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The Economic Implications of Artificial Intelligence

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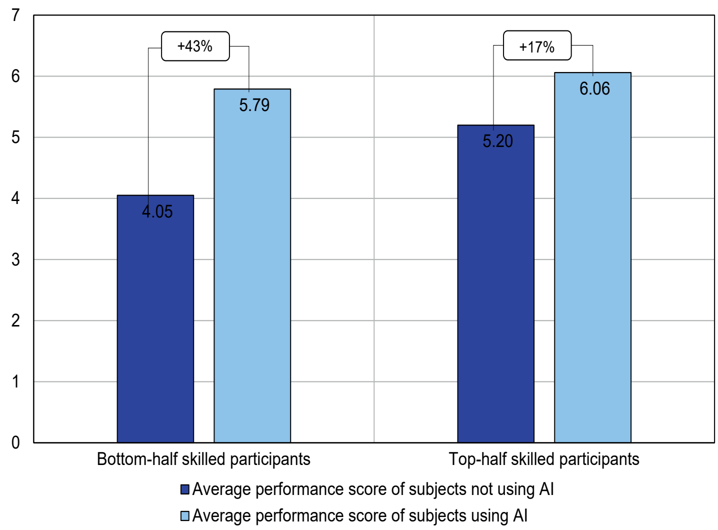
- Artificial intelligence (AI) refers to a set of techniques which enables machines to simulate human intelligence. Its development is a technological revolution which, much like with previous revolutions of this kind, could generate profound economic changes. While research to quantify the impact of AI is still in the exploratory stage, such work provides some preliminary insights.

- On a macroeconomic level, it is too early to empirically discern an impact on growth, but some initial microeconomic studies suggest that certain specific applications of AI have a significant positive impact on individual worker productivity. In a given job, these gains benefit the least productive workers the most, allowing them to catch up to their most productive peers. However, the impact of AI on business productivity has been found to be modest for the time being. This may be due to companies' still limited and uneven adoption of AI, although there is more widespread adoption among large companies and digital firms.

- The theoretical impact of AI on employment is uncertain. In the short term, this impact will depend on the speed at which AI is deployed, the shift of certain occupations towards AI-complementary tasks and the reallocation of labour towards occupations in growing demand. Furthermore, initial empirical estimates indicate that the tasks and occupations impacted by AI will not be the same as those affected by previous technological revolutions. Skilled occupations are expected to be more impacted by AI due to its ability to perform abstract, non-routine tasks, whereas the previous waves of automation and computerisation had impacted unskilled occupations and mid-level occupations, respectively.

- These various findings point to the need to strengthen science curricula in primary and secondary education and AI curricula in higher education, to focus on continuing training for occupations affected by AI and to remove certain barriers to the diffusion of artificial intelligence, particularly by adapting competition policy to its particular qualities.

Impact of AI on the performance of consultants from a consulting firm, by skill at deployment



Source: F. Dell'Acqua, E. McFowland, E.R. Mollick, H. Lifshitz-Assaf, K. Kellogg, S. Rajendran, L. Krayer, F. Candelon, K.R. Lakhani (2023), "Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality", Harvard Business School Technology & Operations Mgt. Unit Working Paper.

How to read this chart: This chart compares the impact of the use of AI on the ability of employees of a global consulting firm to perform creative tasks (developing, launching and promoting new products), based on their initial performance level (without using AI). The y-axis shows the average scores on a 0 to 10 scale.

1. AI's impact on growth is still poorly defined

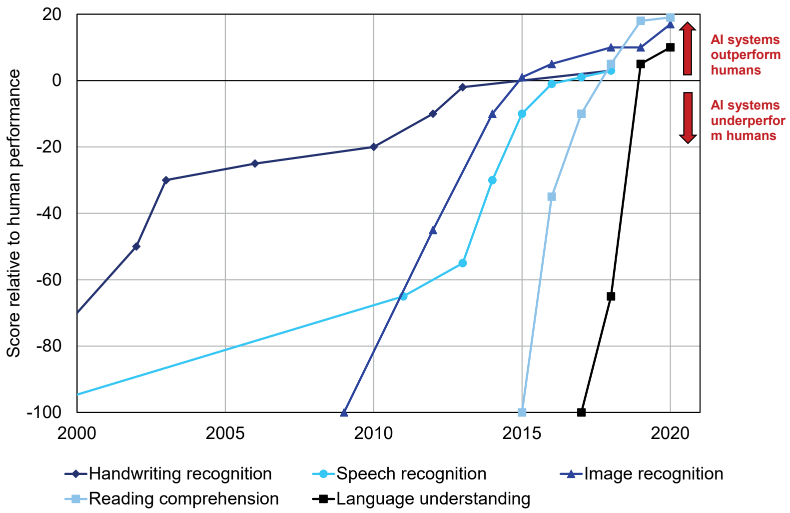
1.1 AI could increase productivity over time

Since they first appeared in the 1950s, artificial intelligence (AI) systems have been performing an increasingly diverse range of tasks, some of which are on par with or even exceed human capabilities. In the last 10 years, advances in AI research and in computing infrastructure have accelerated and made possible the emergence of various types of models – including foundation AI models – which represent significant technological progress. These general-purpose models can be adapted for a specific use case and applied to perform a wide range of tasks, much as generative pre-trained transformer (GPT) models, known to the general public following the success of ChatGPT. Generative foundation models can, among other things, generate text, images and sound in response to a prompt.

AI could usher in significant productivity gains and growth in the production of goods and services.[1] The OECD describes AI as a general-purpose technology (GPT)[2] that could have significant implications for society and the world of work through its application in many occupations and economic sectors. Other GPTs include, for example, the steam engine, electricity and information and communications technologies (ICTs). Their development leads to long-term growth in total productivity via product, process and organisational innovations (e.g. computer-aided manufacturing), following a time lag given their incremental adoption.

AI is different from previous waves of innovation in that it also enables productivity gains in the production of ideas.[3] AI models, particularly foundation AI models, speed up the innovation process since they are able to extract regularities (i.e. text, sound and images) in extremely large and complex databases. For example, AI models are being used to speed up the discovery of new medicines.[4] These models can also accelerate the research process by helping to generate new research hypotheses.[5] AI models could thus change the nature of the innovation process in certain fields and be the "invention of a method of invention".[6]

Chart 1: Language and image recognition capabilities of AI systems



Source: Our World in Data, Kiela et al. (2021) – Dynabench: Rethinking Benchmarking in NLP.

How to read this chart: Image recognition capabilities of AI systems began outperforming human capabilities in 2015. The initial performance scores are normalised as follows: the initial performance of the AI is set to -100 and human performance is set to zero.

(1) According to the French government's Artificial Intelligence Commission report (March 2024), « IA : notre ambition pour la France » (in French only).
(2) OECD (2023), "A Blueprint for Building National Compute Capacity for Artificial Intelligence", *OECD Digital Economy Papers*.
T. Eloundou, S. Manning, P. Mishkin, D. Rock (2023), "GPTs Are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models", *OpenAI*.
(3) I. M. Cockburn, R. Henderson, S. Stern (2018), "The Impact of Artificial Intelligence on Innovation", *NBER*.
(4) M. Mock, S. Edavettal, C. Langmead, A. Russel (2023), "AI Can Help to Speed Up Drug Discovery – but Only If We Give It the Right Data", *Nature*.
(5) R. Van Noorden, J. M. Perkel (2023), "AI and Science: What 1,600 Researchers Think", *Nature*.
(6) T. Besiroglu, N. Emery-Xu, N. Thompson (2023), "Economic Impact of AI-Augmented R&D", *arXiv*.

1.2 AI's macroeconomic impact remains limited and uncertain for the time being

Existing empirical research has not found AI to have a statistically significant impact on growth. There may be several reasons for this:

- AI has not yet been integrated into production processes to any great extent, with major differences among sectors (see Table 1). Prior to the recent development of foundation models, the adoption of AI-related technologies even seemed to have hit a ceiling.[7] Furthermore, the development of AI is heterogeneous across firms, with benefits concentrated among firms that were early adopters of these technologies.[8]

- AI-related profits do not yet appear to surpass the initial costs of adoption. As was the case for the GPTs that came before it, AI forces companies to reorganise, reconfigure working methods and skills, and make additional investments, which means a lagged impact on productivity.[9] The impact of AI therefore follows a J-curve at macroeconomic level.[10]

Several exploratory studies have sought to quantify the potential impact of the widespread adoption of AI on GDP. Before foundation models became readily available, certain studies[11] estimated that AI could add around $13 trillion to global output, boosting global GDP by an average of about 1.2% per year between 2018 and 2030. According to a more recent study,[12] widespread adoption of generative AI could alone increase annual labour productivity growth in the United States by around 1.5 percentage points per year over a 10-year period. By way of comparison, annual labour productivity growth in the United States was 1.3 percentage points over the 2005-2018 period and 0.8 percentage points over the 2010-2018 period. These estimates often rely on very strong, forward-looking assumptions (such as AI investment reports and a broad, relatively fast adoption of AI with limited friction), which weakens the study's conclusions. In addition, the methodology used does not always allow for full macroeconomic feedback, as it extrapolates from microeconomic findings.

Furthermore, some of AI's characteristics could have a mixed impact on innovation. On the one hand, by facilitating the imitation and copying of products and technologies (e.g. via reverse engineering of existing products and services), AI could facilitate technological diffusion and increase competition, ultimately strengthening the conditions of a race to innovate.[13] On the other hand, the fact that AI makes copying easier could discourage innovation by reducing its potential financial rewards.[14]

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(7) According to the "State of AI Report 2023", the share of companies reporting that they have adopted AI in their processes has stalled since 2019.

(8) C. Corrado, C. Criscuolo, J. Haskel, C. Jona-Lasinio (2021), "New Evidence on Intangibles, Diffusion and Productivity", *OECD Science, Technology and Industry Working Papers.*

(9) F. Venturini (2022), "Intelligent Technologies and Productivity Spillovers: Evidence from the Fourth Industrial Revolution", J*ournal of Economic Behavior and Organization.*

(10) E. Brynjolfsson, D. Rock, C. Syverso (2021), "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies", *American Economic Journal: Macroeconomics, American Economic Association.*

(11) McKinsey & Company (2018), "Notes From the AI Frontier: Modeling the Impact of AI on the World Economy", *Discussion Paper.*

(12) Goldman Sachs (2023), "The Potentially Large Effects of Artificial Intelligence on Economic Growth", *Global Economics Analyst.*

(13) N. Bloom, C.I. Jones, J. Van Reenen, M. Webb (2017), "Are Ideas Getting Harder to Find?", *Stanford University manuscript.*

(14) P. Aghion, B.F. Jones, C.I. Jones (2017), "Artificial Intelligence and Economic Growth", *NBER Working Paper.*

Table 1: Rate of adoption of AI systems by a global sample of companies in 2022, by industry and type of model (% of respondents in each industry)

		Industries					
		All industries	Business, legal and professional services	Consumer goods/retail	Financial services	Healthcare systems/pharma and med. products	High tech/telecom
AI capability	Robotic process automation	39	46	25	47	16	48
	Computer vision	34	32	33	24	32	37
	Natural-language text understanding	33	34	22	42	29	40
	Virtual agents	33	30	40	33	14	43
	Deep learning	30	37	36	22	18	45
	Knowledge graphs	25	26	18	29	14	23
	Recommender systems	25	23	32	30	16	34
	Digital twins	24	31	25	18	16	24
	Natural-language speech understanding	23	22	11	30	12	29
	Physical robotics	20	19	24	14	11	15
	Reinforcement learning	20	26	19	19	13	23
	Facial recognition	18	11	19	24	5	16
	Natural-language generation	18	12	20	20	5	24
	Transfer learning	16	16	7	17	9	22
	Generative adversarial networks	11	8	13	13	5	15
	Transformers (e.g. GPT-3)	11	11	11	12	6	15

Source: "Artificial Intelligence Index Report 2023", Stanford Institute for Human-Centered Artificial Intelligence. Data based on McKinsey & Company Survey, 2022.

Note: Data comes from survey responses from global companies representing a comprehensive range of regions, industries and company sizes.

2. There are indications of a positive impact on the individual productivity of certain workers

2.1 Evidence that AI improves business productivity is still rare

If initial empirical research based on US data shows that AI-forward companies are more productive than others,[15] evidence for a causal relationship is still tenuous.[16] AI adoption appears to produce a modest, but not statistically significant,[17] effect on productivity, which could be due to the impact of AI on labour productivity not fully materialising at the time of the study, and to the simultaneous adoption of several technologies, preventing a specific link being drawn to AI adoption. There is also a selection bias because the largest and most productive firms are the most likely to adopt AI.[18] In addition, these large firms have more resources to devote to deploying complementary assets, enabling them to reap all the benefits associated with them.[19]

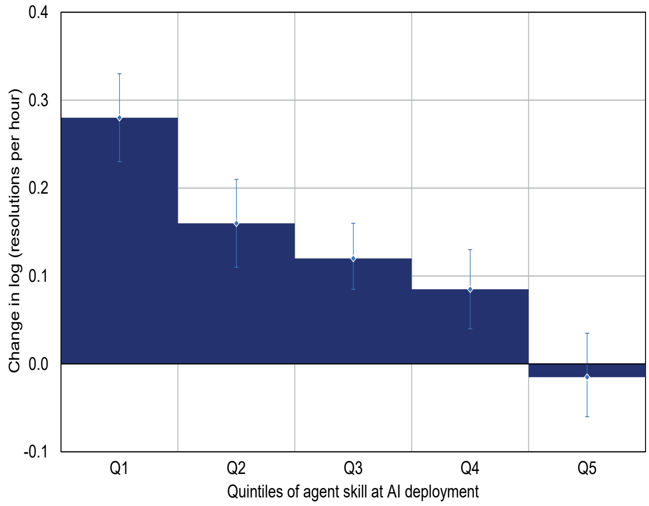
(15) D. Alderucci, L. G. Branstetter, E. Hovy, A. Runge, M. Ryskina, N. Zolas (2020), "Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata?", *Allied Social Science Associations – ASSA 2020 Annual Meeting*.
(16) OECD (2023), *Employment Outlook 2023: Artificial Intelligence and the Labour Market.*
(17) D. Acemoglu, G. W. Anderson, D. N. Beede, C. Buffington, E. E. Childress, E. Dinlersoz, L. S. Foster, N. Goldschlag, J. C. Haltiwanger, Z. Kroff, P. Restrepo, N. Zolas (2022), "Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey", *NBER Working Paper Series.*
(18) D. Acemoglu et al. (2022), op. cit.
(19) F. Calvino, L. Fontanelli (2023), "A Portrait of AI Adopters Across Countries: Firm Characteristics, Assets' Complementarities and Productivity", *OECD Science, Technology and Industry Working Papers*.

2.2 Within a given occupation, productivity gains seem to be concentrated among the least productive workers

Initial empirical microeconomic studies, which cover specific use cases, suggest that the adoption and use of AI – and foundation models in particular – significantly raise the individual productivity of workers. In the IT field, for example, the use of an AI pair programmer by software developers increased their productivity in writing code by 55%.[20] With the development of new generations of AI models, this finding could be replicated in many other sectors.[21] When it comes to basic writing tasks (e.g. grant applications, summaries), the professionals using an AI chatbot raised their average productivity by 37%.[22]

Within a given occupation, this rise in productivity is found to be concentrated among the least productive workers, thereby reducing the productivity gap between workers. For example, the introduction of an AI technology that assists taxi drivers in finding customers by suggesting routes with predicted high demand improved the productivity of the low-skilled drivers but not that of the high-skilled drivers, narrowing the productivity gap between both groups by 14%.[23] Among customer service agents, those with access to chatbots raised their productivity by 14% on average, with the gains concentrated among the least experienced agents. Used in this way, the AI model enables the most experienced workers to disseminate tacit knowledge to other workers, shrinking the productivity gaps that were due to the initial lack of experience of the latter group relative to the former[24] (see Chart 2). This catch-up effect is also at work in high-skill occupations: by way of illustration, consulting firm employees' use of AI to perform creative tasks increased the productivity[25] of the least productive consultants by 43%, while the productivity of the most productive consultants rose by 17%[26] (see Chart on cover page).

Chart 2: Impact of AI on the productivity (resolutions per hour) of American customer service agents, by productivity at deployment



Source: E. Brynjolfsson, D. Li, L. Raymond (2023), "Generative AI at Work", NBER Working Paper Series.

How to read this chart: The customer service agents, the subjects of the study, work for a software firm that specialises in business process software for small- and medium-sized businesses in the United States. Performance is defined as the number of customer issues resolved per hour (three-month average). Quintile 5 groups together the most productive agents within each firm.

(20) S. Peng, E. Kalliamvakou, P. Cihon, M. Demirer (2023), "The Impact of AI on Developer Productivity: Evidence from GitHub Copilot", *arXiv preprint.*
(21) H. Hang, Z. Chen (2022), "How to Realize the Full Potentials of AI in Digital Economy?", *Journal of Digital Economy.*
(22) S. Noy, W. Zhang (2023), "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence", *Science.*
(23) K. Kanazawa, D. Kawaguchi, H. Shigeoka, Y. Watanabe (2022), "AI, Skill, and Productivity: The Case of Taxi Drivers", *NBER Working Paper Series.*
(24) E. Brynjolfsson, D. Li, L. Raymond (2023), "Generative AI at Work", *NBER Working Paper Series.*
(25) Here, productivity is measured by the quality of the consultants' recommendations, graded by a group of consultants and business school students with grading experience.
(26) F. Dell'Acqua, E. McFowland, E. R. Mollick, H. Lifshitz-Assaf, K. Kellogg, S. Rajendran, L. Krayer, F. Candelon, K. R. Lakhani (2023), "Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality", *Harvard Business School Technology & Operations Mgt. Unit Working Paper.*

3. AI development is impacting high-skill occupations

3.1 AI's impact on employment cannot yet be observed

Estimates of AI's aggregate impact on employment are few and far between, but the ones that do exist suggest that this impact remains limited for the time being, without making any predictions about future developments. The OECD[27] specifies that empirical studies using cross-country variation in AI exposure or within-country variation by local labour markets do not find any statistically significant decrease in [aggregate] employment".[28] In this same vein, recent surveys of workers and firms, or case studies of firms adopting AI, find few employment changes. However, another study suggests that AI adoption could be associated with higher growth in sales and employment in AI-adopting industries.[29] These findings have little predictive value in a context where AI adoption continues to be limited,[30] even if there has been a notable surge in AI adoption, and where its impact is still too small relative to the scale of the US labour market to have had first-order impacts on employment patterns outside of AI hiring itself[31] (see Box 1).

Box 1: The AI workforce and AI skills

The AI workforce[a] in OECD countries is still relatively small (0.34% of employment in 2019) but growing fast, almost tripling as a share of employment from less than a decade before.[b] In the United States, AI-related job postings grew rapidly between 2010 and 2018, with an acceleration around 2015-2016. In France, online job postings requiring AI skills accounted for 0.35% of total online vacancies in 2022. The total number of AI vacancies has risen by roughly 45% between 2019 and 2022.[c] This could reflect that establishments whose task structures enable the use of AI have reduced their non-AI hiring.[d] This phenomenon has been associated with a significant reduction in hiring in these establishments, which may choose not to replace those retiring.

Firms that adopt and deploy AI systems are changing the requisite set of skills, both on the extensive margin (new skills) and on the intensive margin (higher skill level than previously required for a given skill). As firms invest in AI, they tend to increase the share of workers with more specialisation in science, technology, engineering and mathematics (STEM) fields.[e] STEM workers are particularly useful for data analysis and IT, areas which require scientific expertise and critical thinking skills. Certain AI skills go hand-in-hand with certain occupations (computer scientists, directors of information technology, data scientists, etc.),[f] but in OECD countries between 2012 and 2019, "demand for AI skills has diffused across a larger set of occupations" and more rapidly "than the demand for the average skill". According to one paper, "[r]obust demand for specialised AI skills" is leading to "new job creation in the field of AI itself".[g] As a result, and avoiding conjecture about future developments, although high-skill workers are more exposed to AI, some of them have (paradoxically) seen their employment prospects improve since the introduction of AI.[h]

a. Green and Lamby (2023) define the AI workforce as "the subset of workers with skills in statistics, computer science and machine learning who could actively develop and maintain AI systems".
b. A. Green, L. Lamby (2023), "The Supply, Demand and Characteristics of the AI Workforce Across OECD Countries", *OECD Social, Employment and Migration Working Papers.*
c. F. Borgonovi et al. (2023), "Emerging Trends in AI Skill Demand Across 14 OECD Countries", *OECD Artificial Intelligence Papers*.
d. D. Acemoglu et al. (2020), "AI and Jobs: Evidence From Online Vacancies", *NBER Working Paper Series*.
e. T. Babina, A. Fedyk, A. X. He, J. Hodson (2022), "Firm Investments in Artificial Intelligence Technologies and Changes in Workforce Composition", *under review*.
f. F. Manca (2023), "Six Questions About the Demand for Artificial Intelligence Skills in Labour Markets", *OECD Social, Employment and Migration Working Papers.*
g. A. Milanez (2023), op. cit.
h. OECD (2023), *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market.*

(27) OECD (2023), *Employment Outlook 2023: Artificial Intelligence and the Labour Market.*
(28) Although employment is not decreasing at aggregate level, Acemoglu et al. (2022) show that the firms most exposed to AI tend to "reduce hiring in non-AI positions and change the skill requirements of remaining postings" (D. Acemoglu, D. Autor, J. Hazell, P. Restrepo (2022), "Artificial Intelligence and Jobs: Evidence From Online Vacancies", *Journal of Labor Economics)*.
(29) T. Babina, A. Fedyk, A. He, J. Hodson (2024), "Artificial Intelligence, Firm Growth, and Product Innovation", *Journal of Financial Economics.*
(30) The reasons the OECD gives for the lack of an impact on aggregate employment are "low overall AI adoption and productivity gains; firms' preference to adjust labour demand through attrition rather than layoffs; the fact that advances in AI and AI exposure do not necessarily imply automation; and the creation of new tasks and jobs".
(31) D. Acemoglu et al. (2022), op. cit.

3.2 AI's long-term impact on aggregate employment falls within the theoretical framework of creative destruction

According to the IMF,[32] 60% of jobs in advanced economies may have a high degree of exposure to AI, while 27% of employment is in high-complementarity occupations, meaning that these jobs are the most likely to benefit from AI, and 33% of employment could be replaced by AI. Based on an ILO working paper,[33] in high-income countries, the number of jobs with augmentation potential from AI deployment (13.4%) is much higher than the number of jobs with automation potential from AI deployment (5.1%). According to other estimates more specifically focused on the advent of foundation models, while 80% of US workers could have at least 10% of their work tasks affected by such models, only 19% of workers may see at least 50% of their tasks impacted and would therefore have a significant risk of replacement.[34]

These findings should nevertheless be interpreted with caution. Indeed, the authors' approach does not take into account either the AI progression curve or changes in AI development costs for companies, even though these two factors largely determine the long-term impact of a technology on employment.[35] According to another paper, while 36% of jobs in US non-farm businesses have at least one task that is exposed to computer vision,[36] only 8% (23% of them) have at least one task that is economically attractive for their firm to automate.[37] This low percentage of automation is due to adoption and development costs that are still too high for automation to be profitable.

In the long term, the impact of AI on aggregate labour demand will depend on mechanisms similar to those observed during the previous technological revolutions, and particularly on the effectiveness and timeliness of Joseph Schumpeter's "creative destruction" process. New general-purpose technologies destroy jobs in some sectors while creating new jobs in others, over a period of several decades.[38] The net effect on total employment comes down to the balance between two opposing forces. On the one hand, the demand for labour is reduced for certain tasks or occupations (where capital can substitute for the labour factor). On the other hand, new technologies generate productivity gains (by substituting labour for more efficient capital or by improving the return on capital in use) and income that amplify the demand for labour. The latter is also increased by the emergence of new tasks and occupations, in which the labour factor retains a comparative advantage, particularly as a complement to new technologies.

In the very long term, once wages and employment have adjusted in the various sectors, AI should not have a significant impact on labour supply or equilibrium unemployment, other than indirectly. Some studies[39] suggest, for example, that AI improves the advice given to long-term unemployed job seekers, which could help to reduce equilibrium unemployment and increase productivity. Overall, the impact on aggregate employment is uncertain and evolving, as it depends on the speed of adjustment of relative wages and workers between old and new jobs, and the magnitude of each impact varies over time – likely following a J-curve.[40]

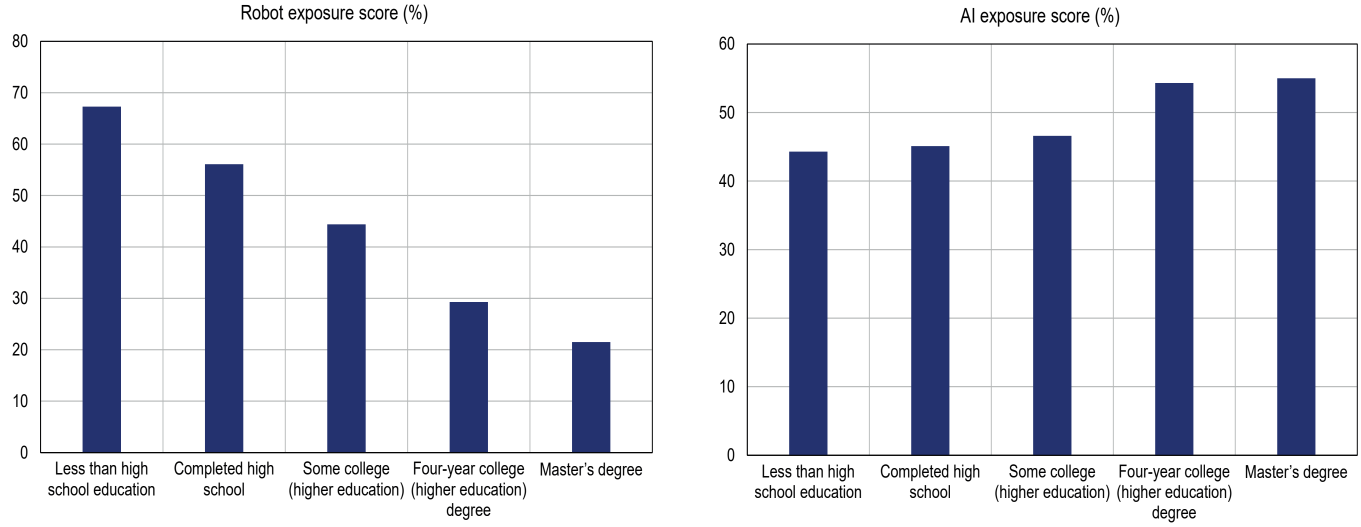
(32) M. Cazzaniga et al. (2024), "Gen-AI: Artificial Intelligence and the Future of Work", *IMF Staff Discussion Note.*
(33) P. Gmyrek, J. Berg, D. Bescond (2023), "Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality", *ILO Working Paper* 96.
(34) T. Eloundou et al. (2023), op. cit.
(35) As W. Nordhaus (2007) shows, taking the computer as an example, in "Two Centuries of Productivity Growth in Computing", *The Journal of Economic History.*
(36) Computer vision is a field of artificial intelligence whose main purpose "is to enable a machine to analyse processes and understand one or more images [or videos] taken by an acquisition system".
(37) B. Svanberg et al. (2024), "Beyond AI Exposure: Which Tasks are Cost-Effective to Automate with Computer Vision?", *MIT Working Paper.*
(38) Based on data from a UK employer survey, Hunt et al. (2022) found that among firms, those using AI have higher rates of job creation and destruction (W. Hunt, S. Sarkar, C. Warhurst (2022), "Measuring the Impact of AI on Jobs at the Organization Level: Lessons From a Survey of UK Business Leaders", *Research Policy*).
(39) M. Belot, P. Kircher, P. Muller (2022), "Do the Long-Term Unemployed Benefit from Automated Occupational Advice during Online Job Search?", *IZA Discussion Papers.*
(40) The negative impact dominates initially before being reduced, or even surpassed, by the addition of the various positive impacts which require labour reallocation.

3.3 Unlike in previous technological revolutions, AI could have a greater impact on high-skill occupations

The previous technological revolutions of the 20th century led to skill-biased technical progress, favouring skill-biased technical progress that benefited high-skill workers,[41] which may have increased economic inequality. Automation[42] at the start of the 20th century and, subsequently, robotisation at the close of the century[43] disadvantaged unskilled manual workers, whereas skilled industry technicians and managerial occupations accrued the benefits of these developments. Computerisation, on the other hand, led to a polarisation of the labour market by penalising, in particular, medium-skill workers employed to perform routine cognitive tasks, and benefiting high-skill workers, for whom demand rose sharply,[44] while having little impact on unskilled workers performing non-routine manual tasks.[45]

Unlike with these first revolutions, the adoption of AI poses a greater threat to high-skill occupations (high-income higher education graduates) in that it substitutes for certain highly-skilled workers performing tasks requiring advanced skills[46] (see Chart 3). Indeed, as AI can perform abstract, non-routine cognitive tasks, it has expanded the scope of substitutable tasks (e.g. translation, making diagnoses).[47] However, these occupations could at the same time be most likely to benefit from the productivity gains enabled by AI adoption. Firstly, the majority of jobs with the highest complementarity to AI are concentrated in these occupations. Secondly, the most educated workers can more easily move from jobs at risk of displacement to jobs in growing demand. Low-skill occupations would also be impacted, but to a lesser extent.

Chart 3: Robot and AI exposure scores in the United States, by level of education



Source: M. Webb (2020), "The Impact of Artificial Intelligence on the Labor Market", Stanford University Series Papers.

How to read this chart: An occupation's technology exposure score indicates the level of patenting activity directed towards the tasks within that occupation, utilising data from the O*NET database of occupational information, which encompasses the US economy. These scores are adjusted based on the total employment in the US for each educational category in 2010.

(41) D. Acemoglu (2000), "Technical Change, Inequality and The Labor Market", *Journal of Economic Literature*: Skill-biased technical progress increases the relative productivity of high-skill workers compared to that of other categories of workers, and thus increases the demand for skilled labour, as the technologies developed are complementary to the skills of skilled workers and quite substitutable with unskilled or medium-skilled labour (depending on the waves of innovation).

(42) C. Frey, M. Osborne (2017), "The Future of Employment: How Susceptible Are Jobs to Computerisation?", *Technological Forecasting and Social Change*.

(43) D. Acemoglu, P. Restrepo (2020), "Robots and Jobs: Evidence from US Labor Markets", *Journal of Political Economy*.

(44) C. Goldin, L. Katz (2007), "The Race between Education and Technology: the Evolution of U.S. Educational Wage Differentials, 1890 to 2005", *NBER Working Paper Series*.

(45) G. Maarten, A. Manning, A. Salomons (2009), "Job Polarization in Europe", *The American Economic Review.*

(46) This finding is illustrated by several papers, including E. Brynjolfsson, T. Mitchell, D. Rock (2018), "What Can Machines Learn and What Does It Mean for Occupations and the Economy?", *AEA Papers and Proceedings*; M. Webb (2020), "The Impact of Artificial Intelligence on the Labor Market", *Stanford University Series Papers*; E. Felten, M. Raj, R. Seamans (2019), "The Effect of Artificial Intelligence on Human Labor: An Ability-Based Approach", *Academy of Management Annual Meeting Proceedings*; H. Xiang, O. Reshef, L. Zhou (2023), "The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market", *Cesifo Working Papers*.

(47) Dell'Acqua et al. (2023), op. cit.: The authors refer to the "jagged technological frontier" created by the capabilities of AI. This frontier expands automation possibilities in a non-linear manner relative to the complexity level of tasks.

Not all skilled occupations should be impacted to the same degree. For example, firms could reduce a larger share of their staff whose occupations involve writing skills and programming, which are more exposed to the risk of displacement by generative models.[48] Aside from the different expected impacts according to worker skill level, the OECD suggests that older workers are more frequently mentioned by employers as being negatively affected by the expanded use of AI.[49] These workers tend to be viewed as more "sceptical towards AI technologies", which "made them less inclined to adapt to change and engage in training programmes". Lastly, the industry-level approach reveals that the tasks carried out in information processing industries are highly exposed to the risks of foundation models, while the manufacturing industry and agriculture demonstrate much lower exposure.[50]

Box 2: Use of AI and well-being at work

By altering the nature of the tasks workers perform, AI can directly impact job satisfaction and workers' well-being (dignity and pride in their work).[a]

Based on initial studies,[b] the employers and workers in the manufacturing and finance sectors surveyed have a positive view about the impact of AI on their working conditions: across all indicators of working conditions considered (job satisfaction, physical health, mental health, fairness in management), AI users were more than four times as likely to say that AI had improved working conditions as to say that AI had worsened them. AI would seem to allow workers to focus on the tasks they prefer, such as those involving interaction with clients/customers and creative tasks.

However, other studies[c] qualify this finding: some workers exposed to AI have reported lower satisfaction in their personal and work life, and have become more concerned by their job security and personal financial situation. In the manufacturing and finance sectors, many workers believe that AI could put downward pressure on wages in the next ten years.[d] While some workers expect AI to increase wages, twice as many expect AI will decrease wages in their sector. However, AI was not found to have a significant impact on mental health, anxiety or depression in the workplace.

a. S. Bankins, P. Formosa, Y. Griep, D. Richards (2022), "AI Decision Making with Dignity? Contrasting Workers' Justice Perceptions of Human and AI Decision Making in a Human Resource Management Context", *Information Systems Frontiers.*
b. M. Lane, M. Williams, 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*; A. Milanez (2023), op. cit.
c. O. Giuntella, J. König, L. Stella (2023), "Artificial Intelligence and Workers' Well-Being", *IZA Discussion Papers 16485, Institute of Labor Economics (IZA).*
d. M. Lane et al. (2023), op. cit.

(48) T. Eloundou et al. (2023), op. cit.
(49) A. Milanez (2023), "The Impact of AI on the Workplace: Evidence From OECD Case Studies of AI Implementation", *OECD Social, Employment and Migration Working Papers*.
(50) T. Eloundou et al. (2023), op. cit.

4. AI's potential will depend on deployment-related measures and on initial and continuing education and training policies

4.1 Initial and continuing education and training policies will play an essential role in supporting AI adoption

To optimise AI's economic potential, public authorities have a role to play in the diffusion of AI in society and in providing support to those impacted by it.

A significant share of AI education and training could occur at the initial education stage. At the primary and secondary education levels, students should be taught basic mathematical and computer skills that will help them understand AI with a view to its use,[51] while specialised AI skills will require vocational and higher education. In addition to data science skills, technical skills in computing management and data management are required to develop and deploy AI models. Furthermore, education and training courses combining AI with other disciplines (e.g. health, law) are needed in order to apply AI techniques to a range of scientific and industrial fields and to support the reorganisation of production processes so that the full benefits of AI can be reaped. Lastly, the development of socio-behavioural skills (e.g. ability to work with others, critical thinking, adaptability) in the classroom is required to make the most of the productivity gains associated with AI adoption.

The impact of AI on employment will also depend on adapting continuing education and training policies so that they respond to new needs, in order to facilitate labour reallocation. This concerns workers whose jobs would be altered or even threatened by this technological shock, as well as those who can acquire new skills in the occupations created by this shock. Education and training policies can assist workers at risk of displacement in making the transition to roles in more complementary sectors.[52]

Lastly, beyond the need to increase the amount of time devoted to additional occupational training, which is inherent in the adoption of new technologies,[53] the nature of training itself could undergo a transformation by becoming more tailored to workplace scenarios. This approach appears especially suitable for the integration of AI.[54]

4.2 AI's impact on growth will depend on competition policy

The evolution of information and communications technologies (ICTs) serves as an example of a new technological development whose diffusion and potential productivity gains were curbed by a relatively concentrated competitive environment. Historically, ICTs mainly benefited a small number of "superstar" firms which were able to develop leading digital platforms[55] as well as to accumulate capital and data and attract top talent. This situation has created major barriers to entry, limiting the access of other firms to technology and innovation.[56]

In the same vein, AI could contribute to the increase in industry concentration[57] and the rise of "superstar" firms, which are often non-European.[58] At the present time, the most sophisticated AI models are largely being developed by, or in partnership with, a small number of major digital companies.[59] These companies have a significant lead in terms of access to the

(51) Provided that teachers can better integrate tools, OECD (2019), "TALIS 2018 Results", France.
(52) S. Benhamou, L. Janin (2018), « Intelligence artificielle et travail », *Rapport de France Stratégie* (in French only).
(53) M. Draca, R. Sadun, R.J. Van Reenen (2006), "Productivity and ICT: A Review of the Evidence", *LSE CEP.*
(54) S. Benhamou (2022), op. cit.
(55) M. Panfili (2019), "Digital Platforms and Competition", *Trésor-Economics*, No. 250.
(56) P. Aghion, C. Antonin, S. Bunel (2019), "Artificial Intelligence, Growth and Employment: The Role of Policy", *Economie et Statistique / Economics and Statistics.*
(57) T. Babina, A. Fedyk, A. He, J. Hodson (2024), op. cit.
(58) D. Autor, D. Dorn, L.
F. Katz, C. Patterson, J. Van Reenen (2020), "The Fall of the Labor Share and the Rise of Superstar Firms", *The Quarterly Journal of Economics.*
(59) R. Bommasani, D. Soylu, T. Liao, K. Creel, P. Liang (2023), "Ecosystem Graphs: The Social Footprint of Foundation Models", *arXiv – CS – Computers and Society*

resources needed to develop these AI models (e.g. computing capability, data, skilled workforce), and benefit from their vertical integration across the value chain. These resources can form barriers to entry, limiting in particular the diffusion of technology and its associated economic benefits, which are instead captured by these major companies only.

In light of these risks, leveraging competition policy tools (e.g. abuse of a dominant position, merger control) will have an essential role in timely anticipating, identifying and resolving any competitive, behavioural or structural problems that may arise.[60] However, the emerging and evolving nature of the market, as well as the economic benefits for consumers associated with network effects and economies of scale, add complexity to the cost-benefit analysis. Public authorities will therefore have to weigh the immediate benefits for consumers against a long-term innovation dynamic.

(60) According to the French government's Artificial Intelligence Commission report (March 2024), « IA : notre ambition pour la France » (in French only).

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