Corso di laurea in Economia e Management

Cattedra di Economic Growth and Development

AI impact on aggregate productivity and labour market

Prof. Paolo Giordani

RELATORE

Francesco Buonincontri

Matricola 271101

CANDIDATO

Anno Accademico 2023/2024

Abstract

This study goes through the potential effects of Artificial Intelligence (AI) on economy, focusing on macroeconomic variables as aggregate productivity (TFP) and labour. AI is firstly analysed as such, and then approached as a new General-Purpose Technology which has potential to strongly affect various industries. Productivity paradox manifests in AI as previous GPTs since effects on TFP data are not recorded at the moment. It is still ambiguous whether AI will have as strong an impact on productivity as everyone expects because making predictions is challenging, mainly due to lack of data and low adoption rates among companies.

AI's unique capacity for autonomy and self-improvement brings to automation issue. The text analyses possible impact on labour markets, showing that for the first time in history the most threatened workers might be white-collars. As for TFP, predictions on the extent of the impact bring to conflicting results.

Lastly, paper investigates some of the main challenges that artificial intelligence poses to policy makers, and how they are facing them (or should in future face them).

Contents

List of figures 5

CHAPTER 1: ARTIFICIAL INTELLIGENCE 6

1.1 Artificial Intelligence 6

1.2 Machine Learning 6

1.3 Generative AI 7

1.4 History of AI and why it is getting developed now 7

1.5 What do we need AI for? 9

CHAPTER 2: ARTIFICIAL INTELLIGENCE AND ECONOMIC GROWTH 11

2.1 What is Economic Growth? 11

2.2 General Purpose Technologies 12

2.2.1 Artificial Intelligence as a General Purpose Technology 15

2.3 Productivity Paradox 16

2.3.1 AI and productivity paradox: an analysis of current data 19

2.4 Growth Accounting estimates 22

CHAPTER 3: THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE LABOUR MARKET 25

3.1 AI Turing trap: labour augmenting or labour displacing technology 25

3.2 Training workers to implement AI 27

3.3 Jobs exposed to AI and AI's Job Creation Potential 29

CHAPTER 4: AI AND REGULATION 36

4.1 Taxation and Fiscal Policy 37

4.2 Market Competition 38

4.2.1 Algorithmic collusion 38

4.2.2 Concerns of monopolies 40

4.3 Privacy 41

CONCLUSIONS 44

BIBLIOGRAPHY AND SITOGRAPHY 46

Bibliography 46

Sitography 52

List of figures

Figure 1: Comparing AI to selected previous GPTs. *13*
Figure 2: Components of growth *14*
Figure 3: Strong positive expectations on AI's role in innovation *16*
Figure 4: Contributions to Labour Productivity Growth (% per year) *18*
Figure 5: Labour Productivity Growth (GDP per hour worked, constant prices; 1990-2023). *21*
Figure 6:TFP growth (5-years averages; 1965-2023). *21*
Figure 7: Opportunities for augmenting humans are far greater than opportunities to automate existing tasks *27*
Figure 8: Share of Industry Employment Exposed to Automation by AI: US. *31*
Figure 9: Share of Industry Employment Exposed to Automation by AI: Euro Area. *31*
Figure 10: Shift of workers from farm industry to other industries. *32*
Figure 11: Innovation leads to new occupations that account for employment growth. *33*
Figure 12: Change in Employment-to-Population Ratio and Exposure to Emerging Digital Technologies. 34
Figure 13: Effect of exposure to robots on employment. 35
Figure 14: Average tax rates in advanced economies (5-year moving average). *37*

CHAPTER 1: ARTIFICIAL INTELLIGENCE

1.1 Artificial Intelligence

According to McKinsey & Company “Artificial Intelligence is a machine’s ability to perform some cognitive functions we usually associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem-solving, and even exercising creativity.” (Mckinsey&Company, 2024). Similarly, IBM states that AI “is the technology that enables computers and machines to simulate human intelligence and problem-solving capabilities.” (IBM, 2024).

Therefore, it is possible to identify AI as the science which develops the architecture required for machines to behave and think as a human brain.

Artificial Intelligence is often mentioned together with Machine Learning (ML) and Deep Learning (DL).

1.2 Machine Learning

Although Artificial Intelligence and Machine Learning are usually used interchangeably, they have slightly different meanings. ML is a subfield of AI, therefore everything related to ML falls under AI, whereas AI does not necessarily include ML in its definition.

The reason why people commonly use the two terms as synonymous is that in the last five or ten years, Machine Learning has become the most important tool most parts of AI are done.

More technically, according to AWS, “Machine Learning refers to the science of developing algorithms and statistical models used by computer systems to perform tasks without explicit instructions and relying instead on patterns and inference” (AWS, 2024). Put more simply, “Machine Learning is a subset of Artificial Intelligence in which computers learn from data and improve with experience without being explicitly programmed” (SAP, 2024).

Many “intelligent” capabilities belonging to AI systems derive from ML models which process huge volumes of data and at the same time learn autonomously from them and their processing errors.

The more data provided, the better an AI system will be able to predict accurate outcomes, which are fundamental to decision-making.
Deep Learning is a more advanced version of ML which can process a larger volume of data and a wider range of inputs, including unstructured data such as images. Compared to traditional Machine Learning, it requires less human intervention and produces more accurate results.
To report an AI pioneer, Geoffrey Hinton (2021) states: "take any old problem where you have to predict something and you have a lot of data, and deep learning is probably going to make it work better than existing techniques.".

1.3 Generative AI

The most up to date AI version is GenAI. This terminology refers to AI model able to generate content in response to a request. Notorious examples are OpenAI's ChatGPT and Gemini, owned by Google.
We can easily forecast the importance of this technology, even if its effective potential and revolutionary power is still uncertain and often debated among scholars as well as ordinary people.
Currently, AI spreading is a reality in everyone's daily life across the world, as it is a stunning, shocking, charming and at the same time even frightening technology.
Just to give some numbers, a recent McKinsey survey asserts that 22% of a sample composed by several corporate executives regularly use AI in their own work and 40% say their organizations will increase their investment in AI overall because of advances in generative AI (Forbes, 2023). Furthermore, S&P 500 listed companies acquired 52 AI startups in 2021 and early 2022, compared with 24 acquisitions five years previous and only in 2023 Apple acquired 32 AI startups, the highest among major tech companies.

1.4 History of AI and why it is getting developed now

The first time the word Artificial Intelligence was mentioned in the history of computer science was in 1956 when John McCarthy used it in a conference in Dartmouth College in Hanover.

Actually, this technology traces its roots back to earlier centuries. Humans have always imagined to be able to recreate our brain capabilities, but it is only with the advent of the first electronic computers, at the turn of the Second World War, that this dream could take a concrete course, leading to the definition of a real research programme.
The years following the conference were characterised by great successes. In this period, work is focused on a more limited conception of the notion of intelligence, such as the ability to play chess or the ability to solve mathematical problems.
However, soon researchers started getting the first complications: methods which were working with simple cases revealed to be inappropriate with complex cases. As a result, public funds were no more invested; this was the beginning of the so called "Winter of Artificial Intelligence", a period of time lasting until the 1980s.
The 1980s, however, saw a real renaissance. The new discipline of 'cognitive sciences' was born and investments increased considerably. Thanks to the spread of computers in companies, some Artificial Intelligence systems dedicated to industry (e.g. for logistics management) started to have success.
Such funding led to the development of the Deep Blue system, which, on 10th February 1996, managed to beat world champion Garry Kasparov in a chess match. Many people cried out for the end of the game of chess and more generally for the supremacy of Artificial Intelligence over human intelligence.
Excellent progress was made in the entire IT sector in the 1990s and early 2000s, culminating in a wave of investment in 2011, when through the development of machine learning it became possible to analyse unstructured data, ensuring the application of this technology in various production sectors.
Although the history of AI spans almost a century, it is only after 2022 that the AI phenomenon becomes extraordinary popular. The advent on the internet of ChatGPT, the world's most clicked generative artificial intelligence, has allowed ordinary people (non-computer and computer-language experts) to approach it and understand its potential, thanks mainly to its innovative language recognition system - Natural Language Model. Just to give a measure of its wide spreading, ChatGPT set online records by attracting fifty-seven million monthly active users in the first month of introduction.
But why is AI developing now?

Nowadays data play a fundamental role in the lives of people, companies, governments, etc. and consequently in the global economy. They allow companies to optimise processes, create strategies or improve marketing and more. They enable people to inform themselves in detail and to make conscious decisions.
They are substantially the basis on which every economic agent makes its choices and plans its strategies.
Today, mainly thanks to technological development, more data is continuously generated and collected and everyday there are new ways to make use of that data and turn it into a useful product or service.
Nevertheless, the volume and complexity of information make it impossible for humans to process and apply it, and therefore the need for the use of AI systems grows year by year. As a consequence, companies invest in R&D, increasingly accumulating all the "ingredients" for its development.
What we need is not a new model of computation or a whole new set of algorithms, but a lot of example data and sufficient computing power to run the learning methods on that much data, bootstrapping the necessary algorithms from data.
Furthermore, other factors such as public awareness, social acceptance and company's workers training are crucial for the effective dissemination and application of AI systems, and in this respect, too, the world is adapting quickly.

1.5 What do we need AI for?

On the basis of what we have been looking so far, readers can understand the real importance of artificial intelligence, in particular how revolutionary it can be in several (if not all) industries.
Being an artificial reproduction of 'intelligence', referring to its most abstract and general conception, AI systems are extremely transversal. ML and AI already find their application in many fields: for instance, they are being used in healthcare and life sciences sector as ML is able to analyse enormous amounts of health data and then assist doctors in diagnosis and therapy in real time.
In addition, entertainment companies are instead using this technology to get a better comprehension of their public interests and customize their product on consumers, as well as to design trailers and advertisements.

To provide a last example, ML can meaningfully improve company logistic management, including production process and storage management.
Generally speaking, IA systems are able to automate and optimise the majority of tasks carried out by humans, achieving better results in less time and, probably in next future, spending less money.
At this point, the most valuable question is: AI will really boost economic performance? What is going to happen to productivity and labour?

CHAPTER 2: ARTIFICIAL INTELLIGENCE AND ECONOMIC GROWTH

2.1 What is Economic Growth?

Before delving into the analysis, we would like to briefly define the macroeconomic concept of economic growth.

Economic growth is defined as the increase in production of economic goods and services in a period of time (usually extended) compared to a previous period.

Traditionally, economic growth is measured in terms of Gross Domestic Product (GDP) or GDP per capita, although alternative metrics are sometimes used.

GDP has been considered the best indicator of a country's economic growth because it accounts for the country's entire economic output, including goods and services sold both domestically and internationally (Mckinsey&Company, 2022), and GDP per capita is universally acknowledged as rough measure of economic wellbeing, however it neglects several factors usually considered important in evaluating the wellbeing of a society.

Economic Growth theory is strictly related to the concept of Productivity, also known as Technology or Total Factor Productivity (TFP).

Productivity refers to the efficiency with which factors of production are converted into output (Weil David, 2013).

It is thus the ability of an economy to produce a given output with given factors of production: country X will have a higher productivity than country Y if, given the same factors of production, country X has a higher output.

Most important long-term macroeconomic theories evidence productivity growth as the main driver of economic growth, since it seems to be the only "force" able to provide a continuous push to GDP per capita over long periods of time.

"Productivity isn't everything, but, in the long run, it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker" said Paul Krugman, Nobel Prize in Economics in 2008.

Opposingly, growth economists tend to agree on factor accumulation and population growth giving just a temporary effect on the growth of income per capita along the transition to a new steady state level, in which growth is flat.

2.2 General Purpose Technologies

Technologies are not all the same. We can basically group technologies in two classes depending on their effect on economy: on one hand incremental technologies, which allow production systems to develop gradually, on the other, those with a revolutionary impact, which impose a new structure of dependencies and complementarities.

General Purpose Technologies (GPTs) belong to this second group.

Paul McDonagh-Smith, senior lecturer of IT at MIT Sloan School of Management, states that "GPTs are technologies that can affect an entire economy" (Forbes, 2022). Alternatively, a General-Purpose Technology has been defined as "a single generic technology, recognizable as such over its whole lifetime, that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many spillover effects" (Lipsey et al, 2005).

As such, it can be expected to be pervasive and to have a significant impact on aggregate productivity growth, possibly for a long period of time and probably after an initial lag.

A GPT can be a product, a service, a process or an organisational system: common examples of GPTs in history include the steam engine, electricity, computers and Internet. Quite possibly, AI will be categorised as a classic GPT, as this technology fits almost perfectly in the technical definition provided by economists.

Specifically, in 1995 Bresnahan and Trajtenberg (first economists to talk about GPTs) listed the fundamental characteristics that technological innovations must have to be classified as GPTs:

1) Pervasiveness: GPTs should spread in most sectors. This is possible because GPTs nature does not specify its field of application and it can be useful in the production of different goods and services across all the economy (Helpman & Trajtenberg, 1994).

2) Improvement: GPTs should improve over time. Commonly, GPTs are initially considered rather rough, and then develop into more sophisticated technologies widely used in a variety of applications.
   Time allows technologies to increase their performance and reduce operating costs in the areas of use, mainly thanks to the invention of supporting technologies, which expand range of use and increase the variety of its practices.
3) Generation of innovation: GPT should be able to spawn complementary innovations, stimulating invention and production of new products and processes. Every era has been marked by a breakthrough innovation, which is followed by a series of incremental innovations that lead to long periods of economic development. As a result, GPTs have been defined by Bresnahan and Tratjenberg as "prime-movers", to affirm that the productivity deriving from research and development increases as a consequence of the GPT (Bresnahan et al, 1992).

In fact, what GPTs often offer is a “method of invention (IMI)”, although, by definition, IMIs and GPTs seem to be different concepts.

Technically, IMIs raise productivity in the production of ideas while GPTs raise productivity in the production of goods and services. However, very often GPTs also provide an IMI and play a relevant role also in increasing the productivity of innovative effort. And this seems to be the case of AI, as we can see from the table below.

	Steam engine and electricity	**Computers and internet**	**Artificial Intelligence**
Main output	Energy	Calculations and information exchange	Advanced analytics (predictions, optimisation) and content generation
Nature of tasks primarily affected	Physical	Cognitive routine and communication	Broad range of cognitive
Autonomy? (operate independently from humans)	No	Limited	Potentially advanced
Capacity for self-improvement?	No	No	Yes
A method of invention?	No	Yes	Yes

Figure 1: Comparing AI to selected previous GPTs. Source: OECD, building on (Lipsey, Carlaw and Bekar, 2005) and (Agrawal, Gans and Goldfarb, 2023)

To sum up, GPTs are economically advantageous because they facilitate the creation and diffusion of complementary factors such as new inputs, new business processes, new skills and new structures. It follows that the economic contribution provided by GPTs, especially in the long term, goes far beyond the expected return from the capital investments made in technologies (Brynjolfsson et al, 2000). They trigger innovation mechanisms, contribute to increasing overall productivity levels and they favour the specialization of the most advanced forms of work (Gambardella et al, 2020).

For all these reasons, General Purpose Technologies (GPTs) potentially provide explanations for long-term macroeconomic growth periods and represent a driving force for the economy as a whole (They have been defined by "real engines of economic growth" and "drivers of seismic macroeconomic shifts" (Strohmaier & Rainer, 2016)).

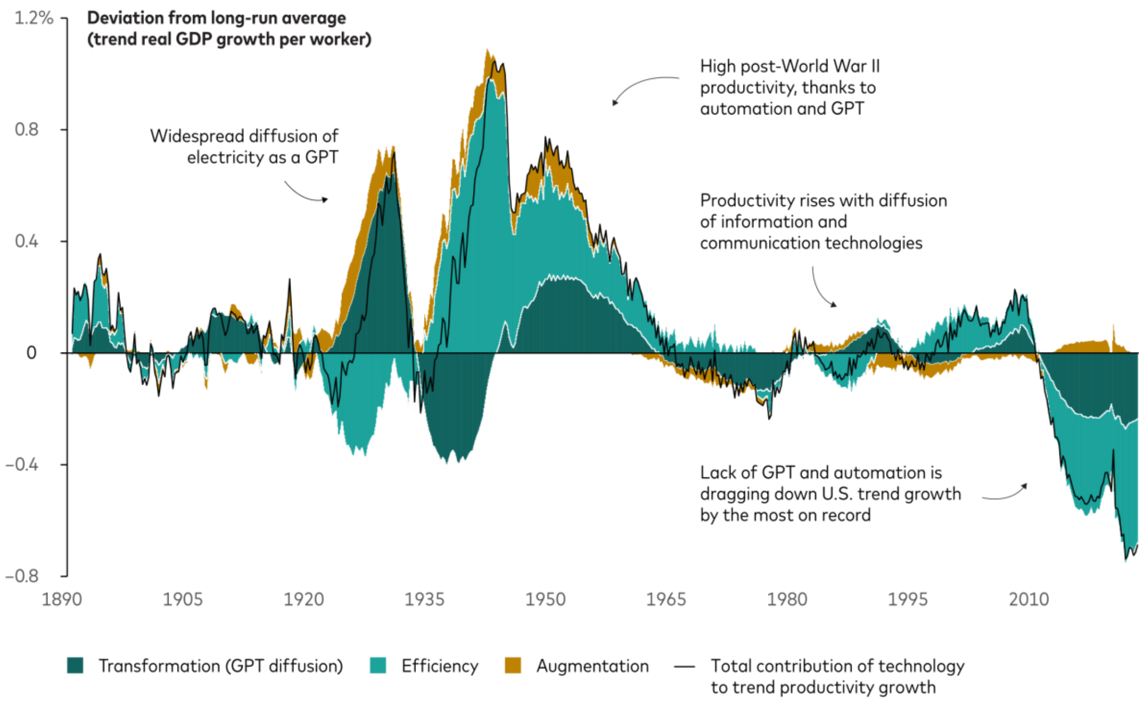

Figure 2: Components of growth, source: 2024, Vangard

Contributions of transformation (GPTs that trigger creative disruption in economy), efficiency (improvements in GDP per capita through automation), and augmentation (raise in human skills due to machines) to the deviation of productivity growth from its long-run average.

2.2.1 Artificial Intelligence as a General Purpose Technology

Is AI a GPT?

For many economists, answer is absolutely yes.

In Philippe Aghion's opinion (2018), for example, AI is rapidly transforming many areas of the global economy and society, including factory automation, autonomous driving, healthcare, entertainment and communications, emerging as a GPT.

On the other hand, many scholars, researchers, technologists, and policy makers do not yet agree with this point of view. According to Robert Gordon, AI is not going to have the same impact as previous innovations like automobile and electrification in terms of income growth, health improvement, mass communications and practical conveniences. Hence, it is hard to define AI as a GPT, at least for the time being.

However, determining what is and is not a GPT is a challenge. It is even more difficult to fully understand the extent of a technological innovation in real time (or even to predict it) than to analyse and catalogue it *a posteriori*.

Those who support the idea of AI as a GPT prove it referring to the key characteristics set out in the previous paragraph.

1) Pervasiveness: As we highlighted in chapter 1, Machine Learning's (and Deep Learning's) capacity to infer patterns from data makes AI 'generalizable', allowing diffusion across markets, industries, applications, geographies, and knowledge domains. To that end, AI 'generalizability' is closely related to pervasiveness.
2) Improvement: it was only after decades of trial and error that machine learning (ML) and later Deep Learning (DL) were developed and embedded in software able to produce valuable outcomes. In addition, Machine Learning systems are even designed to improve autonomously over time (see Machine Learning definition in chapter 1).
3) Generation of ideas: an interesting debate is on whether AI might become a method of invention. If that were the case, AI may be the basis for a Fourth Industrial Revolution, and major channel for its impact as a GPT may be through raising the productivity of R&D. The economist Joel Mokyr of Northwestern University suggests, "Advanced AI techniques could take data analysis to a

whole new level and “become the world’s most effective research assistant (RA)”.

AI is often wrongly believed able to provide solutions as a magic wand. However, according to many AI experts and researchers, the goal of commanding computers to carry out activities in a high-level language without defining how they should be done is still unrealistic, at least in the foreseeable future. A more plausible scenario is where AI is applied as computational method while solving problems in various fields of research and development. Data suggest that AI as a super RA is what we are starting to see right now with drug discovery. A new antibiotic called Halicin was discovered by MIT researchers in 2020 thanks to AI-driven research, but obviously drug discovery isn't the only application for AI as a SuperRA.

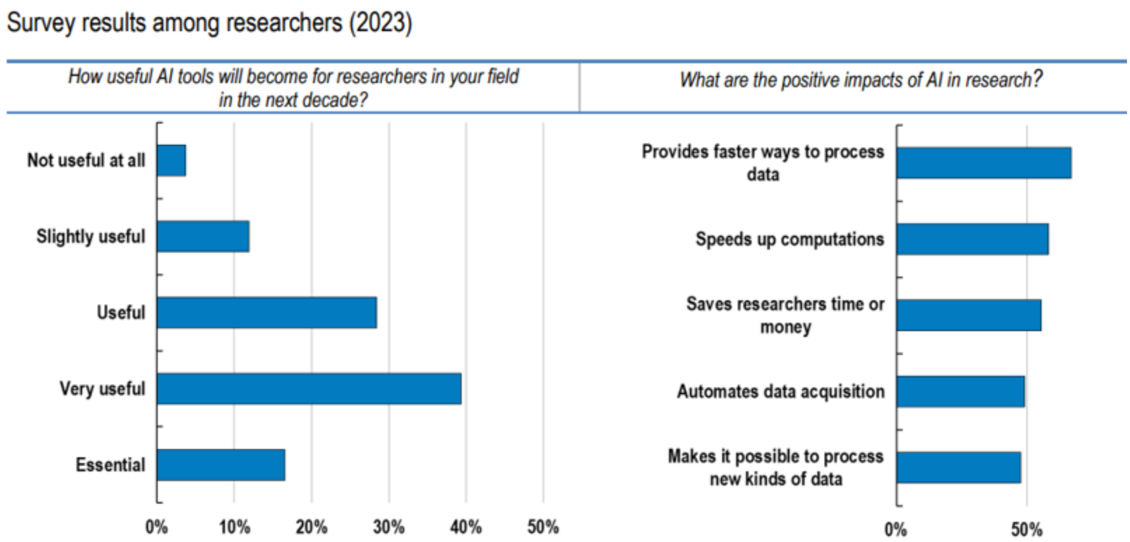

Figure 3: Strong positive expectations on AI's role in innovation. Source: 2023, Van Noorden and Perkel

2.3 Productivity Paradox

In economics, it is theorized that initial adoption of a new GPT may, before improving productivity, actually decrease it. This phenomenon is called “Productivity Paradox”, term coined by Erik Brynjolfsson in a 1993 paper titled "The Productivity Paradox of IT" quoting a famous Robert Solow statement "You can see the computer age everywhere but in the productivity statistics".

Brynjolfsson’s research detected an unpredicted slowdown in productivity growth in the United States during the growth of information technology (IT) between the 1970s and 1980s.

This counterintuitive phenomenon has a real explanation. But before going through it, it is very important to mention false hopes and mismeasurement.

False hopes are often originated by our "non-rational" tendencies as our natural predisposition toward having unrealistic positive expectations from innovations, discoveries, and inventions.

Mismeasurement was for many economists one of the possible reasons of the productivity paradox in statistics. They believe that the traditional TFP calculation is not the best measurement of productivity growth due to technological change, hence they tried to develop new ways of measurement. However, a great number of recent studies (including those of Cardarelli and Lusinyan (2015); Byrne, Fernald, and Reinsdorf (2016); Nakamura and Soloveichik (2015); and Syverson (2017)) each using different methodologies and data, present evidence that measurement errors are not a sufficient explanation.

Against this background, the real explanation is that it takes a considerable time to be able to get benefits from new technologies. The more profound the potential effect on statistics and welfare, the longer the time lag between the initial invention of the technology and its full impact on the economy and society.

Firstly, it takes time to build the stock of the new technology to a size sufficient enough to have an aggregate effect.

Secondly, we need complementary investments to implement the new technology and fully exploit its advantages. Basically, new infrastructure development and creation of skilled workers takes time and capital. These are also required to fund co-inventions and further enhancements needed along the way, even though they are less evident and recognizable compared to the core invention. All this process takes time also because, as noted by Henderson (1993; 2006), incumbents suffer the “curse of knowledge”: they are unable to absorb new approaches and they remain trapped in the current ways of doing things (status quo).

Electricity and ICT are striking cases of the delayed effect of a GPT introduction on productivity. In fact, it took about 40 years to detect large impacts of electricity on United States TFP after Thomas Edison first distributed electrical power in New York in 1882 because American factories had to be reorganised and implemented with electricity.
The reason is that many factories had to redesign their layout and didn't want to renovate their old manufacturing plants before their reasonable physical depreciation, slowing down rate of diffusion of electricity. Similarly, in late 20th century ICT required fundamental changes in business organization (e.g., reshuffling workers to different jobs) and these changes had to be discovered by trial and error. Nonetheless, impact of ICT was much more rapid and larger than electricity, as we can see in Table 1, which shows the delays before maximum impact of some GPTs on productivity growth rates.

	Capital Deepening	***TFP***	***Total***	***% Whole Economy***
Steam (UK)				
1760-1830	0.011	0.003	0.014	5.6
1830-1870	0.18	0.12	0.30	19.0
1870-1910	0.15	0.16	0.31	29.2
Electricity (USA)				
1899-1919	0.04	0.06	0.10	5.6
1919-1929 (1)	0.07	0.07	0.14	3.6
1919-1929 (2)	0.07	0.30	0.37	9.5
1929-1941	0.04	0.16	0.20	8.0
ICT (USA)				
1974-1995	0.41	0.36	0.77	49.4
1995-2004	0.78	0.72	1.50	49.0
2004-2012	0.36	0.28	0.64	41.0

Note: in 1919-1929 estimate (1) does not take account of TFP spillovers but they are included in estimate (2).

Figure 4: Contributions to Labour Productivity Growth (% per year). Sources: Byrne et al. (2013), Crafts (2004), Crafts and Woltjer (2021)

In recent years, impacts are getting detected faster than before. This is not so surprising if we consider the context of superior scientific and technological capabilities, greater expenditure on R&D, and more sophisticated capital markets.
In view of this history, it is quite reasonable to think that AI is still in its early stages of its lifetime and will likely have a significant influence on macroeconomic productivity performance in the future, but possibly relatively sooner compared with previous GPTs.

This is the idea put forward by Brynjolfsson who expects implementation and restructuring lags but emphasizes that machine-learning systems will advance more rapidly mainly because they are designed to improve themselves over time (Brynjolfsson, 2019).

2.3.1 AI and productivity paradox: an analysis of current data

As previously said, AI has the potential to boost GDP and raise productivity growth, but exactly like other GPTs in the past, it won't deliver productivity gains immediately upon arrival.

Goldman Sachs researchers expect to measure an impact on US GDP growth no earlier than 2027 and strongly believe that AI will be a meaningful driver of productivity and GDP growth over a much longer horizon (Goldman Sachs, 2024).

The main reason why there has not yet been an increase in productivity is that AI adoption rates are fairly limited right now. Possibly, we will start to observe productivity gains when governments and companies will start using it widely in order to automate tasks.

In fact, the long-run impact of AI will depend on the extent of its use and how successful its integration into business processes will be. The 2018 Business Survey of 850,000 firms, curated by the Census, suggests that in the US the adoption of AI is still very low, with less than 18% of firms reporting the use of this technology, which is a fairly small share relative to the overall number of companies that it is expected to get benefits from it (McElheran et al, 2023). In European Union the average adoption rate is 7.9%, according to 2021 data, with 21 out of 27 countries not exceeding 10%.

Why so many companies do not use AI?

Almost all firms recognize the potential positive impact of AI, but the majority of them report lack of knowledge about AI, concerns about privacy and security, and concerns about overinvesting in an early version of the technology as barriers, without knowing when (and if) full benefits will be realized.

As a matter of facts, the successful integration of AI systems requires significant complementary investments (in data, skills, processes, reorganisations) and managerial talent, both often concentrated within a few firms (Borgonovi, 2023).

Complementary investments are needed to provide to key intangible and tangible assets which can be considered as AI fundamental inputs.

Among intangible inputs, skills are critical and include highly trained IT engineers, programmers and data scientists (more detail in paragraph 3.2). Then we have another critical input, strictly related to the previous one: software, in the form of the AI model. Such software requires vast amounts of data, challenging collect. In addition, Software and data require a physical AI infrastructure, most importantly computing power and capacity (semiconductor chips) and also connectivity. Advanced AI systems often require top performance semiconductor chips or specialised computing infrastructure not only during the initial pre-deployment phase, but also during the operation phase (post deployment). Furthermore, AI applications often rely on interactions between remote servers and local machineries and terminals, requiring high computing power and connectivity which use massive amounts of energy and exploits high-quality internet infrastructure.

These are just some of the countless factors to be taken into account when a company wants to carry out AI implementation, but it is enough to give an idea of the complexity of the operation and how costly it is.

To conclude, we can understand why large-scale AI adoption takes time and, as a consequence, why it is almost impossible to detect any TFP growth rates increasing at the moment. Data show that productivity growth has slowed in many advanced economies since the early 2000s. And it does not appear that the AI is increasing growth rates, at least now.

The graphs below show an average decline of 1.9 percentage points in productivity growth across six developed regions (South Korea, Canada, US, Japan, Eurozone, UK) from 1990 to 2023. Despite the intense development of AI in the last decade, particularly in the post Covid-19 pandemic years, there has been no significant increase in annual TFP growth.

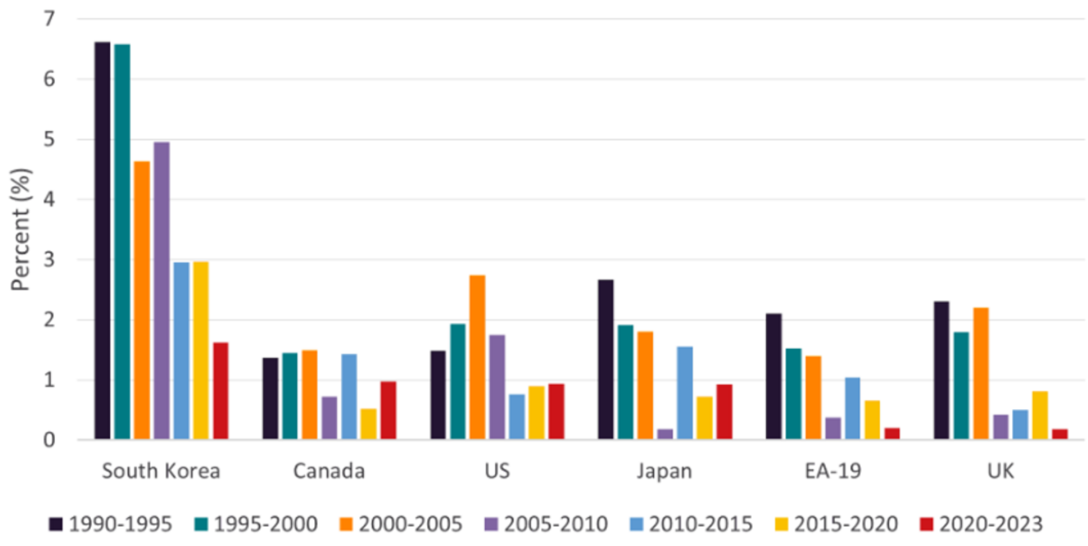

Figure 5: Labour Productivity Growth (GDP per hour worked, constant prices; 1990-2023). Sources: 2024, ECIPE (European Centre for International Political Economy)

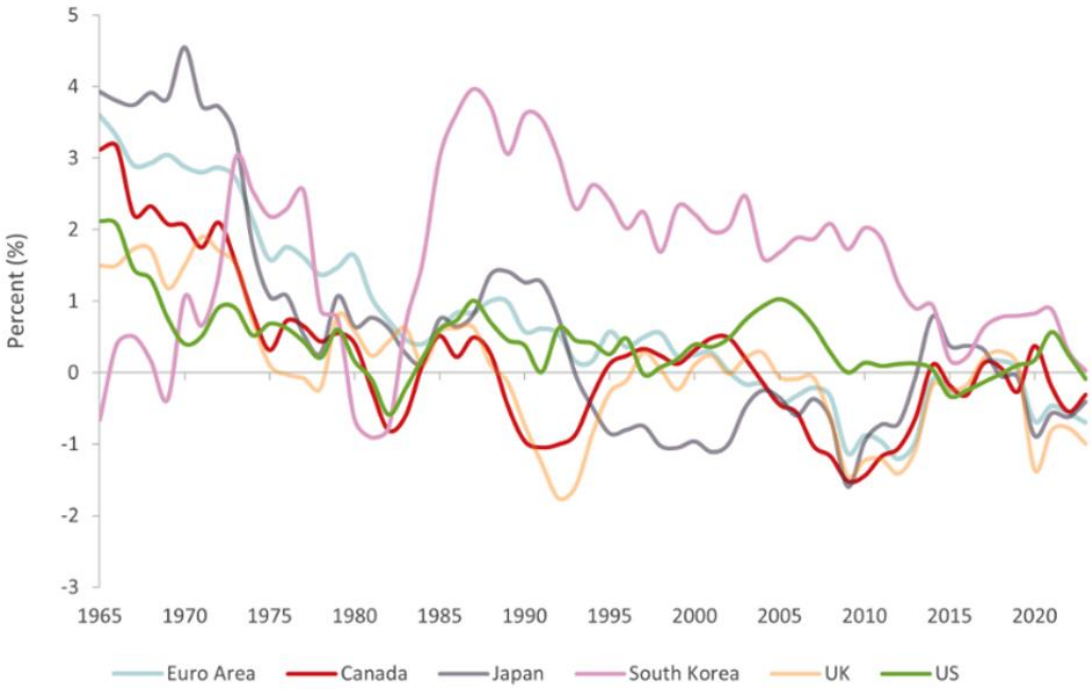

Figure 6:TFP growth (5-years averages; 1965-2023). Sources: 2024, ECIPE (European Centre for International Political Economy)

2.4 Growth Accounting estimates

In this paragraph we explore relationship between AI and economic growth. Despite productivity paradox, AI is expected to influence firms' productivity, hence Total Factor Productivity.

AI will firstly impact trough automation of tasks and processes, reducing operating costs, boosting efficiency and, consequently, an improvement in overall productivity. Secondly, beside automation, AI will stimulate innovation and create innovation opportunities (as we discussed in the previous paragraphs, talking about IMIs). Companies that adopt AI can develop new products and services, enter new markets and improve existing business models. Thirdly, AI can amplify human skills, enabling workers to perform more complex and creative tasks, thereby increasing their productivity. Lastly, because of its ability to improve with use (through machine learning) and to be replicated at very low marginal cost, AI enables companies to achieve significant economies of scale.

All these impacts will occur in all the industries, obviously to different intensity.

Although quantifying AI implications in macroeconomics is very hard, researchers have been trying to build useful forecasts on productivity gains that AI will trigger.

Numerous estimate results show that AI has a considerable influence on economic growth, especially in the long run. According to Goldman Sachs (2023), over a 10-year period global GDP is expected to increase by 7%, equivalent to $7 trillion, and US productivity growth will be around 1.5% per annum. A recent McKinsey Global Institute (2023) forecast predicts that the annual GDP growth rate could produce up to a 3.4 percentage point rise in average annual GDP growth in advanced economies between 2024 and 2040, offering a boost as large as $17.1 to $25.6 trillion to the global economy. Brynjolfsson and McAfee's 2017 article, titled "The Business of Artificial Intelligence," suggests that AI could lead to significant growth in TFP, especially in industries where adoption is fastest and largest. They cite studies and models that indicate potential TFP growth between 1% and 1.5% annually, depending on the speed and scale of AI adoption. This growth is particularly relevant in the advanced manufacturing, financial services, and healthcare sectors, where AI can be applied to dramatically improve operational efficiency.

On the other hand, other forecasters are more grounded. One of the most careful not to overestimate the macroeconomic effects of Artificial Intelligence is Daron Acemoglu, especially in the medium-term (about 10-year).

In his paper "The Simple Macroeconomics of AI" published in April 2024, Acemoglu builds a model with updated data taken from studies carried out by Eloundou et al. (2023) and Svanberg et al. (2024). In his framework, the production of final goods requires a series of tasks to be performed, (allocated to either capital or labour), and AI can improve production efficiency through a number of distinct channels as automation (AI substituting work performed by human being, reducing costs) and task complementarity (work is not fully automated, but AI still raises the marginal product). It is extremely important to specify that this framework doesn't take into account productivity improvements that result from new AI-generated tasks, so completely new, which are likely to boost both TFP and GPT.

Calculations evidence that TFP gains over the next 10 years from AI are about 0.71%, which means approximately a 0.07% increase in TFP growth annually. Effects are positive and not insignificant (non-negligible), but they are modest compared to the revolutionary improvements predicted by Goldman Sachs and the McKinsey Global Institute. Acemoglu then tries to build the same model, but augmenting productivity gains related to AI, using data from Peng et al. (2023). These data predict a strong positive impact, so these values may seem exaggeratedly high and untrue (for instance, cost declines for computer vision tasks are expected to be 10% per year). Nevertheless, TFP growth rate still remains around 1% (0.94%), a quite low number.

Acemoglu uses his TFP estimates to compute GDP effects of AI over 10 years, too. Considering modest increasing in investments in AI, GDP growth due to AI is expected to be around 0.9 and 1.1%, whereas providing a large investment boom, GDP growth rates are in range of 1.6% − 1.8%. Recall, however, that what is relevant for consumer welfare is TFP, rather than GDP. The reason is that GDP accounts for consumption, too, therefore an increase in GDP might not reflect a beneficial change in welfare of people.

An example is the increase in the energy requirements of AI models, which is reflected in the GDP measured. Moreover, values calculated up to now might be overestimated because some of the tasks included in the model are considered "hard-to-learn", which means that productivity gains may be significantly less than those involved in “easy-to-learn” tasks.

Once hard tasks are included in the model, gain in TFP and GDP drops to 0.55% and 0.90%, respectively.

It might seem that Acemoglu is a non-supporter of the new AI technology and a pessimist, but this is not true. The aim of Acemoglu is not to convince readers that AI won’t benefit economics, but simply warn that we should not assume that AI will give stunning boost to macroeconomic variables in a short time, simply automating work.

In sum, it should be evident that it is very challenging to predict how AI will affect the macroeconomy and forecasting often leads to different conclusions. This is mainly because models are based on many speculative assumptions and have strong limitations. Most of the datasets used are small and outdated (they stop before the 2020 covid pandemic, not considering the last few years when AI has significantly developed). Furthermore, studies like Acemoglu’s one do not consider new tasks created by AI, because they are hard to predict, but it certainly will strongly impact TFP in the long-term.

Therefore, we need to wait years for more precise estimates.

CHAPTER 3: THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE LABOUR MARKET

So far, we have focused our analysis on effects, mainly positive, of AI implementation on economic growth. However, there are also other significant aspects that need to be urgently addressed. Foremost, the impact of AI on labour.

This is a topic highly debated among researchers, scholars and companies: on one hand there is the thesis of new job creation and reallocation of workers, on the other specialists worry about potential job losses and rising inequalities.

The justification for an outlook on the future of work lies in the stunning progress that AI has made in recent years, to a point that, in several areas, AI can perform some tasks better and faster than humans or even carry out work impossible for human beings.

However, there are still limitations to what AI can do (so-called 'bottleneck skills' like complex problem-solving, high-level management and social interaction).

It is not known how soon the AI will be able to do these things as well, but considering its learning rate, probably not very long. This raises important and urgent questions about the future of work.

3.1 AI Turing trap: labour augmenting or labour displacing technology

"Turing Trap" is a term coined by Erik Brynjolfsson to describe a risky scenario related to AI development and automation. It refers to a situation where companies and governments overly focus on the development of AI that replaces human capabilities, rather than on technologies that amplify and enhance them.

Alternatively, Turing Trap occurs when AI is developed with the only aim to substitute human intelligence instead of creating solutions that can assist human capabilities and foster more productive and harmonious human-machine collaboration.

This will be the grand challenge of the coming era: to reap the benefits of Artificial Intelligence while avoiding the Turing Trap.

Erik Brynjolfsson states that AI introduction is surely going to be a massive economic disruption, particularly on labour market. "Companies are going to be born and destroyed, as will occupations. Depending on how we use the technology, we can use it in a way that is more likely to create widely shared prosperity, or more concentration of wealth and power".

As many growth economist report, technological change might disproportionately help or hurt some groups, even though it is beneficial on average. Specifically, the distributive effects of IA depend on whether it is used to augment human labour or automate it.

AI augmenting human capabilities means allowing people performing tasks they never could before. In this scenario, humans and machines are complements, which means that people remain necessary for value creation and still have bargaining power in both the labour market and political decision-making.

On the other hand, AI automating human labour refers to machines becoming substitutes of workers, reducing their economic and political power. When technologies automate human labour, they tend to reduce the marginal value of workers' contributions, and most of the gains go to the owners. Consequently, wages go down whereas returns on investments for companies (or entrepreneurs) rise thanks to high productivity, powering economic inequality.

Many workers are concerned by this scenario and think that technological progress involves by definition more unemployment.

The reality is that very often innovations did not replace human work, but most of them supported humans in performing tasks. As a matter of fact, despite the numerous and different technologies introduced over the most recent history, the value of human labour has mostly gone up. When a worker produces more, mainly thanks to innovations, his work becomes more valuable, and this added value is reflected in higher wages. Data show that, on average, today we are paid about 50 times more than couple of hundred years ago.

In many cases, not only wages but also employment grows with the introduction of new technologies. Technological innovations have historically stimulated the emergence of new jobs and, according to many economists, the emergence of these new occupation accounts for most of the long-term employment growth. One of the most heated debates is on whether the balance between new job creation and job destruction caused by AI will be positive or negative, and we will discuss this topic in the next paragraphs.

Summarizing, having machines that imitate or augment human work both create wealth. The difference is who catches this added value: capital owners in the first case, everyone in the second case as wealth would be widely distributed.

Furthermore, simply automating processes in order to make them faster and less costly, does not exploit the full potential of technology because new products/services are not created. And it is known that the greatest value in favour of community come from new revolutionary products/services or industrial processes. “We have iPhones now because somebody invented something new, didn't simply make a cheaper telegraph”, says Brynjolfsson in an interview released by Brookings Institution.

In short, automating labour creates less value than augmenting it to create something new. At the same time, automating a whole job is often much more difficult and requires much more effort.

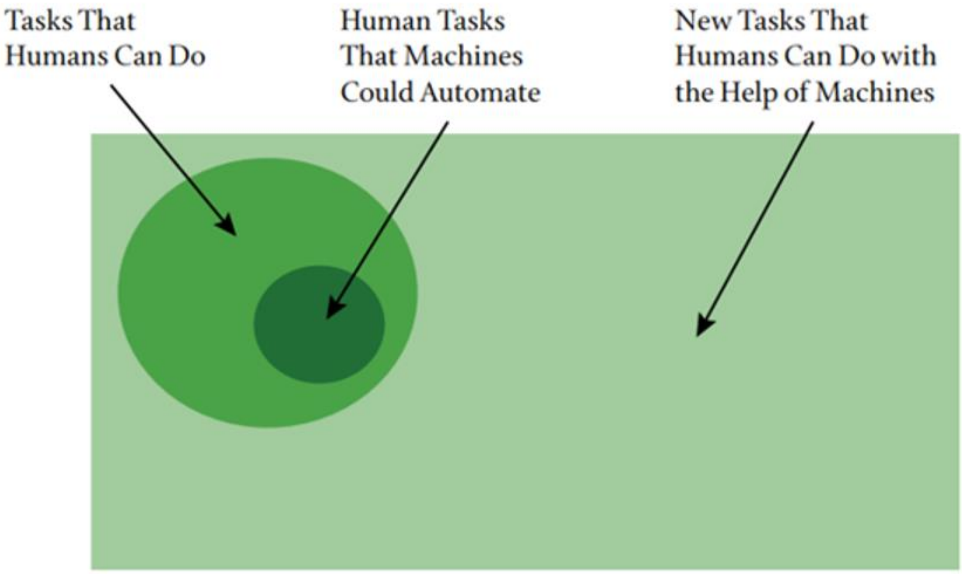

Figure 7: Opportunities for augmenting humans are far greater than opportunities to automate existing tasks. Source: Brynjolfsson, E. (2022). The Turing Trap: The Promise & Peril of Human-Like Artificial Intelligence

3.2 Training workers to implement AI

Regardless of whether the AI revolution will be labour substituting or labour augmenting, the impact on labour market will be disruptive.

Nowadays, current data show little evidence of employment effects due to AI mainly because AI adoption is still relatively low (see previous chapter, 2.3.1). Any employment effect of AI may therefore take time to materialise, but rapid progress, falling costs and the increasing availability of workers with AI skills indicate that OECD economies might be on the brink of an AI revolution.

The available data suggest that the percentage of firms that have adopted AI worldwide remains lower than 10%, although among large companies this percentage is much higher (approximately one company over three) mainly because they have more resources and capabilities to implement AI (Lane, Williams and Broecke, 2023).

Cost was a critical barrier to adoption, but in recent years the cost of AI technologies is rapidly declining. Since 2018, the cost to train an image classification system has decreased by 63.6% (Zhang et al, 2022) and the rate at which these costs fall may be expected to accelerate. Generative AI applications such as ChatGPT are becoming increasingly available at a low monthly fee or even for free.

However, now the biggest obstacle in AI implementation is lack of skills. Although the availability of workers with AI skills tripled between 2012 and 2019 (according to OECD research), AI diffusion is being slowed by global shortage of human capital with skills (as data analytics, machine learning, natural language processing and process automation) to implement AI programs.

In fact, a 2022 Deloitte survey reports that there are only 22,000 AI specialists globally.

The talent pool is so limited that companies face a strong competition to hire these employees. As evidenced by Gartner, high demand for skilled workers goes far beyond IT department: during the past four years, the business areas with the highest demand for AI skills have been marketing, sales, customer service, finance, and research and development.

Unfortunately, there is no quick and easy solution to the AI skills gap. Both creation of a highly-qualified future working force and re-skilling of actual workers take time and effort, emerging as probably the most crucial and interesting point of the AI transition.

Universities lag in providing companies with workers skilled in Artificial Intelligence. The complexity of the subjects covered and the speed with which new technologies and applications are developing do not permit universities to keep up with the evolution of the field. As a result, companies often must invest in in-house training to reskill and upskill workers.

Although both upskilling and reskilling involve learning new skills, they differ in focus. ‘Upskilling’ refers to gaining or enhancing skills that are directly applicable to an employee's present role or industry (Moore et al., 2020), whereas ‘reskilling’ involves acquiring entirely new skills that are unrelated to one’s existing field (Sawant et al., 2022). Recent studies have highlighted that upskilling and reskilling increase competitiveness, both for individuals and organisations. Organisations remain competitive thanks to a skilled and adaptable workforce that can meet the changing needs of the business (Ponce Del Castillo, 2018). Similarly, acquiring the latest knowledge through retraining (learning state-of-the-art knowledge) can help workers stand out from an increasingly competitive labour market and become more attractive to potential employers (Avanzo et al., 2015).

However, implementing upskilling and reskilling programmes demand investments in terms of resources and time. Firstly, a company has to pay for training materials and hire external trainers, secondly has to pay employees to attend workshops, while they are substantially non-productive, as they are not working. This is strictly related to time investments, since absence from work causes interruptions of usual duties and delays in completing tasks (Hiremath et al., 2021). Finally, organisations might overcome resistance to change. Some employees might be unwilling to accept reskilling programs. Learning new skills is challenging and very often people don’t want to invest time and effort in something that steps them out of their comfort zone. Others might be sceptical about the value of training or don’t trust their ability to learn new things.

3.3 Jobs exposed to AI and AI's Job Creation Potential

A large proportion of workers will learn to use the new tools and live with them, probably increasing productivity, benefit through improvements in job quality, worker well-being and job satisfaction. For instance, AI allows to substitute dangerous or tedious jobs with complex and interesting ones, boosting workers’ engagement and even improving health. However, many jobs will be inevitably replaced and automated. Not completely, since we know from studies that it is currently impossible for a machine to perform 100 per cent of the tasks that make up a job, but fewer workers will be needed to carry out the same tasks as now.

Obviously, not all jobs will be affected by AI in the same way. There are many studies on this subject, and the conclusions are often conflicting. According to many, this technological revolution will be different from previous labour market transformations. Previous ones have generally involved the automation of physical and repetitive work, as in the case of the Industrial Revolution or the introduction of information technology. These transformations led to the replacement of many manual jobs by machines, hardly affecting intellectual jobs.

Most scholars (although, as mentioned earlier, there are dissenting opinions) state AI will impact more so-called ‘white collar jobs’, once seen as irreplaceable. The term refers to workforce with functions of intellectual nature, not directly applied to productive activity and unrelated to operation on factory machines.

In other words, highly educated and highly paid workers.

"Surprisingly enough, knowledge workers are facing the highest level of exposure here, which is quite different with what we've seen with other revolutions," reported Svenja Gudell, chief economist at Indeed Hiring Lab, a notorious job-search platform.

The reason behind this phenomenon lies in the nature of AI, which can break down assignments into patterns that an algorithm can follow precisely. Hence, opposing to previous technologies, AI is capable of automating non-routine, cognitive tasks, as information ordering, memorisation and deductive reasoning. As a result, jobs based on basic accounting, document review, data processing and customer support can be easily automated with AI.

Early estimates of occupational AI exposure show that fields like admin. support, science and engineering, business and financial operations, legal and culture are the most exposed to replacement.

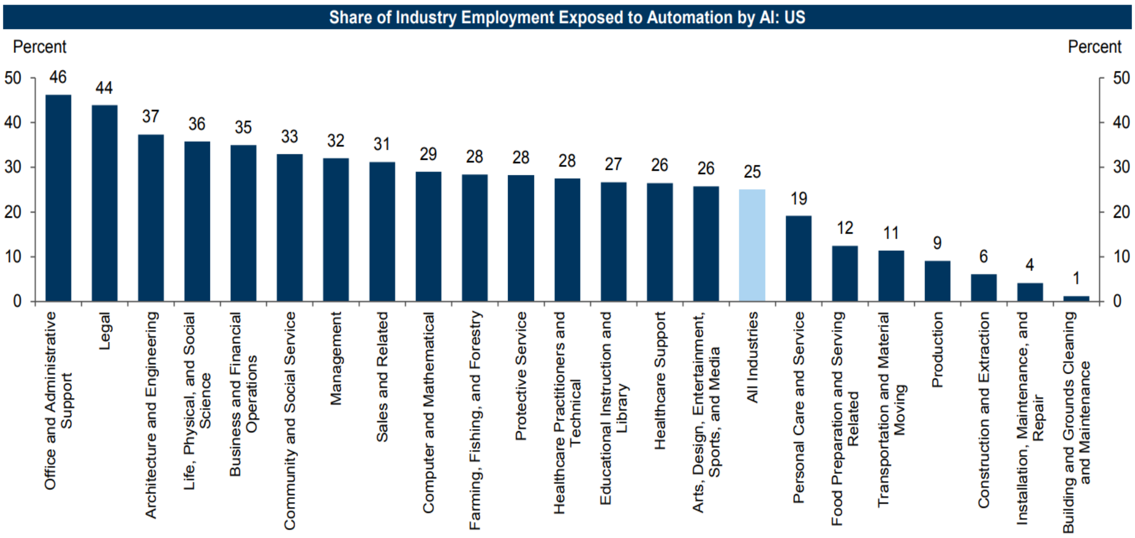

Figure 8: Share of Industry Employment Exposed to Automation by AI: US. Source: Goldman Sachs Global Investment Research, 2023

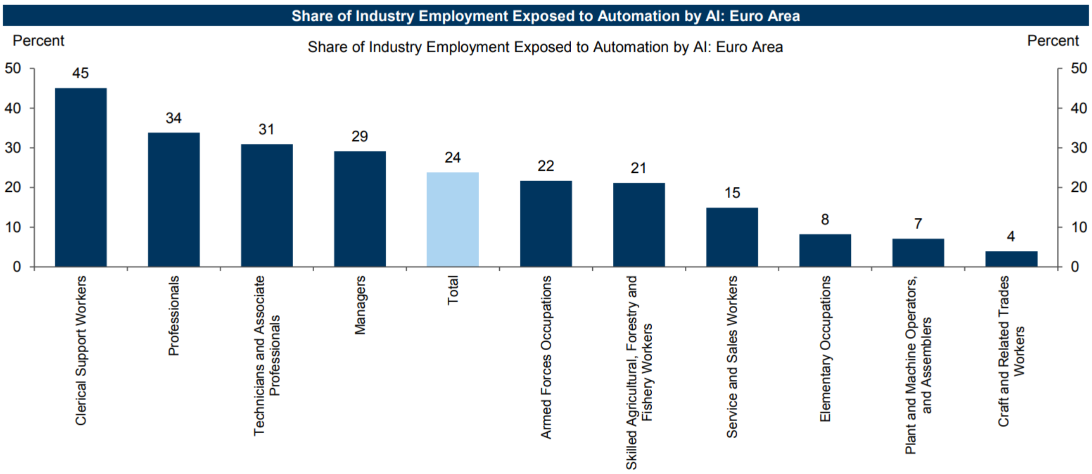

Figure 9: Share of Industry Employment Exposed to Automation by AI: Euro Area. Source: Goldman Sachs Global Investment Research, 2023

On the other hand, jobs requiring creativity, critical thinking, complex problem solving, deep social interaction or human judgement are, at least for now, less vulnerable.

Going through statistics, McKinsey predicts that by 2030, around 14% of the global workforce—or approximately 375 million workers—may need to switch occupational categories due to AI and automation. A 2023 report by Goldman Sachs estimates that AI could lead to the loss of around 300 million jobs globally over the next 10 years, with a particular impact in the administrative, legal and financial sectors. Lastly, World Economic Forum (2023) predicts that by 2027, 83 million jobs could be eliminated due to automation and AI, while 69 million new jobs will be created, leading to a net loss of about 14 million jobs.

Briggs and Kodnani paper published in 2023 point out an employment exposure of 25% for the US, 24% for the euro area, and 18% worldwide, whereas in the same year Ellingrud projects that by 2030, generative AI will automate 8% of the hours that people today work.

Being at the early stages of AI era, we cannot expect perfect accuracy from estimates. They are often conflicting, implying that at least some of them are substantially inaccurate.

Although AI might displace some workers in the short term, it will also create new professions and new businesses in the long run, as happened with previous waves of automation.

A recent study by the economist David Autor found that 60% of today's workers are employed in occupations that didn't exist in 1940. As we can see from the Boston Consulting Group graph below, farm industry in US lost investment and worker shares in the last century, while the non-farm industries experienced strong growth thanks to the technology-driven creation of new positions.

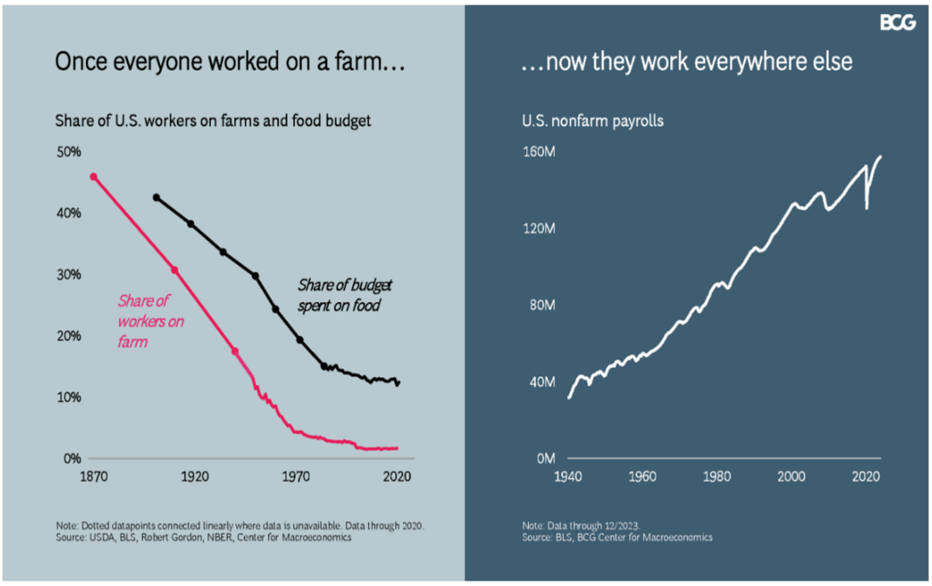

Figure 10: Shift of workers from farm industry to other industries. Source: Us farm and non-farm employment over the long run. Boston Consulting Group

Similarly, the Goldman Sachs graph shows the sectors where the creation of new jobs has been the greatest.

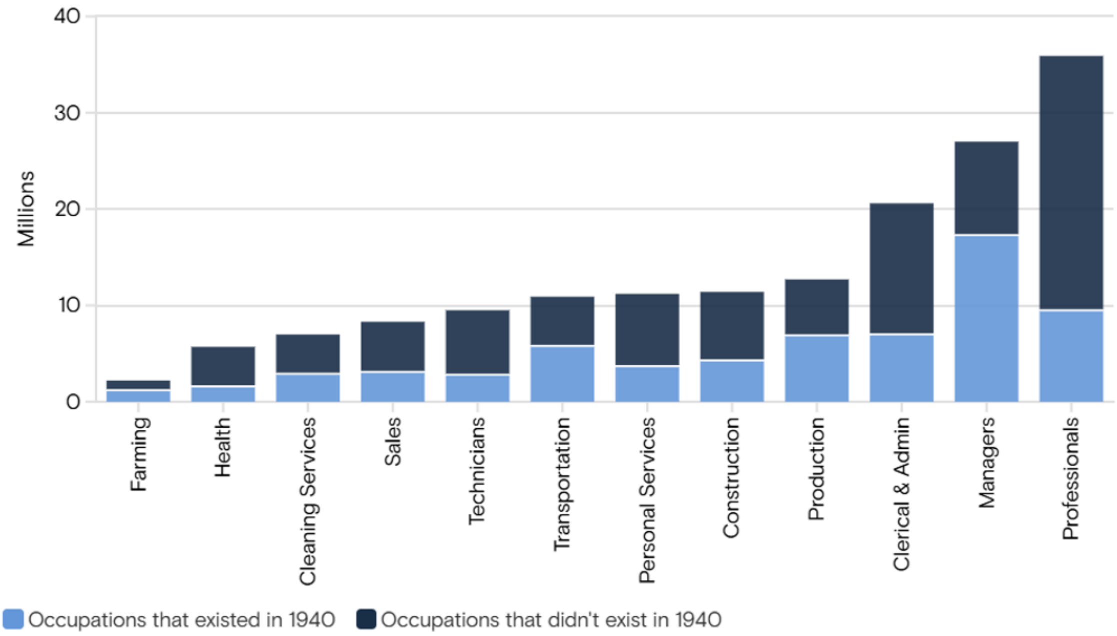

Figure 11: Innovation leads to new occupations that account for employment growth. Source: 2022, Goldman Sachs Research

A 2023 IBM study suggests that by 2025 AI will generate more than 100 million new jobs globally, mainly in the fields of data analysis, AI software development, cybersecurity and human resource management. The European Commission estimates that the AI sector could contribute to creating 12 million jobs in the EU by 2030, particularly in sectors such as healthcare, services and green technology. What AI can do is both rebuilding (redefining) traditional sectors, creating new job opportunities, and opening up new possibilities for non-traditional jobs and entrepreneurship.

The very recent study "The Employment Impact of Emerging Digital Technologies" shows that the overall effect of 40 emerging technologies (including Machine Learning) on employment in Europe is positive. They create more jobs than they displace in the most exposed areas (figure 12).

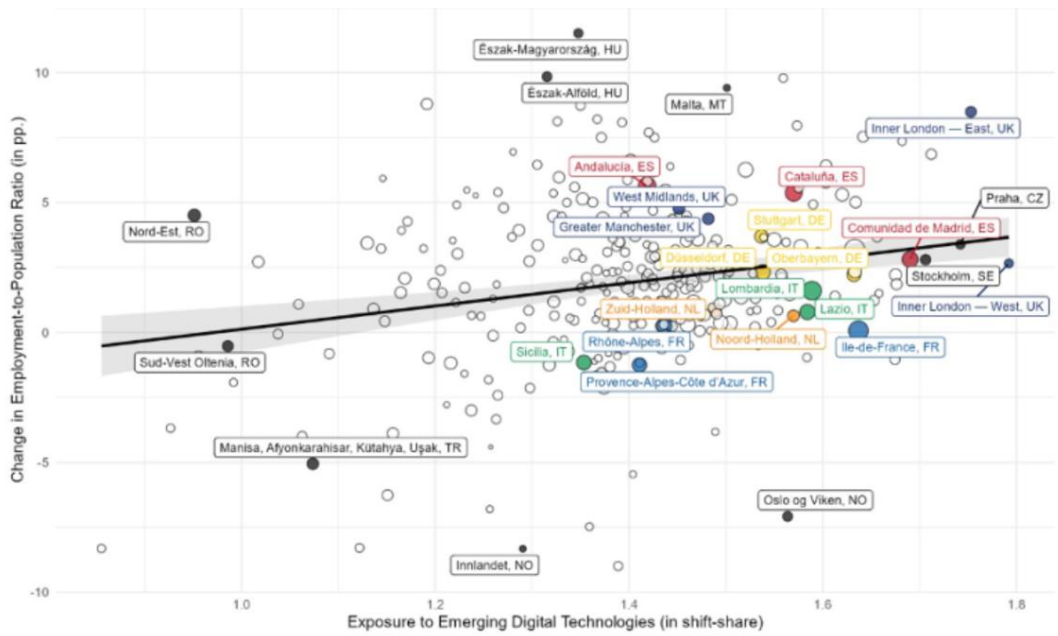

Figure 12: Change in Employment-to-Population Ratio and Exposure to Emerging Digital Technologies. Source: (2024), "The Employment Impact of Emerging Digital Technologies"

Obviously, the results are not geographically uniform, but it can be clearly seen that increased exposure to emerging digital technologies leads to a generalised increase in employer-to-population ratio.

Overall the expectation is that AI should have a positive impact on the employment, but some studies highlight a polarization of jobs: digital technologies are increasing employment in both low- and high-skilled jobs, but medium-skilled workers are losing jobs, in line with trends in recent decades.

Different technologies have different effects. Robots, for example, which are often seen as the main cause of job losses, have a negative impact on employment in the most exposed regions, especially among women and older workers (see figure below). However, the issue is more complex than the simple equality "robots = job losses". Complementary technologies, such as data processing technologies, have a positive effect, as they also support the tasks of less-skilled workers.

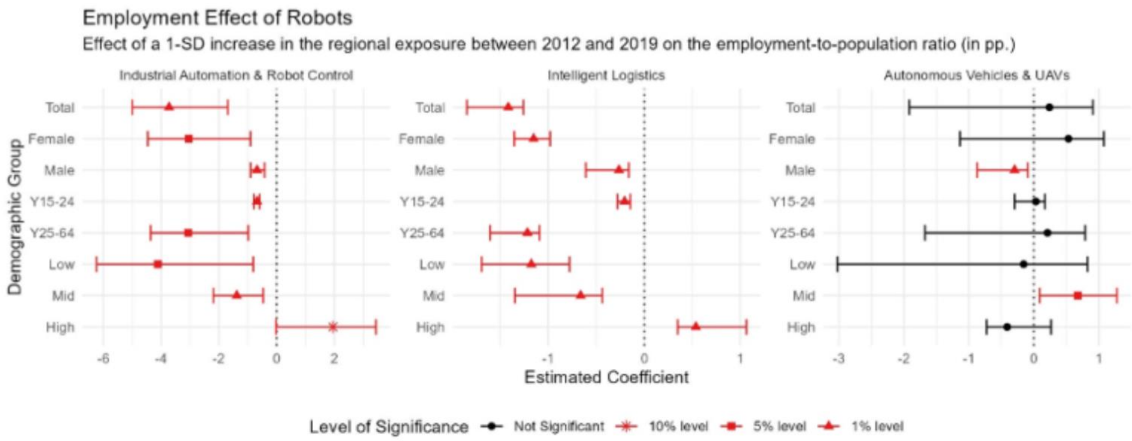

Figure 13: Effect of exposure to robots on employment. Source: (2024), "The Employment Impact of Emerging Digital Technologies"

Office workers are the most exposed to "intangible" technologies, related to smart logistics, electronic and mobile payment, digital authentication and voice communication. Managers, in turn, are among the most exposed to technologies related to workflow management and digital advertising. Plant and machine operators are the most exposed to tangible technologies such as additive manufacturing and robots. Conversely, specialized agricultural personnel, artisans and skilled workers are much less exposed to these emerging digital technologies.

To conclude, the relationship between AI and employment is complex and context dependent. When evaluating the risks and opportunities associated with AI adoption, academics and policymakers should consider the different impact that AI has across countries, locations and sectors depending on the skill level of workforce and institutional environment (Goos et al., 2019).

CHAPTER 4: AI AND REGULATION

Whenever a General Purpose Technology is introduced, policy makers must guide that technological innovation in the right direction. The objective is to find optimal trade-off between the opportunities offered by the technology and the potential risks involved. Therefore, also in the case of Artificial Intelligence, policy instruments will partially determine its success (or failure). AI is particularly worthy of attention because it is a world-wide phenomenon which is spreading fast and widely, involving all the agents in the economy.

One of the first articles to warn about the risks of unregulated AI was written by Acemoglu (2023). The author points out that economic and social threats come more from the current and potential use of AI than from its nature. The article states that the risks of GPTs show themselves over time, as the technology is adopted. Hence, the optimal adoption of technology should be gradual, allowing policy makers to know the associated risks and increase the adoption rate only when the probability of disasters is sufficiently low, especially in high-risk industries.

In fact, the speed of development is one of the main problems to be addressed. It forces policy makers to react as quickly as possible to not leave circumstances unregulated. Thus, the issue is very complex and extremely dynamic.

To deal with it, the European Union approved the AI Act between March and May 2024, becoming the first institution in the world to introduce a comprehensive set of AI regulations. The AI Act classifies AI models using four categories of risk: unacceptable risk, high risk, limited risk, and minimal risk.

AI systems classified unacceptable, as biometric categorisation systems based on protected traits or systems able to manipulate people's free will, will be banned.

High-risk category of AI systems will be evaluated by EU AI Office before entering the market. They must "adhere to regulations that require rigorous testing, proper documentation of data quality and an accountability framework that details human oversight."

Conversely, low-risk AI systems will only have to adhere to transparency requirements, such alerting consumers when they are interacting with AI-generated material.

Lastly, minimal risk tools are allowed to be used freely.

The IA Act is only a first step towards a stricter and more complete system of regulations. It still leaves many areas unregulated and will probably be followed by other acts. In fact, it only partly addresses what are, in the opinion of most scholars, the possible problems of the introduction of AI on economic growth.

The following paragraphs will briefly address the main challenges that the institutions should face.

4.1 Taxation and Fiscal Policy

One of the most debated topics is the taxation of machines, so automation and AI systems. The current tax system and investment credits strongly favour the adoption of capital rather than labour, enhancing the substitution of workers with automation systems.

Since 1986, tax rates on labour have always been higher than those on capital, reaching a maximum gap in 2021 when the top marginal tax rate on labour income was set at 37%, and capital gains at 20%.

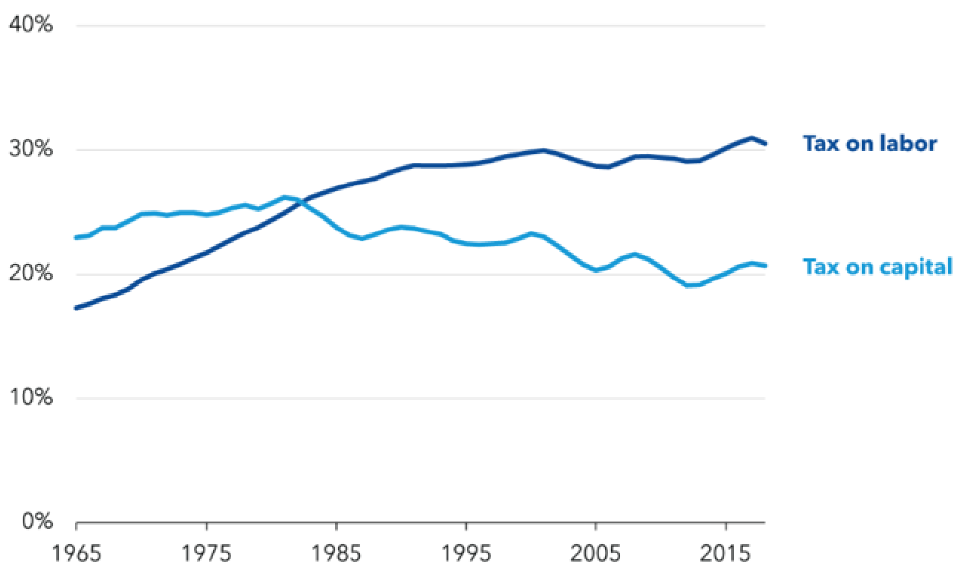

Figure 14: Average tax rates in advanced economies (5-year moving average). Source: Bachas and others 2022 and IMF staff estimates

Acemoglu, Manera, and Restrepo (2020) explain that setting capital taxes too low relative to labour taxes might result in excessive substitution of workers compared to what is socially optimal. In other words, machines become cheaper than workers, causing unemployment.

Therefore, Acemoglu and other economists as Brynjolfsson suggest balancing tax rates on labour and tax rates on equipment and algorithms in order to stimulate adoption of complementary technologies. In addition, higher taxes on capital may increase tax revenues, as the capital share of income has increased in recent years relative to the labour share.

Despite the positive effects this economic move could have on unemployment and tax revenues, it could offset the productivity-enhancing effects of AI.

According to the authors, the way to avoid this phenomenon is not to penalise excessively capital accumulation, which is crucial for investment and economic growth. So, focus of taxation should be on income flows (such as interest, dividends and profits) rather than assets.

This is the reason why a direct tax on AI is not an optimal choice. It could reduce the rate of investment and innovation, stifling productivity gains.

4.2 Market Competition

The widespread use of computer algorithms by Artificial Intelligence companies could soon disrupt traditional competition dynamics. Regulatory authorities such as the UK's Competition & Market Authority (CMA), Germany's Bundeskartellamt and France's Autorité de la Concurrence (and many others) are aware of the competitive threats posed by AI, and plan to act quickly to discourage anti-competitive behaviours.

4.2.1 Algorithmic collusion

The main concerns relate price collusion, self-reference by vertically integrated suppliers and discrimination or predatory pricing.

Algorithm can promote collusive behaviours between competing companies and give birth to new forms of anti-competitive coordination. Technically we talk about algorithmic collusion.

According to international law, collusive activity is distinguished into:

- tacit collusion: coordination based on parallelism of behaviour by competing firms that, although conscious, is the result of autonomous choices and not agreements
- explicit collusion: voluntary agreements between firms to set prices higher than competitive ones.

Explicit collusion is prohibited at EU level by Art. 101 TFEU and at national level by Art. 2 of Law no. 287/1990, whereas tacit collusion is allowed when it does not threat competition.

AI blurs the line between tacit and explicit collusion.

Specifically, pricing algorithms allow competing firms to coordinate on a collusive equilibrium very quickly, through instantaneous reactions (without prior organisation) and without human communication, thus ‘simulating’ a scenario of conscious parallelism of behaviour.

Agreements would occur without explicit communication, but through unilateral warnings and announcements concerning the commercial conditions companies intend to apply (e.g. price), causing an automatic alignment of the companies' behaviour.

There are still no specific regulations regarding the use of algorithms, in particular AI, and penalising algorithmic collusion. The crux of the matter is understanding whether the general rules of competition law are sufficient to repress algorithmic collusion conduct by interpreting the concepts of ‘agreement’ and ‘concerted practice’ broadly.

In a different way, regulation of collusive outcomes achieved through self-learning algorithms is much more complex, as advanced deep learning technologies can make autonomous and self-learning business decisions without any human intervention. Furthermore, in many cases a self-learning algorithm has the goal to define the best pricing strategy to maximise firm's profit, which is certainly legally permitted. However, it might autonomously deduce that one of the most effective ways (if not the most effective way) to achieve this result is to align its own price to that of its competitors on values greater than competition ones.

Therefore, it is highly likely that regulatory action will soon be necessary to detect algorithmic collusion cases and establish unequivocal conditions for the use of algorithms.

The chance of collusive behaviour increases when a company provides information or the algorithm to other firms, building up a so-called ‘hub-and-spoke’ arrangement. This type of logistic enable illicit coordination.

Furthermore, the algorithm supplier may also influence the behaviour of downstream firms, especially if it is a large platform providing services to many competing users, or if it is also active in the downstream market. In the latter case, a vertically integrated intermediary (which is the hub) may have incentives to exclude competitors through its own algorithm (‘gatekeeper’ behaviour). One way to rule out competitors in digital markets is trough ‘self-preferencing’. It is a strategy where a company favours its own products or services over those of its competitors through its own algorithm previously provided to other firms. Google has been investigated by the European Union for such behaviour.

4.2.2 Concerns of monopolies

Increase in adoption of AI systems rise concern over monopoly power in some sectors.

While moderate monopoly power can encourage investment in firm-specific knowledge and innovation, too much monopoly power results in inefficiencies and reduces productivity. Monopolies can exploit their dominant position by reducing output and increasing prices, leading to welfare losses, less technological advancements and slowing down long-term growth.

The main reason why Artificial Intelligence can cause monopolistic effects is creation of barriers to entry. AI needs vast amount of financial and technological resources to be developed and implemented. Hence, large companies tend to gain a competitive advantage over small entrants who often do not have such resources.

Access to data is a strong barrier to entry. Large technology companies, such as Google, Meta and Microsoft, hold a huge amount of data that feeds their AI algorithms. The more data they have, the better their algorithms become, creating a virtuous cycle that strengthens their market position.

Monopolies may also emerge at different stages of the production chain, especially in the manufacturing of chips and semiconductors. These essential physical inputs for AI systems, which are critical physical inputs for AI systems, are in a short supply and geographically located in few specific areas of the planet (Taiwan, South Korea and United States). The dominant position of these countries and few companies such as TSMC and Samsung, makes global markets dependent on limited suppliers and creates geopolitical issues (especially between China and Taiwan or China and the USA).
These circumstances create risks and inefficiency in the supply chain, as well as slowing down technological innovation due to limited competition.
In addition, many large companies use their financial power to acquire innovative start-ups in the field of AI, thus stifling potential competitors before they can become a real threat. These acquisitions reduce the spreading of innovation across the market and create a less competitive environment.
To mitigate these threats to competition, several policies and regulations have been proposed. The AI Act forces companies to adopt Artificial Intelligence in accordance with the principles of fair competition. Similarly, the Digital Markets Act (DMA), approved by the European Union in 2022, aims to prevent the concentration of economic power forcing companies to make their algorithms more transparent and implement regular audits to check for anti-competitive practices.
Finally, it will be crucial to foster models of open innovation and data sharing in order to avoid the monopolisation of key resources needed to develop competitive AI.

4.3 Privacy

AI technologies require and process large amounts of personal information, which could lead to violation and misuse of private data. Privacy laws, as they stand, are unable to address the challenges posed by AI (Daniel J. Solove, 2024).
AI does not create entirely new privacy problems, but rather intensifies existing ones. Many authors (Veale, Binns and Edwards, 2018) emphasise the need for an updated legal framework to address these evolving challenges.
The main problem lies in the dominant model of privacy management, commonly referred to as notice-and-choice. This model is based on the idea that users can actively control the use of their data through notifications and consent options.

This individual control approach turns out to be unsuccessful. Most people is unable to understand privacy policies and others don’t read it.
The idea of ‘managing’ one's own data becomes even more unrealistic in the age of AI, where technological complexity makes it impossible to fully understand how data is used. In J. Solove’s opinion, laws should focus on controlling data collection and use by companies, setting stricter obligations on organisations, rather than relying on individual consent as the main form of regulation.
The second problem is internal assessment: most laws require companies to assess their own risks (e.g. through Data Protection Impact Assessments, DPIAs). This can lead to a lack of objectivity, as companies tend to minimise risks to avoid restrictions.
However, the main threat that Artificial Intelligence brings is its ability to ‘generate’ data through inferences (deductions based on existing data). This process can reveal personal details that people did not expect to share. This revolutionary capability challenges traditional legal protections, as laws often focus only on the direct collection of data, not the creation of new data through analysis.
Data used to train AI systems are extracted from public online sources. This is called Scraping. This practice violates many commonly accepted privacy principles (such as consent, transparency, purpose limitation). However, scraping is often considered acceptable because it concerns publicly accessible data.
According to Solove, even though data are technically accessible, this does not mean that people have given up their expectations of privacy.
Until the advent of the AI act, European data regulation completely contained in the GDPR (General Data Protection Regulation). The GDPR is the European Union's regulation managing how companies and other organisations process personal data, protecting people's right to privacy. After AI Act introduction, the subject becomes more complex: it is important to analyse the relationship between the existing GDPR and the new AI act.
The GDPR specifically regulates the protection of personal data, while the AI act regulates the risks associated with the use of AI systems. Although the two regulations are distinct and operate on different levels, they overlap on some points. Therefore, it is crucial that they are applied in a coordinated manner to avoid regulatory inconsistencies.

Currently, there is no procedure which coordinates the GDPR and the IA Act, but policy makers will operate as soon as possible.

CONCLUSIONS

Artificial Intelligence has certainly been the hottest topic of the last two years and will continue to be so in the next future. The debate about its use, and its potential risks and benefits is very heated.

Most probably anyway AI will have some impacts on the macroeconomic scenarios, market and business context, government and financial institutions decisions and ultimately on our life.

In this short research, an analysis of the current and potential macroeconomic impacts of AI was carried out. To be more specific, we focused on the impacts of Artificial Intelligence on aggregate productivity and the labor market. Empirical evidence does not yet allow us to draw strong and certain conclusions, being at the early stages of the evolution and adoption of this technology. In fact, so far there are still no significant changes in the growth rates of TFP and in the labor market. This is because the technological transition takes time: companies and institutions have to make significant complementary investments in infrastructure, staff training and redefinition of work processes.

Business executives clearly recognize the not yet fully explored potential and the significant impacts AI will have on business models, strategic decisions and operational activities but at the same time they are not yet sure about its implementation methods, its real “use cases”, what the trade-off between expected benefits and costs is, its impact on the workforce to be upskilled and reskilled.

All these open topics explain why there is so much talk about AI, but its full adoption has yet to come.

Moreover, it is key to avoid situations where companies and governments overly focus on the development of AI that simply replaces human capabilities, rather than on technologies that create solutions that can support human capabilities and foster more productive and harmonious human-machine collaboration (“Turing Trap").

Furthermore, it is necessary for institutions to develop intelligent and targeted regulation to promote a balanced and safe transition, increasing productivity without causing economic and social damages.

The analysis then addressed the possible future impacts of AI on productivity and work. Predictive models built by authoritative scholars, consulting firms or economic institutions show in some cases different results, mainly due to the low adoption (even though fast growing) of this new technology: this leads to the lack of historical data, and the numerous assumptions placed at the base of the predictive models. Experts mainly line up on two sides: those who think that AI will have unprecedented impacts on productivity and work, and those who instead invite to curb the general hype towards AI by stating that in the short/medium term there will be limited upheavals at a global level. What many agree on is the potentially relevant impact on white-collar jobs too, making this revolution different from the previous ones. To avoid negative impact on employment for this category of workers, it will be necessary to adopt policies to remodel skills, as well as direct AI new capabilities towards the formation of new businesses and ultimately creation of new jobs that can compensate for the negative effect of automation.

In conclusion, even though it is still not clear how Artificial Intelligence will change the global economic system, it undoubtedly represents an extraordinary opportunity for development and improvement of the quality of life in the medium/long term, but only if its diffusion will occur in a balanced and well-managed way. It is essential that policy makers and companies address the challenges posed by AI and ensure that risks are minimized, and benefits are maximized.

BIBLIOGRAPHY AND SITOGRAPHY

Bibliography

1. Abe, E. N., Abe, I. I., & Adisa, O. (2021). Future of work: Skill obsolescence, acquisition of new skills, and upskilling in the 4IR. In E. N. Abe (Ed.), Future of Work, Work-Family Satisfaction, and Employee Well-Being in the Fourth Industrial Revolution. IGI Global.
2. Acemoglu, D. (2022). The simple macroeconomics of AI (No. w30164). National Bureau of Economic Research.
3. Acemoglu, Daron, Andrea Manera, and Pascual Restrepo (2020). Does the US Tax Code Favor Automation? Brookings Papers on Economic Activity.
4. Acemoglu, Daron, Andrea Manera, and Pascual Restrepo (2020). Does the US Tax Code Favor Automation? Brookings Papers on Economic Activity.
5. Agrawal, A., Gans, J., & Goldfarb, A. (2019). Economic policy for artificial intelligence. University of Toronto and NBER.
6. Agrawal, A., Gans, J., & Goldfarb, A. eds. (2018a). The Economics of Artificial Intelligence: An Agenda. Chicago: University of Chicago Press.
7. Anton Korinek (moderator). (2022). The Turing trap: a conversation with Erik Brynjolfsson on the promise and peril of human-like ai. Brookings institution.
8. Avanzo, S., de Wind, L., Flament, S., Fontaine, M., Rennoir, M., & Plasman, R. (2015). EEPO Review Spring 2015: Upskilling unemployed adults. The organisation, profiling and targeting of training provision (No. 15.01).
9. Bhargava, A., Bester, M., & Bolton, L. (2021). Employees' perceptions of the implementation of robotics, artificial intelligence, and automation (RAIA) on job satisfaction, job security, and employability. Journal of Technology in Behavioral Science, 6, 106-113.
10. Borgonovi, F. et al. (2023), "Emerging trends in AI skill demand across 14 OECD countries", OECD Artificial Intelligence Papers, No. 2, OECD Publishing, Paris.

11. Bresnahan, T. F., & Trajtenberg, M. (1992). General Purpose Technologies: " Engines of Growth". NBER Working Papers.
12. Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? Journal of econometrics, 65(1), 83-108.
13. Briggs, J., & Kodnani, D. (2023). The Potentially Large Effects of Artificial Intelligence on Economic Growth. Goldman Sachs Global Economics Analyst.
14. Briggs, Joseph and Devesh Kodnani (2023). The Potentially Large Effects of Artificial Intelligence on Economic Growth. Global Economic Analyst. Goldman Sachs.
15. Brynjolfsson, E. (2022). The Turing Trap: The Promise & Peril of Human-Like Artificial Intelligence. Dædalus, the Journal of the American Academy of Arts & Sciences, 151(2), 272-287.
16. Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic perspectives, 14(4).
17. Brynjolfsson, E., Rock, D. and Syverson, C. (2019), "Artificial Intelligence and the Modern Productivity Paradox: a Clash of Expectations and Statistics", in A. Agrawal, Gans, J. and Goldfarb, A. (eds.), The Economics of Artificial Intelligence: an Agenda. Chicago: University of Chicago Press, 23-57.
18. Brynjolfsson, E., Rock, D., & Syverson, C. (2017). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics (No. w24001). National Bureau of Economic Research.
19. Comunale, M., & Manera, A. (2024). The Economic Impacts and the Regulation of AI: A Review of the Academic Literature and Policy Actions (IMF Working Paper No. WP/24/65). International Monetary Fund.
20. Crafts, N. (2021). Artificial Intelligence as a general-purpose technology: an historical perspective (Version 1). University of Sussex.
21. Daron Acemoglu & Pascual Restrepo, 2018. "Artificial Intelligence, Automation and Work," Boston University - Department of Economics - The Institute for Economic Development Working Papers Series dp-298, Boston University - Department of Economics.

22. DeSantis, M. F. (2024). Is AI a General Purpose Technology? Doctoral dissertation, Temple University. DOI: 10.34944/dspace/10306.
23. Ellingrud, Kweilin, Saurabh Sanghvi, Gurneet Singh Dandona, Anu Madgavkar, Michael Chui, Olivia White, and Paige Hasebe (2023). Generative AI and the Future of Work in America. McKinsey Global Institute.
24. Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. Technical Report.
25. Ezrachi, Ariel and Maurice Stucke (2020). Sustainable and Unchallenged Algorithmic Tacit Collusion. Northwestern Journal of Technology and Intellectual Property.
26. Ezrachi, Ariel and Maurice Stucke (2020). Sustainable and Unchallenged Algorithmic Tacit Collusion. Northwestern Journal of Technology and Intellectual Property.
27. Filippucci, F. et al. (2024), The impact of Artificial Intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges, OECD Artificial Intelligence Papers, No. 15, OECD Publishing, Paris.
28. Gambardella, A., Conti, R., & Novelli, E. (2020, July 13). La generalità è una specializzazione. SDA Bocconi.
29. Ghosh, D., Ghosh, R., Roy Chowdhury, S. et al. AI-exposure and labour market: a systematic literature review on estimations, validations, and perceptions. Manag Rev Q (2024).
30. Gonzales, J. T. (2023). Implications of AI innovation on economic growth: A panel data study. Economic Structures, 12(13).
31. Goos, M., Arntz, M., Zierahn, U., Gregory, T., Gomez, S. C., Vazquez, I. G., & Jonkers, K. (2019). The impact of technological innovation on the future of work. European Commission, Joint Research Centre.
32. Green, A. (2024), "Artificial intelligence and the changing demand for skills in the labour market", OECD Artificial Intelligence Papers, No. 14, OECD Publishing, Paris.

33. Green, A. and L. Lamby (2023), The supply, demand and characteristics of the AI workforce across OECD countries, OECD Social, Employment and Migration Working Papers, No. 287, OECD Publishing, Paris.
34. Helpman, E., & Trajtenberg, M. (1994). A time to sow and a time to reap: growth based on general purpose technologies. National Bureau of Economic Research.
35. Jiang, Y., Li, X., Luo, H. et al. (2022). Quo vadis artificial intelligence? Discov Artif Intell 2, 4.
36. Jiaxing Du. (2024). The Impact of Artificial Intelligence Adoption on Employee Unemployment: A Multifaceted Relationship. International Journal of Social Sciences and Public Administration.
37. Lane, M., M. Williams and S. Broecke (2023), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", OECD Social, Employment and Migration Working Papers, No. 288, OECD Publishing, Paris.
38. Lassébie, J. and G. Quintini (2022). What skills and abilities can automation technologies replicate and what does it mean for workers? New evidence. OECD Social, Employment and Migration Working Papers, No. 282, OECD Publishing, Paris.
39. Lee, H. J., Probst, T. M., Bazzoli, A., & Lee, S. (2022). Technology advancements and employees' qualitative job insecurity in the Republic of Korea: Does training help? Employer-provided vs. self-paid training. International Journal of Environmental Research and Public Health, 19(21), 14368.
40. Li, L. (2022). Reskilling and upskilling the future-ready workforce for industry 4.0 and beyond. Information Systems Frontiers, 1-16.
41. Lipsey, R. G., Carlaw, K. I., & Bekar, C. T. (2005). Economic transformations: general purpose technologies and long-term economic growth. Oxford: Oxford University Press.
42. Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organisation. Journal of Business Research, 120, 262-273.

43. McElheran, Kristina, J. Frank Li, Erik Brynjolfsson, Zachary Kroff, Emin Dinlersoz, Lucia S Foster, and Nikolas Zolas (2023). AI Adoption in America: Who, What, and Where. Working Paper 31788. National Bureau of Economic Research.
44. McElheran, Kristina, J. Frank Li, Erik Brynjolfsson, Zachary Kroff, Emin Dinlersoz, Lucia S Foster, and Nikolas Zolas (2023). AI Adoption in America: Who, What, and Where. Working Paper 31788. National Bureau of Economic Research.
45. Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., & Pietrantoni, L. (2023). The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. Informing Science: The International Journal of an Emerging Transdiscipline, 26, 39-68.
46. Muro, M., Maxim, R., & Whiton, J. (2019). Automation and artificial intelligence: How machines are affecting people and places. Brookings Institution.
47. OECD (2023), OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market, OECD Publishing, Paris.
48. Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The Impact of AI on Developer Productivity: Evidence from GitHub.
49. Ponce Del Castillo, A. (2018). Artificial intelligence: A game changer for the world of work. Foresight Brief No. 5. European Trade Union Institute.
50. Sawant, R., Thomas, B., & Kadlag, S. (2022). Reskilling and upskilling: To stay relevant in today's industry. International Review of Business and Economics, 7(1), 4.
51. Shen, Y., Zhang, X. (2024). The impact of artificial intelligence on employment: the role of virtual agglomeration. Humanit Soc Sci Commun 11, 122.
52. Strohmaier & Rainer, (2016) , "Studying General Purpose Technologies in a Multi-Sector Framework: The Case of ICT in Denmark", Structural Change and Economic Dynamics 36(4)
53. Svanberg, Maja, Wensu Li, Martin Fleming, Brian Goehring, and Neil Thompson (2024). Beyond AI Exposure: Which Tasks are Cost-Effective to Automate with Computer Vision.

54. Webb, Michael (2019). The Impact of Artificial Intelligence on the Labor Market. Working Paper 3482150. SSRN.
55. Weil David, (2013) Economic Growth (3rd edition) Edinburgh Gate, UK, Pearson Education Limited.

Sitography

1. Accenture. (2024). Cos'è l'Intelligenza Artificiale. https://www.accenture.com/it-it/insights/artificial-intelligence-summary-index#:~:text=L'intelligenza%20artificiale%20%C3%A8%20un,intelligenza%20simili%20a%20quelli%20umani.
2. American Enterprise Institute – AEI. (2022), AI Is the Invention of a New Method of Invention — and Its Potential Is More Amazing Than You Realize. https://www.aei.org/articles/ai-is-the-invention-of-a-new-method-of-invention-and-its-potential-is-more-amazing-than-you-realize/
3. AWS. (2024) Cos'è il machine learning? - Spiegazione del machine learning per le aziende. https://aws.amazon.com/it/what-is/machine-learning/#:~:text=Per%20machine%20learning%20si%20intende,invece%2C%20su%20modelli%20e%20inferenza.
4. CEPR. (2024). Future tax challenges in an AI-driven economy. https://cepr.org/voxeu/columns/future-tax-challenges-ai-driven-economy
5. CEPR. (2024). Should AI stay or should AI go: The promises and perils of AI for productivity and growth. https://cepr.org/voxeu/columns/should-ai-stay-or-should-ai-go-promises-and-perils-ai-productivity-and-growth
6. Ecipe. (2024). The European productivity slowdown in a global context. https://ecipe.org/blog/the-european-productivity-slowdown/
7. Enciclopedia – Treccani. Intelligenza artificiale. https://www.treccani.it/enciclopedia/intelligenza-artificiale_(Enciclopedia-della-Scienza-e-della-Tecnica)/
8. Financial Times - Partner Content by IBM (ft.com). (2024). Closing the AI skills gap. https://www.ft.com/partnercontent/ibm/closing-the-ai-skills-gap.html
9. Forbes. (2023). How Does Artificial Intelligence Create New Jobs?

https://www.forbes.com/councils/forbesbusinesscouncil/2023/07/26/how-does-artificial-intelligence-create-new-jobs/

10. Forbes. (2023). Why GPT Should Stand For 'General Purpose Technology' For All. https://www.forbes.com/sites/joemckendrick/2023/08/08/why-gpt-should-stand-for-general-purpose-technology-for-all/
11. Fordham journal of corporate and financial law. (2024). The First of its Kind: the EU AI Act and What it Means for the Future of AI. https://news.law.fordham.edu/jcfl/2024/04/23/the-first-of-its-kind-the-eu-ai-act-and-what-it-means-for-the-future-of-ai/
12. Goldman Sachs. (2023). Generative AI could raise global GDP by 7% https://www.goldmansachs.com/insights/articles/generative-ai-could-raise-global-gdp-by-7-percent
13. Goldman Sachs. (2024). AI is showing "very positive" signs of eventually boosting GDP and productivity. https://www.goldmansachs.com/insights/articles/AI-is-showing-very-positive-signs-of-boosting-gd
14. IBM. (2024). Cos'è il deep learning? https://www.ibm.com/it-it/topics/deep-learning#:~:text=IBM&text=Holdsworth%2C%20Mark%20Scapicchio-,Cos'%C3%A8%20il%20deep%20learning%3F,potere%20decisionale%20del%20cervello%20umano.
15. IBM. (2024). What is Artificial Intelligence (AI)? https://www.ibm.com/topics/artificial-intelligence#:~:text=Contributors%3A%20Cole%20Stryker%2C%20Eda%20Kavlakoglu,can%20see%20and%20identify%20objects.
16. IMF Blog. (2024). Fiscal Policy Can Help Broaden the Gains of AI to Humanity. https://www.imf.org/en/Blogs/Articles/2024/06/17/fiscal-policy-can-help-broaden-the-gains-of-ai-to-humanity
17. Inc.com. (2024). Will AI Make White-Collar Workers Obsolete? https://www.inc.com/bruce-crumley/will-ai-make-white-collar-workers-obsolete.html

18. Information Week. (2024). The New IT Driven by Multifaceted Skill Sets. https://www.informationweek.com/it-leadership/the-new-it-driven-by-multifaceted-skill-sets
19. Lavoce.info. (2024). Quali sono i lavori minacciati dalle intelligenze artificiali? https://lavoce.info/archives/105733/quali-sono-i-lavori-minacciati-dalle-tecnologie-digitali/
20. Machtech. (2024). Apple acquired 32 AI startups during 2023. https://www.mactech.com/2024/02/07/stocklytics-apple-acquired-32-ai-startups-during-2023/amp/
21. McKinsey&Company. (2022). What is economic growth. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-economic-growth
22. McKinsey&Company. (2024). What is AI (artificial intelligence)? https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-ai
23. MIT Sloan. (2021). Machine learning, explained. https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained
24. SAS Analytics Software. (2024). Che cos'è l'Intelligenza Artificiale e come funziona. https://www.sas.com/it_it/insights/analytics/what-is-artificial-intelligence.html
25. Sciences Po Women in Business. (2024) Artificial Intelligence and the Labor Market. https://www.sciencespo.fr/women-in-business/en/news/article-artificial-intelligence-and-the-labor-market/
26. Stanford.edu. (2022). The AI Index Report 2022: Artificial Intelligence Index. https://aiindex.stanford.edu/ai-index-report-2022/
27. Swiss Economics. (2022). AI and its effects on competition. https://swiss-economics.ch/blog-en/items/ai-and-its-effects-on-competition.html
28. Wikipedia. General-purpose technology. https://it.wikipedia.org/wiki/General_purpose
29. Wikipedia. Productivity paradox. https://en.wikipedia.org/wiki/Productivity_paradox

30. World Economic Forum. (2024). Why AI will not lead to technological unemployment. https://www.weforum.org/agenda/2024/08/why-ai-will-not-lead-to-a-world-without-work/