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Organizational and social impact of Artificial Intelligence

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ABSTRACT: Modern information technologies and the advent of machines powered by artificial intelligence (AI) have already strongly influenced the world of work in the 21st century. Computers, algorithms and software simplify everyday tasks, and it is impossible to imagine how most of our life could be managed without them. However, the emergence of artificial intelligence (AI) has its own advantages and disadvantages. With the recent boom in big data and the continuous need for innovation, Artificial Intelligence is carving out a bigger place in our society. Through its computer-based capabilities, it brings new possibilities to tackle many issues within organizations. It also raises new challenges about its use and limits. Over the past few years, developments in artificial intelligence (AI) have captured the imagination of tens of millions of people around the world. Both the sophistication and the societal impact of intelligent technologies are set to increase substantially in the coming years and decades, as are the associated policy challenges. This includes how government agencies protect consumers and citizens from unethical, unsafe or unsound use of AI systems employed in critical contexts such as health, finance, or employment by companies or individuals. Some of the impacts of AI on organizations include: power shifts; reassignment of decision making responsibility; cost reduction and enhanced service; and personnel shifts and downsizing as some jobs are done Robots. This paper aims to provide a better understanding of the organizational and social impact of Artificial Intelligence in the organizational decision making process. Unemployment is not the same as leisure, and there are deep links between unemployment and unhappiness, self-doubt, and isolation understanding what policies and norms can break these links could significantly improve the median quality of life. Empirical and theoretical research on AI came up with discussions and findings that with time the negative perceptions will be addressed.
KEYWORDS: *Artificial Intelligence, Algorithms, Decision making, Robots, Technologies.*

I. INTRODUCTION

As AI systems become larger and more visible, the possibility for outside organizations (including unions and regulatory agencies) to have an impact on their development and deployment increases. Artificial Intelligence (AI) has moved from research laboratories into businesses. Despite the proliferation of the technology, managers and developers understand little about the practical issues associated with the interaction of AI, management and organizations. This is an important topic because the success of an AI system depends on the resolution of a variety of technical, managerial and organizational issues; yet academic research is limited. Many people believe that the emergence of AI intelligent algorithms and production of robots leads to mass unemployment whereas by way of some research, the authors show how AI will change the world of work fundamentally as it will bring improvement for those whose jobs is to make organizational decisions. The continuous interaction and integration of data, algorithms and use cases are driving AI development. AI has cut positions, broken the bottleneck of human efficiency, reduced standardized and repetitive work, changed the nature of work and enhanced work efficiency. At the same time, it has created new jobs. To be more specific, AI technology will change the business world in three aspects: automation, intelligence and creation. In the financial sector, it will make some jobs redundant, while at the same time increasing efficiency and creating jobs.

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

Although AI is not new, its development has taken a new dimension for the last 15 years (Pan, 2016). While AI had been constrained for years, major changes in the information environment have allowed AI research and development to take a second breath (Pan, 2016). Until the 2000's, the work on AI had been slowed down by the limited amount of available data and the lack of perceptible practical applications. However, today, the rise of internet and the increase in the power of machines, together with the emergence of new needs within society, have allowed a renewed interest in AI, that is called AI 2.0 or the 4th industrial revolution (Pan, 2016). The 3rd industrial revolution with the Internet described by Dirican (2015) changed considerably the way of working and gave way to a new society to emerge, the digital world. Holtel (2016) thinks that AI will trigger tremendous changes in the workplace and especially for the managers. One of the future challenges of management will rely on the adaptability of the organization to handle change and transform themselves. Literature reveals that there are two kinds of artificial intelligence:

• **Weak artificial intelligence:** The computer is merely an instrument for investigating cognitive processes – the computer simulates intelligence.

• **Strong artificial intelligence:** The processes in the computer are intellectual, self-learning processes. Computers can 'understand' by means of the right software/programming and are able to optimise their own behaviour on the basis of their former behaviour and their experience. This includes automatic networking with other machines, which leads to a dramatic scaling effect.

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

II. ORGANIZATION DESIGN

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

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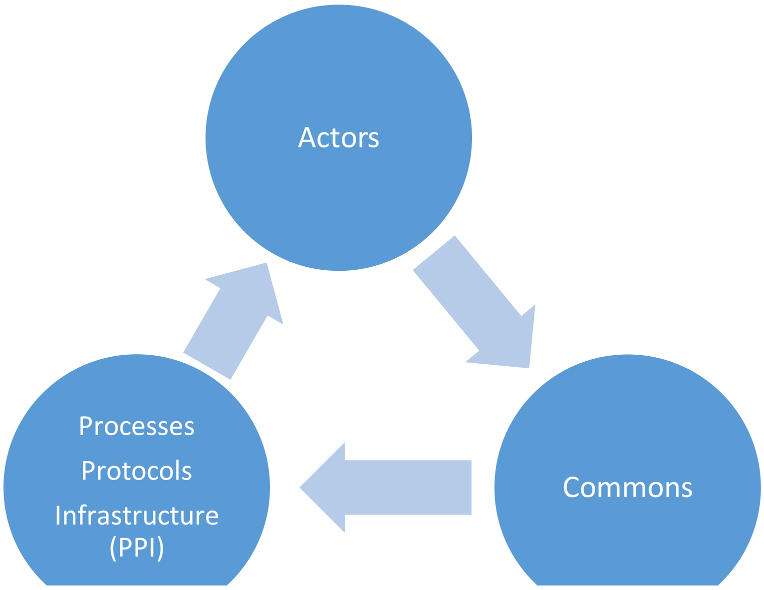

Figure 1: Organizational design in KIFs: an actor-oriented architecture

According to Dettmer, et.al., 2016, the economic use of AI can be separated into five categories:

• **Deep learning**

This is machine learning based on a set of algorithms that attempt to model high-level abstractions in data. Unlike human workers, the machines are connected the whole time. If one machine makes a mistake, all autonomous systems will keep this in mind and will avoid the same mistake the next time. Over the long run, intelligent machines will win against every human expert.

• **Robotisation**

Since the 19th century, production robots have been replacing employees because of the advancement in technology. They work more precisely than humans and cost less. Creative solutions like 3D printers and the self learning ability of these production robots will replace human workers.

• **Dematerialization**

Autonomous software will collect necessary information and send it to the employee who needs it. Additionally, dematerialization leads to the phenomenon that traditional physical products are becoming software, for example, CDs or DVDs are being replaced by streaming services. The replacement of traditional event tickets, travel tickets or hard cash will be the next steps, due to the enhanced possibility of contactless payment by smartphone.

• **Gig economy**

A rise in self-employment is typical for the new generation of employees. The gig economy is usually understood to include chiefly two forms of work: 'crowdworking' and 'work on-demand via apps' organized networking platforms. There are more and more independent contractors for individual tasks that companies advertise on online platforms (e.g., 'Amazon Mechanical Turk'). Traditional employment relationships are becoming less common. Many workers are performing different jobs for different clients.

• **Autonomous driving**

Vehicles have the power for self-governance using sensors and navigating without human input. Taxi and truck drivers will become obsolete. The same applies to stock managers and postal carriers if the delivery is distributed by delivery drones in the future.

The consequences of technological change on working conditions and different demographics of societies

Humphries (2016) and Mokyr et al. (2016) set out how economic, social and cultural changes are deeply linked, and suggest that some of the characteristics of work we may give for granted are in fact relatively new. Technological change came with the move of textile production from the home to the factory, which implied:

- Workers now being monitored and placed in a hierarchical structure;
- A new separation of place of work from home and place of leisure;

Moreover, Humphries & Weisdorf (2015) points to differences in the impact of these changes across different demographic groups. Work as textile artisans was a source of independence for many married women, even where this work involved relatively limited hours and earnings. Industrialization and the separation of work and home limited their opportunities to access relatively well remunerated casual work. At the same time, the wages of young unmarried women, who were more likely to be able to accept full-time work in industry, tracked those of young unskilled males. At the same time, there has also been an increase in the inequality of earnings – specifically, an increase in the distance between high earners (the top 10%) and other workers. There is a broad but not universal consensus in the economics literature that job polarization is explained in large part by the increasing importance of Information and Communication Technology (ICT). The mechanism through which ICT leads to polarization has been explained using a 'task-based' model of the economy (Autor, Levy & Murnane, 2003, Acemoglu & Autor, 2011). This model considers a starting situation where workers are assigned to jobs as follows: low-educated workers perform mainly routine cognitive tasks and non-routine manual tasks; middle-educated workers perform mainly routine cognitive tasks; high-educated workers perform mainly non-routine cognitive tasks. The model assumes that ICT substitutes for workers in performing routine tasks, while complementing cognitive non-routine tasks. This means that:

Middle-educated workers, who tend to perform routine cognitive tasks, are displaced.

Middle-educated workers move towards low-education occupations, dampening wage growth for low-educated workers. This is because high educated workers have a strong comparative advantage over middle-educated workers in performing non-routine cognitive tasks, and therefore middle educated workers will not be able to move into high-education occupations.

Demand for high-educated workers, who are complemented by the technology that can now perform routine cognitive tasks, increases. This model is consistent with evidence on polarization described above, where low- and high-education occupations grow at the expense of middle-educated occupations, and high-education earnings grow relative to other workers'.

Theoretical work on the role of AI in shaping future employment

A growing body of recent theoretical work in economics builds on the literature on job polarization to consider the potential impact on labor of the adoption of AI. The aim of this work is to establish a framework that models how technology that could automate work would feed through the economy. This explicitly sets out the underlying mechanisms and generates non-quantified predictions of the impact of technology on economic growth, employment and earnings. This literature includes Acemoglu & Restrepo (2016, 2017b, 2017c), Aghion, Jones and Jones (2017), Bessen (2017), Caselli & Manning (2017), among others.

These articles typically set out a model of the economy where final goods are produced using capital and labor as inputs, and labor consists of a number of distinct tasks. A new technology (AI) that allows automating a proportion of tasks is assumed to become available. The models analyse how this changes firms' demand for capital and labor. This is consistent with models used to analyse the recent effect of digitalization (specifically, 'job polarization'). This is however a novel approach compared to traditional economic analysis of technology – where technology is seen as augmenting, not substituting, labor, and therefore as generally leading to greater earnings for workers both in the short and the long term. Bessen (2017) and Caselli & Manning (2017) adopt different modelling choices to focus, respectively, on the effect of technology on employment in a specific industry, and on the impact of technology on labor in the long run.

The impact of AI on specific groups of workers

As discussed by Bessen (2017), the direction of consumer responses to productivity effects could matter to determine what happens to workers in specific industries. If productivity effects lead to sufficient additional demand for products from automated industries, employment in those industries can increase despite the increasing automation. This has been the case for manufacturing industries, up to a point - until the 1930s for textiles and the 1950s for steel in the United States. Bessen's model implies that faster adoption of automation does not necessarily make job losses in the automating industry more likely. The outcome depends not only on the capabilities and speed of adoption of technology, but also on the response of consumers – though it is worth noting that in a globalized world the choices of consumers in one country may have relatively little effect over patterns in global demand.

IV. DRIVERS OF THE IMPACT OF AI

In the baseline models discussed in Acemoglu & Restrepo (2018b) and Caselli & Manning (2017), technological progress leads to increasing earnings for all workers in the long run. However, these articles also discuss how different assumptions may lead to different results.

First, limited competition between producers could lead wages to fall in the long term, as indicated in Caselli & Manning (2017). Sufficient competition in product markets, and limited market power of employers over their employees are necessary for workers to benefit from productivity gains.

There are indeed concerns that several markets have become less competitive in recent years. Recent research has documented a possible recent increase in profits in the United States, potentially linked to technology (Autor, Dorn, Katz, Patterson & Van Reenen 2017; De Loecker & Eeckhout, 2017). Furman & Seamans (2018) also note that digitalization includes potential drivers of market concentration:

i) the emergence of 'platform' markets, which tend to be dominated by one or few firms (e.g. Facebook in social media, Uber in urban transport);

ii) the importance of large datasets for the development of machine learning algorithms, which could limit the extent to which market leaders can be challenged by smaller competitors (for example, it could be very difficult to challenge Google's position in internet search without access to the data on past searches Google holds);

iii) the use of algorithms to set prices, which could make collusion between competitors easier to implement and harder to detect.

The regulation of technology firms and evolution of competition policy to reflect challenges posed by digitalization are a widely debated topic, beyond the scope of this review. However, the evidence reviewed here suggests that policy measures aiming to reduce the market power of employers or mitigate its effects could help ensure that workers benefit from technological change. Moreover, AI could lead to changes in the innovation process. The models discussed so far by many studies generally consider a one-time increase in the work tasks that are automated. However, if adopting AI makes it easier to then generate new automation, as considered in Acemoglu & Restrepo (2016), the impact of AI for workers could be worse. In this case, the countervailing effects described above (productivity effects, creation of new tasks) still help maintain employment and wages, but it is more likely that fewer people will work and that the share of income flowing to workers will fall in the long run. However even this situation does not necessarily imply a jobless future. In Aghion et al. (2017), as automation takes over an increasing proportion of work tasks, industries where production is automated shrink as a share of the economy. This is consistent with the long-term impact of technological progress in agriculture and to a lesser extent in the manufacturing sector, as noted by Bessen (2017). As automated sectors shrink, the share of income that goes to labor remains constant despite increasing automation.

From research to innovation and adoption in society

The literature reviewed suggests that the use of AI will be driven not only by technical feasibility, but also by economic, social, and cultural factors. However, this review has identified relatively little discussion of social and cultural factors in the literature relative to AI and work. Indeed, this is one of the points raised in Wajcman (2017), in a review of four recent books dealing with the impact of automation on the future of work.14 There is work in progress around the public perception of AI and on the factors that shape the interaction between humans and machines, including robots and decisions made on the basis of statistical models, but we have not identified published outputs from this research that discussed the implications of these factors for the future of work. Wajcman (2017) is critical of the discussion of technology in the debate on the future of work as a 'neutral inevitable force driving these changes in work. She suggests that more attention should be devoted to:

- The factors driving how technology is developed and used. The essay raises concern around the power of a small elite of leading companies and their staff in shaping the technical systems they design – even as the work of this elite may displace other elites. Wajcman (2017) points to Urry (2016)'s explanation of how social practices are 'constitutive' of technology.
- The way in which technological change is discussed. Urry (2016) argues that visions of the future imply ideas about 'public purposes and the common good', and can have powerful consequences. Wajcman (2017) warns against visions of the future that focus on the potential capabilities of technology while turning 'their backs to society'

The current state of business adoption

The AI Index shows increasing research outputs related to AI (a nine-fold increase in the number of Computer Science papers tagged with the keyword 'Artificial Intelligence' in the Scopus database of academic papers); increasing early-stage funding in the United States for private companies developing AI systems (attracting over US$3bn in 2016 compared to just over US$500m in 2010); increasing shares of on-line job postings requiring AI skills in the United States (a five-fold increase in October 2017 compared to January 2013), in Canada (an eleven-fold increase), and in the UK (a nine-fold increase). This suggests rapidly increasing interest in AI, not only in research but also among businesses.

In the UK, a RSA/You-Gov poll performed in 2017 finds that 14 percent of business leaders are currently investing in AI or robotics, or plan to in the near future (RSA, 2017). The UK adoption rate implied by this poll does not appear significantly lower than international adoption rates as estimated, for example, in McKinsey (2017b), where 9-12% of business leaders across 10 advanced economies reported having adopted AI. RSA (2017) also discuss data from the International Federation of Robotics showing that in 2015 the UK had 10 robot units per million hours worked, compared with 131 in the United States and 133 in Germany.

V. CONCLUSION

In the new wave of AI, opportunities and challenges exist at the same time. On the positive side, AI could increase automation, support intelligent analysis and decision-making, and create new business models and industries. But AI also carries a series of risks. In the financial industry, potential risks include micro-financial risk and macro-financial risk. The former could influence the stability of markets, causing turmoil. The latter could trigger risk around market concentration, market loopholes, connection and technology. Machine vision and speech recognition give machines cognitive skills, allowing AI to be applied in real-world contexts, which will change all aspects of society in the future.

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