The artificial intelligence economy

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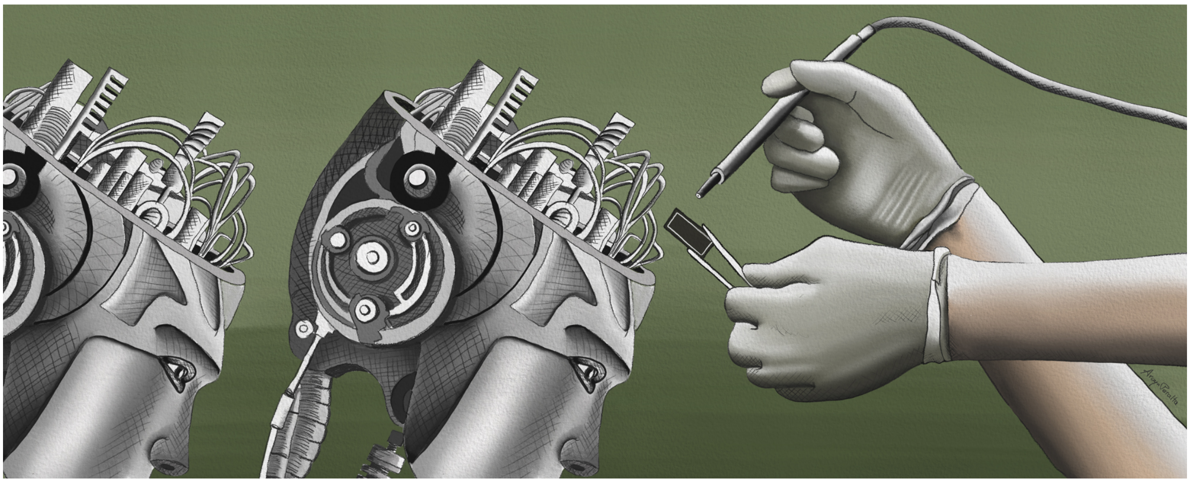


Araya Peralta

Artificial intelligence as a new technological platform

In economics we generally use the term artificial intelligence (AI) to describe the process of creating and developing non-human intelligent technological agents. [1] AI can be seen as a traditional technological innovation process in the sense that science and technology are applied to create machines, software and algorithms that act on economic activities, especially production, by either complementing or substituting them. However AI is also a radical, disruptive technological innovation process because these technological agents act intelligently, as they are capable of recognising and responding to their environment. [2]

Comparison with human intelligence can be very helpful in understanding the disruption generated by AI. Human intelligence consists of a range of different mental actions with a clear impact on the behaviour of economic agents, markets and the main economy-related functions, such as productivity and labour. Such actions include simple computing, data processing, pattern recognition, prediction, varieties of problem-solving, ability to express judgement, creativity and communication.

In its formal beginnings, back in the 1950s, computer science, psychology and economics researchers such as Herbert Simon and Allan Newell attempted to develop intelligent machines capable of recreating this set of mental activities. The basic idea was substitution, i.e. creating intelligent machines with computing, prediction, analysis, problem-solving, communications and even creativity capabilities. This approach soon had to be tempered and the resurgence of AI in the 1990s came with more modest goals: first replicating and then improving human intelligence.

> The development of AI-based innovation methods that improve human capabilities, instead of devaluing their work, requires a profound review of education systems.

In this second phase, the basic idea of AI is complementarity. Intelligent technological agents substitute certain actions, especial more routine ones or those that need greater calculating capacity or complex representations, but also complement other actions innate to human intelligence, such as communicative capabilities and creativity. For instance, even before AI, computers were already much better than human intelligence at computation, data processing and behavioural pattern recognition and prediction. These capabilities have clearly been improved with new AI applications, such as facial and voice recognition and algorithms for processing and analysing large quantities of unstructured data. However, human intelligence is still unbeatable in activities involving intuition, creativity and communication. [3]

As the end of the second decade of the 21st century nears, this more modest approach to AI as a complementary technology is the more common one, both in research, where it is often termed 'narrow AI', and in most of its economic and business applications. Having abandoned the goals of total substitution of human intelligence, the economic disruption of AI comes about through other channels, especially advances in machine learning and deep learning. The former refers to statistical techniques that permit computers and algorithms to learn, predict and perform tasks based on large quantities of data, often not initially structured, and without being explicitly programmed. The latter refers to algorithms that use multi-layered programs, such as neural networks, to improve machine learning, statistical inference and optimisation.

Indeed it is the ability to learn that provides AI with its platform capabilities, as a connector between different technologies. One example of this capability is linking AI to robotics. Like other technologies, robots use AI to process and analyse data and recognise and predict behaviour patterns. However, unlike automation and digitalisation technologies, robots differ in their interaction with the physical world (movement, transformation, reorganisation, connection and manufacture of factors or products), so by associating them with AI they are capable of learning and responding to changing needs in the physical environment. Nevertheless, their economic uses in production and work are specific, based on limited task automation, replacing some of the competencies of human labour, especially routine cognitive and non-cognitive tasks, while also complementing other actions of human intelligence, especially non-routine cognitive tasks.

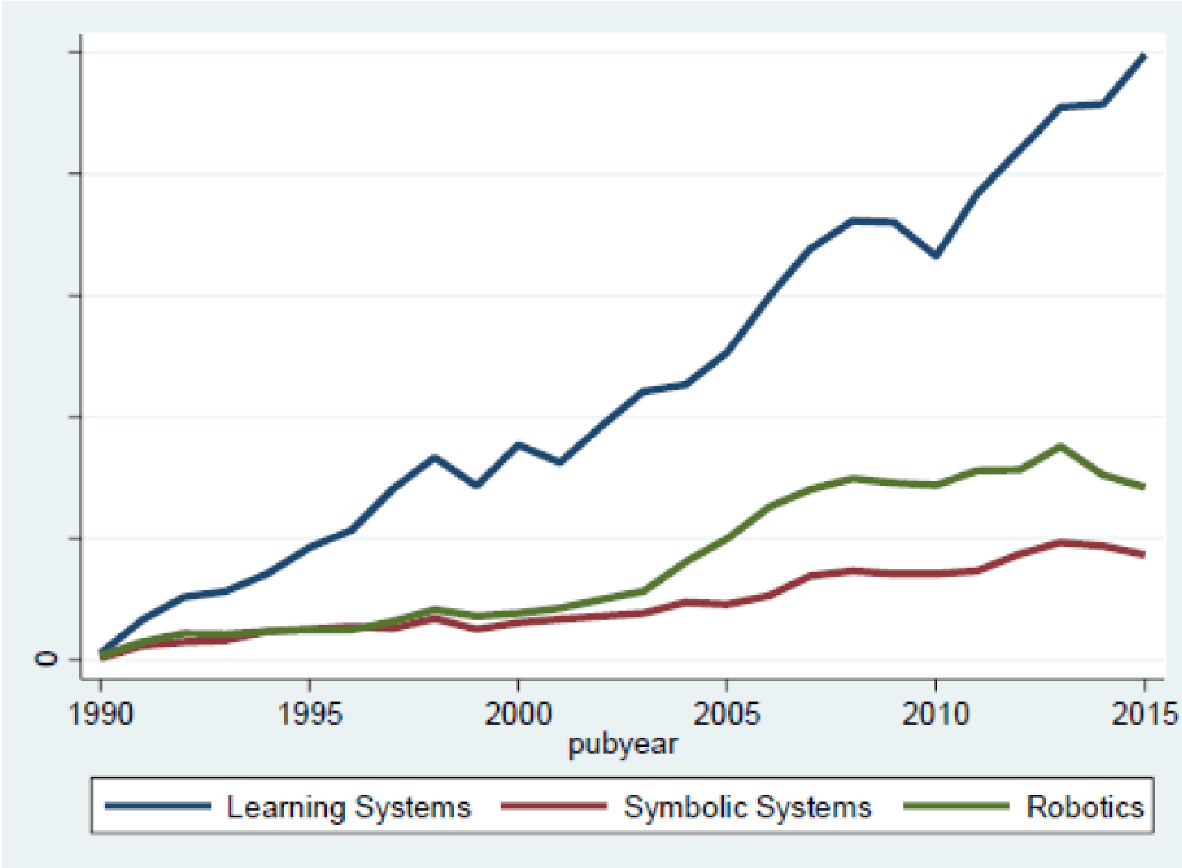
Furthermore, through this capacity for technological convergence, AI is becoming a general purpose technology (GPT), i.e. a technology through which complementary innovations can be developed, thus becoming a source of efficiency and economic growth. This will be shown below.

Artificial intelligence as a general purpose technology

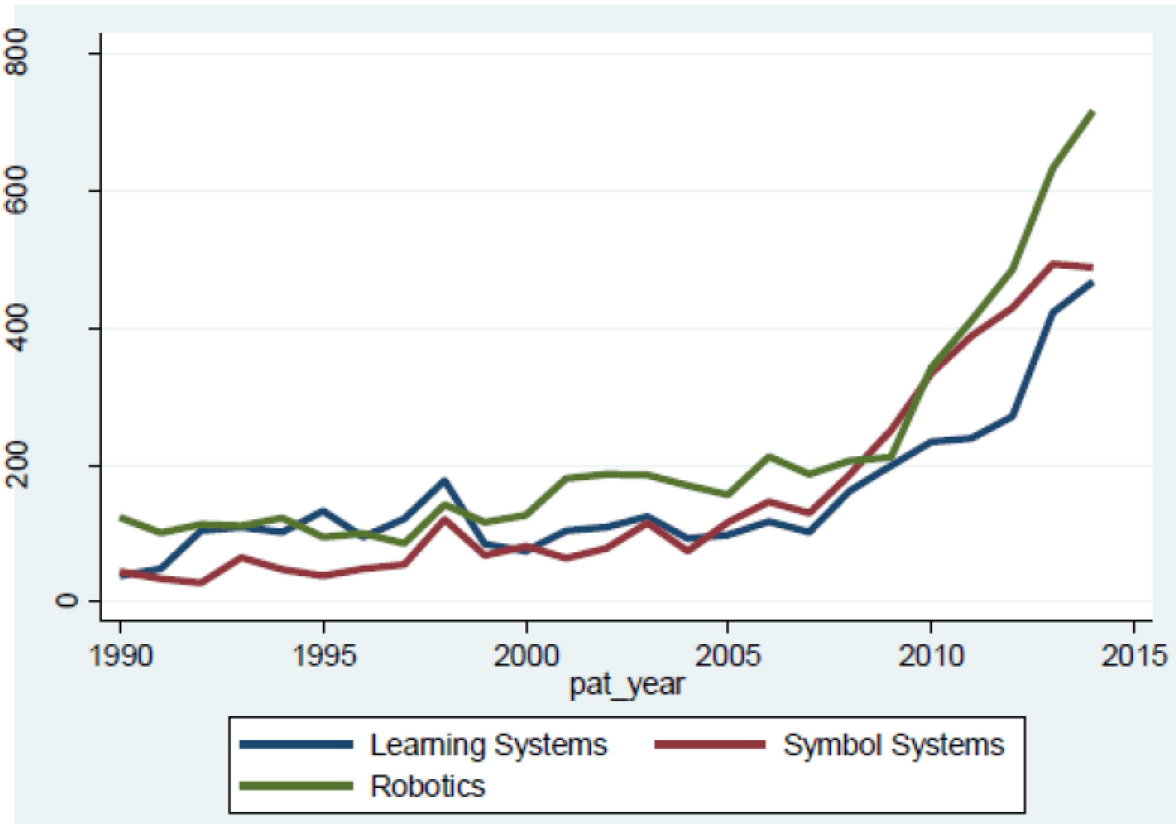
In economics, we generally understand technology as the sum of social knowledge of the industrial arts. In other words, all knowledge that has an impact on economic activity, not just scientific and technological (know-what and know-why), but also the skills of economic agents and organisations (know-how and know-who). Thus, we approach technology with a full range of instruments, machines and techniques for instrumental action. [4] GPTs are higher order families of applied knowledge, in the sense that specific or lower order technological applications are derived from them. For instance, technologies associated with the steam engine, electricity, the internal combustion engine and the computer are considered GPTs, because their capacity for connecting with other technologies (as a platform) means they create processes of technological convergence, derived innovations, complementarities with other economic assets, such as investment in intangibles, and, finally new business models, new sources of efficiency and levers for economic growth. [5]

The three main factors that turn a technology into a GPT are: pervasiveness, constant improvement and innovation spawning; in other words, the capacity of a family of applied knowledge, in the form of instruments, machines or techniques, to: (1) spread to all economic activity; (2) improve over time, thus reducing the use costs; and (3) facilitate the invention and innovation of products and processes. Although these three criteria have been used to empirically demonstrate the general purpose of previous technological families, such as computers, there is not yet enough specific empirical evidence on the matter in the case of AI. In particular, we still do not have a robust analysis of the empirical effects of AI on innovation and productivity. Nevertheless, experience with other disruptive technologies and an analysis of the literature on scientific processes and intellectual property protection (patents), prior to the productive application of AI, provide very interesting results.

If we start with processes prior to the productive application of AI, a recent study has shown that there has been significant change in trends in the field since 2009. [6] Specifically, there is a sharp rise in publications on intelligent learning systems, [7] to the detriment of two other traditional elements in AI research: robotics (computer vision, robotic systems, human-robot collaboration, sensor networks and control systems) and symbolic systems (processing, recognition and analysis of images, languages and symbols). Furthermore, other scientific fields (natural, life and social sciences) also demonstrate this rising trend in the literature, to the detriment of publications in scientific journals on computing and telecommunications. There has also been a sharp rise in patents registered in the field of learning systems. Thus, applied developments of AI learning capabilities could consolidate its position as a GPT if prior publications and patents are converted into productive activity. In fact, this increasing applicability of research could consolidate AI, especially intelligent learning systems, as a general purpose invention method.



Articles on AI published at ISI Web of Science (1990-2015)
Source: Cockburn, I., Henderson, R., Stern, S. (2017). The impact of Artificial Intelligence on Innovation. *NBER Conference on Research Issues in Artificial Intelligence*. Toronto: September 2017.



AI registerd patents (1990-2015)

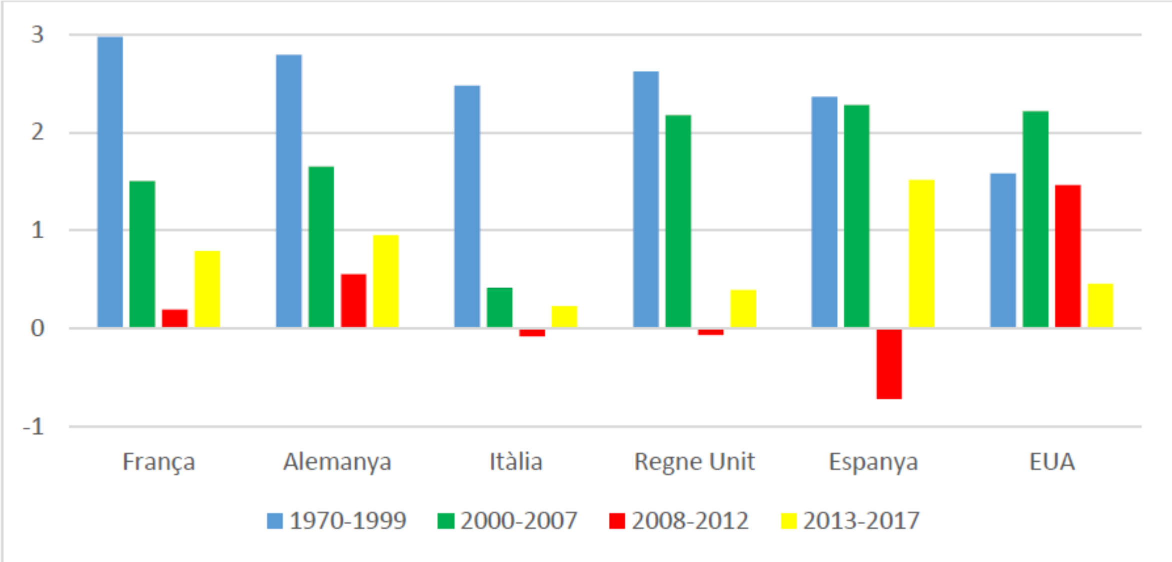
Source: Cockburn, I., Henderson, R., Stern, S. (2017). The impact of Artificial Intelligence on Innovation. *NBER Conference on Research Issues in Artificial Intelligence*. Toronto: September 2017.

Furthermore, digital data and all the potential for analysis, representation and prediction that can be provided by intelligent and deep learning multi-layer systems could provide powerful incentives for companies and organisations to build, acquire and analyse large sets of critical data and specific algorithms for the purpose. This complementarity between learning through AI, big data and advances in computing capacity could also generate a multiplier effect, which some researchers have already begun to discern. [8] The question is how likely it is for the full potential of AI to spread beyond everyday and routine tasks to substitute human labour. If we apply AI to all productive processes associated with data analysis and management, the effects of complementarity with human labour could spread to a broad range of activity sectors, especially, but not only, personal care, health and education. However, the development of AI-based general purpose invention and innovation methods that improve human capabilities (human-enhancing innovations), instead of devaluing their work (human-substituting innovations), requires a profound review of education systems. The AI economy requires a workforce with a completely new set of skills and competencies based on analytical, creative, interpersonal and emotional capabilities.

Artificial intelligence as a source of efficiency and work

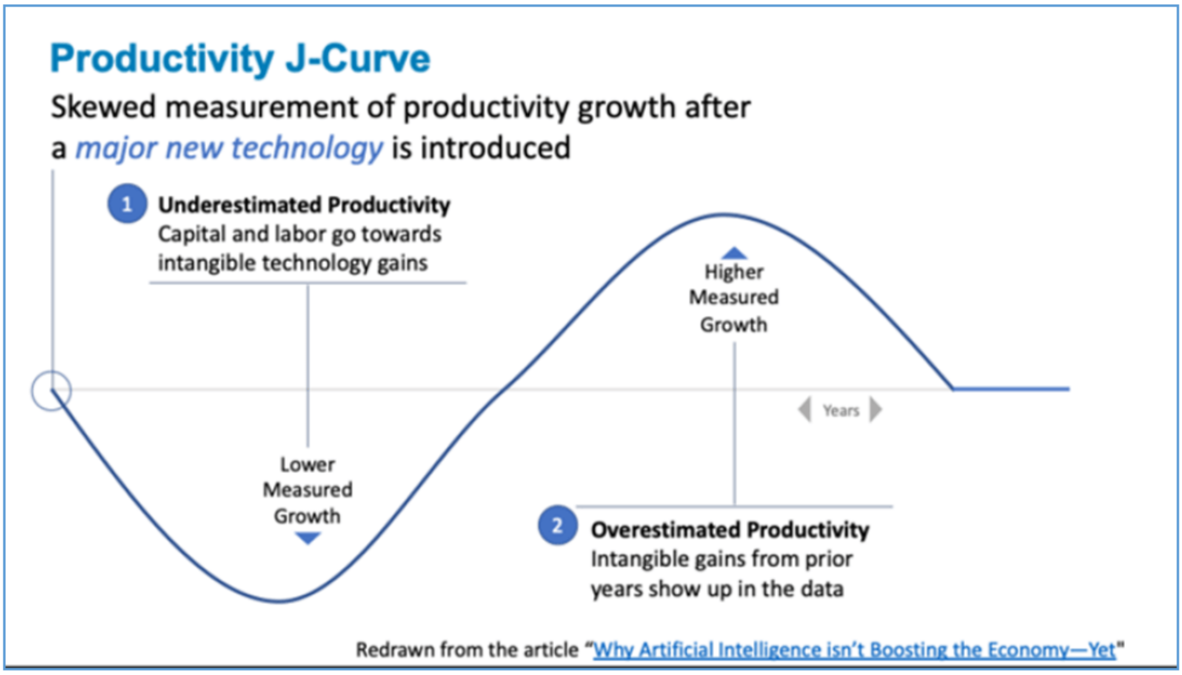
With regard to specific effects of AI on productivity and work, again, available evidence is not especially precise. For some time, economic research has noticed how automation processes have clearly positive effects on productivity and aggregate economic growth in many countries. [9] At the same time it has also highlighted that automation and digitalisation processes will be less important in creating and more important in displacing jobs in the long term. [10] However, this evidence comes from either robotic density data (robots per worker or per hour worked), independently of the uses of AI by robots, or is obtained indirectly through total-factor productivity analysis.

Thus we still do not have any specific research on how the three fields of AI (robotics, symbolic systems and learning systems) impact on productivity and work. One may add a further paradox to this lack of data and specific research on AI: the drop in aggregate productivity in most of the world’s economies in the last decade. Thus, economists are now asking an important question: why has the second wave of digitalisation (which covers a broad range of disruptive and convergent technologies, such as AI, robotics, big data, cloud computing, the Internet of Things, social and professional networks and collaborative platforms) still not had a positive impact on productivity and jobs? In recent years significant progress has been made towards providing an answer, which is obviously multidimensional, to this question.



Productivity performance (GDP working hour). 1970-2017
Source: Own work with data from EU-KLEMS.

One argument is associated with past experience and what we have already learned from other phases of transition to a new general purpose technology. In particular, we can infer that the overall effects of AI on productivity and work will not become generalised until we see new waves of related innovation. As with the first digital wave (ICTs and the non-interactive internet), we are beginning to observe complementarity relations between AI and investment and innovation in intangible assets, such as the redesign of business processes, product innovation, organisational changes and new worker skills and competencies. However these intangible assets are generally incorrectly measured and end up generating bad metrics of productivity, resulting in an erroneously J-shaped curve. In the initial stages of GPT adoption, companies accumulate intangible reserves of capital and labour (underestimated productivity), while in the final adoption stages, companies generate measurable flows of services and results from these hidden intangible stocks (overestimated productivity).



Productivity J-Curve

Source: Brynjolfsson, E., Rock, D., Syverson, Ch. (2018). The productivity J-curve: How intangibles complement general purpose technologies. *National Bureau of Economic Research (NBER) Working Paper*, No. 25148.

Thus, one of the reasons for the low effect of AI on productivity and work lies in underestimating productivity and the lack of complementary innovations, as is typical in this initial technological stage. [11] Indeed, it is precisely this lag that is cause for optimism. While being necessarily cautious in making future economic forecasts, everything seems to suggest that the feeble and partial effects of AI on overall economic activity will improve as this technology, and especially the complementary investments and innovations, begin to spread. There are two practical, business-related reasons for optimism. Firstly, the incentives are high. Entrepreneurs, managers, workers and users have at their disposal a technology whose uses are spreading and which is lowering prices with a growing applicability in learning to recognise objects, understand human language, make precise predictions, solve problems and interact with the environment with greater dexterity and mobility. Secondly, specific applications of intelligent learning systems will eventually generate strong relations of complementarity with all kinds of intangible assets. If we look at what happened in the first wave of digitalisation, the value of intangible assets was 10 times higher than the complementary direct investment in computer hardware. There is nothing to suggest that the values are any lower in the case of AI.

The artificial intelligence economy

The second argument in response to the lack of a match between AI and its economic impact is the need to build new formal apparatuses, new theories, models and indicators for economic interpretation. Economists have learned a significant lesson from research into industrial revolutions, i.e. disruptive changes to technology (GPTs) and the economic structure (tecno-economic paradigms or long-lasting economic cycles) that are interconnected with major social and cultural upheaval. In each of the previous three industrial revolutions, one or more factors became a major source of economic growth and changes in labour skills and social structure (see Figure 5). These factors are not the technology on which economic change is based; for instance, in the first and second industrial revolutions, we talk about the industrial (manufacturing) economy, instead of the steam or electricity economy. Similarly, in the third industrial revolution, we talk about the information or knowledge economy, rather than the ICT or digital economy. In all three cases the technology led to improvements in efficiency (total-factor productivity) and, above all, the appearance of new sectors of activity. However, the multiplier effect, the generation of new productivity factors, means that goods and services generated by the new technological wave are employed by all other economic activities and interact with productive factors, business models, market structures and the organisation of the economy.

> AI research has already shown the road towards the construction of a new historic phase in the general digitalisation process.

In this context, if AI is to become the base technology, the base material for the fourth industrial revolution, what will be its key productive factor/s? What will be the basic input/s that explain/s the advances in productivity, economic growth and changing labour skills and social structure? It is still too soon to answer this basic question, but we can already discern a movement towards the importance of tasks and micro-tasks. The multi-task or mass-task economy and society (known as the gig economy) is still in its early embryonic stage, but AI research has already shown the road towards the consolidation of a new GPT, towards the construction of a new historic phase in the general digitalisation process. Only time will provide an answer to how this new GPT (1) interacts with the rest of the economy, determines new productivity factors and generates a new long-term economic cycle; and 2) interacts with culture and the social structure to bring about a fourth industrial revolution.

One way of understanding the historic relation between technology and labour is through the skill-biased technological change process. When a technology is incorporated into a business process or a job, it generally produces a skill-substitution process, which impacts on the competencies of workers and executives. Through this process (for instance, the new skills required to interact with computers, the internet or AI algorithms), a wide range of interactions are established that are mediated by personal, educational, organisational, strategic, business and even public policy factors. The effects of skill-biased change on work will be positive or negative depending on these interactions. Generally, short-term losses in value and jobs are compensated by the long-term value and jobs generated by new, more efficient business initiatives, through compensatory mechanisms associated with cost savings, greater productivity and increased demand.

In the industrial age, when work was homogeneous and routine, skill substitution by technology equated tasks with people. With flexible specialisation and the service economy, technology eventually replaced routine skills and tasks, and complemented non-routine skills and tasks. Thus there was a differentiation between workers and tasks. With the eruption of digitalisation, especially the progressive generalisation of automation processes driven by robotics and AI, task substitution and complementarity take on new dimensions. Today, people are already a function of production, so that most tasks or micro-tasks they carry out in their work interact with technology, which substitutes some tasks and complements others. [12] Especially interesting is the case of interaction between AI and sharing economy platforms, i.e. the use of learning algorithms on peer-to-peer (P2P) digital platforms, where access or use of all kinds of goods and services, rather than property, are exchanged (such as Uber and Airbnb). In this case, the traditional functions of production, work and consumption are significantly diluted, with a clear combination of roles. [13]

> This path must be accompanied by training people in the right skills for interacting with AI, and with active labour policies that minimise the costs of transition.

In the context of mass exchange facilitated by the use of AI, as in sharing platforms, but also in the convergence with other technologies such as robotics, 3D printing and the Internet of Things, the sharp reduction in transaction costs clearly weakens the idea of the company as an alternative to the market. In some ways we are returning to organisational models that existed before the Industrial Revolution. The ‘platformisation’ of the economy once again highlights the importance of the market, to the detriment of the company, in the sense that it facilitates mass exchange between users and platform providers, bypassing an intermediary production organisation. However, platform markets are very different from traditional exchanges or even first-generation digital exchanges. The transition towards such platform exchange must consider these differences in the behaviour of market agents and structure, while taking note of the ‘disintermediation’ and ‘disorganisation’ produced by platforms and alternatives to company-organised business models.

One last point arising from the economic application of AI is the evolution of the concept of network. Through the dilution of traditional economic figures and the progressive importance of tasks, market structures acquire two or more heads or tails (two-sided markets). Unlike the first digital wave, where network economies interconnected multiple nodes without modifying the nature of economic agents, in the AI-driven gig economy, the effects of the network are to connect tasks or micro-tasks regardless of the nature of the agent performing them. This is a fundamental change because it bestows new importance on the organisational structures of production and the markets: the two sides. Two-sided exchanges are characterised by the fact that users on one side of the market benefit from participation on the other side of the market. Thus users on both sides benefit from growth of both sides of the market. In other words, the value to users on one side of the market (for instance, the supply of AI algorithms on a platform) is a linear combination of the number of users on the other side of the market (for instance, uses of the algorithms on the same platform), and vice-versa. The implications of the two-sided task market to entrepreneurship, innovation and business strategy are multiple and largely unexplored.

Corollary: economic intelligence or artificial intelligence

We have shown how AI, and its learning systems in particular, is starting to open the doors to a disruptive change in how we organise business activity, the economy and work. The first uses of AI, closely linked to robotics, have produced clear improvements in productivity, while skewing the impact on labour towards a process of substitution. However, in its most recent and numerous evolution, intelligent learning systems, technological platforms and complementary invention and innovation methods open the doors to a sea of new opportunities, especially in digital data analysis and the professionalisation of business and personal care services. On this new path, the impact on work could be easily skewed towards a process of task complementarity, incentivising capacities for analysis, creativity and communications in human labour. However this path must be accompanied by training people in the right skills for interacting with AI, and with active labour policies that minimise the costs of transition. This is nothing new: it is a matter of applying economic intelligence to artificial intelligence.

REFERENCES

1 — For a description of artificial intelligence, its applications, history and philosophy, see:
• Nilsson, N.J. (2009). *The Quest for Artificial Intelligence: A History of Ideas and Achievements*. Cambridge, MA: Cambridge University Press
• Russell, S. J., Norvig, P. (2016). *Artificial Intelligence: A Modern Approach*. Malaysia: Pearson Education Limited.
• Neapolitan, R.E., Jiang, X. (2018). *Artificial Intelligence: With and Introduction to Machine Learning*. Boca Raton, FL: CRC Press.
• Floridi, L. (2019). What the near future of Artificial Intelligence could be. *Philosophy & Technology*.

2 — Acemoglu, D., Restrepo, P. (2019). The wrong kind of AI? Artificial intelligence and the future of labor demand. *National Bureau of Economic Research (NBER) Working Paper, No. 25682*.

3 — Daugherty, P., Wilson, P.H. (2018). *Human + Machine: Remaining Work in the Age of AI*. Boston, MA: Harvard Business Review Press.

4 — Torrent-Sellens, J. (2004). *Innovació tecnològica, creixement econòmic i economia del coneixement*. Barcelona: Consell de Treball, Econòmic i Social de Catalunya (CTESC), Generalitat de Catalunya.

5 — For an explanation of general purpose technologies and their business, economic and social effects, see:
• Bresnahan, T.F., Trajtenberg, M. (1995). General purpose technologies “engines of growth”? *Journal of Econometrics*, 65: 83-108.
• Helpman, E. (Ed.) (1998). *General Purpose Technologies and Economic Growth*. Cambridge, MA: MIT Press.
• Jovanovic, B., Rousseau, P.L. (2005). General purpose technologies. A, Aghion, P., Durlauf, S.F. (Eds.). *Handbook of Economic Growth*. Amsterdam: North-Holland/Elsevier. Vol. 1, pp. 1181-1224.
• Bodrozic, Z., Adler, P.S. (2018). The evolution of management models: A neo-Schumpeterian theory. *Administrative Science Quarterly*, 63: 85-129.

6 — Cockburn, I., Henderson, R., Stern, S. (2017). The impact of Artificial Intelligence on Innovation. *NBER Conference on Research Issues in Artificial Intelligence*. Toronto: September 2017.

7 — The scientific fields identified in this area of AI are: ‘machine learning’, ‘neural network/s’, ‘reinforcement learning’, ‘logic theorist’, ‘Bayesian belief networks’, ‘unsupervised learning’, ‘deep learning’, ‘knowledge representation and reasoning’, ‘crowdsourcing and human computation’, ‘neuromorphic computing’, ‘decision making’, and ‘machine intelligence’.

8 — See:
• Trajtenberg, M. (2018). AI as the next GPT: A Political-Economy Perspective. *National Bureau of Economic Research (NBER) Working Paper*, No. 24245.
• Acemoglu, D., Restrepo, P. (2019). The wrong kind of AI? Artificial intelligence and the future of labor demand. *National Bureau of Economic Research (NBER) Working Paper*, No. 25682.

9 — See:

• Graetz, G., Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100: 753-768.

At the business level, especially among SMEs, the results are more modest. See:

• Torrent-Sellens, J., Díaz-Chao, A. (2018). Coneixement, robòtica i productivitat a la PIME industrial catalana: evidència empírica multidimensional. A, Ferràs, X., Alcoba, O., Torrent-Sellens, J. (Coords.). *Transformació Digital i Intel·ligència Artificial*. Barcelona: Col·legi d'Economistes de Catalunya, pàgs. 91-126.

10 — See:

• Autor, D., Salomons, A. (2018). Is automation labor share–displacing? Productivity growth, employment, and the labor share. *Brookings Papers on Economic Activity*. Spring: 1-63.10.

• Bessen, J. (2018). AI and jobs: the role of demand. *National Bureau of Economic Research (NBER) Working Paper*, No. 24235.

11 — See:

• Brynjolfsson, E., Rock, D., Syverson, Ch. (2017). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. *National Bureau of Economic Research (NBER) Working Paper*, No. 24001.

• Brynjolfsson, E., Rock, D., Syverson, Ch. (2018). The productivity J-curve: How intangibles complement general purpose technologies. *National Bureau of Economic Research (NBER) Working Paper*, No. 25148.

12 — In this context, new formalisations of production functions have recently appeared where production activity is interpreted as the aggregation of tasks that interact with automation technologies. See:

• Acemoglu, D., Restrepo, P. (2018). The race between machine and man: Implications of technology for growth, factor shares and employment. *American Economic Review*, 108: 1488-1542.

13 — Torrent-Sellens, J. (2019). Collaborative behavior and the sharing economy: Pan-European evidence for a new economic approach. A, Orlando, B. (Ed.). *Strategy and Behaviors in the Digital Economy*. London: IntechOpen, pp. 1-19.

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