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Organizational Knowledge Sharing Overview - Early 2020s Assessment

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Abstract

As technology's pace gets faster and faster every day, more "classic" domains started to adopt automation in order to keep up with the increased demand for results from the society. In the last few decades, this type of fast-paced rhythm led to the appearance of a new successful type of organization which is mainly focused on the knowledge rather than being product oriented. These types of organizations are called knowledge intensive organizations and they mostly rely on what is being known as "knowledge workers".

This paper aims to discuss and present how the recent breakthroughs in Artificial Intelligence (mainly GPT-3) can eventually impact even these seemingly "new" organizations, by allowing them to automate the work of the "knowledge workers".

In the second part of the present paper we will discuss and analyse the most prone activities and domains/sectors to be automated in the near future and we will analyse data coming from Eurostat in order to determine how many people are at risk of being replaced by automation if their organizations decide to adopt automation systems in the coming years. Also, we will consider the current global epidemic caused by Covid-19 in order to see if it can influence that decision in any way.

Keywords: Knowledge sharing, knowledge workers, generative artificial intelligence, sharing rationales, global pandemic.

JEL Classification: M100

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1. Introduction

At the beginning of 2020, the total number of bytes in the digital universe was 40 times larger than the number of stars in the observable universe - approx. 44 Zettabytes (Desjardins, 2019). Moreover, by the end of 2020, according to Domo - Data Never Sleeps 6.0 report, it's being estimated that for each person on earth, over 100 Mb of data will be created every minute (Domo, 2018). Adding to this trend, 2020 has also been "forced" into even more digitalization due to the Covid-19 global pandemic and the lock-down restrictions imposed in most developed countries. The result of everything mentioned above is that we are witnessing a "data explosion" in the digital environment as the 2020s started and more is to come by the end of this decade. Two other emerging technologies are going to take the amount of generated data to the next level: 5G and IOT devices (more precisely, the complementary implementation of the two).

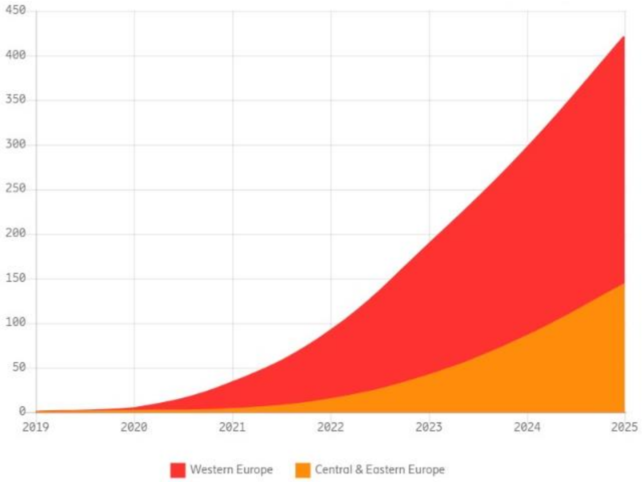

Figure 1. Number of 5G subscriptions in Europe
Source: Ericsson Mobility Visualizer (2020)

As we can see in the data provided by Ericsson Mobility Visualizer (Figure 1*)*, 5G networks are set to take off by the end of 2020 in Europe. This will prepare the stage for the widespread adoption of IOT devices, as the 5G network will be the backbone on which data collection using IOT devices will work and communicate.

2. Problem Statement

Right now, we are witnessing a "perfect storm" consisting of massive amounts of digital data, state-of-the-art programs that allow us to analyse the data, scalable processing power (cloud-based) and a context that "force" a lot of organizations to become even more digitized (the global pandemic). The "data-driven" mindset is being embraced to varying degrees by organizations depending on their industry and field of activity all around the world. However, it's still an act of balance and the risk of falling into the "big data trap" can have adverse consequences, like blurring the distinctions between knowledge and data (Grover, 2019). The problems that such large amounts of data create for organizations are practical ones, like who can analyse and interpret such enormous quantities of data (will people still be able to do that or will it be mandatory for big organizations to use artificial intelligence/machine learning). Also, there are ethical questions that organizations need to answer, like choosing between implementing an AI system in a certain data processing department or keeping 20 people hired to do the same job (even though the AI system has better perspectives). These are really hard questions to figure out by corporations all over the world, questions the answer of which could have long-term repercussions on the organization well-being (Kuzior et al., 2019).

3. Aims of the research

The purpose of the present paper is to analyse the rate at which data/information is being created and to try to determine whether or not a widespread transition to Artificial Intelligence systems is mandatory in organizations. Also, we will analyse the implications of such a transition for the corporations and their employees, especially in the light of recent events happening worldwide.

When saying "recent events", we are trying to cover two main topics: the prolonged work from home period that was implemented by organizations all over the world for their employees (caused by the global pandemic) and the recent breakthroughs in Artificial Intelligence, mainly OpenAI's new language generator - GPT-3.

Our objectives are focused on determining what activities/domains of work are the "endangered" ones and how many people are at risk of being replaced by automation systems in the near future.

4. Research Methods

In order to achieve the objectives of this paper, we first started by looking into other scientific papers that describe in detail the differences between data, information and knowledge, papers like "*Human-Centred Dissemination of Data, Information and Knowledge in Industry 4.0*" (Li et al., 2019) and *Opportunities of Harnessing Organizational Knowledge* (Bejinaru, 2019).

Once we had a clear image of the data-information-knowledge paradigm we started looking for recent breakthroughs in technology that would allow a computer to process data and information into knowledge (or at least the closest technology ever got to achieving this). Researching for the most up-to-date AI system out there, we found an article in MIT Technology Review magazine, written by W.D. Heaven and called "*OpenAi's new language generator GPT-3 is shockingly good - and completely mindless*" and then continued to search more information about GPT-3 as it looked like "the latest and greatest" as far as Artificial Intelligence goes, at this moment.

Next, we gathered data and information from Eurostat, McKinsey and Ericsson, we analysed it and tried to identify the jobs that would be prone to extinction due to the widespread implementation of AI automation systems. We also tried to do a correlation between the domains affected and the number of people working in those domains, thus showing an approximation of how many people that are currently working in Europe would be affected in the following years.

5. Findings

5.1 Artificial Intelligence creating knowledge - OpenAI's neural network

Everything stated above was true for most of the time since humanity existed, but the breakthroughs in artificial intelligence that happened in recent years can make us question how and who can create knowledge.

A good example is GPT-3 (stands for Generative Pretrained Transformer) and it was created by a company called OpenAI. GPT-3 is interesting because rather than being fine-tuned for a specific problem (like Google's AlphaGo Zero was), it is only given an instruction and some examples (a few lines of text) and it's expected to identify what to do based on this alone (Hassabis, 2017). This approach is called "in-context learning" because the system needs to pick up on patterns in its "context", which is the text that we ask the system to complete. To give a quick explanation of how the system works in plain English, GPT-3 is looking at the text that was imputed by the user and then tries to figure out what is the most appropriate word (from a statistical/mathematical point of view) to follow. It then repeats this process for every word, until it completes the sentence or the text that was requested by the user. The system can do this, because it was previously "trained" using an enormous amount of text and data consisting of hundreds of billions of words from the internet, the whole Wikipedia and also large libraries of digitized books (Askell, 2020).

The interesting part however are the results. In one "experiment", Mario Klingermann (a programmer and artist from Munich, Germany) asked GPT-3 to write an article about Twitter, as if it was Jerome K. Jerome (the famous British writer that lived between 1859 and 1927). All the input that was introduced in the system was the article title "The importance of being on Twitter", the author's name "Jerome K. Jerome" and the first word "It". The resulting article is truly amazing, describing a dialogue between the author (Jerome K. Jerome) and a sexton from London, in the summer of 1897 (keep in mind, the imaginary discussion was about Twitter, a platform invented in 2006). The full article generated by GPT-3 can be found here: shorturl.at/boK18. The implications of such an early version of AGI (Artificial General Intelligence) are massive for organizations all over the world, the system being eligible for use in many "creative" domains which were considered out of the reach of computer automation, at least for this time being. Another astonishing use of GPT-3 is the one built by Sharif Shameem (CEO of debuild.co). He managed to configure GPT-3 in such a way, that it could write computer code. All the user has to do, is to describe in plain English what the code should do and then click generate. GPT-3 will automatically generate the code (so far it can work with HTML and

MySQL) and also show a preview of the results. A more generalized and streamlined implementation of this kind could have great implications in organizations worldwide, IT being one of the largest industries out there (Heaven, 2020).

5.2 The implications of automation for organizations and their employees

As presented above, automation starts to make its way into various new domains, some of which were hard to foresee, like writing articles or programming. This is very important for organizations, as both practical and ethical choices will have to be made in the near future, like choosing to use an AI system to do a certain process rather than a team of people (thus cancelling the jobs of those people). When analysing what jobs are in danger of being cancelled due to automation, it is important to look at the work activities performed by the employees rather than at the occupation itself, as those are the parts of the job that can be taken over by an automated system (Chui et al., 2016).

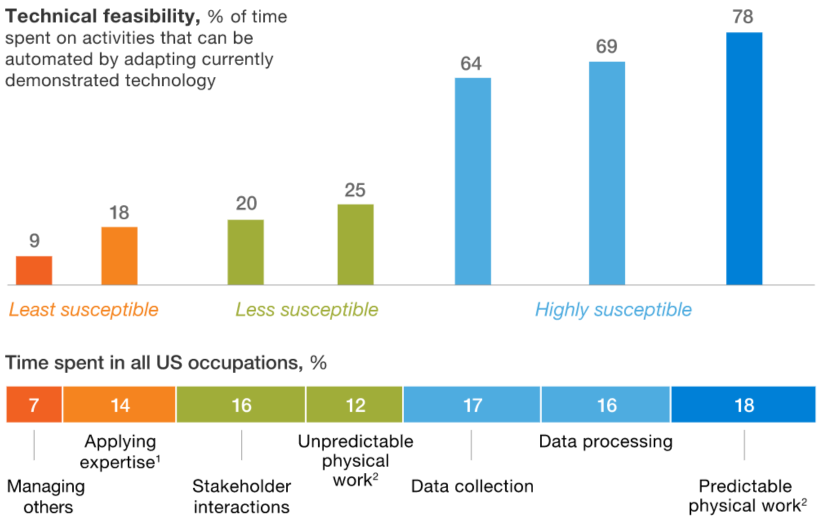

Figure 2. Work activities prone to automation
Source: McKinsey (2016)

As we can see in the *Figure 2*, some of the "safer" activities are the ones that require managing and applying expertise (these are complex activities that require a great level of experience in order to perform, thus being very hard to achieve with automation). At the other end of the spectrum, we have the activities that are most likely to be automated in the near future, activities like data collection, data processing and predictable physical work. The ones that are of interest for this paper are the activities related to data collection and data processing, as the automation of those two could affect the way organizations work all over the world and also how knowledge is created and shared. After carefully analysing the data provided by the McKinsey & Company report called "The technical potential for automation in the US", we managed to extract the % of time spent on activities like data collection and data processing in a few key domains (McKinsey, 2016). We then corroborated those % with the number of people working in each domain in Europe (data from Eurostat - 2019 was used) to obtain the results that can be seen in the Figure 3 bellow.

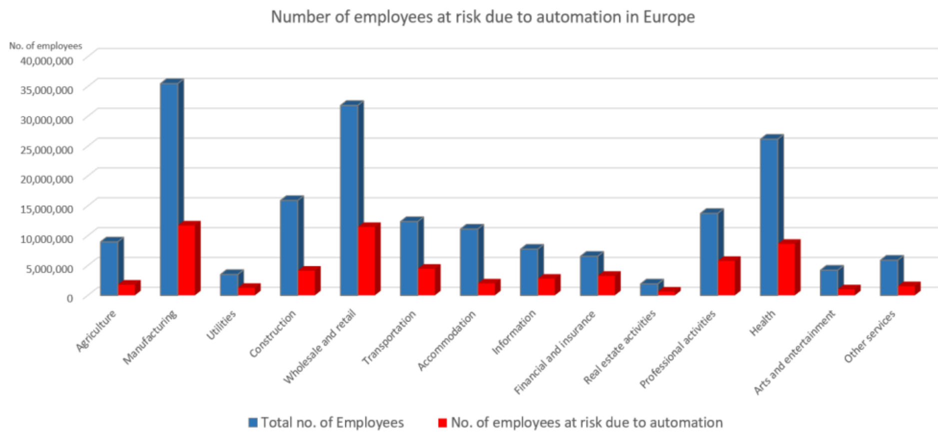

Figure 3. Number of jobs at risk in Europe due to automation
Source: McKinsey and Eurostat (2019)

The results of this data correlation showed that some of the domains where organizations don't need to worry about firing people in the near future are Arts and Entertainment, Accommodation and Construction. On the other hand, we can also observe some domains where automation is coming soon, domains like Financial and Insurance, Information and Transportation. Bear in mind, that it is not the number of people at risk in the Figure 3 above that is the most important (although that is also warring), but rather the % that number represents out of the total number of people working in that domain. For example, out of the total number of people working in Finance and Insurances, approximately 50% are at risk of being replaced by automation systems in the coming years, this being one of the more susceptible domains when it comes to automation. To all of this automation "threat" we can then add the global pandemic that has created even more problems for organizations, some of which were forced to go bankrupt (for example Hertz). We managed to find some data from a more recent McKinsey report and created the graph bellow to showcase the problem that organizations and their employees face in Europe.

As we can see in Figure 4, the Covid 19 pandemic more than doubled the number of the jobs that are at risk in Europe, some of which (approx. 10% of the total number of jobs in Europe) being at risk from both automation and the pandemic. Some of the more in-depth studies carried out by McKinsey Global Institute suggest that not all countries in Europe will be affected the same by the two factors showcased above (automation and the Covid-19 pandemic) and that the Western Europe is more likely to experience automation in the coming years due to its more developed economy (Sven et al., 2020).

6. Conclusions

As showcased above, the line between human-created knowledge and computer-created knowledge is getting thinner day by day. This should encourage organizations to rethink their knowledge creation and sharing strategies more often, adapting them to the current state of technology and also preparing their systems (and employees) for what is to come (Grigorescu et al., 2019). Although nobody can say for sure at this moment if a "knowledge-revolution" is coming our way, systems like OpenAI's GPT-3 Artificial General Intelligence are surely going to make a difference in the way organizations create and share their knowledge in the future. A lot of ethical and moral dilemmas will soon arise for the senior management boards in large organizations, as they will have to choose whether to make decision based on insights provided by Artificial General Intelligence systems or still rely on knowledge and insights created by humans (Fedorko et al., 2019). Most likely, based on what we've seen so far, we are heading towards an augmented-management, where decisions are still made by humans but the managers are "augmented" with real-time insights by various AI systems (Sven et al., 2020).

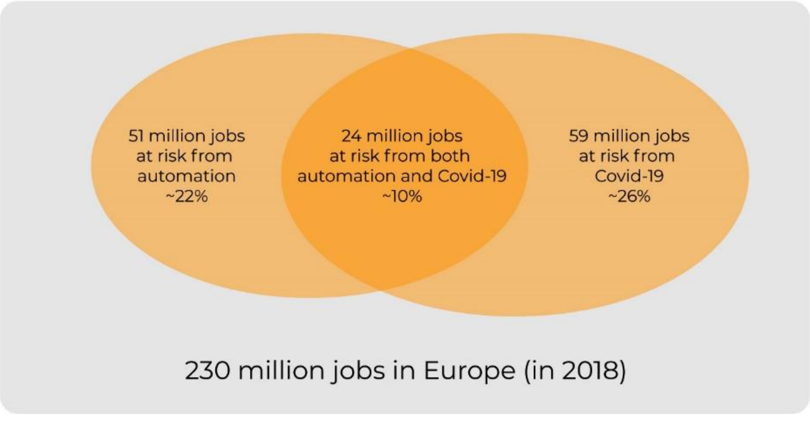

Figure 4. Jobs at risk from automation and Covid 19
Source: McKinsey (2020)

It is equally important to further perfect the way tacit knowledge is shared in organizations, as in the near future it could have a significant impact on the edge that an organization has compared to its competition. As AI's will be accessible to everyone, the tacit knowledge of the employees could be the one that will make a difference and give organizations a competitive advantage (Bernstein, 2013). A great emphasis regarding automation will have to be taken into account in European higher education in the coming years, in order for the future generations to have a reliable workplace (Dima & Vasilache, 2016).

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