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# The impact of Artificial Intelligence on unemployment: a systematic literature review

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#### Abstract

The world is currently witnessing the effects of that period of fast technological advancements which has become known as the "Fourth industrial revolution". Featuring it, there is the introduction of a broad set of new technologies, like big data and analytics, 3-D printing, the internet of things, and autonomous robots. If, on the one hand, the introduction of Artificial Intelligence allows firms to perform a wide range of tasks more efficiently, on the other hand, there are bad consequences its implementation may lead to. The focus of this thesis is the relationship between employment and Artificial Intelligence. Experts in the AI field and part of the literature warn about the massive technological unemployment that might occur in the near future. The common thinking is that thanks to AI, practically all jobs might be done by machines. In order to find out if the implementation of AI machines leads to unemployment, a systematic literature review is undertaken. The findings show the actual scenario is more complicated, with many factors to be taken into consideration.

#### 1. Introduction

The last decade has witnessed great technological improvements. In the context of the so-called Fourth Industrial Revolution, disparate technologies began to be applied at the industrial level. Among others, like the use of big data and analytics, mobile technologies, and the internet of things, increasing investments have been undertaken on Artificial Intelligence (AI).

The implementations of AI machines in companies leads to several advantages, the main important:

- the possibility to automate a vast range of tasks, making them more efficient
- augmenting the ability of the employees to perform manual and cognitive tasks faster and better

• helping people to make better decisions by analyzing great amounts of data (America, no date; Geisel, 2018; Jarrahi, 2018)On the other hand, the possibility for companies to exploit Artificial Intelligence raises some concerns. One of them is the negative repercussions that it might have on employment. Unlike the previous revolutions, this time the application of new technologies will affect many kinds of jobs: employment will continue to decrease in the primary and secondary sectors (Makridakis, 2017; Lloyd and Payne, 2019), but also a vast range of employees

belonging to the tertiary sector will probably suffer the impact of AI (see, for instance, (David, 2017; Michailidis, 2018; Ernst, Merola and Samaan, 2019)). Technological unemployment associated with the use of AI is the focus of this thesis. The attempt is to understand what the near future will look like for human employment. The research question this thesis tackles is: does the implementation of artificial intelligence in companies lead to unemployment, in the sense that humans are replaced by machines? To answer the research question, a systematic literature review is undertaken. The conduction of the review follows the indications given by (Tranfield, Denyer and Smart, 2003). Documents published recently, from 2016, are analyzed.

This thesis is structured as follows: chapter 2 consist of a brief presentation of the history of industrial revolutions and of the evolution of Artificial Intelligence, as well as of a presentation of the most influential literature on the topic; chapter 3 explains the methodology through which the systematic literature review was conducted; chapter 4 presents the findings; in chapter 5 a discussion on the findings is undertaken; chapter 6 presents limitations and conclusion of the thesis.

#### 2.Context and theory

Starting from the end of the 18th Century, the world has witnessed the advent of several periods of accelerated technological progress, that in the latter years have become known with the name of "industrial revolutions". The first industrial revolution, which started in Great Britain, was represented by the invention of the steam engine, that allowed the transition to a new manufacturing process. (Xu, David and Kim, 2018) The second industrial revolution, know also by the name of "technological revolution", began almost a century later, in the 1860's (Xu, David and Kim, 2018), and saw the introduction of electricity and production line at a industry level. The third revolution, also called "the digital revolution", started in the 1950s, and saw the proliferation of digital computers and the rapid development of Information and Communication Technologies (ICT). Computers "became filekeeping devices used by businesses to sort, store, process and retrieve large volumes of data, thus saving on the labor involved in information-processing activities." (Peter, 1999, p. 10). In the last years, according to (Xu, David and Kim, 2018) starting from the early 2000s, a new revolution is building on the third one. The term "Fourth industrial revolution" has been coined by Klaus Schwab, founder, and

executive chairman of the World Economic Forum. According to Schwab: "We stand on the brink of a technological revolution that will fundamentally alter the way we live, work, and relate to one another. In its scale, scope, and complexity, the transformation will be unlike anything humankind has experienced before." (Schwab, Chairman and Forum, 2016, p. 1). The fourth industrial revolution is characterized by the widespread use of a broad set of new technologies: artificial intelligence, internet of things, robotics and 3-D printing, among others (Schwab, Chairman and Forum, 2016) In the year 2011, the German government began to heavily support the industrial sector with a strategic initiative that took the name of Industry 4.0 (Rojko, 2017). The program, which was followed also by other European nations, aims to facilitate incorporation within the manufacturing industry of all the technologies associated with the fourth industrial revolution. The ideal factory of this new period takes the name of "smart factory" (Rojko, 2017), which is featured by a high degree of flexibility and re-configurability, therefore efficient in the production of highly customized products (Wang et al., 2016). In Schwab's opinion, this revolution, like the previous revolutions, will bring benefits by raising global income levels and improving living standards around the world. on the other hand, there is no doubt, that it is bringing with it challenges that societies are going to face. (Schwab, Chairman and Forum, 2016)

As already mentioned, the fourth industrial revolution expanded the possibilities of operations automation, already improved with the digitalization revolution, with the introduction of a new technology that takes the name of Artificial Intelligence, or AI.

The definition of Artificial Intelligence is not univocal in the literature. The term was coined by John McCarthy, an American computer scientist, in 1956. In his idea, Artificial Intelligence "...is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable." (Mccarthy, no date, p. 2). The modern definition by Cambridge Dictionary, instead, goes beyond and reveals to be more precise, by defining AI as: "the study of how to produce machines that have some of the qualities that the human mind has, such as the ability to understand language, recognize pictures, solve problems, and learn". However, for the scope of this thesis, the best fitting definition is probably the one given by (Kaplan and Haenlein, 2019), that is: "a system's ability to correctly interpret external data, to

learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". Therefore, although it appears that the concept of Artificial Intelligence is still difficult to define in a precise way, in general terms the idea underlying AI is one of a machine being able to replicate very closely the abilities of a human being.

A distinction can also be made between weak AI and strong AI. Machines that make use of weak AI " operate strictly within the confine of the scenarios for which they are programmed" (Miailhe and Hodes, 2019, p. 5). These machines often reveal to be extremely efficient in solving the tasks they are programmed for: " machine learning, pattern recognition, data mining or natural language processing are examples of weak AI" (Perez *et al.*, no date, p. 6). A system equipped with strong AI -also called High Level Machine Intelligence (Walsh, 2018)-, instead, thinks and reasons very similarly to how a human does, and it is able to reprogram itself after having assimilate information. (Perez *et al.*, no date).

Already in 1950, hence before McCarthy coined the term, the idea we could face intelligent machines was starting to spread. That year, Alan Turing wrote a seminal paper called "Computing Machinery and Intelligence", where he proposed the idea that it is actually possible to create robots that are able to "think"(Buchanan, 2006). Later, thanks to the spread of the computer system in the 1970s and 1980s, it was demonstrated how artificial machines could solve computational problems extremely quickly by processing a certain amount of given data. A remarkable milestone in AI history occurred in the year 1997. The previous year, reigning world chess champion, Garry Kasparov, had engaged in a chess match against a computer produced by IBM, called DeepBlue. The match (1996) went to Kasparov. However, in 1997 a rematch was proposed, and with great surprise, DeepBlue was able to win with a score of 3½ to 2½. (Campbell, Hoane and Hsu, 2002)The event represented the first clear demonstration of how a computer could truly be more efficient than a human being in a case of a well-structured problem-solving situation that requires to use logic, computation and data processing.

The last 20 years witnessed a boom in the Artificial Intelligence field. Machines have started to be part of everyday life in disparate ways. In the early 2010s, the introductions of Apple's Siri and Microsoft's Cortana represented a milestone in the development of an interactive form of Artificial Intelligence.

There is increasing cultural interest in research fields connected to AI. As of the beginning of 2020, by running a search of the string "Artificial Intelligence" on

Scopus (Elsevier) online database, the number of documents that are identified is 338,033. Figure 1 shows the documents that have been published in the last 20 years, confirming the increasing interest this topic is having among scholars.



Figure 1: number of documents published on Scopus containing the word "Artificial Intelligence" in the title or abstract

Moreover, the economic interest toward AI is proven by the increasing investment industries are undertaking on intelligent systems. According to International Data Corporation, in 2019 there has been an increase of 44% on the global spending on AI systems, in comparison with 2018, and "Worldwide spending on n AI systems will more than double to \$79.2 billion in 2022 with a compound annual growth rate (CAGR) of 38.0% over the 2018-2022 forecast period." (Anon., IDC, 2019)

With robots getting always closer to imitate human intelligence in memorizing, learning, and processing, some major concerns have arisen in the last years. One of them is about how much importance humans workers will maintain in the future context of employment. A key concept this thesis focuses on is technological unemployment, which the Oxford Dictionary of Economics defines as: "Unemployment due to technical progress. This applies to particular types of workers whose skill is made redundant because of changes in methods of production, usually by substituting machines for their services."( (Black et al., 2012), cited by (Campa, 2019, p. 3)). This concern reveals to be extremely actual, as confirmed by the CIO Survey by Gartner, stating that in 2019, 37% of the interviewees reported their enterprises would make use of AI in some way. (Anon., 2018) Moreover, for what concern the Industry 4.0 program, "Pwc, in 2017, asked leading companies to determine their priorities among a group of concepts: smart systems, humans in industry 4.0, smart production and people skills were identified as the highest priorities" (Morrar *et al.*, 2017, p. 14)

The relationship between the implementation of AI in firms and consequent unemployment is the starting point of this thesis. The research on technological unemployment brought by automation is still in an early stage, as it will be shown in the next chapters. However, there are few works that had a great success among scholars. The common idea underneath these contributions is that *this time*, what renders a job more or less susceptible to automation is the degree of routinization of the tasks that must be performed. (Autor, Levy and Murnane, 2003; Ford, 2016; Frey and Osborne, 2017; Manyika *et al.*, 2017). The past revolutions led to a decline of the employment in the primary and secondary sectors, but on the other hand, contributed to the development of the tertiary sector (Makridakis, 2017; Marengo, 2019). Now, also a vast range of cognitive jobs seem to be under threat. The spread of automation, heavily supported by improvement in AI technologies, is a challenge that many more workers will have to deal with.

The most influential work is the study conducted by (Frey and Osborne, 2017), which take into consideration 702 current occupations in the US, and tries to estimate the risk for each one of them to be performed by machines in the near future. They distinguish between high, medium and low-risk occupations. The result shows about 47% of total US employment is in the high-risk category (more than 70% of probability to be automated). This category includes transportation and logistics workers, as well as office and administrative support workers. Moreover, also most of the service occupations are under the threat of computerization. Certain tasks, however, remain non-susceptible of automation, especially the ones that can be defined as non-routine. There are indeed some variables, which they call bottlenecks, that hamper automation. (see Table 1) These are declinations in the workplace of certain kinds of intelligence. Another study, which led to similar results, is (Manyika et al., 2017). Like (Frey and Osborne, 2017), this study tries to depict the near-future situation of overall employment in the US. The results seem to be in line with the latter paper's results, as it is estimated almost half of the current activities people are paid for could be already be automated by using existing technologies. More than 2000 activities across 800 occupations are analyzed. Moreover, if only 5% of occupations could be currently automated completely, at least 60% of overall occupations have at least 30% of tasks being susceptible to automation. Activities having a higher risk to be automated are physical ones, taking place in highly structured and predictable environments. (Manyika et al., 2017)

| Computerization bottlenecks | O*NET variables                       |
|-----------------------------|---------------------------------------|
|                             | .Einger devterity                     |
| Percention                  | Manual dexterity                      |
| and manipulation            | ·Cramped work space.                  |
|                             | awkward position                      |
|                             | ·Originality                          |
| Creative intelligence       | ·Fine arts                            |
|                             | ·Social perceptiveness                |
|                             | ·Negotiation                          |
| Social intelligence         | ·Persuasion                           |
|                             | •Assisting and caring for each others |

Table 1: computerization bottlenecks according to (Frey and Osborne, 2017)

The idea routine jobs are more susceptible to automation is not new: already in 2003, (Autor, Levy and Murnane, 2003) sustained that computers have different effects on workers. On the ones "performing routine tasks that can be readily described with programmed rules" (Autor, Levy and Murnane, 2003, p. 1322) they have a substitution effect, whereas they serve as a complement for workers "executing non-routine tasks s demanding flexibility, creativity, generalized problem-solving capabilities, and complex communications" (Autor, Levy and Murnane, 2003, p. 1322) (see *figure 2*). Similar concerns are expressed by (Brynjolfsson and McAfee, 2014) in the book *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* By bringing many examples, they show how, thanks to Artificial Intelligence, most of the cognitive task could actually be automated. Like the previous authors, they envision a future where routine tasks, both cognitive advantage when it comes to using higher forms of deep thinking. (Brynjolfsson and McAfee, 2014)



Figure 2: categorization of jobs used by(Autor, Levy and Murnane, 2003) Source: (Bruun and Duka, 2018, p. 4)

Among these, the main work with the most pessimistic view on the topic is the book by (Ford, 2016) *Rise of the Robots: Technology and the Threat of a Jobless Future*. In his opinion, recent technological development is threatening blue-collars as well as white-collars occupations, making *this time* clearly different from the previous revolutions. Hence, he emphasizes the disruptive effect of Artificial Intelligence, sustaining in the next future practically every current occupation might be automated. (Ford, 2016).

Swimming against the tide, the study conducted by (Walsh, 2018) revealed that experts in robotics and AI are actually more cautious when it comes to estimate the extent of technological unemployment caused by automation. The key point of the study is that, according to experts in this field, High Level Machine Intelligence is expected to need several decades longer than what many non-expert think to be significantly developed and implemented at a practical level (Walsh, 2018)

A better understanding of the impact Artificial Intelligence is having on many kinds of occupations is the reason for the conduction of this systematic literature review. The main goal is to collect and analyze the main ideas that emerge from the most recent literature (starting from 2016), which can contribute to better understand the challenges that the implementation of AI is bringing on. In particular, my intention is to answer the following question: does the implementation of Artificial Intelligence in companies lead to unemployment, in the sense that workers are replaced by machines? This thesis, therefore, aims to present the main factors that influence the likelihood of an occupation to be automated.

#### 3. Conduction of research

To investigate the impact of artificial intelligence on employment, a Systematic Literature Review was conducted. The approach I decided to apply follows the indications delivered by (Tranfield, Denyer and Smart, 2003). Hence, this review starts with a planning stage, where the identification for the need for a review was identified; a second stage consists of the conduction of the review: identification of research and selection of studies are undertaken, and findings are presented; the third and last stage consists of reporting and dissemination.

The process of identification of the studies was composed of two stages. The first one was the conduction of the online research of valid documents. The second was the scanning of documents' titles and abstracts, and, if necessary, of a full-text read of the documents.

The three following inclusion criteria, chosen to conduct the search process, were selected:

- The document must be written in English (stage 1)
- The document must have been published at least in 2016 (stage 1)
- The document must belong to an area of study pertinent with the master thesis (stage 1)
- The document must give a useful contribution to answering the research question (stage 2)

The chosen database to conduct the research is Scopus (by Elsevier). Also, Google Scholar has been taken into consideration. However, I decided to exclude it. The main reason is it has more limitations in the application of eventual research filters, like the impossibility to apply the boolean operators "OR" and "AND", or to restrict the research only to selected areas of study.

The next step, after the selection of the database, was the identification of keywords, and so of the associated strings, on which the search process would base. By basing on the topic of the thesis, two groups of keywords were identified.

- The first group contains words related to artificial intelligence: "Artificial Intelligence" OR "AI" OR "automation".
- The second group contains words related to employment: "employment" OR "unemployment" OR "labor" OR "labour" OR "job". Even the word "work" was considered, but it was later judged inappropriate because misleading.

Indeed, it is often not intended as a synonym of employment or job, but rather as a synonym of study, paper, etc.

The selected words (at least one for each group) needed to be present in the title or in the abstract.

Overall, 16,054 documents were found. After limiting the research to documents published in the years 2016 to 2020, the results were 4,905. Hence, research was limited only to three fields of study, judged appropriate for the scope of this thesis, namely:

- social sciences (589 documents);
- economics, econometrics, and finance (199 documents);
- business, management, and accounting (390 documents).

The research produced 991 results. Among these, English written papers, according to Scopus, were 923.

The second stage consisted of a long process of examination of titles and abstracts of the documents. In some cases, the title already revealed a scarce pertinence of the document with the scope of this thesis, therefore they were excluded right away. In case the title was considered pertinent, the next step to be undertaken was the reading of the abstract. Some abstracts were not available, therefore the document was excluded. If the abstract was ambiguous, a reading of the full text of the document was undertaken, to decide if to include it or not. Unfortunately, in many cases, title and abstract were judged appropriate for the research scope; however, the document was not available, neither directly on Scopus nor on the publisher webpage, or it was accessible through a purchasing operation. In these cases, documents were excluded from the research. Other times it occurred that once the document appeared useful, it was downloaded and it turned out to be written in another language, like (Heinen, Heuer and Schautschick, 2017; Stojanova, Lietavcova and Raguž, 2019) or protected by a password, as (Kovacova, no date). Even in these cases, the document was excluded. Of course, also documents with abstract and title considered good were read in full text to decide if to select them or not. The process of abstracts' scansion was supported by the use of MAXQDA software. Once the full-text stage was completed, 31 documents were considered to be appropriate for this study. Figure 3 shows the process described above.

Once the final set of studies to be analyzed in-depth was compiled, I proceeded with the data extraction and synthesis stage (chapter 4 and 5). Chapter 4 is composed of two sections:

- Descriptive results: in this section, articles are described from different points of view: journals where they were published, methodologies used, the focus point of analysis useful for this thesis, and geographical area of analysis.
- Literature review: in this section different findings regarding the contents of the articles, useful for the scope of this thesis, are presented.

In chapter 5 findings are discussed in order to show linkages among them, in the attempt to give a clearer picture entailing different contributions from the literature.



Figure 3: selection process of the articles to be analyzed for this systematic literature review

#### 4. Findings

#### 4.1 Descriptive results

*Table 3* reports the bibliographical information regarding the 31 articles that have been studied to conduct this systematic literature review. The table illustrates the year of publication, the journal on which each article was published, and the

CiteScore for the year 2018, assigned by Scopus, which measures the citation impact of a journal. The first thing which stands out is that whit the exception of two articles (Fossen and Sorgner, 2019; Zemtsov, Barinova and Semenova, 2019), which were published on *Foresight and STI Governance*, all the articles were published in different journals. This is indeed an interesting insight, confirming that research concerning the topic is extremely fragmented. Another interesting aspect that can be noticed regards the publication year. While only 6 articles were published in 2016 or 2017, all the others were published in the last two years: 11 articles in 2018 and 14 articles in 2019. This underlines the increasing interests that literature is giving to the topic.

In *table 4* is reported information regarding the methodological design of every article, which resulted to be quite diversified. 22 papers use a qualitative approach to deal with their research purpose, while only 9 can be classified as quantitative. The difference is then rather marked. This is indeed an important insight, as it confirms that, despite in the last year the attention of the literature toward the effects o AI implementation has certainly increased, there is a lack of quantitative research.

Among quantitative papers, different methodologies have been utilized. Two surveys (Brougham and Haar, 2018; Chen and Lee, 2019) are based on interviews, that have been conducted on a sample of different workers and students, respectively. (Arntz, 2016) and (Arntz, Gregory and Zierahn, 2017) decided to use a task-level approach to oppose to the occupation-level approach used by (Frey and Osborne, 2017). They then re-estimate the risk of substitution by integrating information taken from the PIAAC database, which focuses also on socio-economic and job-related characteristics. (David, 2017) took the necessary data from the Career Matrix database. They then rely on the Random Forest algorithm to make their estimations, the same thing that (Frey and Osborne, 2017) did. (Zemtsov, Barinova and Semenova, 2019), to assess the potential of adaptation of different Russian areas to digitalization, uses a model that takes into consideration various variables, like the number of residents for a certain area, the level of education, and the share of workers in different industries. (Zemtsov, Barinova and Semenova, 2019)The data are taken from the Rosstat database. The article by (Bruun and Duka, 2018), instead, includes calculuses based on information taken from the German Statistical Office, to assess the validity of their UUBI program proposal. The last quantitative paper is (Zhou et al., 2020): also this study estimates the potential share of unemployment but in China. The estimation is based on an adoption rate, calculated by the authors, and

the theoretical substitution probability, adopted from the previous study by (Frey and Osborne, 2017).

Qualitative papers, as aforementioned, are the most numerous. The structures of the articles, in this case, appear to be more similar. Only 3 articles were found to undertake an empirical approach. Two of them (Bhattacharyya and Nair, 2019; Lloyd and Payne, 2019) rely on interviews with experts conducted by the authors. In the case of (Lloyd and Payne, 2019), the set of interviewees is ore variegate, as other than experts -people with several years of expertise in the technology development field- they interrogated also stakeholders, like employer unions representatives and public policy "Think-tanks". The study of (Bhattacharyya and Nair, 2019), other than on surveys, relies also on a systematic literature review regarding the relationship between employment and AI in India. The study by (Fossen and Sorgner, 2019) conducts a cluster analysis to categorize a set of different occupations under four groups (figure 5) and assesses the transformative and destructive effects of automation for each one of them. They rely on information taken from (Frey and Osborne, 2017), and from the O\*Net. All the remaining papers are based on what can be defined as a "theoretical analysis": by analyzing the existing literature or, in some cases, evidence coming from the application of AI in different contexts (see (Geisel, 2018; Lent, 2018; Michailidis, 2018; Ernst, Merola and Samaan, 2019), authors draw their conclusions about a certain topic related to automation. Table 2 shows the classification of the papers based on the different methodologies they use. Another distinction that has to be made regards the main focus of the articles in relation to the research question of this thesis. Indeed, from this point of view, the papers can be split into two groups. On the one hand, there are documents whose primary focus of analysis is the different jobs there are more at risk to be substituted. Some of them treat the problem taking into consideration a large number of occupations, being them more or less detailed (Arntz, 2016; Arntz, Gregory and Zierahn, 2017; David, 2017; Fossen and Sorgner, 2019; Zhou et al., 2020). Others, instead, take into consideration only a restricted group of jobs (like (Levy, 2018; Michailidis, 2018; Ernst, Merola and Samaan, 2019)). On the other hand, there are papers that offer valuable insights for this thesis by examining other factors influencing the effects of widespread automation and AI implementation. In these cases, analysis is focused on themes like labor cost (as in (Estlund, 2018b; Fleming, 2019)), country-specific characteristics (as in (Lloyd and Payne, 2019; Zemtsov, Barinova and Semenova,

2019)) or the role of public institutions (as in (Bruun and Duka, 2018; Beliz, Basco and de Azevedo, 2019)).

| Total articles: 31   |                                  |  |  |
|--|----------------------------------|--|--|
|  | Qualitative (22)                 |  |  |
| Quantitative (9)   | Empirical(3)                     | Theoretical(19)  |  |
| <ul> <li>Interviews</li> <li>Random forest</li> <li>Houthakker model</li> <li>Fractional response model</li> <li>Theoretical substitution<br/>probability</li> <li>Others</li> </ul> | ·Interviews<br>·Cluster analysis | •Analysis of the literature<br>review<br>•Presentation of actual<br>cases of application<br>•Development of a theory |  |

Table 2: classification of the 31 selected articles on the methodologies used

The last point of this section regards the geographical area of analysis. *Table 4* reports the countries studied in the different articles. 14 papers do not specify explicitly their area of focus, because is not relevant for the scope of their research. However, a high degree of differentiation can be observed among papers treating specific countries. The United States is the most studied country (5 papers focus on it: (Arntz, Gregory and Zierahn, 2017; Makridakis, 2017; Estlund, 2018b; Levy, 2018; Fossen and Sorgner, 2019)). The United Kingdom is analyzed by 2 papers (Makridakis, 2017)and (Lloyd and Payne, 2019). All the other papers are different from this point of view. In the case of (Bruun and Duka, 2018), Germany is the main focus of the study, but also other nations are taken into consideration, in the attempt to give other examples of the application of an eventual UUBI program: Finland, India, Kenya, and Namibia. The only paper that takes into consideration a vast set of countries is (Arntz, 2016), focused on the OECD area.

#### 4.2 Literature review

*Table 4* reports a brief description of the content of each analyzed article.

Before analyzing what are the concrete changes that the spread of machines is likely to have on employment, a point of debate that emerged from the articles revolves around the attitudes toward this phenomenon (. For instance, (Morgan, 2019) criticizes the amplification of the substitution problem part of the existing studies are characterized with. In particular, he moves critics to the study by (Frey and Osborne, 2017), for four main reasons. First, they don't take into consideration the new kinds of works that will be created. Second, the study is based on experts' opinions, and not on real tests, therefore there is a lack of evidence. Third, they underestimate technology bottlenecks that hamper automation. And fourth, they consider technology as isolated from institutions, behavior, and law. (Morgan, 2019)

By analyzing existing literature, several authors clarify different positions among experts and scholars toward the actual extent of the fourth industrial revolution and their attitude (optimistic or pessimistic) about it. (Makridakis, 2017; Pulkka, 2017; Boyd and Holton, 2018; Estlund, 2018b; Lloyd and Payne, 2019; Marengo, 2019) (Boyd and Holton, 2018), by focusing on the sociological implications of the fourth industrial revolution, make a clear distinction between two analytical positions therefore focusing on the nature of the phenomenon, rather than on positive or negative consequences brought by it- prevailing among experts, that they call "no real change" and "very real transformation". (Boyd and Holton, 2018, p. 334,336)Similar positions are reported by (Pulkka, 2017), who makes the distinction between "this time is different" ad "this time is no different". (Pulkka, 2017, p. 297,298)The first one claims this revolution is in most of its aspects comparable to the previous ones -industrial and digital revolutions- and despite admitting massive unemployment as a possible consequence, it will not result in a profound change of our social life (Boyd and Holton, 2018). Moreover, history shows how humans always managed to adapt to changes by undertaking a process o re-skilling, hence the fear of massive unemployment reveals to be exaggerated. (Pulkka, 2017) However, this position is by far the less common in the literature. (Boyd and Holton, 2018) A similar position is described by (Makridakis, 2017): he calls this part of the experts Doubters(Makridakis, 2017, p. 52): they think AI revolution is not possible, as some humans' skills cannot be replicated by robots. This position was prevalent in the past century but nowadays seems outdated, in light of new advancements in the AI field in the last 30 years(Makridakis, 2017). The major part of the literature, instead, tends to support the "very real change" position, thinking to AI revolution as a watershed bringing great changes never witnessed before (Boyd and Holton, 2018)

#### Table 3: bibliographical information of the 31 articles

| Author                         | Publication year | Source  | Citescore(2018) |
|--------------------------------|------------------|---|-----------------|
| Agarwal                        | 2018             | Public Administration Review                                | 3,03            |
| Agrawal, Gans and Goldfarb     | 2019             | Journal of Economic Perspectives                            | 8,52            |
| Arntz, Gregory and Zierahn     | 2017             | Economics Letters   | 1,1             |
| Arntz                          | 2016             | OECD Economic studies                                       | N/A             |
| Beliz, Basco and de Azevedo    | 2019             | Economics   | 0,91            |
| Bhattacharyya and Nair         | 2019             | Journal of Management Development                           | 1,73            |
| Boyd and Holton                | 2018             | Journal of Sociology  | 1,42            |
| Braña                          | 2019             | Journal of industrial and business economics                | 0,97            |
| Brougham and Haar              | 2018             | Journal of Management & Organization                        | 1,34            |
| Bruun and Duka                 | 2018             | Basic Income Studies  | 0,47            |
| Chen and Lee                   | 2019             | Sustainability  | 3,01            |
| David                          | 2017             | Journal of The Japanese and International Economies         | 0,88            |
| DeCanio                        | 2016             | Journal of Macroeconomics                                   | 1,13            |
| Ernst, Merola and Samaan       | 2019             | IZA Journal of Labor Policy                                 | 1,48            |
| Estlund                        | 2018             | Yale Law Journal  | 2,01            |
| Fleming                        | 2019             | Organization Studies  | 4,37            |
| Fossen and Sorgner             | 2019             | Foresight and STI Governance                                | 1,3             |
| Gera and Singh                 | 2019             | Indian Journal of Labour Economics                          | 0,14            |
| Geisel                         | 2018             | International Journal of Scientific and Technology Research | N/A             |
| Huang and Rust                 | 2018             | Journal of Service Research                                 | 8,04            |
| Jarrahi                        | 2018             | Business Horizons   | 4.42            |
| Lent                           | 2018             | Career Development Quarterly                                | 1,75            |
| Levy                           | 2018             | Oxford Review of Economic Policy                            | 2,31            |
| Lloyd and Payne                | 2019             | New Technology, Work and Employment                         | 2,14            |
| Makridakis                     | 2017             | Futures   | 3,14            |
| Marengo                        | 2019             | Journal of International and Business Economics             | N/A             |
| Michailidis                    | 2018             | Cyprus Review   | 0,19            |
| Morgan                         | 2019             | Economy and Society   | 3,96            |
| Pulkka                         | 2017             | Transfer  | 1,19            |
| Zemtsov, Barinova and Semenova | 2019             | Foresight and STI Governance                                | 1,3             |
| Zhou <i>et al.</i>             | 2019             | China Economic Journal                                      | 0,81            |

| Authors                     | Design       | Content description  | Country        |
|-----------------------------|--------------|--|----------------|
| Agarwal                     | Qualitative  | Investigates the<br>technology-related<br>challenges societies are<br>facing | Not relevant   |
| Agrawal, Gans and Goldfarb  | Qualitative  | Investigates the impact of automation on jobs                                | Not relevant   |
| Arntz, Gregory and Zierahn  | Quantitative | Estimates the risk of substitution   | United States  |
| Arntz                       | Quantitative | Estimates the risk of substitution   | OECD countries |
| Beliz, Basco and de Azevedo | Qualitative  | Proposes the creation of<br>a platform to create new<br>jobs                 | G20 countries  |
| Bhattacharyya and Nair      | Qualitative  | Investigates the future of employment  | India          |
| Boyd and Holton             | Qualitative  | Analyzes literature on<br>the fourth industrial<br>revolution                | Not relevant   |
| Braña                       | Qualitative  | Analyzes the effects of<br>digitalization                                    | Spain          |
| Brougham and Haar           | Qualitative  | Measures STARA<br>awareness and its effects<br>on employees                  | New Zealand    |
| Bruun and Duka              | Quantitative | Proposes the adoption of UUBI program  | Germany        |
| Chen and Lee                | Quantitative | Investigates students'<br>perceptio of AI                                    | Taiwan         |
| David                       | Quantitative | Estimates the risk of<br>substitution  | Japan          |
| DeCanio                     | Quantitative | Investigates the relation<br>between AI adoption<br>and wages                | United States  |
| Ernst, Merola and Samaan    | Qualitative  | Discusses the impact of<br>AI on employment and<br>society                   | Not relevant   |
| Estlund                     | Qualitative  | Discusses policies to<br>prevent workers to be<br>substituted                | United States  |
| Fleming                     | Qualitative  | Discusses the extent of<br>the substitution process<br>due to Al             | Not relevant   |
| Fossen and Sorgner          | Quantitative | Categorizes jobs basing<br>on the risk of<br>substitution                    | United States  |
| Gera and Singh              | Qualitative  | Contributes to the debate on technology                                      | Not relevant   |
| Geisel                      | Qualitative  | Explore the impact of AI in firms  | Not relevant   |
| Huang and Rust              | Qualitative  | Investigates the impact of AI on services sector                             | Not relevant   |
| Jarrahi                     | Qualitative  | Investigates the relation between workers and AI                             | Not relevant   |

| Lent                           | Qualitative  | Analyzes the impact AI<br>has on career<br>development experts                       | Not relevant  |
|--------------------------------|--------------|--|---------------|
| Levy                           | Qualitative  | Estimates the future<br>unemployment level i<br>certain jobs due to Al               | United States |
| Lloyd and Payne                | Qualitative  | Analyzes the institutions<br>and societies shape<br>technological<br>development     | UK and Norway |
| Makridakis                     | Qualitative  | Investigates the future of employment  | UK and US     |
| Marengo                        | Qualitative  | Analyzes literature on<br>the fourth industrial<br>revolution                        | Not relevant  |
| Michailidis                    | Qualitative  | Investigates the impact of AI on HR practices  | Not relevant  |
| Morgan                         | Qualitative  | Criticizes literature on<br>fourth industrial<br>revolution                          | Not relevant  |
| Pulkka                         | Qualitative  | Analyzes the Universal<br>Basic Income   | Not relevant  |
| Zemtsov, Barinova and Semenova | Quantitative | Investigates factors<br>affecting technological<br>development of different<br>areas | Russia        |
| Zhou <i>et al.</i>             | Quantitative | Estimates the future<br>unemployment level due<br>to Al                              | China         |

Table 4: content information of the 31 articles

The main argument of this thesis stems from the evidence of a long number of recent robot applications in cases requiring a certain degree of "social" intelligence and interaction with humans. (Boyd and Holton, 2018) Although the authors acknowledge the importance of this consideration, they also point out the limits of this argument, the most important being difficulties in the measurement of the actual efficacy of robots, as well as the unemployment generated by their use. For these reasons what they propose is the adoption, in the debate concerning problems of AI, of a third position, less deterministic, placing at the center of focus complexity and uncertainty. Rather than reasoning on the two extremes of the spectrum -that is, dystopian or utopian future generated by AI-, a number of alternative futures should be evaluated, and different social issues they involve should be analyzed. (Boyd and Holton, 2018). It appears, anyway, they are convinced a revolution is most likely to happen, and it will bring profound changes in society. A relatively similar analysis of the literature was founded in (Marengo, 2019), who opposes the *optimistic view* to

the *pessimistic* one. The first supports a series of long-term advantages offsetting the short-term disadvantages of AI, as the creation of occupations related to the use of machines and the spreading of "better" jobs involving a more human dimension, like health care and creative goods production; the second, looking at AI as a serious threat for very different kind of human positions, given the high codification and learning capabilities featuring modern machines. The author seems to have a pessimistic vision of the future concerning human employment, as consequences proper of this technological revolution make it almost impossible to replicate the virtuous cycle created by previous revolutions. The main reasons being firms pushed to choose capital over human labor, the plausible high concentration favored by network economies and a paradoxical miss in the increase of productivity. (Marengo, 2019). Also (Makridakis, 2017), again, describes optimists and pessimists. In his analysis, the optimists think future unemployment is good, as we will be able to harness AI machines to perform the actual work, therefore focusing, if we want, on jobs of our interests, a scenario taken into consideration also by (Huang and Rust, 2018). Similar considerations are moved by several experts in the field interviewed by (Lloyd and Payne, 2019): if a job could be automated, it would lose its importance for humans. The pessimists, on the other hand, are afraid of a future where all the important decisions are taken by machines, resulting in humans covering a secondary role, being a sort of "computer pets" (Makridakis, 2017, p. 50), unmotivated to work and afraid to take decisions. There are, then, also the pragmatists, who are associable in some aspects to the optimists, as they believe AI will be always be controlled by humans, who will be able to stay a step ahead and moderate robots' negative effects by using norms, as well as use concrete means as safe chips to maintain security. That been said, (Makridakis, 2017) points out they, as well as the *doubters*, are an extreme minority among the experts. Despite admitting it is impossible to predict the exact future state of things, the idea supported by (Makridakis, 2017) is a revolution is certainly going on, and it will come into full force by the next twenty years, changing employment patterns and bringing new challenges for human workers, like job polarization and most likely lower wages. Other concerns are raised also by (Estlund, 2018b), who seems to have a pessimistic vision on the future. The reason is, while the positive or negative final outcome is being discussed by the literature, there seems to be no controversy on three negative trends this revolution is bringing on, at least in the united states: growing inequality, erosion of labor standards and fissuring of work (Estlund, 2018). Even though someone argues the implementation of intelligent machines might have lower effects than many think (see, for instance, (Arntz, Gregory and Zierahn, 2017)) it appears in the last years, probably also due to the advancements in AI and digital technologies, the importance of this topic has gained increasing recognition, and different related problems that might raise have been discussed.

Historically speaking, the fourth industrial revolution is interesting for several reasons, that distinguish it from the previous ones. The first one is that it is impacting a larger number of nations (hence, of people). (Beliz, Basco and de Azevedo, 2019; Bhattacharyya and Nair, 2019)While most part of the western countries has already witnessed previous revolutions and their consequences, social and economical, this process is actually new for emerging countries like India and China (Bhattacharyya and Nair, 2019). Related problems and negative effects, therefore, might even be amplified by the degree of novelty and the high number of people who live in these countries. There might be the need to tackle the problem by posing a the center of the strategy the cooperation between different countries (Beliz, Basco and de Azevedo, 2019)

The second particular aspect is the rapid pace of related innovations. Several authors give credit to *Moore's law*, which states that "digital processing power doubles every 18 months" (Fleming, 2019, p. 25). Parallelly to processing power, also the ability of computers to perform more tasks grows. AI machines reflect this development, being increasingly able to adapt to tasks that were always thought impossible to computerize (Bruun and Duka, 2018). Even though many authors recognize the rapid growth of innovations, high uncertainty unravels: overall, no predictions on exact years in the future are made. The only two exemptions are (Levy, 2018) and (Zhou *et al.*, 2020). In particular, (Levy, 2018) tries to predict job losses by the year 2024 by hypothesizing the diffusion of three technologies, namely *autonomous long-distance trucks, automated customer service responses,* and *industrial robotics*, and the impact they might have on related jobs.

The third aspect, already mentioned, is related to the kind of jobs the widespread machine implementation is affecting. While previous revolutions usually affected manual tasks, performed mostly by blue-collar workers, the AI revolution is threatening to substitute, according to many studies, also white-collar workers (Agarwal, 2018)performing routine tasks (Boyd and Holton, 2018)that were traditionally thought to be immune to automation (Jarrahi, 2018). AI machines are already used in different company functions. In marketing and sales, AI technologies

allow firms to "analyze vast amounts of customer data and identify the characteristics of high-value customers" (Geisel, 2018, p. 118) better identify profitable markets for services and products and help salespeople to acquire clients and generate revenues (Geisel, 2018).Moreover, in accounting and finance AI programs enable decision-makers to save a great amount of time, by creating information that is useful for the user from a huge quantity of data, in disparate occasions, from contracts analysis to risk evaluation (Geisel, 2018). Also in HR, AI technology is already used in a wide range of operations, especially in employee selection practices (Michailidis, 2018). Other than increasing the speed of the scanning process, AI helps HR teams to evaluate the capabilities of the current workforce. As a consequence, time and money are saved, and better candidates are chosen (Michailidis, 2018).

A topic of debate is the creation of new jobs as a consequence of AI machines' implementation. (Makridakis, 2017; Estlund, 2018b; Levy, 2018; Beliz, Basco and de Azevedo, 2019; Fossen and Sorgner, 2019) The fourth industrial revolution would not create all these concerns and fears if, after all, replaced workers were able to find new jobs. Previous revolutions contributed profoundly to the growth of the tertiary sector (services), over manufacturing and agriculture (Makridakis, 2017; Marengo, 2019)(Makridakis, 2017) shows both in the UK and United States the labor force employed in the services sector in 1820 was less than 20% whereas, as of 2014, it is more than 75% of the overall labor force. The creation of new jobs, as well as the elimination of part of existing ones, connected to the new technologies introduced, is a natural consequence of every revolution. (Beliz, Basco and de Azevedo, 2019). Notice that with the expression "new jobs" are indicated both new kinds of jobs and new job spots. Indeed, it is sure that new professions strictly related to the use of new technologies will appear (Estlund, 2018b). On the other hand, the increased consumer income thanks to augmented productivity can generate new demand for products and services, then more human labor might be needed. (Estlund, 2018b) Automation could also affect indirectly the demand for human labor by favoring firms' expansion. It is the case of bank tellers: the introduction of ATMs should have reduced the number of bank tellers needed, as their job was partly automated; however, the spread of ATMs raised at the same time also the number of banks' branches, that increased, in turn, the demand for bank tellers. (Levy, 2018). In the past, the fear of technological unemployment was demonstrated to be unfounded, as the creation of new jobs thanks to technological advancements was greater than the labor-saving impact stemming from the adoption of new technologies (Arntz, Gregory and Zierahn, 2017). The crucial question is if "this time" the same thing will happen or the technological unemployment will be so important that workers will be not able to shift to other jobs. Optimistic views on this problem have been founded, like (Agarwal, 2018), who trusts the ability of society to create new jobs like in previous cases, and (Arntz, Gregory and Zierahn, 2017). (Marengo, 2019), instead, given the features of this revolution, believes unemployment is not going to be absorbed by the creation of new jobs. Again, however, it is impossible to predict exactly what will happen; societies are challenged to decide in an era of uncertainty (Beliz, Basco and de Azevedo, 2019).

As already stated in the descriptive results section, research on technological unemployment caused by machines' proliferation is very fragmented, covering very different geographical areas. Only 4 quantitative studies presenting estimations on the risk of automation in the coming years have been identified. (Arntz, 2016; Arntz, Gregory and Zierahn, 2017; David, 2017; Zhou *et al.*, 2020) The first one is the study by (Arntz, Gregory and Zierahn, 2017) It represents an interesting case, as it contradicts (Frey and Osborne, 2017)<sup>1</sup>, to which, as shown above, much credit is given. The thesis brought by the authors is that the study, which predicts the probability of substitution of men by machines for a very large list of occupations is essentially biased, as the approach they use is wrong. (Frey and Osborne, 2017) work is indeed based on an occupational-level approach, meaning to be analyzed is only a representative occupation (Arntz, Gregory and Zierahn, 2017). If this approach might seem valid at a first sight, it has a drawback: it doesn't consider the variations of tasks within that profession. This is a key assumption, as machines, always according to the authors, struggle in performing some of the tasks of the occupation.

The study is conducted by adopting a job-level approach, that acknowledges heterogeneities within the same occupation. As a result, automation risk for US jobs decreases from 38% to 9%. (Arntz, 2016) By applying the same logic, the study by (Arntz, 2016) found that in OECD countries similar results came out, with 9% of the jobs are potentially automatable. In Germany and Austria, 12% of the workers face high risks of automation, while in Korea and Estonia only 6% do (Arntz, 2016). (See figure 4)

<sup>1: (</sup>Frey and Osborne, 2017), the document cited in this paper, is the new version of the study conducted in 2013.



Figure 4: share of people doing job at high risk of automation in OECD countries. Source: (Arntz, 2016)

Moving outside the US, other attempts to estimate the probabilities of substitution of human employees engaged in different works in the coming years have been made, by (Zhou *et al.*, 2020) and (David, 2017), whose subject of analysis are two Asian countries, China and Japan, respectively. According to (Zhou *et al.*, 2020) estimations, by 2049 around 35% of the workers (142 million) in the urban areas and 40% in the rural zones (130 million) will be substituted by machines. (David, 2017), instead, estimates 57% of the current jobs in Japan can be considered to be at risk of automation.

Important ideas emerged when trying to understand what are the effects AI has on jobs, as well as the factors that render a job more susceptible to automation.

It is useful, for this analysis, to re-examine the concept of intelligence. A prevailing idea is that overall intelligence can be broken down into different parts, corresponding to different "types" of intelligence. (Geisel, 2018; Huang and Rust, 2018; Jarrahi, 2018) Different jobs are associated with the form of intelligence that is

more used to perform them. The descriptions of different types of intelligence differ within the analyzed literature. Thus, forms of intelligence are called in different ways. However, they can certainly be compared in terms of the skills and capabilities they are associated with. A first, basic distinction can be made between analytical and *intuitive* intelligence: the first, useful to solve problems requiring logical reasoning and based on a structured process; the second, allowing to perform tasks that need a certain degree of intuition and creativity (Jarrahi, 2018)A more precise description is presented by (Huang and Rust, 2018), who distinguishes four types of intelligence by the degree of learning and adaptation, two abilities that can come from different sources. Thus, intelligence can be: mechanical (minimum degree of learning and adaptation capacity), analytical (based on given data), intuitive (based on a learning process), and *empathetic* (based on experience). They develop an evolutionary theory of AI: at the beginning, machines replicate only mechanical intelligence; then, they evolve over time until they become able to use all four types of intelligence. Four types of AI are described also by (Geisel, 2018), who adopts the categorization of (Hintze, 2016): what changes from type 1 to type 4 is the amount of "self-awareness" of the machine. Although the concept of self-awareness is certainly more complicated, it is comparable in general terms to the one of experience, used by (Huang and Rust, 2018). In this case, however, types 3 and 4 of AI don't exist yet: they involve a high degree of understanding of the self interior status. (Geisel, 2018)

Three reasons that favored the advancements in the AI field. The first is a drop in the production cost of computers and other devices utilizing an operative system; the second is the widespread adoption of the internet; the third is the lower cost of capital for digital technologies, which contributed to the diffusion of start-ups able to uproot incumbents. (Ernst, Merola and Samaan, 2019)In the past years, the idea machines could replace humans in a vast range of jobs had already started to emerge. Machines were already thought to be better at performing tasks that follow a predefined set of rules.(see chapter 2) The manufacturing sector, for instance, has already witnessed a dramatic loss of human employment in the last decades . (Makridakis, 2017; Levy, 2018). The prevailing thought was humans do maintain a comparative advantage in professions involving non-routine tasks, either manual or cognitive. This idea is retrieved also by (Bruun and Duka, 2018), who present in their paper a matrix developed on the information by (Autor, Levy and Murnane, 2003) (see *figure 2*).

The idea AI revolution will have disruptive effects for many manual and routine jobs remains solid. Several articles support this thesis. (Pulkka, 2017), for example, shows how this is a common point on which both the "real change" and the "no real change" visions in the existing literature agree. The work that reflects best this thesis is the one by (Fossen and Sorgner, 2019). They collocate many occupations with these characteristics in a group he defines *collapsing occupations*, on which digitalization has a strong destructive effect. This category of jobs is already witnessing a substitution process, and the next advancements in AI will most likely make it possible for all the tasks to be performed by machines. (Fossen and Sorgner, 2019) (see *figure 5*).



Figure 5: categorization of US occupations, in regard of the different effects of automation on them. Percentages refer to the share on US employment. Source: (Fossen and Sorgner, 2019, p. 12)

(Huang and Rust, 2018) agrees on the idea these kinds of jobs cannot be considered to be "safe", as they require only mechanical intelligence to be performed, that is the lower level of artificial intelligence. Results coming from the study of (Bhattacharyya and Nair, 2019)show that repetitive and rule-based jobs are more likely to be substituted also in emerging countries like India. As shown by their study:" There will be a net loss of jobs because of widespread adoption of automated technologies, (...) there will be loss of jobs in the manual and routine category of jobs".(Bhattacharyya and Nair, 2019, p. 184) Other evidence is furnished by (Levy, 2018) who, taking several representative jobs, shows how repetitiveness and structured work environment are the main causes of their vulnerability. This is the

case, for example, of radiologists and bank tellers. (Levy, 2018) This thesis seems to be corroborated by two studies analyzed, regarding different countries: (David, 2017) (Japan) and (Zhou *et al.*, 2020) (China). One necessary note to make is while (Zhou *et al.*, 2020)'s gives precise information on the future years analyzed (they're calculations refer to 2049) (David, 2017) stays vaguer, referring to "next years" (David, 2017, p. 77)as the time of analysis. (*see table 5*)

| David                    | Probability | ZHOU  | Probability |
|--------------------------|-------------|---|-------------|
| Packing worker           | 0.97200     | Clerical workers  | 0,74880     |
| Truck driver             | 0.97200     | Food service workers  | 0,74620     |
| Hotel worker             | 0.97428     | Building materials producing and processing workers                     | 0,67070     |
| Tourist bus driver       | 0.97428     | Weaving, knitting, and bleaching<br>workers                             | 0,64190     |
| Road patrol worker       | 0.97428     | Tailoring, sewing, and leather and<br>leather and fur producing workers | 0,64190     |
| Computer-assisted-design | 0.98173     | Machine producing and processing workers                                | 0.64190     |
| Data entry keyer         | 0.98173     | Machine repairers   | 0,64190     |
| worker                   | 0.98173     | Rubber and plastic producing workers                                    | 0,64190     |
|                          | 0.00170     | Oil, food, beverage, and theirmaterials producing and                   | 0.64400     |
| Mail deliverer           | 0.98173     | processing workers  | 0,64190     |
| Computerized typesetting |             | Tabaco producing and processing   |             |
| operator                 | 0.98173     | workers   | 0,64190     |

#### Table 5: occupations facing higher risks of being automated. Sources: (David, 2017; Zhou et al., 2020)

These tables present some professions that, according to their studies, face high risks of being replaced. Their main characteristics, indeed, are either to be repetitive, to make use of analytical intelligence and not to require particular interactions with other people. Results, then, seem to coincide with (Fossen and Sorgner, 2019) also for what concerns the type of technology bottlenecks proper of these professions.

The study conducted by (Chen and Lee, 2019) shows similar arguments as well. It was conducted to find out the perception of a set of Taiwanese students on the risk for 12 occupations to be substituted. Not surprisingly, jobs like retail sales operators, translators, and home service workers were thought to face a higher risk than jobs like tutors, artists, and researchers. Automation for manual and routine jobs is indeed

a critical issue regarding the near future:38% of current US employment can be reconducted to this category of jobs (Fossen and Sorgner, 2019).

However, things change when jobs requiring a higher level of cognition or less structured tasks are taken into consideration. Despite the concerns about machines substituting humans also in these jobs, the analysis conducted reveals many authors are more cautious, highlighting actual limits AI machines still have. A useful consideration is that an occupation can be seen as a set of tasks. (Huang and Rust, 2018) Usually, it is not the occupation, but only a few tasks that compose it to be under threat of substitution (Arntz, 2016). Firstly, an advantage humans have over machines in many occasions is their ability to work properly in an unstructured environment.(Levy, 2018; Ernst, Merola and Samaan, 2019). For instance, machines can hardly replace workers who, despite being low-skilled, have to deal with simple unpredicted changes in the workplace, like janitors, who sometimes have to work on a wet ground (Levy, 2018).

The same applies also to lawyers, as most of the time their work is unstructured, for example when it comes to preparing legal arguments (Levy, 2018). The difficulties for a robot to work in a non-structured environment are stressed also by (Lloyd and Payne, 2019), who report how, in the case of hospitals, they can hardly work in wards or single-occupancy rooms.

Secondly, in many cases, to be crucial is the type of intelligence that is mainly used to perform a job to make it more or less vulnerable. Tasks requiring analytical intelligence are the easiest to replicate (Jarrahi, 2018). AI is becoming particularly useful in jobs involving *classification* tasks. These are a broad set of jobs based on text and image recognition. We find examples of these tasks in many fields, like legal services, medicine, accounting, and auditing. (Ernst, Merola and Samaan, 2019). The same applies to jobs involving tasks matching supply with demand(Ernst, Merola and Samaan, 2019) a typical feature of jobs belonging to the marketing function, another field where AI is revealing to be better than humans in performing operations related to market identification or advertising (Geisel, 2018)

Anyway, machines using analytical intelligence are still in an early phase of development. (Huang and Rust, 2018)but it seems reasonable to think with the advancements on the field, their impact on employment will not be indifferent (Bruun and Duka, 2018)Other insights sustaining the idea that a *complete* substitution process will hardly happen were found in the study by (Lloyd and Payne, 2019) according to which major parts of interviewed experts in the UK and Norway

find it difficult to replicate humans in the service sector, in contrast with the ideas brought by (Huang and Rust, 2018) and (Michailidis, 2018). Even though tasks might be automated, it is not said that they will disappear all at the same moment (Huang and Rust, 2018; Ernst, Merola and Samaan, 2019). Many jobs still need different forms of intelligence to be performed. Thus, rather than substitution, human-machine integration (like in (Jarrahi, 2018)) is seen by several authors as the most plausible near-future scenario. 48% of the US total employment is composed of jobs that will probably face profound *transformative effects* of digitalization, that is, even though the nature of tasks will probably change due to digitalization, machines are seen as complements of humans, rather than substitutes (Fossen and Sorgner, 2019). In the same line of thinking, (Ernst, Merola and Samaan, 2019) sustains many jobs will still require a human component, as someone will anyway still have to check for the correct setup and functioning of machines; moreover, human workers will spend more time on certain job tasks rather than on others, therefore automation doesn't necessarily equal unemployment. (Ernst, Merola and Samaan, 2019)In many cases, digitalization cannot take over the job tasks that require creative and social intelligence, so human workers are considered to be safe, at least in the short term (see figure 5) (Fossen and Sorgner, 2019). Similar considerations are moved also by (Fleming, 2019), who, by coining the word "Bounded automation" (Fleming, 2019, p. 28) referring to the famous concept of Bounded rationality introduced by Simon, sustains AI cannot yet perform a large number of tasks currently executed by humans. Human-machine integration will most likely feature also managerial jobs, where the decision-making process assumes particular importance (Geisel, 2018; Jarrahi, 2018). A future where inside companies every decision, even important ones, will be taken by machines might seem realistic, as they are less subject to make mistakes when it comes to deal with complexity, that is, once great amounts of data are available(Geisel, 2018; Bhattacharyya and Nair, 2019). However, the decisionmaking process is featured also by:

-uncertainty: a lack of information on all the alternatives and their consequences -equivocality: conflicting interests between stakeholders (Jarrahi, 2018)

According to (Jarrahi, 2018): "When the ambiguity is overwhelming (as in the case of much organizational decision making), or when the organization is faced with situations for which there is no precedent, an intuitive style of decision making may prove more helpful" (Jarrahi, 2018, p. 5).

Moreover, an environment characterized by equivocality makes the decision-making process become subjective and political: when the objectiveness in making the best decisions is overshadowed by interests of stakeholders, the ability to negotiate, in which humans still have a comparative advantage over machines, becomes by consequence more important (Jarrahi, 2018). While AI works better than humans in a complex environment, human approaches, based on intuition and charisma, are still to be preferred in dealing with uncertainty and equivocality. (Jarrahi, 2018) Furthermore, elite managers usually merge technological capabilities with responsibility, a difficult mix to replicate that render them particularly valuable, strengthened by their ability to make alliances with relevant stakeholders (Fleming, 2019). Also, the study by (Bhattacharyya and Nair, 2019) seems to support this thesis: according to some interviewed experts: "Human skills in leadership, working under complex, ambiguous and stressful contexts would be valuable" (Bhattacharyya and Nair, 2019, p. 184).

In general terms, also in jobs involving creativity, design, and system thinking, humans will still play a fundamental role (Bhattacharyya and Nair, 2019). According to (Huang and Rust, 2018), even in the worst-case scenario, where machines will be able to use all kinds of intelligence, meaning they become at least as intelligent as humans, integration might still be more probable than substitution. The authors also present different alternatives for how integration might occur -one does not exclude the others-:

- Humans and machines offer the same service independently. This might be possible because some people could still prefer a service to be performed by humans -for example, due to a mere preference matter- relegating human job to be a "niche preference". (Huang and Rust, 2018)
- Humans and machines cooperate in the production and delivery of a service; in this case, humans are enhanced by machines, but they are not substituted by them. (Huang and Rust, 2018)
- Machines serve humans, doing only jobs that humans are reluctant for; this is the most positive scenario, where humans, by leveraging machines, can focus exclusively on what they like. Moreover, machines can help humans in solving everyday problems and improve their lives, like it already happens in the cases machines help paralyzed people in writing and moving. (Huang and Rust, 2018)

Agreeing with this idea, (Lent, 2018) sustains that in jobs like career developers, although computers have an advantage in performing a certain number of technical tasks, humans are still preferred by clients, as counselors help them to make sense of information and arrive at a reasonable choice. Public acceptance is indeed an obstacle for the implementation of machines, at least in the services sector. That is the reason why some jobs, despite being easily replaceable by machines, still exist, like call center operators: there is the necessity of human interaction with customers, simply because this is better seen and accepted in comparison to a robotic one (Fleming, 2019). In line with this reasoning, (Arntz, Gregory and Zierahn, 2017) argue that "another aspect that should be considered is a strong societal preference for the provision of certain tasks and services by humans as opposed to machines. As an example, nursing or caring for the elderly may remain labor-intensive sectors, even if service robots increasingly complement these professions in the future." (Arntz, 2016, p. 22). Similar arguments in favor of this thesis are brought always by the study of (Fossen and Sorgner, 2019), who locates 12% of the US occupations in the category they call human terrain (see figure 5): these jobs are the safest ones from substitution, even in the long term. Their main characteristic is to involve the ability to assist and care for the others, which are backed by empathetic intelligence, the most difficult to replicate. (Huang and Rust, 2018; Fossen and Sorgner, 2019) Nonetheless, social interactions contribute to a more articulated structure of the environment (Levy, 2018), a crucial factor for a job to be more difficult to replicate, as mentioned above. The importance of social skills, like "the ability to connect with people" is highlighted also by (Bhattacharyya and Nair, 2019, p. 182)

| Occupation                | Probability |
|---------------------------|-------------|
| Speech therapist          | 0.01378     |
| Lawyer                    | 0.01872     |
| Stylist                   | 0.02108     |
| Classical musician        | 0.02531     |
| Theater decorator         | 0.02531     |
| Stage director            | 0.03129     |
| High school teacher       | 0.03275     |
| Vocational school teacher | 0.03275     |
| Make-up artist            | 0.03549     |
| Radio director            | 0.03806     |

Table 6: occupations with low probability of being automated. Source: (David, 2017)

As it can be seen by the *table 6* above, (David, 2017) study forecasts almost no risk for professions like speech therapists, lawyers, high school teachers, and radio directors: a common feature of all these jobs is the amount of time involved in engaging social relations and work with other people. Indeed, also the perceived fear to be substituted is lower among workers whose job consists mainly of tasks based on social contact with clients or other people. For instance, bartenders seem to believe "…human interaction is a lot different compared to a robot…" (Brougham and Haar, 2018, p. 251) or physicals activity educators said: "…don't see STARA<sup>2</sup> having an effect as my role is all about the interpretation of each client's unique health status. This interpretation requires personal interaction with the patient that technology, at this point, capable of." (Brougham and Haar, 2018, p. 251)

These results coincide as well with the above consideration by (Bhattacharyya and Nair, 2019): also in jobs where creativity is fundamental, as classical musicians, theater decorators, and make-up artists, humans will still have a comparative advantage against machines.(Ernst, Merola and Samaan, 2019), in turn, sustains there will be an increasing demand for social skills. This might indeed be a positive thing, as also people who can hardly access the knowledge for advanced technical skills may be able to find work once they get out of their students' careers.

All the aforementioned ideas revolve around the nature of the tasks that are supposed to be performed by intelligent machines. However, also other kinds of factors influencing the spread of AI and, in turn, of technological unemployment, have been identified in the literature.

Psychological factors, for instance, affect directly the overall diffusion of automation technologies. Some people, managers included, are actually hesitant about using AI simply because they do not know how to use it (Geisel, 2018)There are also matters of "public image" of power holders to take into account. In this sense, the widespread implementation of automation might be hampered by the decisions taken by public institutions, that can be more or less willing to promote it or not. For instance, in the last year, in countries like Japan, the spread of digital technologies was favored by a positive attitude of the authorities. (David, 2017)Moreover, public and private employers, who have the possibility to decide to substitute workers, are certainly constrained in doing so by potential bad legal consequences, as well as a

<sup>2</sup> STARA: smart technology, artificial intelligence, robotics, and algorithms. Source:(Brougham and Haar, 2018)

detriment of their personal public image -or of the companies/institutions they leadthey might run into if doing so. (Fleming, 2019). Public perception becomes particularly important also for problems connected to privacy, that many people think might be at risk if AI use is pursued with no criteria. (Geisel, 2018)

Also, the environment affects the strategic choices of firms, and so also the spread of automation. For example, in developed countries, investments in AI rather than traditional capital might be hampered by intellectual property rights or limits to access natural resources (Ernst, Merola and Samaan, 2019). The opposite, instead, usually happens in developing economies, where "the capital price of AI relative to traditional capital is likely to be lower, given more restricted access to capital and higher risk premia overall as regards investments." (Ernst, Merola and Samaan, 2019).

The relation between environmental conditions and risks connected to automation is the focus of the (Zemtsov, Barinova and Semenova, 2019) study. It shows that new industries are more likely to emerge in regions that are able to attract and retain human capital, which are the ones characterized by favorable investment conditions, diversified economy, and a developed ICT infrastructure.

In general, another key factor to take into consideration that might be positive for workers is the position of the firm in the Global Value Chain. This, together with the specialization of a national economy, contributes to determining the jobs needed locally for production activities (David, 2017). In the case of Japan, for instance, many global firms decided to keep close activities that require creativity and design thinking, while offshoring low return activities. (David, 2017). Other occupations, like janitors and home health aide, cannot be offshored because they have to be performed in person, thus are protected by automation (Levy, 2018). Other countries, like Norway, are witnessing a process of reshoring, hence more locals are hired. This because fewer workers due to automation imply less great labor costs, and the closeness of some activities to the local market is preferred (Lloyd and Payne, 2019). A similar hypothesis is brought by (Arntz, 2016), whose study shows that there are cross-country differences that influence the risk for workers to be substituted, even though they belong to the same industry. She sustains the reasons behind these differences should be associated with "general differences in the workplace organization, and differences in the adoption of new technologies" (Arntz, 2016, p. 25).

The study by (Zhou *et al.*, 2020) analyses also the risk of automation in relation to personal characteristics of workers, like age, gender, income, and education. For what concerns age, the study shows youngest workers (20-29 years old) are the less likely to be substituted, they are usually more capable of using new technological means. In contrast, the oldest workers are more at risk, as unless they acquired new skills, their knowledge is usually obsolete. (Zhou et al., 2020) This reveals an interesting contraposition between *actual* and *perceived* risk of substitution. Oldest workers are indeed less concerned about being replaced, as it is shown by the study by (Brougham and Haar, 2018). However, This seems reasonable, as older workers are closer to retirement, and by consequence give for sure less importance to a longrun negative scenario. On the contrary, young workers are more discouraged when they consider the effects automation might have on their career possibilities, perhaps because they are more aware of the potential capabilities of these technologies. (Brougham and Haar, 2018; Zhou et al., 2020). Note that population age might as well represent another obstacle for technological unemployment. This is, for instance, the case of Norway (Lloyd and Payne, 2019) -but it is possible to extend this scenario to every country where the average population age is increasing- where an aging population will increase the demand for jobs in health and social care.

Gender is another point of debate (David, 2017; Beliz, Basco and de Azevedo, 2019; Chen and Lee, 2019; Ernst, Merola and Samaan, 2019; Lloyd and Payne, 2019; Zhou et al., 2020). Some concerns about the possible accruement of gender social gaps that might occur have arisen (Ernst, Merola and Samaan, 2019). (Beliz, Basco and de Azevedo, 2019), in the same line of thinking, sees a challenging future for women. The point is previous revolutions involved the most industries where men employment dominated, like manufacturing. The advent of new technologies, instead, affects also industries where women traditionally prevail, like food and beverages and retail. Despite, like (Lloyd and Payne, 2019), they consider the possible growth in sectors like healthcare and social services -where the share of women is greater- in the future important opportunities will probably come from jobs requiring educational paths that are, at least at the moment, undertaken mostly by men (Beliz, Basco and de Azevedo, 2019). Supporting this idea, the study by (Chen and Lee, 2019) shows that female interviewees have a more negative perception of the impact of AI in professions. However, studies by (Zhou et al., 2020) and (David, 2017) counteract these concerns. Regarding the substitution probabilities, women and men are not facing significant different risks in the next future. In China, the gap

is only 1 percentage point (37,50% for men against 38,60% for women) (Zhou *et al.*, 2020). In the same way, the (David, 2017) study regarding Japan did not find any significant difference from this point of view.

What plays a rather important role, instead, is education (see also later). Overall, there is a drop of 15 percentage points in the substitution probabilities between people having a high-school degree and university graduates (Zhou *et al.*, 2020). Not surprisingly, people having even a lower degree, as primary school, or even illiterate, face higher risks.

What emerges from the articles analyzed, therefore, is an accruement in the job polarization phenomenon. This means, there will be a higher demand for jobs that require high skills and low skills, while medium-skilled occupations will tend to decrease. This idea was actually already sustained by a large part of previous existing literature (see (Pulkka, 2017; Sorgner, 2017)). Most likely, just a small part of workers currently employed in mid-skilled jobs, but in possession of higher skills, will move to the upper end: as in (Fleming, 2019), it is more probable that the majority of workers will move toward low-skilled jobs. Problem is, these jobs often correspond to lower wages. Labor cost is indeed a crucial factor affecting the risk of automation (David, 2017; Estlund, 2018b; Ernst, Merola and Samaan, 2019; Fleming, 2019; Lloyd and Payne, 2019). There are indeed some jobs that are not worth automating simply because the wage of the workers is so low that an investment in machines to perform certain tasks would not make sense from an economic point of view (Fleming, 2019)it is the case, for instance, of part-time jobs, or many poorly paid jobs in emerging economies, where a large supply of lowskilled labor is still available, making firms somehow reluctant to choose in favor of automation (Ernst, Merola and Samaan, 2019; Fleming, 2019). (Lloyd and Payne, 2019) contribute to this argument, specifying in cases where high wages costs are not justified by the high-skills or strong relationships with stakeholders, firms are pushed to invest in machines and substitute human workers. This is happening, for instance, in Norway, where high wages characterize also the manufacturing and agriculture industries, which are witnessing an increasing process of automation (Lloyd and Payne, 2019). This is the negative side also of all those laws that contributed to social justice: their positive aspect is certainly to create conditions for "decent work" and are certainly worth to be pursued. However, on the other hand, they raise inevitably the costs of employment, and push firms to find ways to avoid it, as well as related risks for the employers -one, of course, is investing in automation-, a consequence that affects especially mid-skilled work (Estlund, 2018b). Crucial importance to labor cost is given also by (Braña, 2019), who states that: "relative wages and productivity are also determinants of which jobs will remain in a country and which will be lost to foreign competitors." (Braña, 2019, p. 420). With AI being able to replace many medium-skilled jobs, wage premia of high-skilled workers might also be reduced (Ernst, Merola and Samaan, 2019). A crucial factor that will mitigate or accrue the negative effects of AI on wages is the elasticity of substitution between capital and labor (Ernst, Merola and Samaan, 2019). The same idea is shared by (DeCanio, 2016), the article that best investigates the relation between AI application and wages. He states that: "...if the elasticity of substitution between human and robotic labor is greater than the 1.7-2.1 range, proliferation of robots will have a depressing effect on human wages." (DeCanio, 2016, p. 289). The range is calculated by applying different distributions that, according to the author, fit well to study this phenomenon: Lognormal, Weibull, Gamma, Generalized Gamma (DeCanio, 2016). He does not consider it hard to happen, reporting how the elasticity of substitution between graduate and non-graduate workers in the period 1963 to 2008 was equal to 2.9. (DeCanio, 2016) Of course, it should be verified what is the actual elasticity of substitution between humans and AI machines is greater or less than the one between graduate and non-graduate students, but considering that in 2016 AI was already able to perform various tasks, a great reduction of the gap between human workers and AI does not seem an improbable scenario. Moreover, the manufacturing sector should see a decline in wages even for a smaller value of human-robot elasticity (DeCanio, 2016).

A positive effect on wages might occur in the case AI complements workers. In other words, it is labor augmenting rather than capital augmenting. This leads to higher labor productivity, therefore wages should increase. This idea is shared both by (Ernst, Merola and Samaan, 2019) and (Arntz, Gregory and Zierahn, 2017).

A direct consequence of job polarization is the increasing importance in the future of the educational sphere, another topic that emerges in several papers (Boyd and Holton, 2018; Bruun and Duka, 2018; Levy, 2018; Beliz, Basco and de Azevedo, 2019; Bhattacharyya and Nair, 2019; Zemtsov, Barinova and Semenova, 2019; Zhou *et al.*, 2020). Education involves both the educational system -schools and universities- and the process of retraining, that workers with obsolete knowledge should undertake. It has already been shown how the higher the education of the individuals, the lesser they will be vulnerable to automation (Zhou *et al.*, 2020).

The idea that the usefulness of most of the current education systems should be questioned is recurrent in the literature. (Levy, 2018), for example, gives general suggestions, proposing a reform of the educational institutions to help students to obtain the necessary skills to be introduced to the work world. On this topic, (Bruun and Duka, 2018) vision and proposals are certainly the most drastic. They invoke for complete structural reform. According to them, the problem with the current education is that in many cases knowledge is taught separately: students specialize in a certain field, isolated by the others throughout the learning path, and are prepared to execute repetitive jobs, when often AI already can perform better than humans. The education system should focus only on the essential knowledge that van be useful in the future. A preparation for programming and algorithms since an early age could be very effective, as it would be to remove barriers between different study fields, so to equip students with skills in multiple disciplines, characteristic that will give them a comparative advantage over machines (Bruun and Duka, 2018). Similar ideas are shared by a small part of experts interviewed by (Lloyd and Payne, 2019), who think young people are really not being prepared to manage future knowledge. Further food for thought is offered by (Huang and Rust, 2018), who warns how the boom in the attendance of courses that require analytic intelligence can be dangerous, as AI machines are supposedly going to perform better than humans the jobs these specific courses prepare for. The importance of diversity in the possessed skills is stressed also by some findings from (Bhattacharyya and Nair, 2019):" Employees will need to know something about everything and everything about something" (Bhattacharyya and Nair, 2019, p. 182). (Beliz, Basco and de Azevedo, 2019) paper, where some similarities with (Bruun and Duka, 2018) were founded, is focused on how the collaboration between G20 countries might accelerate the creation of new jobs, connected to the fourth industrial revolution. In his vision, a first step to achieve this goal is to prepare people, making them ready to do certain jobs. It is still impossible to know exactly which jobs will be created, but the principle does not change. The educational system should aim, on the one hand, to develop peoples' ability to use new technology, and on the other hand to make them able to navigate highly dynamic work environments. Moreover, there is the necessity to push women to undertake studies in the STEM fields, that are more promising for the future (Beliz, Basco and de Azevedo, 2019). Other useful fields of study, according to (Zemtsov, Barinova and Semenova, 2019), are entrepreneurship and creativity. Similarly, (Ernst, Merola and Samaan, 2019) criticizes the fact current education tends to provide young people with just one set of knowledge that they are supposed to use over their entire careers once they finish their studies. This is not plausible in a world where careers are getting always longer (Ernst, Merola and Samaan, 2019). Moreover, social and empathetic skills are considered to be an advantage over machines -see above-. The current learning, however, is focused mostly on technical skills. They should, therefore, integrate the development of social skills as well. The increasing demand for social skills favorites low-income countries, that often o not possess economic means to set up an education system as wide and as structured as more developed countries (Ernst, Merola and Samaan, 2019). Furthermore, some predict a future where importance is given to single projects, therefore a long time of work experience will matter less, in comparison with the actual ability to solve a problem (Bhattacharyya and Nair, 2019).

As already mentioned, other than education coming from universities or schools, also the importance of retraining and acquisition of new skills over career years is recognized. (Bhattacharyya and Nair, 2019) paper highlights it. Some experts interviewed by him suggest it should be useful to devise small courses that would favor the former students to get new knowledge useful to stay updated with technological changes. Again, some said:"..constant re-skilling and learning is crucial..." (Bhattacharyya and Nair, 2019, p. 182). Moreover, in the future workers should be in possess a high level of knowledge, which allows them to make sense of the huge mole of data they will be in contact with. (Bhattacharyya and Nair, 2019)The same idea is shared by (Bruun and Duka, 2018). They go further by proposing the implementation of a public online portal, that, under the payment of a fee, is easily accessible by a large number of citizens, useful to equip the with searched skills.

Similar considerations come from the study of (Lloyd and Payne, 2019), which stresses the importance not only for the workers to be willing to constantly improve their skills but also of the workplaces to set up an environment where the learning of new capabilities is favored. Moreover, most of the required skills are actually of a basic level, hence they can be acquired just by staying in contact with technology that is used in everyday life (Lloyd and Payne, 2019).

Also, topics regarding social inequality and wealth distribution have emerged with the study of the articles. Different authors (Pulkka, 2017; Bruun and Duka, 2018; Agrawal, Gans and Goldfarb, 2019; Bhattacharyya and Nair, 2019; Gera and Singh, 2019) mentioned, and in some cases analyzed precisely, some measures governments could introduce to curb the negative effects of automation, in particular, an insufficient consumer demand, at least in the short and medium-term (Pulkka, 2017), that could paradoxically neutralize the positive effects automation might have on productivity. A key theme that emerges in the literature is the universal basic income. This seems to be the main countermeasure that has been considered to face the eventual problem of mass unemployment. Three papers, among others, stress the possible positive effects of this program. This instrument consists of a certain amount of cash that would be regularly (i.e. every month) paid to citizens who have the right to access it, that would help them to meet their basic needs. (Pulkka, 2017; Bruun and Duka, 2018; Bhattacharyya and Nair, 2019). There are several positive aspects that a reform of this kind should lead to. In general, its main aim would be to protect an individual from the negative effects of automation by mitigating the temporary condition of unemployment (Bruun and Duka, 2018; Bhattacharyya and Nair, 2019)-This is achieved by increase their purchasing power and allowing them to adapt to the new changes while searching for a new job. (Bruun and Duka, 2018). Moreover, it seems that in countries already applying it brought to a major consumption, stimulating economic growth. Thirdly, it helped to improve the psychological condition of many (Bruun and Duka, 2018). Given a large number of unemployed people generated by the automation of most of the repetitive jobs, universal basic income seems to be considered a valuable option also by (Agrawal, Gans and Goldfarb, 2019; Gera and Singh, 2019) and basing on the results presented by (Bhattacharyya and Nair, 2019). Other than benefits, challenges characterizing it have been identified, especially by (Bruun and Duka, 2018). The first to be considered is how to fund such an expensive program. There could be the necessity to use additional taxes, for instance, a robot tax (see later) that might be useful to provide monetary income to be destined o the program. However, the point of (Bruun and Duka, 2018) is that Universal Basic Income would substitute most part of welfare programs, pension plans, and health insurance. Second, a large number of costs generated by the public agencies currently in charge of managing such programs would be saved. Another issue is to decide who is going to benefit from this program. They must be defined as precise criteria to make a person eligible for getting the money. Another challenge is related to how much every individual should receive. In this case, it might be useful to take into consideration the consumer price index and historical data on national household expenditure. Another critique highlights the fact that if a person is sure to get money from such a program, he/she

might not be actually pushed to find a job. That is why (Bruun and Duka, 2018) thinks the Universal Basic Income program should cover only the most basic needs, like food and housing. (Bruun and Duka, 2018). *Table 7* summarizes challenges e solutions of the UUBI program.

| Challenge   | Solution  |
|---|---|
| Who can benefit from UUBI?                            | •Citizens who have paid taxes since<br>a number of years<br>•Citizens who are remaining in the<br>country for an established period                                 |
| Individuals rely on UUBI instead of looking for a job | Establish an optimal UUBI value to incentive individual   |
| How to decide on the right amount of UUBI?            | Base on consumer price index and<br>historical data on national<br>household expenditure  |
| How to fund the UUBI<br>program?                      | <ul> <li>Costs are saved from welfare,<br/>pensions, and health insurance<br/>programs</li> <li>Close the government agencies</li> <li>Apply a robot tax</li> </ul> |
| Necessiy of political<br>consensus                    | The UUBI program suits both right and left parties  |

#### Table 7: challenges e solutions of an eventual UUBI program. Source: (Bruun and Duka, 2018)

Another point of debate is the use of taxes to counter the negative effects of automation. (Bruun and Duka, 2018; Estlund, 2018b; Ernst, Merola and Samaan, 2019; Gera and Singh, 2019). In the analyzed literature, two main different forms of taxation proposals have been founded: the robot tax and the negative income tax.

The negative income tax is mentioned in three papers and might be a useful way to achieve social wealth distribution in countries like the United States (Estlund, 2018b) As for the universal basic income, the robot tax is not a new idea. It has already been proposed, among others, by Bill Gates and Elon Musk (see (Estlund, 2018b; Ernst, Merola and Samaan, 2019)). This measure is seen extremely positively by (Bruun and Duka, 2018) for two reasons: on the one hand, this tool would provide additional funding for an eventual universal basic income program, and on the other hand, it would discourage firms to invest in robots, thus decreasing the probability for

workers to be substituted. The same idea is shared by (Ernst, Merola and Samaan, 2019) and (Estlund, 2018b), who consider it a helpful method to significantly increase fiscal revenues and if combined with other taxes, to hamper the accruement of social inequality, helping with the redistribution of health. Also, (Gera and Singh, 2019) seem to be favorable to its introduction. Also the robot tax, however, is featured by some challenges. There would be the need to recognize AI machines as "technological life forms" (Bruun and Duka, 2018, p. 9) in order for them to be subject to an income tax. This also poses the necessity o find a shared definition of "artificial intelligence" shared globally, to avoid wide differences between different countries, and encourage local firms to invest abroad (Bruun and Duka, 2018; Estlund, 2018b). The same (Estlund, 2018b)seems anyway to be somehow skeptical toward the actual discouraging effect a tax like this would have on companies: given the importance that an increment of productivity has for them, they would probably give just marginal importance to such a measure.

The last major theme concerning societies which was found in the literature is the need to foster public debate. (Makridakis, 2017; Beliz, Basco and de Azevedo, 2019; Fleming, 2019; Zhou et al., 2020) The challenges AI implementation and, more broadly, the fourth industrial revolution are bringing over are multiple and complex, given especially the uncertainty in which many countries find themselves to operate (Beliz, Basco and de Azevedo, 2019). Several authors, indeed, believe that the impossibility to forecast the future can be tackled by stimulating the attention on the problem, in order to develop more alternatives and consequent solutions. (Beliz, Basco and de Azevedo, 2019), for instance, sustains that developing countries are faced with many challenges regarding the future and the creation of new jobs. These challenges are about policies and strategies. "encouraging further debate about their specific challenges is an important first step". (Beliz, Basco and de Azevedo, 2019, p. 8). (Fleming, 2019), instead, thinks the current debate considers the problem of automation as isolated, then proposing solutions -like the robot tax- which are in the interests of a restricted group of stakeholders, rather than of the entire community. The creation of *public organization studies*, led by ethical interests, would give the opportunity to echo voices that are also affected by the ongoing changes, but too frequently are neglected in common debates involving themes as work, gender, and races (Fleming, 2019). (Makridakis, 2017) looks at the public debate as a great opportunity to curb the negative aspects of automation. In his opinion, one of the positive aspects of the uncertain situation many societies are facing is that "there is plenty of time to debate the issues and take wise actions to deal with them effectively." (Makridakis, 2017, p. 59). Also (Zhou *et al.*, 2020), in the same line of reasoning, gives great importance to the study of this phenomenon. An accurate examination is the first step to undertake in order to formulate proper policies that may help to contrast its negative effects.

#### 5. Discussion

Some interesting insights emerged with the study of the literature.

A few considerations can be drawn, first of all, from the descriptive results. There is no doubt the debate around Artificial Intelligence is raising increasing interest: the number of articles produced per year, related to this topic, has kept on increasing, especially in the last five years. However, research seems to be still in an early stage, at least in the fields concerning this thesis, hence social sciences, business and management, and economics. This is demonstrated by the high heterogeneity that characterizes both the geographical areas of study and the journals on which the articles have been published. In general terms, research reveals to be scarce in particular for what concerns empirical studies. Most of the articles analyzed consist of either an analysis of the existing literature review or of some observable cases of application of AI machines in different fields. Then it follows a presentation of the authors' ideas on how the future might be shaped and, in some cases, a pessimistic or optimistic opinion regarding the future scenario of employment. Only 9 studies found can be classified as quantitative. Moreover, although they are certainly valuable, considering that the new ideas they bring are useful to study the different facets of automation, it can also be seen that most of them depend highly on the two studies conducted by (Frey and Osborne, 2017), demonstrating once again that there still is a lack of original contributions considered valuable to study the problem. The only exceptions, in my opinion, are the studies conducted by (Arntz, Gregory and Zierahn, 2017) and (Arntz, 2016), which, going against the approach Frey and Osborne used, offer a new starting point of analysis that might stimulate future research and debate on this topic.

On the other hand, there are only 3 qualitative studies using an empirical approach.

The research question of this thesis is: does the implementation of Artificial Intelligence in companies lead to unemployment, in the sense that workers are replaced by machines? From the literature review that has been conducted, no clear answer to this question emerges. By connecting different ideas brought by the articles, a complicated scenario unravels. An impulsive answer would say: yes, AI leads to unemployment, because the execution of quite an extended range of tasks, furthermore expected to grow, can be now performed by machines. However, this does not necessarily mean that workers are being substituted. They must be taken into consideration also obstacles that hamper the diffusion of AI, as well as offsetting actions that may curb its negative effects. A clear thing that stands out by reading the articles is that this topic is highly characterized by uncertainty and complexity. Uncertainty is given by the unpredictability of the future: there is nothing to guarantee that things will go exactly in a certain way, even though the study of the problem can help to identify certain scenarios that are more likely to verify; many authors explicitly acknowledge it. Complexity is given by the fact that there are many factors to take into account when trying to foresee how the future of work will look like, and what are the risks people will face. All these factors are more or less influenced by each one of the others, therefore they are interlinked. They can be classified, in my opinion, under three categories: task-related factors, actors, and external factors.

The task-related factors refer to the intrinsic features of the different occupations. It has already been shown how, at the moment, literature agrees there are certain jobs there are more susceptible to automation. These are the ones that are characterized by a high repetitiveness of operations, a structured environment, and scarce use of high-level intelligence. The definition of high-level intelligence is not univocally defined. What emerges from the papers is that this intelligence is characterized by the use of intuition (Jarrahi, 2018), empathy toward the others (Huang and Rust, 2018), and the possession of a short memory that allows it to learn by recent experiences (Geisel, 2018). On the contrary, jobs based on contact with other people or by the flexibility of the decision-making process given by a low-structured environment can be considered to be "safer", at least in the short term.

The second group is composed of a plurality of actors that make their own choices and alter more or less indirectly the likelihood for the individuals to face the risk of substitution. The actors to be taken into consideration are individuals, firms, and public institutions.

Individuals contribute to decreasing their chances of being at risk of substitution in different ways. There is, first of all, a matter of personality to consider. People who are more inclined to engage in and handle relationships with others can be favored in the future. Examples have been shown by the papers of (Jarrahi, 2018) and (Fleming, 2019) where different kinds of relationships are considered with the clients and with the stakeholders. Second, they also influence the stability of the others' occupations with their preferences. In (Fleming, 2019) and (Huang and Rust, 2018), for instance, is explained how the preferences of certain clients to relate to a human employee, rather than to a machine, can determine the survival of certain jobs, even though they are in theory perfectly replaceable. Third, they certainly play an active role in their own future by choosing among different educational paths. Overall, it has been shown how a higher level of education seems to influence positively the chances of not being substituted by machines (Zhou et al., 2020). More specifically, it has also been shown how, according to some authors such as (Beliz, Basco and de Azevedo, 2019) and (Zemtsov, Barinova and Semenova, 2019), the importance of some professions, especially the STEAM ones, will increase in the future. As a consequence, also the importance of taking conscious decisions concerning the university programs and courses to undertake will increase. Young students beginning the universitarian path must be aware that, in the future more than ever, certain types of educational degrees will guarantee more than others stability in the workplace. Therefore, there might be a need to give more importance to what is actually considered useful by society, rather than to the own personal cultural interests.

Firms contribute to affect the chances for individuals to be substituted by making decisions on investments and strategies. The choice to invest in Artificial Intelligence machines implies, of course, that less human work will be necessary (Ernst, Merola and Samaan, 2019). However, the needed level of human employment is determined also by choices regarding processes of offshoring or reshoring, (David, 2017; Lloyd and Payne, 2019), that are highly affected by the environment (see later). Moreover, the public image of the company can influence these choices (Fleming, 2019).

The third actor to take into consideration are public institutions. They indeed play a pivotal role. With their action, they influence both individuals and firms. Governments, for example, can enact laws aimed to protect employees' interests (Estlund, 2018b). Importance must be given also to the workers' unions, which can more or less hamper the substitution process, depending on how strong they actually are and on how much political power they can exercise (Fleming, 2019). Moreover, public institutions have a direct influence on education. With reforms concerning the educational system, they can certainly contribute to the construction of an

environment that favors and assists the individual in different phases of their careers: from education to a correct entry in the labor market, to eventual process of reskilling which will be useful for every employee to stay updated with the necessary competences (Bruun and Duka, 2018; Beliz, Basco and de Azevedo, 2019; Bhattacharyya and Nair, 2019). They will be also responsible to curb the negative effects of the fourth industrial revolution related to an eventual massive unemployment situation. As it has been shown, several authors give credit to the introduction of a universal basic income program (Pulkka, 2017; Bruun and Duka, 2018; Bhattacharyya and Nair, 2019). In this way, they might stimulate consumption and, by consequence, increase the opportunities of the individuals to be hired by firms, or at least to reduce the chances for the current workers to be substituted.

The external factors are the environment and technological progress. Considering the environment from this literature, there emerged three characteristics that influence the automation phenomenon and related problems. The first one is the presence of high-skilled human capital (Zemtsov, Barinova and Semenova, 2019), which is certainly favored by the density of educational institutions (Beliz, Basco and de Azevedo, 2019; Zemtsov, Barinova and Semenova, 2019). The second one is the conditions of the ICT infrastructure, that determines the demand for certain occupations (which are probably going to be increasingly important in the future) to be higher in a geographical area (Zemtsov, Barinova and Semenova, 2019). The third one, that appears to be the more important, is the cost of labor. It strongly influences firms' choices (like in (Estlund, 2018b; Ernst, Merola and Samaan, 2019; Fleming, 2019)) regarding investments on Artificial Intelligence capital, as well as their strategies of offshoring and reshoring (David, 2017; Lloyd and Payne, 2019). Moreover, it contributes to keeping poorly paid occupations "safe" (Fleming, 2019). Finally, to be considered is also the technological development, which stands as the basis of any potential new applications of Artificial Intelligence. Recent years have shown fast advancements in AI technology. Even though uncertainty must always be taken into account, authors seem convinced the progress in this field will certainly continue at a very fast pace. Several authors, for example, give credit to the Moore's

Law (Makridakis, 2017; Boyd and Holton, 2018; Bruun and Duka, 2018; Jarrahi, 2018; Ernst, Merola and Samaan, 2019; Morgan, 2019). The law states that computing power backing information and communication technologies doubles every two years (Boyd and Holton, 2018). Therefore, "As the ability of processors to complete larger numbers of simultaneous computations grows exponentially, so too

does the scope and depth of the tasks that can be efficiently computed". (Bruun and Duka, 2018, p. 1). *Figure 6* summarizes the various factors involved in the analysis about technological unemployment.



Figure 6: factors influencing technological unemployment by automation on the basis of the findings. Source: compiled by the author.

Another discussion that can be made regards the optimistic or pessimistic vision that one might have on the whole fourth industrial revolution phenomenon. Overall, the picture that emerges from the analyzed literature seems to be rather pessimistic for what concerns employment. Some authors (like (Arntz, 2016; Arntz, Gregory and Zierahn, 2017; Fleming, 2019)) take a more "relaxed" position than others, emphasizing the obstacles that AI application, at the current moment, is facing in certain industries. Moreover, some optimistic considerations sustain that they are actually humans to shape the future scenarios concerning robots (Morgan, 2019), and the extent of the overall impact that automation has on society is regulated by socioeconomical forces, "which regulate why, how and whether a job or task is automated". (Fleming, 2019, p. 24)

However, there seems to be no doubt that the future is going to be highly challenging for every actor involved in his process. An interesting consideration is moved by (Loi, 2015). His paper revolves around the idea of *Human Disenhancement*, a term that he coins to define "the worsening of human individual abilities and expectations through technology" (Loi, 2015, p. 201). Essentially, he goes against some opinions

that have been found in this literature that consider the possibility to devolve the robots for the execution of jobs that are considered "bad" by humans (see, for example, (Lloyd and Payne, 2019)) as an opportunity for life-improvement. This is certainly a valuable consideration, however, (Loi, 2015) analyzes the other side of the coin. With an accruement of the job polarization phenomenon, indeed, many people will be led to do jobs that "may turn out to be less desirable than the jobs most human could find in the past" (Loi, 2015, p. 201).

To conclude the discussion, I would like to point out some gaps in the research. It is clear that research on this topic is still at an early stage. Two impressions emerged particularly by analyzing the articles. The first is that there is still much confusion around the definition of Artificial Intelligence. This is understandable, given the fact that there is not even a univocal definition of "intelligence". This is indeed a big problem, as artificial intelligence is supposed to be nothing but "intelligence created by humans". However, this also leads to inevitable confusion in the research. Some authors, for instance, in their analysis consider the relationship between workers and robots equipped with the most modern form of AI (see (Geisel, 2018; Huang and Rust, 2018; Michailidis, 2018)). Instead, (Brougham and Haar, 2018) considers Artificial Intelligence as part of STARA, and because STARA is actually the subject of his analysis, it is not possible to assess what are the effects that Artificial Intelligence has as taken alone.

The second aspect is the lack of quantitative research. As already mentioned in the descriptive results, only 9 analyzed papers out of 31 can be considered to belong to this category. I don't want to discredit the value of the others. However, in my opinion, more quantitative research on the problem should be stimulated. This is true both for what concerns restricted geographical areas, for instance at a country-level, but also for broader ones (see, as an example, the research by (Arntz, 2016)). I agree with (Zhou *et al.*, 2020) and (Makridakis, 2017)in the opinion that to curb the negative effects of AI, the problem must first be studied in depth. With more quantitative research, easily comparable and possibly based on different approaches (like (Arntz, Gregory and Zierahn, 2017), criticizing (Frey and Osborne, 2017)), valuable insights might be extrapolated, to facilitate the undertaking of effective targeted policies by public institutions and stakeholders.

#### 6. Conclusion

The motivation for the study is the consideration that Artificial Intelligence is increasingly becoming part of our everyday life, with its applications involving a vast range of actions: from simple online searches to self-driving cars. The aim of this research was to deepen the problem of technological unemployment revolving around the widespread use of Artificial Intelligence at an industrial level. The research question of this study is: does the implementation of AI in companies lead to unemployment, in the sense that workers are replaced by machines?

In order to get an answer, a systematic literature review was undertaken. Relevant ideas and insights have been collected from recent literature (documents published from 2016 to 2020). The attempt was to put them in order and present a clearer picture regarding linkages, similarities, and contrapositions that are useful for the scope.

The analysis of the literature revealed that research on the topic is still at an early stage. No clear answer to the research question emerged. The overall picture concerning this topic is more complicated than one might think. There are different factors to take into consideration, that go beyond the technical feasibility of implementation of a machine to perform a job, that mainly depends on the characteristics of the tasks themselves and on the technological advancements in the scientific fields related to AI. These are actors involved in the process (individuals, companies, institutions), which play an active role on the technological unemployment process, as well as the environment, that affects actors' behavior with its characteristics.

I acknowledge that this study presents limitations. First, it considers only papers published on one online database Scopus (by Elsevier). The choice was motivated by the possibility to implement precise criteria to conduct a research that fits better for the scope of this study, like precise filters regarding publication years, the language of the documents, or fields of study. This criteria are indeed the second limitation of this study. Only English papers are considered, belonging to fields of social sciences, business and management, and economics and econometrics. Although useful insights may have been extracted from documents of other fields, these three were considered sufficient. Third, the intention to examine only recent contributions to the topic leaves inevitably the possibility to have excluded relevant contributions. However, the fact that research is still at an early stage, combined with the high number of papers presenting extended literature analysis, certainly reduces this risk. To be considered is also that a number of documents that appeared valuable were excluded by the analysis because they could not be accessed.

To conclude, I would like to point out some gaps in the research, that might be useful to identify future research avenues. Two impressions emerged particularly by analyzing the articles. The first is that there is still much confusion around the definition of Artificial Intelligence. This is understandable, given the fact that there is not even a univocal definition of "intelligence". And this is indeed a big problem, as artificial intelligence, by definition, is supposed to be nothing but intelligence created by humans. However, this also leads to inevitable confusion in the research. Some authors, for example, consider in their analysis only High Level Machines Intelligence, like (Chen and Lee, 2019). Others examine the effect of a broader set of technologies, like (David, 2017) and (Brougham and Haar, 2018). It would be useful, in the future, to get to a shared definition of Artificial Intelligence, as well as to a precise classification of different types of AI. The usefulness would be twofold: on the one hand, the research on the topic could be more targeted, and on the other hand, eventual political initiatives could be more transparent.

The second aspect is the lack of quantitative research. As already mentioned in the descriptive results, only 9 analyzed papers out of 31 can be considered to belong to this category. I don't want to discredit the value of the others. However, in my opinion, more quantitative research on the problem should be stimulated. This is true both for what concerns restricted geographical areas, for instance at a country-level, but also for broader ones (see, as an example, the research by (Arntz, Gregory and Zierahn, 2017)). I agree with (Zhou *et al.*, 2020) and (Makridakis, 2017) in the opinion that to be ready to curb the negative effects of AI, the problem must first be studied in depth. With more quantitative research, easily comparable and possibly based on different approaches (like (Arntz, 2016), criticizing (Frey and Osborne, 2017)), valuable insights might be extrapolated, to facilitate the formulation of effective policies by public institutions and stakeholders.

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### Declaration\*

| I,  |  |
|---|--|
| <br>Surname, first name   | Dall'Anese Davide  |
| <br>Matriculation number  | 762935   |
| declare that I have follow<br>while writing the present<br>Bachelor's thesis  | ed the Principles of Good Scientific Practice <ul> <li>Master's thesis,</li> <li>Diploma's thesis.</li> </ul>  |
| I have written the paper/th<br>sources or aids than thos<br>from other works word-fo                                | hesis independently and have used no other<br>a given and have marked the passages taken<br>r- word or paraphrased.  |
| <br>Supervisor<br><b>Prof. Dr. Andreas Pyka</b>   |  |
| Topic of the paper/thesis:  | the impact of artificial intelligence on   |
| <br>unemployment: a system  | atic literature review   |
|   |  |
| <br>Semester: 5th   |  |
| I furthermore declare that<br>exactly and without except<br>the printed copy of the pat<br>version being checked fo | t the submitted unencrypted electronic document<br>otion corresponds to the contents and wording of<br>aper/thesis. I give my consent to this electronic<br>r plagiarism with analytical software. |
| Hohenheim, Stuttgart, 12  | 2/03/2020 Dall'huse Dawide   |
|   |  |

\* This declaration is to be included into the independently written paper/thesis as an annex. Papers/theses not including this declaration will not be accepted.