longer to do what she does in milliseconds. So it's not just the answer itself, it's also my time in reading what is the answer given to me; without the presence of EY-Q I would have to look it up from different sources which may not actually be what I'm interested in"*. Similarly to respondent 9, respondent 4 also identified time as the main advantage, but added another very interesting aspect by stating that "*The main advantage is definitely the reduction of the time needed to perform a given task, so mostly a productivity advantage. Various operational tasks are done in half the time and in consulting, which is exactly a deadline-driven job as you have to keep up with various projects, decisions and tasks, time is the most precious resource we have. EY-Q helps us by giving us more time to divide between the various projects*". It is clear that in an industry where the pace is ever faster and deadlines follow one another, the ability to obtain timely responses is an invaluable competitive advantage. Related to this concept, EY-Q also makes it possible to automate repetitive tasks such as drafting minutes, preparing presentations or producing entire documents, allowing employees to save the time they previously spent on these tasks and devote it to other phases of the decision-making process where a more human component is required. The value of EY-Q also lies in its versatility, and this is understood both as versatility from the point of view of tasks, since it is able to range over an innumerable series of activities performed, and as versatility from the point of view of use, since it can be dropped into different contexts, but above all into different sectors. Accordingly, two employees highlighted the knowledge of EY-Q as an additional advantage: respondent 6 reported that "*one of the main advantages of generative AI is definitely the understanding of topics. The benefit is really to have someone who explains to you technical terms or topics that are not in the scope of your competences and gives you a fairly comprehensive explanation*" and equally respondent 7 said "*very often I use it as an interlocutor to reason with, maybe I don't have the answer and I don't even know how to ask the question, but with a kind of dialogue with the generative AI the answers slowly start to give me a series of inputs and a series of feedbacks that help me even just to clarify my ideas on the direction I have to take, but also on how I have to structure the work. So, it helps me both when I have clear ideas but also when I don't have them".* An interesting insight that emerged from these interviews is the fact that employees are beginning to see artificial intelligence as a "real entity" with which to dialogue and establish a relationship. In doing so, AI not only facilitates the daily work, but also contributes to the professional growth of the consultants, expanding their know-how on unfamiliar realities or aspects. I would like to stress this point since the vision of EY-Q as an "interlocutor" marks a change in the way EY employees see technology: no longer as a threat that could replace their work, but on the contrary as a complement that facilitates, but above all enriches the work process. All this may have positive implications for the acceptance and integration of these technologies within the different business realities. Finally, a further benefit that was identified by the respondents is in terms of creativity, respondent 1 stated that "*even on the creativity side, I found myself needing to ask for ideas for projects I had to do; maybe at that moment I was lacking creative ideas and so I asked for help to AI which was very helpful in providing me with a broad overview and then of course I was the one to choose and determine which of these ideas could be implemented and which could not".* This is a skill that is often underestimated, however, AI, and in this case EY-Q, is able to generate ideas and offer solutions that might not otherwise be considered, thanks to the wide range of information it draws upon. At times when consultants would need different thinking than usual, or at times of stalemate, this creative stimulus from AI is particularly useful. Nevertheless, it is important to recognize first of all that although artificial intelligence may suggest new ideas, the final selection and implementation remain human tasks as the interviewee pointed out. Moreover, this support from EY-Q does not eliminate the need for critical thinking on the part of consultants, it is still a two-way interaction in which AI ideas are supplemented or enriched by human creativity.

Nevertheless, the introduction of AI is not without its challenges. One of the biggest sticking points remains "trust", and in particular confidence in the information provided. Despite the effectiveness of the tools seen above, respondents showed a strong awareness of the need to always keep an eye on and not passively rely on every output returned by AI. According to respondent 4: "*The biggest problem is that we are gradually neglecting the reliability of this tool, so maybe we take it for granted that what EY-Q is saying is right, while it can get confused being an AI language, so it can rely on other knowledge or data taken from the wrong internet. Sometimes we need to double-check the content we are given*". This concern is especially directed towards Generative AI, and according to EY's consultants, in order to ensure a high quality of work it is always good practice to double-check information and sources. Connected to the concept of trust, there is the reverse problem, namely those who rely too much on this tool, respondent 5 pointed out that "*many people use this tool by taking the information as it is, even from the point of view of the text, so there is a great tendency to copy and paste without paying attention to the form and correctness of the expression. In my opinion, one disadvantage is that often, no matter how precise the question may be, there are a few repetitions or decontextualisations that are normal, in the sense that then those who have been in it for a while, especially at work, realize that there are things that have nothing to do with it. So at best they have to be reworked, at worst they have to be eliminated altogether*". From here, a clear concern emerges as this behavior could compromise the quality of the entire work, specifically the blind reliance on AI could lead to a result that is not fully aligned to the specific context or to the client's requirements. All this could have a negative impact on the perception of added value brought by consultants. A further challenge encountered by the employees is knowing how to educate the gen AI tools to the specific requirements because it can happen that sometimes these devices have encountered difficulties in interpreting the input and consequently generate answers that do not correspond to expectations. This problem was encountered both by respondent 1: "*it may happen that the AI does not actually understand the question I am asking it, in fact it happened sometimes that I had to rephrase the question and then get the right answer*" and by respondent 6: "*the main challenge in my opinion is to know how to put it into the operative, it is a problem of educating the tool to your requests*". It is evident from these statements that AI tools do not yet possess the ability to interpret the nuances and context of human questions as accurately as a human being. As a result, misunderstandings may arise that require users to reword their requests or intervene manually to correct the output. Finally, employees reported one last concern - dependence on AI tools. This was particularly strong among one manager who stated "*I have concerns especially about young people. The* *fact that they struggle to do things in my opinion is the biggest problem because it's like not trying hard enough to achieve the goal*". In order to better explain what she meant, she used a simile that, in my opinion, invites everyone to reflect. He took the example of Bolt, who in order to break the 200m world record had to work and toil; today it is as if this goal could be achieved without the fatigue and effort sustained by the athlete. In fact, in her opinion it is two completely different things to close an analysis after months of reasoning and close it after 3 min as it was done by EY-Q. Here also raises another important issue according to the manager, namely the concept of gratification. Even on a psychological level, it is not the same thing to close an analysis or even a simple task alone with one's own skills and to close it with the help of AI. The consequence of this is a lack of ex-post gratitude.

In the figure below (Figure 9), we can see a summary of what the main benefits and challenges were highlighted by EY employees. Already visually, we can see that the participants focused more on the benefits brought by these tools rather than the concerns.

Figure 9: Benefits and Challenges of AI tools



One conclusion we can draw from all this is that despite the presence of challenges and concerns, employees are showing a positive attitude towards AI by recognizing the added value it can bring. In fact, the benefits experienced such as time optimization, versatility, and facilitation in understanding complex issues far outweigh the difficulties encountered.

However, it is always good to accompany the use of these tools with a critical eye in order to maximize results and ensure that their impact on decision-making is positive.

4.4. Training and support on the use of AI

In this chapter, we are going to study the topic of "training" and the analysis of the answers of the interviewed employees revealed very varied experiences and attitudes towards education and support on the use of AI within the company. Specifically, during the interviews I covered two different topics, the first one concerns the training and support obtained in EY, while the second one is about autonomous learning, so we are going to see how the employees behaved towards these two topics.

The first aspect analyzed was the training provided in the company or possibly scheduled. From the results it appears that this was not provided evenly among the various levels of the hierarchy or between the two different service lines. The two interns in the Business Consulting department said that they had not received any training; however, these two figures had mixed views on the usefulness of the latter. Respondent 1 said, "*I have not received any training, however, for the time being and for the AI we use, basic training is necessary and it is learned through experience so it is not necessary to have done training*" in contrast Respondent 2: "*No, regard formation I have not received any but certainly providing training on the optimal use of AI could be useful in the work environment*". This difference in testimony highlights a crucial point, namely individual experience, and the different comfort they have with the technology. Already from these first two responses comes a very interesting insight, that is that there is no one-size-fits-all approach on AI for all employees; some may find that learning in the field is the most effective way to acquire the necessary skills, while others might benefit from specific trainings that provides a deeper understanding of the tools used. On the other hand, the intern who is part of the Technology Consulting team said that he received training from EY and specifically stated that the company gave him the opportunity to attend a seminar that talked specifically about the application of AI. The first aspect they covered was about the office package with the co-pilot that was going to be included in the spring; then they also discussed the application of the Microsoft planner with regard to the division of tasks within the team, time management etc. This first difference might stem from the diverse type of service line, in fact since Technology Consulting is a department that interfaces with technology on a daily basis it becomes apparent that knowledge of it is essential. Going forward with seniority, and this applies to both service lines, the courses made available become mandatory. Respondent

8 told us about a course that was held in November and December on AI in general and then went on to address EY-Q more specifically, since it is the phenomenon of greatest interest at this time and consequently also the one most used. Respondent 3, on the other hand, pointed us to a mandatory course on AI concerning more generally the different uses that can be made of it, but also more specific topics such as the right "prompting" model. However, she was not aware whether this course was only for her level, i.e., Senior 1, or extended to higher levels as well. Finally, a very important aspect was found by respondent 10, who said "*In theory there are courses made available by EY but, I have to be honest, I have not taken them, or rather I have only taken one. I'm sure they put a lot of emphasis on it and have done several training meetings, I'm the one missing*". A substantial point emerges here: EY needs to make sure that training meets everyone's different needs, and this in a twofold sense: on the one hand, the needs in terms of the skills one wants to develop and the level of confidence one wants to achieve, and on the other hand, the exigencies in terms of time. Since, thanks to AI, a very high level of personalization is being achieved, an important element for EY could be to bring to life a flexible and personalized training program that combines formal sessions with hands-on learning opportunities. This could ensure that all employees are able to use AI effectively and safely.

A common theme among most of the interviewees is autonomous learning, or rather as it is referred to by them as "self-training". This approach reflects a growing trend among EY staff to take their professional development into their own hands, tailoring the learning process to their own needs and work pace. On the one hand there are those who, like Respondent 4, said that they go to the internet to document themselves to find out about new trends in AI; this one in particular emphasized his interest in finding out what functions are periodically integrated into EY.Q. This represents a personal curiosity of his, but one that he believes can be very useful in the work context as well. On the other hand, there are those who, like respondent 7, describe themselves as self-taught claiming in fact he affirmed that "*using online resources, I have never had any particular difficulty using EY-Q and prompts. I never needed to not use AI because it was not satisfactory in that context, it always satisfied me and had the result I expected"*. Self-training is a very important aspect since when combined with training provided by the company it can greatly increase employees' knowledge, interest and consequently also their business performance.

Finally, the last aspect worth mentioning is the culture of collaborative learning that turned out to be there within EY. This point was raised by candidate 5, saying "*I started using EY-Q when I had already been with the company for a while, among other things at the urging of other guys who came in with me and were already using it. In fact, they were the ones who introduced this subject to me and then slowly I approached it by doing various trials".* Interaction among colleagues, exchange of ideas and practical experiences become valuable resources that contribute to the professional growth of each individual and, consequently, of EY as a whole.

In summary, training is a key element since while it is true that AI tools enable employees to optimize their time, it is also true that without proper instruction on the same this saved time could be lost. This "wasted" time would be spent understanding how these tools work, a complex and time-consuming task without primary guidance. In this context when we talk about training we mean all three different types - the company's mandatory training, self-training, and informal support provided by colleagues - since each of these modalities contributes differently to the development of employees' skills. First, mandatory corporate training ensures that all employees have a common knowledge base and are aligned with EY's policies. Second, self-training allows employees to personalize their learning path by exploring specific areas of interest and delving into skills they feel are most relevant to their professional development. Finally, informal support among colleagues could provide knowledge where the first two types of training did not reach. Consequently, all forms of learning should be valued within EY.

4.5. Future expectations on the use of AI

The last aspect I studied concerns what employees expect from AI in the near future. The responses were varied and different from each other, but some common themes clearly emerge.

Foremost among them is the automation and optimization of Processes: while many respondents had already reported this as an advantage found in the use of AI to date, they anticipate that AI will become increasingly crucial in the future. This is particularly evident in the responses of interns, who see their current tasks as simple, operational, and consequently potentially automatable. Candidate 1 said, "*As for my tasks that are basic, I think they could be replaced or facilitated by even more advanced AI tools that will be implemented in the future. Precisely, because they are basic they can also be done by AI"*, and the same respondent 4 "*In my opinion, AI will go to replace us in those tasks that are repetitive, in those tasks that are* *alienating to humans and involve only performing tasks that are operational, without much reasoning behind them"*. From these statements we can see how there is a great belief of the respondents in the capabilities of AI, and consequently great confidence in delegating those basic tasks. Behind respondent 4's statement we can also catch a relief as he judges the first tasks being done in the company as "alienating". This also has a direct consequence on the motivation, desire, and job satisfaction of employees, who by tackling more "interesting and challenging" tasks right away can have the perception that they are doing work that has a real and positive impact. Another fundamental reflection also emerges from this first point: if many think that the figure of the consultant will be replaced in the future because AI will be able to generate slides, make reports etc, this is not what EY consultants think. On the contrary they firmly believe that this professional figure can never be replaced because there are directional and managerial decisions that AI is not able to deal with, but also because a fundamental aspect of the consultant's work is the human relationship that is developed with the client. When I went to ask the respondents if they agreed with the statements that many are making today about the future of the figure of the consultant, no one agreed and I want to point out the response of an employee who invites everyone to reflect on this issue "*Let's say that the talk of 'we will be supplanted' is partly true partly debatable in that, in my opinion, AI will supplant us on those tasks that do not require creativity, moral judgment, the emotional intelligence of humans, in those tasks that do require it will only provide support to humans. In conclusion, those who will not be supplanted by humans will be those who simply know how to ride the wave of this trend and leverage AI as a tool and not as a co-editor"*. Consequently, we need to see how the question "will Artificial Intelligence replace the consultant?" is interpreted; the answer is affirmative if mere operational tasks are considered, but negative if the role of consultant is considered overall.

The second common theme that emerged and that, more than an expectation can be considered as a desire of EY consultants, is the integration of artificial intelligence within business tools. Specifically, respondents 3, 6, 7, 9, and 10 expressed a wish for AI to also become an intrinsic component of software already in use within the company. This implies deep integration with everyday tools like Word, Excel, and PowerPoint, with communication systems such as Microsoft Teams, and with other industry-specific software. Such direct integration would facilitate the use of AI because without the requirement to switch to other platforms it would not interrupt the workflow undertaken. This approach could bring two major benefits, one in terms of efficiency and quality and the other in terms of transparency: on the efficiency/quality side, the integration could give rise to new features such as voice assistance for drafting word documents; while it could bring great results on the transparency side since, to give a concrete example, instead of exporting data from Excel to analyze it with external AI software, an integrated AI module could provide analysis directly within the spreadsheet. Moreover, when candidates introduced the concept of 'integration', they were talking about integration in the full sense and thus not just the mere addition of AI tools within business tools, but also in the actual work. Candidate number 6, in particular, expressed a desire for AI "*to become a tool that assists you in a more organic way, it would also be nice that he knows what you do, your type of work, and so you don't have to be there every time to explain things to it*". Such a level of integration could even personalize the user experience, learning from their work habits and adapting to their specific needs. This means that AI could, over time, anticipate consultants' requests and provide proactive solutions, further improving efficiency. Consequently, AI integration turns out to be key to a future in which technology not only assists but amplifies human capabilities, making daily work more fluid, intuitive, and impactful.

Finally, employees have acknowledge that AI is indeed revolutionizing their everyday lives, but more importantly, it is redefining the very concept of work. It is now perceived as an essential tool that brings invaluable added value. Probably this feeling and optimism also stems in part from the company culture within EY, from the values and principles it tries to convey. Respondent 9 opined that "*In EY they push a lot on AI, and rightly so, especially our technology area has to be like this, you cannot absolutely disregard it*". In the opinion of employees, although there is still a long way to go, this proactive approach to AI reflects EY's commitment to remain at the forefront of technological innovation and to always seek new ways to enable continued growth. After the interview conducted, respondent number 9 thanked me as in reasoning about this concept, she realized the strategic importance of this phenomenon and that while EY is so committed to pursuing this technology trend, she must also be ready to engage. Her exact words were, "*I have to make the switch myself for a moment, I realize I have to find the time because I know it is an important thing, I am aware. In fact, I thank you because you have given me the opportunity to reconsider, I will refocus and put that in my to-do as well*".

In summary, expectations for the future of AI at EY are characterized by a mix of enthusiasm for its potential and an awareness of the challenges of adopting this technology. Employees are ready to welcome AI as an ally in their work, and eager to see significant evolutions in the near future. We can say, then, that the vision shared by EY workers is one of a future in which AI is not just a technology trend, but a transformative element that permeates every aspect of work, from the quality of service provided to clients to personal satisfaction. And in this future they position themselves with an open mindset, an ability to learn quickly, and a desire to be active players in this true technological revolution.

Chapter 5: Conclusion

This chapter will answer the research question, coming to the conclusion and answer whether Artificial Intelligence is able to positively influence decision making in the consulting industry. Then, starting from the limitations of this study, it will go on to identify what could be future research or developments of this thesis.

The purpose of this thesis was to understand what role Artificial Intelligence plays in enhancing decision making within consulting firms. Specifically, the different applications of this technology and how it is used by employees of EY, one of the so-called "Big Four" consulting firms, were examined. To achieve this goal, it was necessary to study the impact of AI at each stage of the decision-making process, assessing the opportunities and challenges arising from its use. The research question that guided this thesis and to which we will now try to provide an answer by drawing conclusions is, "*How can the use of artificial intelligence improve the decision-making process within consulting firms?*".

Analyzing the results of the interviews conducted, it was found that AI has greatly improved the decision-making process, bringing significant benefits and making the entire working model of consultants more efficient. AI has had a particularly positive influence on the initial phase of decision making, namely the intelligence phase. This is the phase where consultants used to spend the most time as it involved gathering and analyzing information to fully understand the problem/opportunity that emerged. Tools such as EY-Q enabled employees to access large amounts of data in an extremely short period of time, consequently providing a solid basis for making more informed and strategic decisions. An initial positive response to our research question stems from the fact that from a more precise understanding of the problem to be addressed, AI has enabled consultants not only to accelerate the intelligence phase but also to improve the quality of data analysis, allowing, for example, variables to be taken into account that would otherwise have been too onerous to analyze manually. A second way through which the use of AI has allowed for the improvement of the decision-making process has been through the creation of alternatives, suggestions or insights in the design phase. In fact, it can sometimes happen that decision makers stick to solutions that have been successful in the past or that they believe are the best possible option, without exploring new ones. Artificial Intelligence can help in overcoming this problem by providing a range of solutions based on emerging trends that may not be immediately apparent to the human eye. In addition, decision making has also benefited from AI for its predictive ability: in fact, thanks to its ability to simulate different scenarios with their respective outcomes, consultants can assess their potential risks and benefits before taking a definitive path, thus increasing the probability of success of the implemented decision. However, it should be remembered that the use of AI is not without risk, so it is up to the skill of employees to know how to effectively integrate this new technology into the decision-making process, knowing how to always maintain a balance between what the AI says and their own human judgment.

As seen above, this thesis is confined to studying a single organization; consequently, it may not fully reflect the use of AI-based tools in other business settings. The first suggestion for future research, therefore, would be to extend the study to a larger sample of companies in order to be able to generalize the data. A second avenue for future research would be to integrate quantitative studies. My research is qualitative in nature, relying on interviews and observations made within EY; a future study could combine analyses of company performance data with what respondents say to have more objective measurements on the phenomenon. Finally, an additional aspect that could be developed in the future is the evolution of AI adoption over time. In this case, the research could also remain limited to one organization, but study how the integration of these tools changes over time or adapts to changing market conditions. Indeed, we have seen how AI is a dynamic, ever-changing reality, so future research could focus on studying new applications of it and how AI-based decision making will evolve.

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Appendix

Interview guide

Section 1: Introduction
· Can you briefly tell me about your current position in the company? · In your role, what kind of decisions do you make and what is the impact of those decisions?
Section 2: Use of Artificial Intelligence in daily work
· How often do you find yourself using AI-based tools/systems in your daily work? o What types of AI-based tools do you regularly use, and how do they assist you? · At which stage of the decision-making process do you think AI has had the greatest impact? (e.g., information gathering, choice, implementation…)
Section 3: Impact of Artificial Intelligence on decisions
· What types of decisions do you feel more confident entrusting to AI-based tools compared to those made personally? · Have you noticed improvements in the accuracy or efficiency of your decisions thanks to the use of AI tools?
Section 4: Benefits and Challenges of using Artificial Intelligence
· What are the main advantages you see in using AI within EY? (e.g., better data analysis, time optimization, task automation, customization of solutions…) · What are the main challenges or concerns you encounter when using AI-based tools for decision-making? (e.g., lack of trust in the answers it provides, privacy, lack of precision, dependency on it…)
Section 5: Training
· Have you received adequate training or support to effectively use AI-based tools in your work? · Have you sought out self-learning opportunities on the subject?
Section 6: Future Expectations
· What are your expectations for the future of AI in EY?