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The impact of Artificial Intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges

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The impact of Artificial Intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges

Abstract

This paper explores the economics of Artificial Intelligence (AI), focusing on its potential as a new General-Purpose Technology that can significantly influence economic productivity and societal wellbeing. It examines AI's unique capacity for autonomy and self-improvement, which could accelerate innovation and potentially revive sluggish productivity growth across various industries, while also acknowledging the uncertainties surrounding AI's long-term productivity impacts. The paper discusses the concentration of AI development in big tech firms, uneven adoption rates, and broader societal challenges such as inequality, discrimination, and security risks. It calls for a comprehensive policy approach to ensure AI's beneficial development and diffusion, including measures to promote competition, enhance accessibility, and address job displacement and inequality.

JEL classification codes: O4, D4, L8, O15
Keywords: Artificial Intelligence, productivity, competition, inequality

L'impact de l'Intelligence Artificielle sur la productivité, la répartition et la croissance : Mécanismes clés, premières preuves et défis politiques

Résumé

Cet article explore l'économie de l'Intelligence Artificielle (IA), en se concentrant sur son potentiel en tant que nouvelle Technologie Générale d'Utilité qui peut influencer de manière significative la productivité économique et le bien-être sociétal. Il examine la capacité unique de l'IA pour l'autonomie et l'auto-amélioration, qui pourrait accélérer l'innovation et potentiellement revitaliser la croissance de la productivité languissante à travers diverses industries, tout en reconnaissant également les incertitudes entourant les impacts de l'IA sur la productivité à long terme. L'article discute de la concentration du développement de l'IA dans les grandes entreprises technologiques, des taux d'adoption inégaux, et des défis sociétaux plus larges tels que l'inégalité, la discrimination, et les risques de sécurité. Il appelle à une approche politique complète pour assurer un développement et une diffusion bénéfiques de l'IA, incluant des mesures pour promouvoir la concurrence, améliorer l'accessibilité, et adresser le déplacement d'emplois et l'inégalité.

Classification JEL*:* O4, D4, L8, O15
Mots-clés : Intelligence Artificielle, productivité, concurrence, inégalité

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Main Findings

1. The paper adopts a "production function" view of AI systems to characterise their main economic features and implications. In particular, AI systems are considered as combining intangible **inputs** (software, skills, data) and computing capacity to produce a wide range of **outputs** (analytical tasks like prediction, recommendations or optimisation; content generation; and physical tasks in association with robotics).
2. Potentially higher **autonomy,** the ability of some AI systems to **self-improve** and to speed up the **pace of innovation** by boosting research may distinguish AI from previous major General Purpose Technologies, posing both opportunities and risks:
    a. AI may have the potential to revive sluggish productivity growth and lead to gains in aggregate welfare, as suggested by initial positive evidence on innovation and workers' and firms' productivity;
    b. But it could also exacerbate distributional divides and bring broader societal risks, which could backlash on AI developments and productivity.
3. Despite initial encouraging micro evidence, **longer-run aggregate productivity** outcomes of AI are still uncertain:
    a. Will productivity gains by early AI adopters and firms at the productivity frontier trickle down to other firms?
    b. Will labour **reallocation** (within and across sectors) sustain aggregate growth or result in a new "Baumol-disease" weighing on productivity growth, notably due to extensive labour automation and reallocation towards lower productivity growth sectors?
    c. Will measures taken to address **societal issues** slow down AI development and adoption?
4. A number of conditions could promote the favourable effects of AI, where *policies* can play a key role, as also specified by the OECD AI Principles:
    a. Competitive AI systems **development** and widespread **diffusion** (*e.g., ease AI access*)
    b. Strong **human complementarity** on the AI user side (e.g., skills, new tasks) prevailing over human substitution via the automation of tasks (*e.g., steering of AI development, education and training for AI)*
    c. **Acceptance/reliability/trust** in AI development and adoption (e.g., *AI governance*)
5. Current evidence suggests that these conditions are far from being met:
    a. Advanced **AI inputs are concentrated** in big tech;
    b. **AI adoption** is still limited and uneven across firms and sectors;
    c. The balance between AI use that is **human-augmenting vs. human-substituting** (via complementarity vs automation) is still uncertain, with Generative AI putting even knowledge-intensive occupations at risk of automation, especially at entry levels.
6. Not meeting these conditions could lead to economic and welfare costs from AI, which could hinder its potential to significantly raise productivity. These risks include:
    a. Increasing **market power** and reducing **dynamism of AI developers and AI users;**
    b. Increasing **inequality** and hampering **inclusion;**
    c. **Broader societal risks**, such as growing misinformation, biases and privacy violations, along with longer term existential risks.
7. To mitigate these risks, a broad range of **policy domains** are under discussion:
    a. Most immediate priorities include ensuring market competition and broader access to AI technologies while preserving innovation incentives.

b. The consequences of AI for job displacement and inequality also call for prompt action related to training, education and redistributive measures.
c. Reducing risks related to bias, misinformation and privacy.
d. Devising governance mechanisms that are able to cope with rapid and unpredictable improvements of AI capabilities.

1. Introduction

This paper focuses on the economic benefits and costs of Artificial Intelligence (AI), with a strong emphasis on its potential in driving productivity growth both at the micro- and at the macro levels. It discusses the key mechanisms, presents initial empirical evidence and highlights the main policy challenges. The burgeoning field and the very active policy discussion AI underscores the strong expectations and fears that the technology presents both unprecedented opportunities and significant challenges. To advance a common understanding of these issues, the OECD, spearheaded by the OECD Policy Observatory on AI (OECD.AI), has been at the forefront in developing a unified terminology with a range of stakeholders. These efforts have had a strong impact on the global discussion in particular regarding technical, legal and regulatory aspects, culminating in the widely endorsed AI Principles ((OECD, 2019[1]) and a summary in Table A.1) and in the broad acceptance of the OECD's AI definition in legislative work.[1]

This paper builds on and complements this work.[2] It considers the "production function" of AI systems to characterise the economic features of AI, identifies key inputs, outputs and the type of tasks it carries out (Section 2). In particular, AI systems are regarded as combining intangible inputs such as software, skills, and data with substantial computing capacity and complementary technologies (e.g., robotics, biotech), while having the capacity to generate a diverse array of outputs ranging from complex analytical tasks (prediction, recommendations, optimisation, etc.) and content creation to contributing to the execution of physical tasks (e.g., autonomous vehicles). These features set the stage for AI's transformative role, shaping the backbone of its economic potential as a new General-Purpose Technology.

AI's uniqueness stems not just from its ability to perform complex tasks, but particularly from its enhanced potential for autonomy and self-improvement, accelerating innovation. These characteristics differentiate AI from previous major technologies – often referred to as General Purpose Technologies in the literature on growth and innovation (Lipsey, Carlaw and Bekar, 2005[2]) – , including in the digital sphere, such as computers and the internet. Early evidence linking AI to enhanced productivity and performance at the microeconomic level, along with several promising innovations in various industries, lend support to the expectation that AI's development and widespread adoption may be capable to revive sluggish productivity growth and to raise wellbeing (Section 3).

However, the overall long-term productivity outcomes of AI at the macroeconomic level are still uncertain, contingent on various factors such as how AI impacts market dynamism and market functioning. Critical questions are: Will the productivity gains achieved by early AI adopters extend to other firms? Will AI exacerbate performance disparities and distributional divides? What will be the consequences of AI for inclusion? And, importantly, will labour reallocation, both within and across sectors, fuel sustained aggregate growth; or will be a drag under a new form of "Baumol's disease," spurred by extensive AI-driven labour automation and a large share of the workforce ending up in low-productivity activities? (Sections 4 and 5)

To navigate these uncertainties and ensure favourable outcomes, several conditions must be met, with policy playing a crucial role. These include competitive AI system development and widespread diffusion, in a way that strikes a balance between augmenting human skills (complementing) and automating human tasks (substitution) with AI. However, current trends indicate that we are far from achieving these ideals. Critical AI inputs are largely concentrated in big tech firms, AI adoption remains limited and uneven across firms, and the balance between human-augmenting and human-substituting uses of AI is still in flux. This

[1] The OECD.AI site also showcases the broad range of AI-related work across the OECD in various domains.

[2] In parallel, several national and international institutions have been working on overviews on the economic implications of AI, such as (Comunale and Manera, 2024[185]) from the IMF, (Artificial Intelligence Commission of France, 2024[184]) from France and (Council of Economic Advisers, 2024[8]) from the US, among others.

is particularly pertinent with the advent of Generative AI (e.g., models creating text, image and other media), which poses risks of automating even knowledge-intensive occupations, especially at entry levels.

Moreover, as pointed out by a group of experts on AI Futures designated by the OECD (OECD, 2022[3]), AI's implications extend well beyond productivity effects, encompassing broader societal challenges such as power concentration, mass persuasion and manipulation (e.g., by malicious governments or corporations), misuse (e.g., in cyber weaponry or critical infrastructure), overreliance on AI in critical decision-making despite known flaws. They also include deteriorating training data quality and misalignment between AI systems and human goals or values, which could even lead to existential risks. Focusing on implications that can backlash on economic outcomes, some of these issues are briefly mentioned in the paper – such as threats to privacy, the potential for growing misinformation and loss of human control over AI decisions (Section 6). These challenges, if unaddressed, could also undermine the potential productivity and welfare benefits that AI beholds, especially if the societal issues they raise lead to a slowdown in AI development and diffusion.

To effectively manage these downside risks and harness AI's full potential, a comprehensive approach encompassing education, competition, redistributive, and regulatory policies will be discussed in Section 7. The most immediate priorities involve promoting market competition and enhancing widespread availability of AI technologies while ensuring their reliability (e.g., via auditing requirements) and preserving innovation incentives and capabilities. The consequences of AI on job displacement and inequality might take a bit more time to appear, but they still require prompt policy action in terms of training, education, and redistribution measures. Policymakers should also devise both national and international governance mechanisms that are able to cope with rapid and unpredictable improvements of AI capabilities to ensure, for instance, that minimum requirements are met in terms of their safe and ethical development and use.

2. What is AI and what does it do? An economic view

According to the recently updated OECD definition, “an AI system is a machine-based system that for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment.” (OECD, 2023[4]). This definition formed the basis for the definition of an AI system used in the EU AI Act and the 2023 US Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence. A stylised conceptual view is provided in Figure A.1.

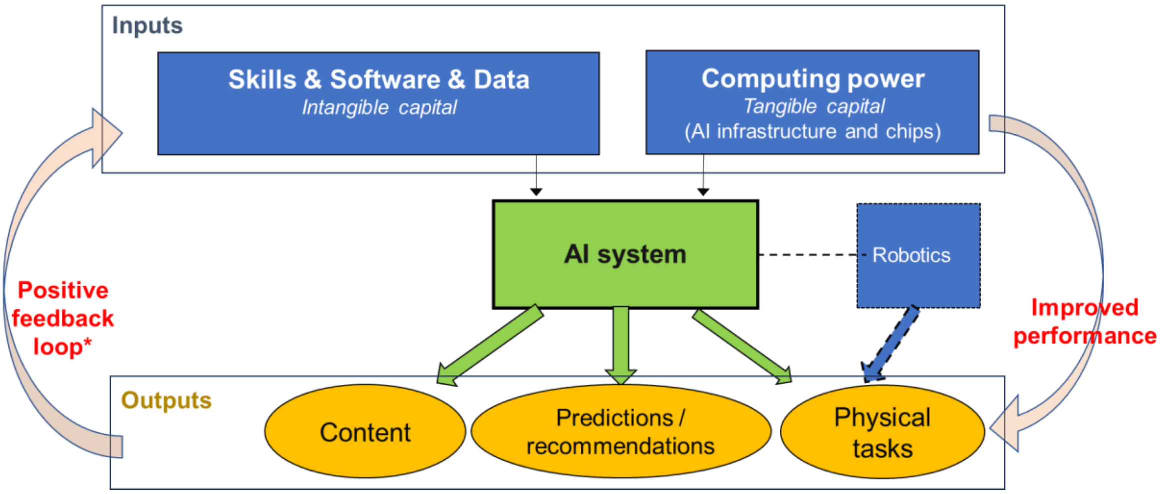
Economists tend to use various definitions of AI, for instance: “AI is a loose term used to describe a range of advanced technologies that exhibit human-like intelligence including machine learning, autonomous robotics and vehicles, computer vision, language processing, virtual agents, and neural networks.” (Furman and Seamans, 2019[5]) or “AI is an umbrella term that refers to a computer system that is able to sense, reason, or act like a human.” (Brynjolfsson, Li and Raymond, 2023[6]). Recent work jointly carried out by computer scientists and economists (Sastry et al., 2024[7]) writes: “Artificial intelligence (AI) refers to the science and engineering of building digital systems capable of performing tasks commonly thought to require intelligence, with this behaviour often being learned rather than directly programmed.”

2.1. AI systems in a production function view: requirements (inputs) and capabilities (outputs)

Given the focus of this paper on economic and, in particular, on productivity implications, AI systems are considered as a type of production technology which relies on a range of inputs and produces a range of outputs, as discussed below and illustrated on Figure 1. This approach captures most of the elements discussed by economists regarding AI’s capabilities (i.e. the type of jobs and tasks potentially affected by

AI), similar to others featured in recent policy analysis (Council of Economic Advisers, 2024[8]) or emphasised by regulatory bodies (e.g., (CMA, 2023[9])) as well as previous OECD work on building computing capacity (OECD, 2023[10]). The two subsections below explain and discuss the key components. For ease of exposition regarding the main economic features and implications of AI systems, the terminology may differ from reports with a more technical focus, notably (OECD, 2023[10]).

Figure 1. AI systems in a production function view: inputs and outputs



Note: see more detailed explanations in Section 2.1 on inputs and outputs. For ease of exposition regarding the main economic features and implications of AI systems, the terminology may differ from reports with a more technical focus, notably (OECD, 2023[10]).
*Positive feedback loop refers mostly to the training, pre-deployment phase.
Source: OECD, building on (CMA, 2023[9]) the AI Blueprint for Building AI Compute Capacity (OECD, 2023[10]) and (Sastry et al., 2024[7])

2.1.1. Inputs

AI systems rely on a few key intangible and tangible assets which can be considered as *inputs.* These are sometimes also called "elements of the AI value chain" (CMA, 2023[9]). These inputs are all strongly complementary to each other, so much so that AI systems can also be seen as a bundle of these assets (Corrado, Haskel and Jona-Lasinio, 2021[11]). Among intangible inputs, **skills** are critical and include highly trained IT engineers, programmers and data scientists. Their knowledge is embedded mostly in another critical input: **software**, in the form of the AI model. Such software requires **data** - often vast quantities of it –, the third key intangible component. It can take various forms and can enter the system at various phases: either for the development phase of AI, which is typically large scale training data used prior to deployment, or for its actual use phase (post-deployment), when additional data may used by the AI model to execute a query. For a more elaborate and detailed discussion of the various phases of the AI system "lifecycle" – including AI design and research, validation and verification, deployment and actual operation –, see (OECD, 2022[12]) (summarised in Figure A.2).

Software and data require a physical (tangible) AI infrastructure, most importantly **computing power and capacity** (semiconductor chips) and also connectivity.[3] Advanced AI systems often require top performance semiconductor chips or specialised computing infrastructure not only during the initial, mostly developmental phase (pre-deployment), but also in actual operation, during the use phase (post-

[3] (Artificial Intelligence Commission of France, 2024[184]) also notes this as a key concern. For more details on AI infrastructure and computing capacity, see (OECD, 2023[10]).

deployment).[4] The development, training or some applications of AI often rely on interactions between remote servers and local machineries and terminals. Maintaining such high computing power and connectivity requires an intensive use of energy and high-quality internet infrastructure, both being possibly critical inputs.

This input-based perspective also provides guidance to resolving challenges of measuring investments carried out specifically to build AI systems (AI investments, in short) in official statistics among the various intangible assets. In particular, such investment partly overlaps with computerised (digitised) information (software and databases); the development of new, original AI algorithms falls in R&D; while applications of existing AI might also be found in market research and IT consulting services (included in organizational capital). AI investments – including both tangible and intangible ones – are also likely to be complementary to these assets.

2.1.2. Outputs and AI types

Current AI systems can carry out or assist with *cognitive* tasks, such as creating content (text, program code, visuals, etc) or with taking decisions based on sophisticated predictions, recommendations and optimisation (Agrawal, Gans and Goldfarb, 2023[13]).[5] When combined with robotics – machines equipped with sensors and fine motor capacities, such as autonomous vehicles – they can also perform *physical* tasks, as in the case of autonomous vehicles (Brynjolfsson and McAfee, 2014[14]). Recent multi-modal AI systems combine several capabilities.

Based on the typical use of their outputs, a useful distinction can be made between more recent **Generative AI** and prediction, optimisation or decision-oriented AI, to be called in the paper – for the lack of an alternative term which is established and evocative – **non-Generative AI** (sometimes also being referred to as Discriminative AI or pre-Generative AI).[6] Both of these two broad types of current AI models are deeply tied to probability as they evaluate a myriad possible outputs and select one based on learned probabilistic distributions. Hence the dichotomy between these two categories is not always clear-cut, with many modern AI systems blending data-driven techniques with cognitive structures. Nevertheless, it is still useful to differentiate them according to their capabilities and typical use as they can accomplish - or assist with - different types of tasks:

- **Non-Generative AI** primarily relies on algorithms that draw information directly from vast data sets to detect patterns, forecast outcomes and support decisions. The dominant technique is Machine Learning (ML), and its more sophisticated subset, Deep Learning (DL). This kind of AI employs probabilistic models to predict outcomes and give recommendations. ML models power core AI tasks such as pattern recognition (e.g. , text, image, audio), even detection (anomalies), personalisation (e.g. user behaviour analyses) and goal-driven optimisation (e.g. traffic routing) (OECD, 2022[12]). The strength of recent non-Generative AI lies in the ability to handle extremely large and potentially unlabelled and unstructured datasets.
- **Generative AI** systems – the more recent type of AI – are mainly designed to produce content, such as text, program code, images, videos, or sounds in response to natural (human)

[4] Some chips are specifically designed for AI-related calculations, such as tensor processing units (TPUs), or various chips are combined to achieve enormous amounts of computing power for running AI models (strings of graphical processing units, GPUs in super computers operating in the cloud).

[5] Sometimes a broader definition of AI is used than in these papers, which encompasses somewhat less recent software and hardware that carry out sophisticated calculations, including ones that are *not* based on probabilistic calculations and predictions (see (Kotlikoff, 2022[200])), citing as an example GPS navigation systems *without yet* real time traffic information).

[6] A recent speech by Fed Governor Lisa Cook differentiates Generative AI from "discriminative AI", which carries out mostly image and text classification (Cook, 2023[208]).

language queries, or prompts. Large Language Models (LLMs) fall under this category, with ChatGPT[7] by Open AI being a key example. Generative AI systems are enabled by the "transformer" architecture developed in 2017, which are more efficient than their predecessors (recurrent neural networks) because they can process natural language input in parallel rather than merely in sequence, thus effectively reducing training and computing time (OECD, 2023[79]). This breakthrough allowed for exponential increases in scale and complexity, with the most refined models featuring billions of parameters (Lorenz, Perset and Berryhill, 2023[15]). Some Generative AI models are considered "foundation" models, given their broad applicability in a range of fields, as opposed to tailor-made models targeting a specific task. Besides text, foundation models can produce sophisticated software code, sounds, artworks or photorealistic images (e.g. Stable Diffusion or DALL-E) and video (e.g. Sora).

As shown in Figure 1, most current AI systems that fall under one of these categories are also characterized by a **positive feedback-loop**, that is self-improvement capacity or learning (hence the expression machine *learning*) that can lead to better performance. On the one hand, self-improvement may occur while being trained, that is optimising and finetuning the model parameters without yet changing the basic design of the AI model itself (e.g., pricing algorithms). Sometimes this process occurs continuously, while in actual use (technically called *inference phase*, see (OECD, 2022[12])), allowing the system to quickly adapt to evolving situations (e.g., designing targeted ads, refining pricing algorithms). On the other hand, there is a distinct future possibility of a more fundamental self-improvement of AI that creates a *new* AI model. This is seen as one of the various potential avenues through which Artificial General Intelligence (AGI)[8] would be achieved in the future, which is usually defined as an AI that surpasses human level intelligence on nearly all cognitive domains.[9] This carries inherent risks to the extent that AI-generated successive AI models may deviate from the goals and intentions of the initial human-designed AI model (Korinek, 2023[16])(see Section 6 on broader societal risks).

2.2. How is AI different from previous technologies?

Recent major technologies that have had a strong economic impact include computers, the internet, and previously the steam engine and electricity. These are typically referred to as General Purpose Technologies, because of their ubiquitous nature as key components in a wide range of technical and economic applications including innovation (Lipsey, Carlaw and Bekar, 2005[2]) (Bresnahan and Trajtenberg, 1995[17]).[10] AI can be considered as the latest element on this list (Varian, 2019[18]); (Agrawal, Gans and Goldfarb, 2019[19]), enabling further innovation and thus possibly generating a long-lasting positive impact on productivity, especially in combination with other recent or emerging General-Purpose Technologies such as robotics or biotechnology (Cockburn, Henderson and Stern, 2018[20]) (Ing and

[7] The GPT acronym in ChatGPT stands for Generative Pre-trained Transformer, and does not refer to General Purpose Technologies. Throughout the paper the acronym GPT alone refers to General Purpose Technologies, and ChatGPT refers to the AI product developed by OpenAI.

[8] Ongoing work by the OECD expert group on AI Futures investigates AGI (OECD.AI).

[9] This could lead to what is often called the technological singularity – a point where technological advancement becomes self-sustaining, advancing rapidly and without significant human input, thus accelerating dramatically and uncontrollably (Kurzweil, 2005[197]).

[10] Some authors (for instance, (Jovanovic and Rousseau, 2005[198]). consider a broader encompassing term – Information Technologies – instead of computers and the internet as the relevant General-Purpose Technology.

Grossman, 2022[21]).[11] At the same time, AI has a few key features that differentiate it from previous General-Purpose Technologies (GPTs) (Table 1) (Agrawal, Gans and Goldfarb, 2023[22]).

Table 1. Comparing AI to selected previous General Purpose Technologies

	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

Source: OECD, building on (Lipsey, Carlaw and Bekar, 2005[2]) and (Agrawal, Gans and Goldfarb, 2023[22])

Previous General Purpose Technologies such as steam and electricity provided energy as their main output, and as such affected primarily physical tasks at the time of their invention. In contrast, computers and the internet produce intangible outputs such as calculations and the ability to exchange information remotely, thus affecting mostly cognitive tasks (while still being capable of impacting physical tasks when controlling machinery and equipment). AI is similar to the latter in affecting cognitive tasks, but AI "produced" tasks tend to be more versatile and more advanced, thanks to highly sophisticated predictions, analytics and generated content. Key differences emerge when considering the higher degree of AI's autonomy compared to computers – the extent to which the technology can operate without human intervention –, and the capacity for self-improvement, which are even more specific to AI. Self-improvement in turn increases AI's model complexity possibly exceeding the human capacity to understand its functioning ("black box" type behaviour), thus reducing model transparency and predictability. Further, when increasing its scale (parameter size, training data, etc.) an AI model may also produce unexpected outcomes, such as when LLMs acquired the ability to reason and translate (Wei and et al, 2022[23]). These distinct features – high autonomy and self-improvement – thus offer opportunities for self-sustained welfare gains but come with a risk of moving beyond human control.

The idea generation and idea testing capacity of AI makes it not only an automation technology – raising productivity mostly in a one-off, static manner through improving on current production and current processes – but a **method of invention** or invention technology – with the potential to lift productivity

[11] Machine learning, a subset of AI technology, is considered a General-Purpose Technology only as part of a broader cluster of recently developed technologies – including enhanced data collection and processing (data mining) and natural language processing (Goldfarb, Taska and Teodoridis, 2023[199]).

growth boosting research and innovation (Cockburn, Henderson and Stern, 2018[20]).[12] This would allow AI to counterbalance the threat of a “scarcity of ideas” possibly emerging with declining populations (Jones, 2023[24]), as well as to make it easier to “build taller and taller ladders” to go beyond the low hanging fruits of scientific discovery (Mokyr, 2018[25]); or to overcome the diminishing returns to innovation inputs contributing to slowing innovation outcomes (Bloom et al., 2020[26]).[13]

The perception of AI being an emerging method of invention is broadly shared in the research community (Bianchini, Müller and Pelletier, 2022[27]). For example, Figure 2 below reports the results of a global survey among researchers from a broad range of fields, which found that more than 80% of respondents believes that AI will become either essential or (very) useful for their work in the next decade, while only 4% doubts that it could be of any use (Van Noorden and Perkel, 2023[28])[14]. According to the survey, its primary benefits would be speeding up cognitive tasks such as data processing and computations. To a lesser extent, AI is expected to open up new paths for research, such as processing unstructured data (e.g., images), optimising experimental setups and generating new research hypotheses, as recently demonstrated by (Ludwig and Mullainathan, 2024[29]). This is in line with evidence showing that companies that increase investment in AI skills successively achieve higher innovation as measured by number of trademarks, patents and new products (Babina et al., 2024[30]). Case studies and opinions of field experts also point out that the latest developments in AI can be pivotal as they allow to verify scientific claims or to direct research efforts, among others. Preliminary results from such improvements are already detectable in fields such as biology (e.g., protein folding, (Jumper et al., 2021[31])), chemistry, mathematics, physics or medicine (e.g., drug discoveries and diagnosis) (Microsoft Research, 2023[32]; OECD, 2023[33]).

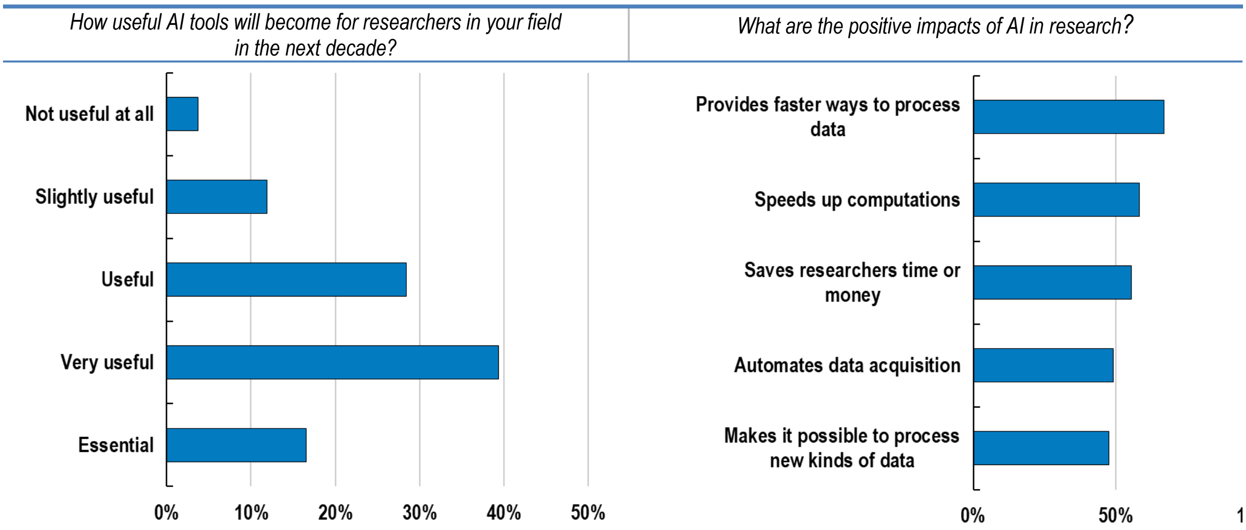
[12] Some authors consider innovation-boosting potential already as part of the key defining characteristics of GPTs (Jovanovic and Rousseau, 2005[198]).

[13] However, several dangers are associated with implementing AI in research, such as further contributing to and speeding up the spread of false information, bias, plagiarism, and fabrication, as noted by a survey among scientists (Figure A.1; also (Dougherty, 2024[176]) and Section 6). These issues could jeopardise the market for information and scientific research, as consumers and researchers might pre-emptively distrust both authentic and potentially fake results.

[14] The authors stress that results might not be representative of all scientists, due to high non-response rates in the survey. However, the assessment on the usefulness of AI varies minimally between scientists who declare using AI and those who still do not. This indicates that non-response behaviour – to the extent it is driven by a lack of experience in AI use – is likely to lead only to a small bias.

Figure 2. Strong positive expectations on AI's role in innovation

Survey results among researchers (2023)

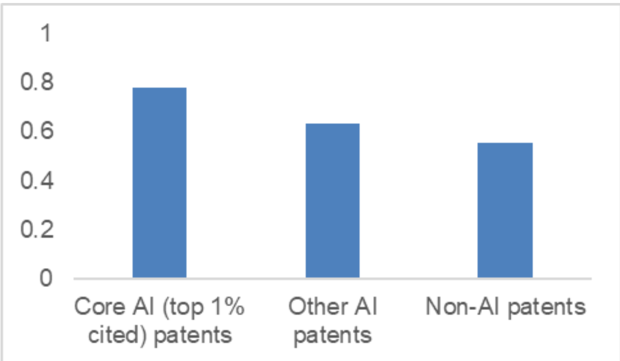


Source: (Van Noorden and Perkel, 2023[28]), *Nature*.
Note: Results based on a survey questionnaire among 1,600 active researchers across the globe and in a broad range of fields. Responses were voluntary and, as noted by the authors, may thus predominantly reflect the view of those who are interested in AI.

The breadth of the technological domains in which AI patents are referred to – captured by a technological generality index – indicates the general nature of the technology: AI-related inventions are more broadly cited than non-AI ones (Figure 3). This is consistent with AI being a GPT in the field of invention as well (Lipsey, Carlaw and Bekar, 2005[2]), although the full impact of AI's innovative potential in downstream, more applied, industries has yet to be seen.

Figure 3. AI patents are widely cited across a range of technologies

Based on patent citation intensities of AI and non-AI related patents (2010-2018)



Note: Vertical axis shows values of the technical generality index, derived from patent citation intensities.
Source: (Calvino et al., 2023[34])

These emerging unique capabilities of AI pose both enormous opportunities and challenges. Taken together, they are conducive to potentially extreme and uncertain outcomes including large gains and devastating harms if uncontained. Focusing on the economic implications, AI may have the potential to revive the sluggish productivity growth observed in most advanced economies during the past decades ((Goldin et al., 2024[35]) ; (Andre and Gal, 2024[36]) provided that early micro-level evidence (Section 3) can be extended to the macro level, as shown by some illustrative long-term scenarios suggested by (Baily, Brynjolfsson and Korinek, 2023[37])(Section 4). More generally, AI can also lead to improvements in overall welfare, notably through breakthroughs in healthcare, by providing better quality services and taking over more tedious elements of work. However, AI also has the potential to exacerbate performance and distributional divides and large-scale job displacement (Sections 5 and 6), and to undermine information and trust systems that are key prerequisites for economic activities and could present more fundamental risks to humanity, sometimes referred to as "existential risk" (Acemoglu and Lensman, 2023[38]). (Jones, 2023[39])(Section 6).

3. Early micro level evidence: AI can yield substantial performance gains

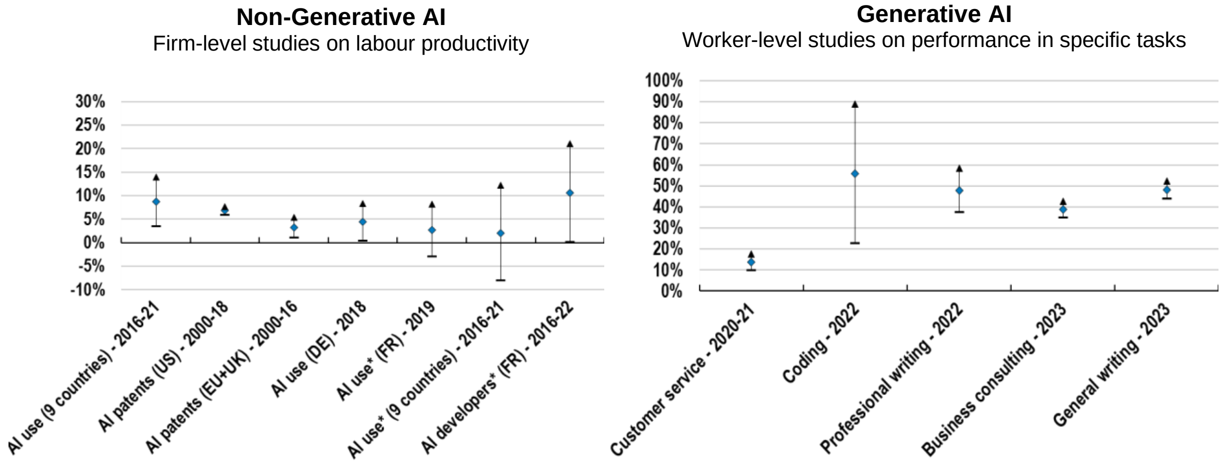
AI systems are improving their performance in a variety of domains at dramatic pace (Felten, Raj and Seamans, 2021[40]). Even if the technology is fundamentally built on solving prediction problems, a large and increasing number of tasks can be (re-)framed as prediction problems, and thus effectively solved by AI, ranging from image recognition to optimisation problems as well as to text and image generation. This, in turn, has the potential to raise productivity in various economic activities, a perspective that generated enthusiasm about the broader positive impacts of AI (Furman, 2016[41]; Furman and Seamans, 2019[42]).

Since the 2000s, academic studies have assessed the impact of evolving AI technologies on various performance and productivity measures in different countries and economic contexts and by using different metrics for AI use (Figure 4). Before the advent of Generative AI, empirical research examined the impact of AI adoption primarily at the firm level (left panel). The estimated effects on firm-level labour productivity range from 0 to 11%. Some of these gains are sizeable and comparable to estimates of gains from the adoption of other digital technologies (Brynjolfsson and M. Hitt, 2003[43]) (Gal et al., 2019[44]) :

- OECD research covering 9 OECD economies during 2016-2021 highlights that AI use, as measured by yes/no questions in employers surveys, is associated with significantly higher productivity on average. However, the correlation becomes insignificant, with the exception of a few countries, when trying to isolate the marginal effect of AI by controlling for the use of other ICT technologies (Calvino and Fontanelli, 2023[45]) (labelled as *AI use (9 countries)* in the Figure).
- A more detailed study on France among firms developing or using AI shows a similar finding (*AI use (FR)*), with the exception of AI developers where the marginal effect of AI remains statistically significant even after controlling for ICT (*AI developer (FR)*) (Calvino and Fontanelli, 2023[46]).
- Other scholars used patents data to measure AI technologies in firms, finding a positive effect of both an AI-patenting 0-1 indicator in the US (Alderucci et al., 2020[47]) (*AI patents (US)*) and of a continuous measure of the number of patents by firms in the EU and UK (Damioli, Van Roy and Vertesy, 2021[48]) (*AI patents (EU+UK)*).
- Using a more robust identification strategy to isolate the causal effect of AI use, a recent article finds a significant positive effect of AI in German firms based on self-reported AI adoption (Czarnitzki, Fernández and Rammer, 2023[49]) (*AI use (DE)*). [15]

[15] The estimate of (Czarnitzki, Fernández and Rammer, 2023[49]) is more robust to endogeneity of AI use as they exploit an instrumental variable strategy using as instruments industrial investment in AI, past innovation expenses per employee, and internal resistance to innovation.

Figure 4. The relationship between AI and productivity or worker performance: selected estimates from the literature



Note: *controlling for other ICT technologies. In the left panel, "AI use" is a 0-1 dummy obtained by firm surveys, while AI patents refers either to a 0-1 dummy for having at least 1 patent (US study) or to the number of patents in firms (for the EU+UK study, where the average number is 0.48 with 2.6 standard deviation, so that firms cumulating more than one patents are relatively few). Two of the estimates in the panel ("9 countries, 2016-21") relate to the same study (Calvino and Fontanelli, 2023[45]), but the second estimate controls for other ICT technology use and thus better isolates the marginal impact of AI. Given that the study reports separate estimates for all 9 countries, the median estimate across countries is shown on the Figure.
Source: authors' compilation from micro level studies. See more details in the text and in Table A.2.

Following the introduction of Generative AI technologies, in particular Large Language Models such as ChatGPT, more recent research has studied the effect of specific AI tools on worker performance (Figure 4 right panel). This line of research typically uses experimental methods which deliver more causal identification and hence more robust evidence than is typically the case for firm-level studies cited above. These more recent estimates of Generative AI indicate large effects on worker performance in specific tasks, ranging from 10% to 56%:

- Researchers in the US exploited the staggered adoption over time of AI-based support to customer service employees in business process software developer companies in 2020-2021, finding a large and significant increase in the number of case resolutions per worker (Brynjolfsson, Li and Raymond, 2023[50]) (labelled as *Customer-service, 2020-21* on the Figure).
- Another study estimated the effect of AI coding assistants on software developers, finding an extremely high and significantly positive effect on the number of coding tasks completed (Peng et al., 2023[51]) (*Coding - 2022*).
- Finally, the advent of ChatGPT spurred a number of randomized controlled experiments estimating its effect on workers, finding a large and significant positive effect of the AI technology:
    - on the speed and quality of professional writing tasks (Noy and Zhang, 2023[52]) (*Professional writing – 2022*),
    - business consulting performances (Dell'Acqua et al., 2023[53]) (*Business consulting – 2023*),
    - and time and quality of writing tasks for a sample of workers (Haslberger, Gingrich and Bhatia, 2023[54]) (*General writing – 2023)*.

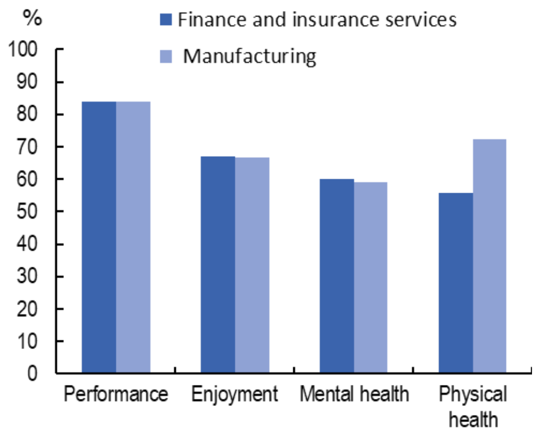
However, considering the different focus (firm-level vs worker- and task level), these two sets of studies – from which key estimates are shown on the two panels of Figure 4 –, are not directly comparable. Especially, it is not straightforward to extend large worker-level and task specific gains to firm-level productivity increases. Moreover, worker-level studies are carried out in companies that are keener to experiment with the technology (early adopters), and hence the results do not necessarily apply to typical firms. Notwithstanding these caveats, the early micro-level evidence suggests that productivity gains from AI can be substantial, especially among early adopters of the latest generation of AI.

These average effects also hide considerable heterogeneity. For instance, (Calvino and Fontanelli, 2023[45]; Calvino and Fontanelli, 2023[46]) show that larger firm size seems to yield an additional premium on AI's productivity effects. Using Generative AI for completing tasks is also found to yield considerably higher gains for inexperienced workers, up to one-third higher output per hour compared with 14% for workers with average levels of experience (Brynjolfsson, Li and Raymond, 2023).[16]

The positive effects on productivity found in the studies mentioned above are corroborated by an OECD survey (conducted in early 2022, thus focused on non-Generative AI). It emerged that the majority of employees who use AI at work report not only that AI has improved their performance, but that it has also improved job enjoyment and their mental and physical health (Figure 5). In addition, qualitative evidence suggests that companies in different sectors reacted to AI adoption by restructuring the internal organisation rather than reducing reliance on labour, reallocating workers towards tasks where humans hold a comparative edge rather than displacing them (Milanez, 2023[55]).

Figure 5. A majority of workers report benefits from using AI

% of respondents who work with AI reporting improvement in performance, job enjoyment and health



Note: Workers in companies that have worked with AI were asked: "How do you think AI has changed your own job performance (performance)/how much you enjoy your job (enjoyment)?/your physical health and safety in the workplace (physical health)?/your mental health and well-being in the workplace (mental health)?" The figure shows the proportion of AI users who said that each of these outcomes were improved (a lot or a little) by AI.
Source: (Lane, Williams and Broecke, 2023[56])"The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", https://doi.org/10.1787/ea0a0fe1-en.). Survey responses were broadly similar in the manufacturing sector and in a knowledge-intensive service sector with heavy AI use (finance and insurance) (OECD, 2023[57]).

Case studies in specific sectors also offer preliminary evidence about the transformative potential of AI on production processes. An early example has been the integration of AI in technically-advanced activities in pharmaceuticals (e.g., assisting with drug discoveries), aerospace (e.g., developing new materials

[16] The impact of AI on different categories of workers is further explored in Section 5.1.

(Merchant et al., 2023[58])), semiconductors, mining, and construction (OECD, 2020[59]). In the pharmaceutical sector, the adoption of Generative AI could lead to an annual increase in value added by 2.6 to 4.5 percent, primarily via helping with the research and development of new drugs (McKinsey, 2023[60]). Important applications are also found in services sectors, such as finance, where a fourth of hedge-fund managers reports at least 80% of decision making is relying on AI. Moreover, investment in AI-related ventures has tripled over the past five years, and AI research intensity has increased fivefold in the last two decades (OECD, 2021[61]; BarclayHedge, 2018[62]; OECD, 2023[63]). Even in sectors that were not the most rapid to adopt digital technologies, such as the transport or the public sectors, studies suggest that AI can significantly contribute to raise efficiency (Berryhill et al., 2019[64]; Kanazawa et al., 2022[65]). Yet other evidence points to higher market valuations of firms whose workers are in occupations that are more "exposed to" the latest class of Generative AI models (that is, likely to be *more affected by,* either now or in the future) compared to those that are non-AI exposed but otherwise comparable (Eisfeldt, Schubert and Zhang, 2023[66]).

Since the technology's advancements were developed and began to be utilized very recently, the findings at the micro or industry level mainly capture the impacts from early adopters and likely indicate short-term effects. The long-run impact of AI on macro-level productivity growth will depend on the extent of AI use and its successful integration into business processes, as adoption could differ widely across firms with different characteristics. Moreover, broader economic adjustments could occur as a consequence of wider adoption and general equilibrium effects may play out, notably in labour markets. The next section takes a more macroeconomic perspective, considering the various channels through which these microeconomic and short-term effects may (or may not) translate into longer-term gains in aggregate productivity.

4. Longer run aggregate productivity gains are uncertain and depend on various conditions

4.1. A conceptual framework and a few illustrative estimates

The rapid pace of AI development has spurred an active debate about its transformative potential and its effects on aggregate growth and productivity. The key question is whether AI can materially enhance aggregate productivity (Vollrath, 2020[67]). So far, the acceleration of AI development and diffusion has not been associated with higher productivity growth at the macroeconomic level, thus failing to counterbalance the prolonged productivity slowdown, driven mainly by weakening multi-factor productivity (MFP) (Andre and Gal, 2024[36]; Goldin et al., 2024[35]). However, delayed aggregate productivity responses are common to General Purpose Technologies.[17] (Brynjolfsson, Rock and Syverson, 2021[68]) recently argued influentially that new technologies initially require investment in complementary inputs – not well measured in National Accounts yet – before they can bring productivity gains. This leads to a Productivity- J curve, characterising the adoption of a new General Purpose Technology. In the first stage of adoption, both output and input are systematically underestimated because of unmeasured intangible investment but in a second stage there is an overestimation of MFP once the benefits of technological complementary intangible assets materialize. Indeed, a good deal of AI investments are intangible assets that are currently hardly measured and integrated into macroeconomic statistics. As a result, their overall aggregate effects may be difficult to capture.

Conceptually, after a period of experimentation and learning, AI adoption will impact workers with various skill levels, either by augmenting their tasks or by (partly) automating them (Autor, 2024[69]). In the case of

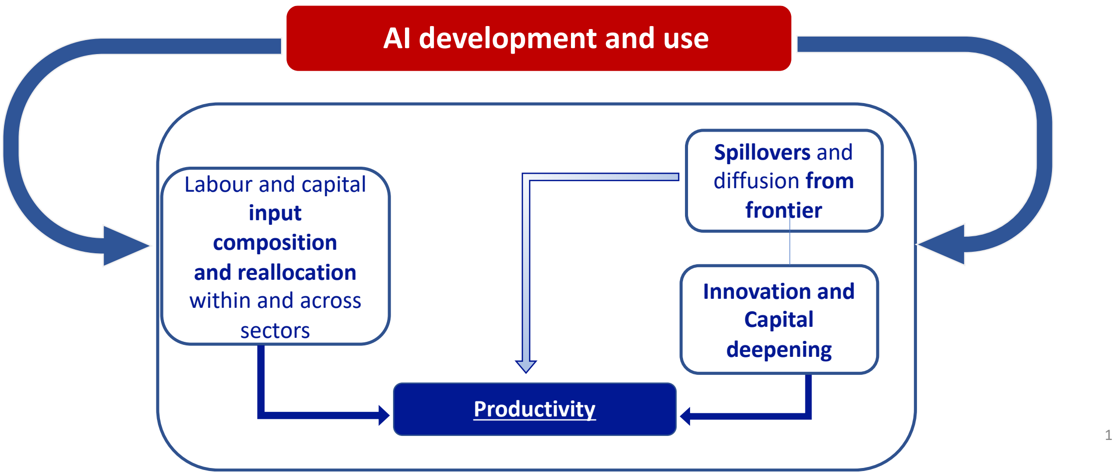
[17] "You can see the computer age everywhere but in the productivity statistics." – quipped Robert Solow in 1987, referring to the lack of apparent productivity gains despite the widespread use of personal computers, also known as the Productivity Paradox of the 1970s and 80s.

automation, AI performs tasks *instead of* humans, consisting of a substitution of labour with capital. In the case of augmentation, AI performs the job *with* humans, acting as a complement to human capabilities. Of course, this definition can be blurred, and the automation of some workers could be the augmentation of others (Agrawal, Gans and Goldfarb, 2023[13]) and the effect will change as technology evolves.[18] These effects will be discussed more fully in the light of recent labour market evidence, in Sections 4.2 and 4.3. In either case, the first-round effects of AI driven automation and augmentation at the firm- or sector level will in general contribute positively to aggregate productivity.

In addition, more productive sectors and firms relying on AI could attract more resources (labour and capital) as demand for their AI-powered products and services rises (resulting from the combination of cheaper and higher quality outputs), generating also a positive contribution to aggregate productivity from reallocation (Figure 6). These direct effects can be counteracted by a longer term dynamic reallocation effect as labour resources move away from heavily automated AI-impacted sectors to other parts of the economy, especially if demand increases for such AI-impacted activities cannot compensate for such reallocations (see Baumol effect in Section 4.2).

In a sources of growth framework, AI can be considered as a knowledge investment (investment in innovation) and becomes itself an accountable source of output growth as part of intangible capital.[19] On the one hand, it can affect labour productivity growth ***directly*** via an acceleration of capital accumulation that boosts the growth contribution of capital deepening; on the other hand, it can boost productivity growth ***indirectly*** by fostering knowledge diffusion and generating spillovers, resulting in an increase in multifactor productivity (MFP) (Corrado et al. 2022). By feeding the innovation process as a method of invention, AI may continuously push out the productivity frontier and feed knowledge spillovers and diffusion. Consequently, the greater and more widespread use of AI can enhance productivity growth via both channels (Figure 6).

Figure 6. AI and aggregate productivity over the long run: main channels



[18] For instance, machine translation and GPS assisted driving may automate core tasks of translators and taxi drivers, respectively, but they complement many other workers who only occasionally rely on translation and navigation. Similarly, LLMs that help with writing may disrupt those with writing as a core task but can act as a complement for workers in other jobs where writing is sometimes needed but is not a core activity – such as manual workers, for instance (plumbers, repairmen) (Agrawal, Gans and Goldfarb, 2023[13]).

[19] Growth accounting evaluates the direct contribution of factor inputs (labour and capital) and the indirect contribution of technological progress (MFP) to overall output growth (Barro, 1999[201]).

However, AI's productivity effects may be limited by its rising use of data in the creation of commercially valuable knowledge. Recent work by (Corrado et al., 2023[70]) analyse the growth contribution of data – a key AI system input as well as part of intangible assets. They suggest that the rising data share in intangibles has had possibly two opposing effects. On the one hand, the increasing investment in data assets might have generated an efficiency effect, boosting the contribution of intangible capital to productivity growth by up to ¼ percentage point. On the other hand, the increased role of proprietary big data in production processes, especially in the production of commercially valuable knowledge, might have weakened the diffusion of innovations, slowing down MFP growth via an appropriability effect. In other words, the broader use of proprietary data can produce a change in the composition of intangible capital that may have diminished its potential for increasing returns to the extent that the data capital of individual firms cannot be freely replicated. They evaluate that the negative appropriability effect might have, so far, more than offset the efficiency effect. Thus, the rise of modern data capital might have been a substantial contributor to the productivity slowdown. The future interplay of the two effects could shape the growth contribution of AI, as data are a key important input into the development and use of AI models and the share of AI-powered activities will tend to increase as the new technology spreads out. Their net impact on AI's growth contribution may also be influenced by policies concerning data ownership and access, including intellectual property rights (e.g., access to copyrighted data for AI training purposes, see following sections).

In addition, there are also dynamic reallocation effects, related to the balance between the labour-automation and labour-augmentation nature of AI, that come into play with possibly negative impacts on aggregate productivity growth. These are discussed in Section 4.3 on market dynamism.

4.1.1. Illustrative scenarios

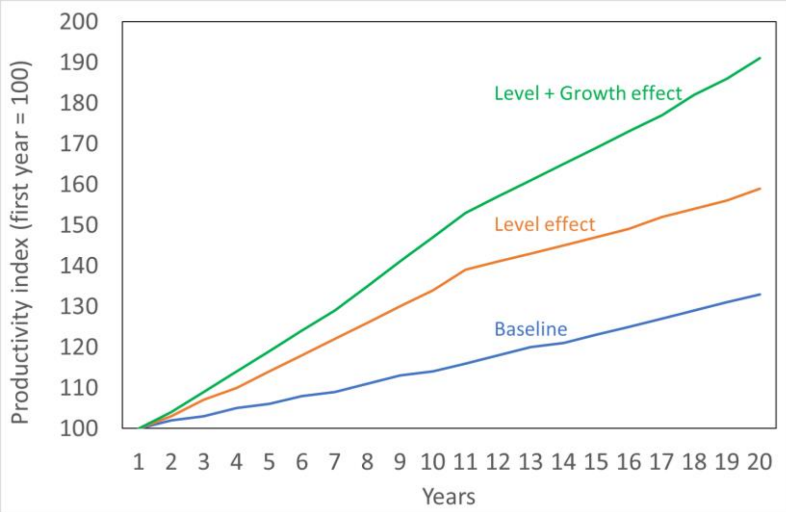
Notwithstanding these uncertainties, various recent scenario-based studies foreshadow AI future growth contributions that would raise productivity growth substantially relative to current rates. A recent (Goldman Sachs, 2023[71]) report predicts an annual 1.5 percentage point boost to US labour productivity over the next decade or so if widespread adoption of AI is achieved (Goldman Sachs, 2023[71]), compared to recent annual US productivity growth hovering around 1% per annum (Andre and Gal, 2024[36]).[20] Other scholars consider these estimates reasonable, moreover, they stress that most of the long term impact will likely be larger and generated by persistently faster growth rates rather than by a level shift with only transitory growth effects (Baily, Brynjolfsson and Korinek, 2023[37]) (Figure 7). The main drivers of growth are assumed to result from faster rates of innovation driven by higher efficiency of researchers (which is an advanced cognitive task that AI is likely to make more productive; see Section 2.2).[21]

[20] This central scenario is surrounded by large uncertainty, ranging from 0.3 to 2.9 percentage point gains per year, depending on various assumptions about the evolution of AI capabilities.

[21] The assumption about the size of the growth rate increase in the illustrative scenario implicitly assumes that the productivity of researchers and innovators increases by 2/3rd (=1pp increase /1.5pp baseline), which is higher than what the authors assume for the general productivity increase in cognitive tasks (30%). Further, it is also assumed that research and innovation outputs translate one-to-one into higher aggregate productivity gains, thus neglecting lags in the diffusion and adoption of new inventions. Both of these assumptions can be considered fairly optimistic. Nevertheless, an alternative approach used by (Artificial Intelligence Commission of France, 2024[184]) assumes productivity-boosting impacts will be similar to previous major technologies (1.3% per year for electricity, and 0.8% for ICT) which imply similarly high numbers.

Figure 7. The potential effects of AI on productivity levels and growth rates over the long run

Illustrative scenarios by Bailey, Brynjolfsson and Korinek (2023)



Note: The baseline trajectory follows 1.5% growth per annum, which is the current projection by the Congressional Budget Office. The level effect assumes an 18% rise over 10 years, resulting from a 30% productivity increase in cognitive tasks which make up 60% of labour inputs. The growth effect assumes a 1 percentage point increase in the baseline annual growth rate, driven by higher productivity of cognitive workers engaged in research and innovation.
Source: (Baily, Brynjolfsson and Korinek, 2023[37]), Machines of mind: The case for an AI-powered productivity boom | Brookings

These views are not uniformly shared. Recent calculations by (Acemoglul, 2024[72]) yield much lower figures – partly due to being much more conservative regarding AI's innovation boosting potential –, in the ballpark of less than 1% *cumulative* productivity growth over 10 years. In addition, as stressed even by the authors of the more optimistic scenarios, their predicted large positive impacts are by no means a foregone conclusion. Their realisation hinges on meeting several conditions that would make AI development and use conducive to such high growth rates. These conditions range from continued improvements in AI capabilities and fast widespread adoption to ensuring complementarities with human skills and other technologies. As discussed below, public policies might have a large role to play in ensuring that these conditions realise.

4.2. Market dynamics, labour reallocation across sectors and aggregate productivity

AI-induced structural change and the effects of AI on market dynamism are key mediating factors for longer-term aggregate productivity outcomes. Notwithstanding AI's peculiar expected impact on boosting innovation and disrupting economies and societies more broadly, it can also be seen as yet another step in an automation process that over the past two centuries first involved agriculture and then manufacturing (Aghion, Jones and Jones, 2018[73]). AI induces a range of supply and demand-driven structural changes that are reminiscent of the "Baumol cost disease" (Baumol, 1967) phenomenon, which characterised the transition from manufacturing to services and prior from agriculture to industry. In essence, this means that slow productivity growth sectors become increasingly larger in the economy, weighing on the expected positive aggregate productivity impact. In other words, "Economic growth may be constrained not by what we do well but rather by what is essential and yet hard to improve" (Aghion, Jones and Jones, 2018[73]).

As productivity increases in activities that are exposed to AI, a number of market forces are set in motion: the relative prices of products resulting from these activities decline fast and the level and composition of demand changes, also reflecting the increases in real incomes resulting from productivity growth. In fact, when new technology boosts production in certain industries, demand for its products will not increase infinitely as prices fall and income rises (due to market satiation or non-homothetic preferences). Rather, demand will concentrate in other sectors, thus decreasing the importance of the sectors where technological change boosted production. This reasoning might apply also to AI-exposed sectors, so that the share of the AI-exposed sectors in GDP may shrink relative to the share of activities that are not exposed to AI use.[22] In this case, while overall productivity *levels* in the economy will be higher than pre-AI, the gain in productivity *growth* from AI could be attenuated in the long run. In fact, productivity growth in AI-exposed activities will be counterbalanced by the reallocation of labour towards activities that have slower productivity growth (e.g., potentially less knowledge intensive, personal services – at least based on current AI technologies).[23]

An historical comparison can be found in the rise of the share of services in GDP which exerted a moderate but persistent drag on productivity growth in advanced economies – as services tend to have lower labour productivity growth rates (Sorbe, Gal and Millot, 2018[74]). The same may happen for activities not exposed to AI in the future, with significant uncertainties about the pace and size of the phenomenon given the rapid and unpredictable gains in AI capabilities.[24]

4.2.1. The degree of AI complementarity with human skills matters greatly

To shed more light on the drivers of the long-run aggregate productivity effects of AI, it is useful to consider three main factors, pertaining to both the supply side (how AI interacts with labour) and the demand side (how AI-powered products and services are consumed):

- First, in activities exposed to AI, the tasks executed by the new technology can be either complements or substitutes to labour (Susskind, 2020[75]), with both of these cases leading to labour productivity increases in the affected sectors.
- Second, as the technology evolves, new tasks and jobs are created, further sustaining aggregate productivity gains. For instance, the introduction of computers and internet fostered the creation of high-paying occupations such as programmers, designers, etc. However, future generations of AI could automate these new tasks as well, contributing again to a further shrinkage in the role of labour (Susskind, 2020[75]).

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[22] (Bessen, 2018[140]) shows that both income and price elasticities of demand can change over time, shaping the impact of technological change on employment in affected industries. He argues that, in the past, changes in price elasticities over time have induced inverted U-shaped employment growth patterns following automation-driven innovations in specific industries such as textiles and more recently automobiles. It is unclear however to what extent these results can apply to a general-purpose technology such as AI given that reaching saturation levels in demand could be less likely across a vast range of AI-powered products and services.

[23] Consider a very simple illustrative example, with a low labour productivity growth and a high labour productivity growth sector (e.g., personal services, at 1% per year, *vs.* IT, with 3% per year). Suppose they have an initial 50-50% employment share, which implies a 2% per year aggregate labour productivity growth: 0.5 x 1% + 0.5 x 3% = 2%.

What happens when AI induces a strong labour substitution effect in the IT sector, which is not compensated by higher demand for its output? It will lead to a fall in its employment share, assume for illustrative purposes, to 20%, from the initial 50%. This shift raises the employment share of the other sector from 50% to 80%. Once the large initial labour-substitution driven productivity boost fades in the IT sector, aggregate labour productivity growth will decelerate: 0.2 x 3% + 0.8 x 1% = 1.4%.

Slower aggregate productivity growth also occurs even if the long run productivity *growth rate* of the AI-exposed sector increases, for instance, from 3 to 5%: 0.2 x 5% + 0.8 x 1% = 1.8%.

[24] More recent evidence from EUKLEMS & INTANProd data (https://euklems-intanprod-llee.luiss.it/) revisits the role of labour reallocation, measured by hours worked, shaping aggregate labour productivity growth in Europe and the US, and finds that it has been very small over recent decades.

- Third, higher demand due to AI-driven increases in incomes could sustain aggregate productivity growth if the increased demand is directed mainly towards labour intensive and high productivity growth sectors, such as engineering and other highly knowledge intensive professional services. Conversely, productivity growth could be further hindered if additional demand is directed toward labour intensive and low productivity growth sectors such as personal services.

These phenomena typically occur during the diffusion of General Purpose Technologies in the economy. In the case of AI, given the recent advances in ease of use – particularly with language and image generating models – the speed of diffusion may be faster than in previous technological waves. However, successfully integrating AI capabilities with existing business models, which requires additional complementary investments in data, skills, etc., may still take time. Another key distinction from previous major technologies could be the rapid pace of AI's ongoing development, which has been notably swift in recent years and with the exponential rise of computing capacity, it is likely to remain fast in the future. This has implications on the capacity of labour markets and skills to adjust fast enough.

To sum up, if AI mainly automates human tasks, after the AI-driven initial boost to aggregate productivity levels, reallocation could induce lower productivity growth over time driven due to the increasing employment share of low productivity growth activities that are not yet automated by AI (e.g., elderly care, hospitality, etc.) and the shrinking share of labour in the AI-using activities (Aghion, Jones and Jones, 2018[73]). On the contrary, if AI will still require substantial complementary human labour for specific tasks, create new tasks for humans, or increase demand for labour-intensive high-productivity sectors[25], structural change could exert only a minor counteracting influence on the AI-driven aggregate productivity boost. However, if AI development is very fast, it is not clear that new tasks can be created, and relevant human skills can be built up, at sufficient speed to support the positive scenarios.[26]

4.2.2. Early suggestive evidence from labour markets

It is early to tell which of these forces will dominate, but looking at current evidence from labour markets can give some initial indications. Numerous studies have concentrated on assessing which industries and occupations will be most impacted by AI (OECD, 2023[57]), for instance looking at exposure to Predictive AI (i.e., their *potential* to be affected by the technology) (Felten, Raj and Seamans, 2021[40]). These studies show that exposure is concentrated in knowledge-intensive services – such as ICT, telecommunications, finance and professional services – which are already characterised by high productivity levels *and* growth, in some cases similar to those observed in manufacturing (Sorbe, Gal and Millot, 2018[74])(Figure 8).[27] On the other hand, the evidence for less knowledge-intensive services – which generally have weak productivity performance – is mixed, some being exposed and others not. Other sectors, including manufacturing, overall tend to be less exposed.[28]

Besides identifying how much a sector's tasks are exposed to AI, a crucial question lies in the nature of AI's exposure in these industries. Namely, how much AI can automate workers' tasks or augment workers'

[25] E.g., as might occur if those activities supply mostly superior goods.

[26] A more clear elaboration of the role of various conditions in driving long-run aggregate productivity effects would be explored in planned further work, especially in light of other ongoing long-term structural changes such as demographics (ageing and workforce shrinkage).

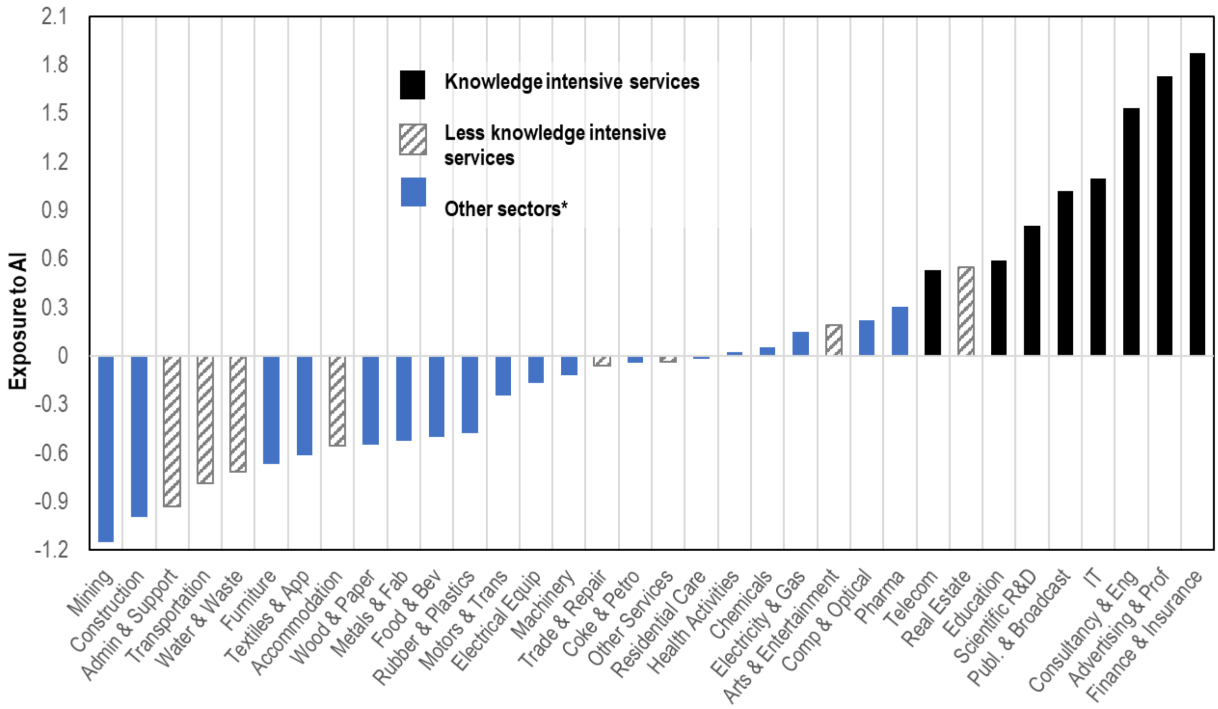
[27] These sectors are also characterized by higher income, hence AI might entail an overall more equal income distribution, as discussed in Section 5.

[28] Some jobs, like in administrative and support services, might show low AI exposure because the index focuses more on non-Generative AI and less on recent Generative AI. Still, early research suggests that jobs impacted by earlier AI are also likely to be affected by Generative AI, with graphical and interpersonal jobs being more influenced by the latest AI technologies (Felten, Raj and Seamans, 2023[202]).

abilities. The balance between automation and augmentation can be investigated, for example, by defining as potentially automatable tasks those that can be performed by AI without needing to solve ambiguous problems, to work together with others, or to validate outputs (WEF, 2023[76])[29]. Based on these assumptions, Figure 9 reports tasks that are prone to AI automation or augmentation, as a share of the total amount of time spent on all tasks in the sector. Interestingly, knowledge-intensive activities (e.g., some occupations related to R&D, ICT, finance) are more at risk of automation. However, high-skilled occupations are also substantially more prone to be complemented than other sectors, at least at the current stage of Generative AI development, confirming findings by other policy reports on AI (Council of Economic Advisers, 2024[8]) and on previous waves of automation (Lassébie and Quintini, 2022[77]).

Figure 8. High productivity and knowledge intensive services are most affected by AI

AI exposure of workers by sector (2019), standardized deviations from mean

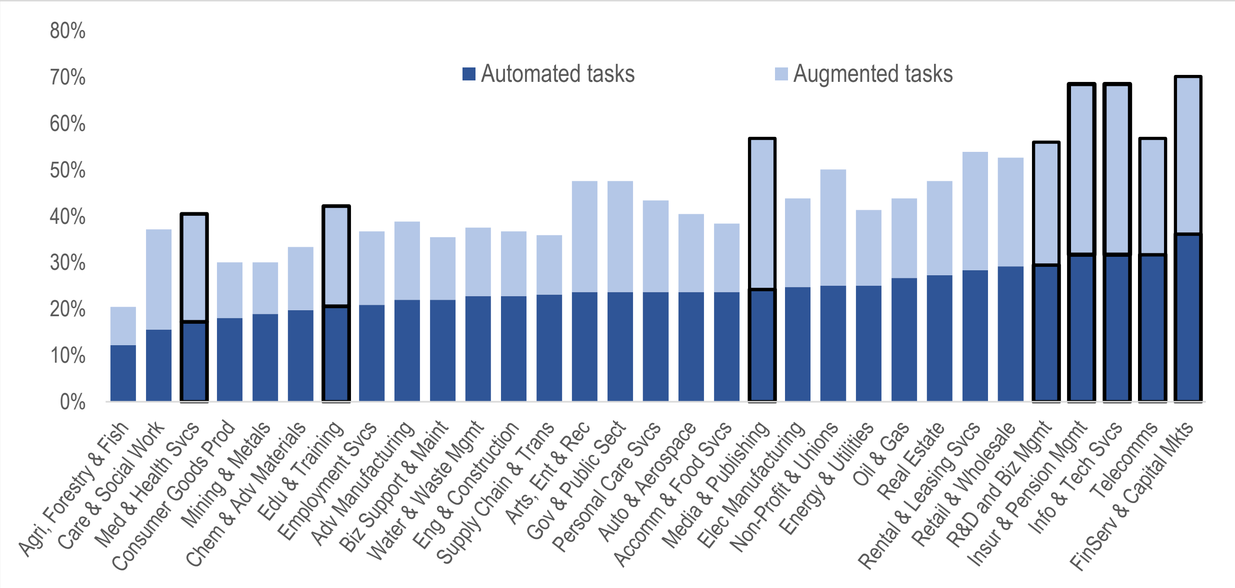


Note: The index measures the extent to which worker abilities are related to important AI applications. The measure is standardized with mean zero and standard deviation 1 at the occupation level and then matched to sectors. The figure does not yet include recent Generative AI models. The countries included are Austria, Australia, Belgium, Brazil, Canada, Switzerland, Costa Rica, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Greece, Hungary, Ireland, Iceland, Italy, Lithuania, Luxembourg, Latvia, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovenia, Slovakia, United Kingdom, and United States. See more details in the source.
*Including non-market services, manufacturing, utilities, etc.
Source: OECD Global Forum on Productivity, based on (Felten, Raj and Seamans, 2021[40])

[29] Using a more narrow focus on a specific AI-technology, i.e. Computer Vision, a more recent approach predicts how much the technology will automate vs. substitute jobs by estimating which tasks can be automated in an economically attractive way (Svanberg et al., 2024[207])

Figure 9. Tasks in knowledge intensive services are more prone to automation by text-based Generative AI

Automated and augmented tasks by Generative AI language models, as a share of the total amount of time spent on all tasks*, by industry, US (2022)

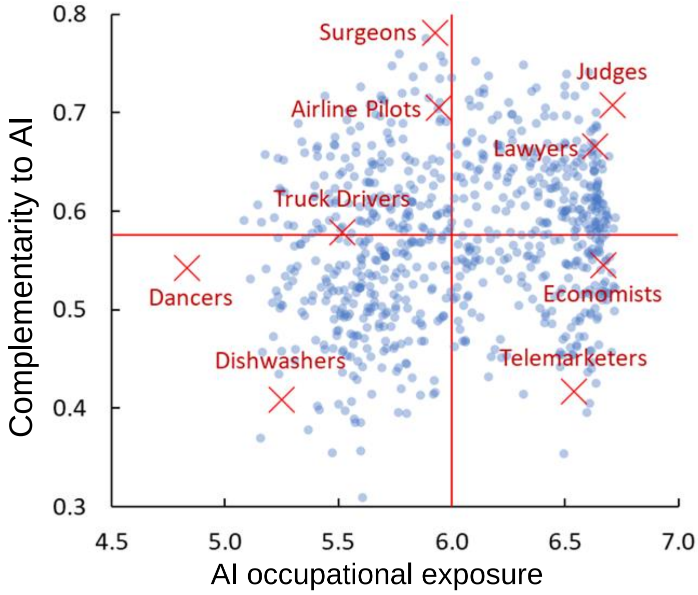


Note: *The remaining share of tasks includes non-AI exposed ones, where AI has an undetermined ambiguous impact.
Knowledge intensive service occupations are marked by bordered bars.
Source: (WEF, 2023[76])

This initial evidence suggests that Generative AI could usher in a shift in the pattern of jobs at risk of automation from technological change, as knowledge-intensive activities were previously thought to be less susceptible to automation. However, given current limitations of Generative AI (occasional unreliability and tendency to hallucinate, among others) (Perez-Cruz and Shin, 2024[78]) (OECD, 2023[79]), both regulation and market pressure could require businesses and other organisations to "keep the human in the loop" and avoid complete automation of jobs, to allow for double checking and for discriminating across various content produced by AI (Korinek, 2023[16]). Partly due to such risks, the regulatory and social acceptability of AI "decisions" will ultimately determine the degree of automation risk (hence, inversely, the degree of complementarity) that AI represents in practice.

Recent estimates of the degree of AI occupational exposure and the degree of complementarity accounting for risks and limits to automation reveal in fact a nuanced picture ((Cazzaniga et al., 2024[80]), reproduced in Figure 10). For instance, judges and lawyers are both highly exposed but also highly complementary, reflecting the notion that they are unlikely to be automated in practice. OECD research also indicates that employment has grown in occupations that are highly exposed to AI and have high computer use, suggesting complementarity between AI and labour in these occupations (Georgieff and Hyee, 2021[81]).

Figure 10. The AI occupational exposure and complementarity of jobs: a nuanced picture



Note: The degree of complementarity to AI reflects not only the technical feasibility of using AI as a complement or substitute for the tasks carried out by these occupations but also the social acceptability of doing so. For more details, see the source.
Source: (Cazzaniga et al., 2024[80]).

More speculatively, labour demand in AI-exposed activities may increase due to the creation of *new, emerging* tasks made possible by AI, such as "prompt engineering" (the ability to ask the right question to the Generative AI language model). In parallel, AI may also increase relative labour demand in less AI-exposed activities, i.e., in services characterised by frequent personal interactions, such as accommodation, administrative services, personal care. This would especially be the case when demand-driven market forces will push into the same direction, via falling prices of AI-powered goods and services and more income available for spending in services not automated by AI. Of course, it is currently hard to foresee the labour market impact of yet-to-arrive occupations and the type of skills they require as well as to what extent shifts in consumer demand will be relevant.

These potential changes will also have consequences for overall employment, wages and inequality (Cazzaniga et al., 2024[80]) and Section 5 below). Which workers will be automated and which ones will instead exploit AI for improving their productivity will be crucial for determining not only how AI will affect aggregate productivity, as highlighted in the previous subsection, but also how it will change the distribution of income, both across workers and between labour and capital. Moreover, the overall labour and distributive impact of AI adoption will be affected by the way government policies influence AI development, diffusion and use as well as the reallocation of labour across the economy.[30]

[30] For instance, (Acemoglu and Johnson, 2023[182]) make the case for public policies that could promote a "pro-worker" AI. Similarly, (Korinek and Stiglitz, 2021[180]) and Brynjolfsson (2022) also discuss the benefits of steering AI development away from a human-automating focus. (Agrawal, Gans and Goldfarb, 2023[13]) argue, on the other hand, that it would be a misplaced approach, not only because it is very hard to achieve given the long-established incentives of AI developers and businesses, but also because automation technologies (e.g., writing, in the case LLMs) can act as complements to many activities (e.g., everyone who needs to write in their job but is not talented at it) and hence have the potential to raise productivity of those activities.

4.3. AI diffusion, market functioning and dynamism

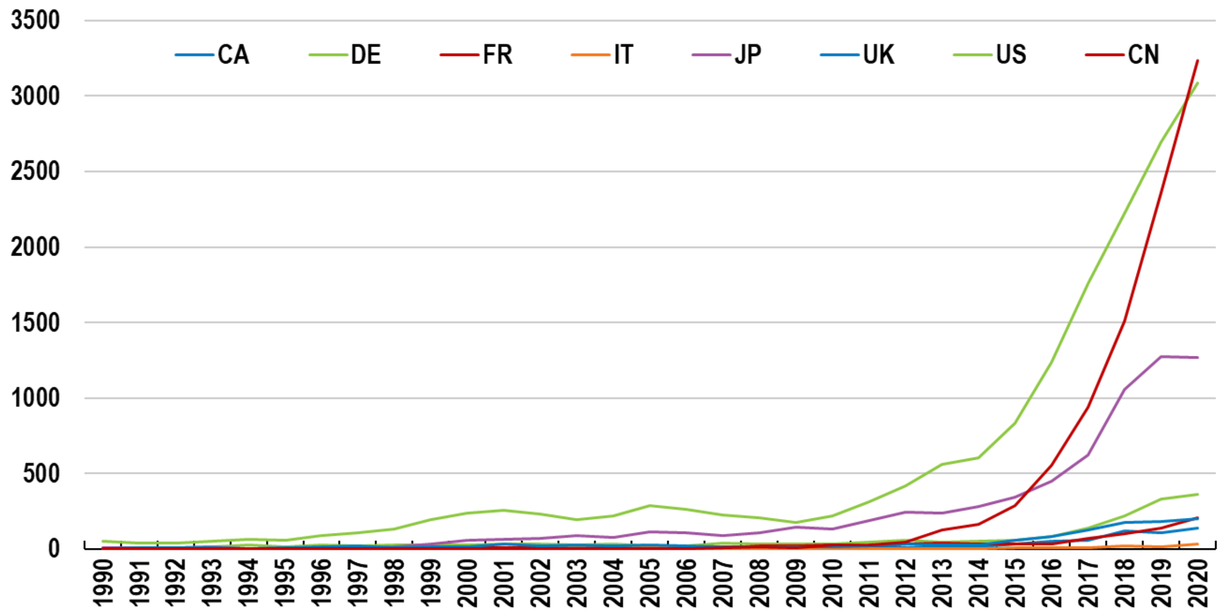
The extent, pattern and speed of AI adoption across the economy will have a key influence on the size and persistence of aggregate productivity gains by affecting market efficiency, competitive pressures, firm demographics and innovation incentives. In this, a key role may be played by bottlenecks in access to the key tangible and intangibles resources required by AI development and use.

4.3.1. AI diffusion: evidence and driving forces

Fast adoption of AI technologies, a requirement for reaping their productivity benefits, should not be taken for granted. The attempts to build AI have a long history, building on concepts and techniques in computer sciences which have been invented long time ago (Anyoha, 2017[82]). However, the speed of technological development in AI has undergone a dramatic acceleration starting with the second half of 2010s. Thus, the key moment for AI development is only a recent one, thanks to a combination of advances in computing capacity and the dramatic increases in the availability of data that can be used for training. For example, Figure 11 estimates the number of patent applications in AI-related technologies under the Patent Cooperation Treaty (PCT), where identification of AI-related patents follows the OECD methodology detailed in (Baruffaldi et al., 2020[83]). It also highlights the strong geographic concentration of AI patenting activity in the US and China, with Japan and the EU substantially lagging behind and other countries contributing very little.

Figure 11. AI patenting increased dramatically, with high cross-country concentration

Number of PCT patent applications in AI-related technologies

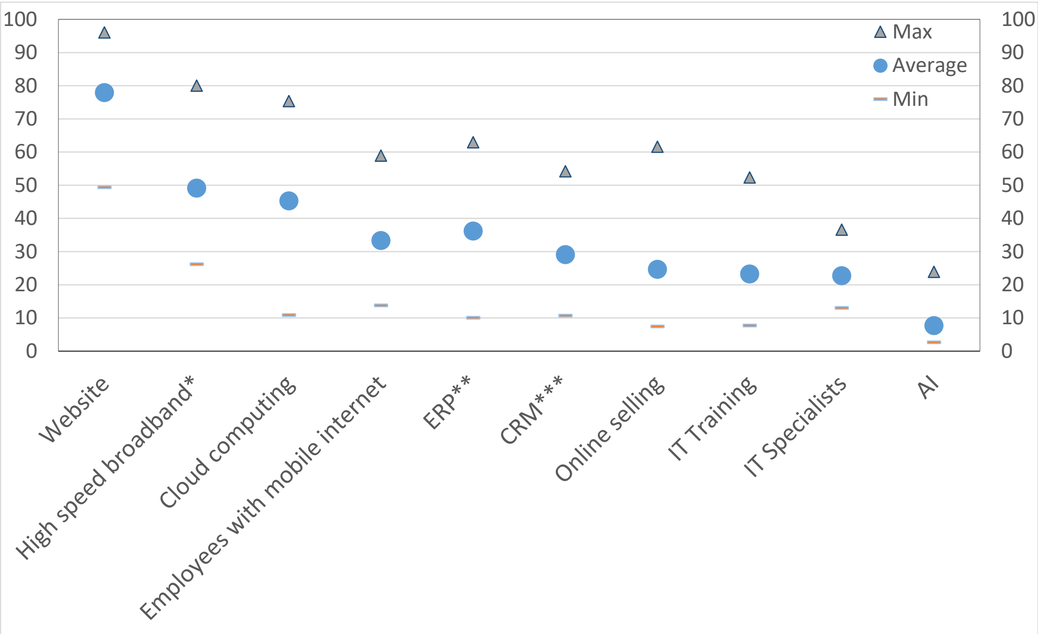


Note: Number of PCT patent applications in AI-related technologies. Data refer to patent applications filed under the Patent Co-operation Treaty (PCT), according to the filing date and the applicant's location, using fractional counts. AI-related patents are identified according to the methodology described in (Baruffaldi et al., 2020[83]).
Source: OECD, STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats, January 2024.

The available survey evidence from official cross-country statistics shows that AI adoption – mostly non-Generative AI – is still at an early stage compared to other ICT technologies. (Figure 12). Moreover, cross-country average adoption is very close to the minimum, suggesting that a large number of countries concentrate close to the lower end of the cross-country distribution of AI adoption.

Figure 12. The adoption of AI is much lower than that of other digital technologies+

% of firms adopting digital technologies (2021 or latest available)



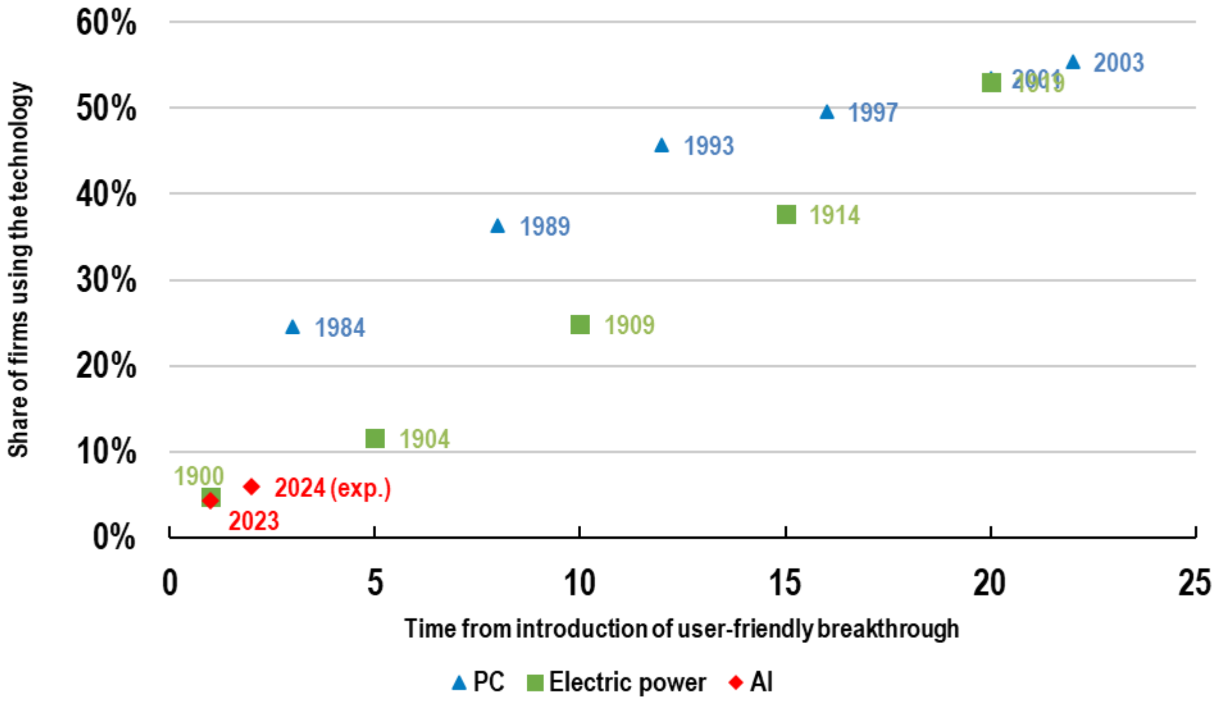
Note: for the average OECD country (average) and the lowest (min) and highest (max) adoption country, at least 10 employee firms.
+Since the latest data refer to 2021, AI adoption predates – hence largely excludes – Generative AI models.
* High speed broadband is defined as having at least 100Mbit/s download speed.
** ERP stands for Enterprise Resource Planning systems.
*** CRM stands for Customer Relationship Management systems.
Source: OECD ICT Access and Usage by Businesses Database.

A slow adoption pace and gradual learning of how best to adapt production processes to make most of the new technology is typical of General Purpose Technologies. They usually require significant complementary investments, often concentrated in intangibles that take time to build and can be difficult to finance (Corrado, Haskel and Jona-Lasinio, 2021[11]). Put differently, "plug and play" applications of transformative technologies are rare: for the technology to deliver important gains, businesses need to implement substantial adjustments in the way they manage staff, organize production, collect and use information and interact with customers and suppliers. This requires creativity and experimentation by managers, which is risky and time consuming (see J-curve hypothesis in Section 4.1). Moreover, AI adoption could be slowed down in some sectors, given regulatory restrictions that are aimed at ensuring trustworthiness and systemic stability, such as in finance.

Comparing adoption rates of AI among firms in the United States with the adoption trajectory of two previous General Purpose Technologies (electricity and computers) shows that while the initial path followed by AI seems similar, its adoption is still relatively limited (Figure 13) despite the development of AI having started decades ago. Based on official US Census Bureau data collected from large scale firm-level surveys, the Figure shows that AI is still very far from the 50% threshold of adoption across *firms* which is sometimes considered a reference point for a productivity boost to become detectable in macroeconomic data (Goldman Sachs, 2023[71]). However, since it's mostly big companies who are adopting AI, the share of *workers* exposed to AI is already large. In 2018, among US firms, 18% of workers were in companies that adopted AI to some extent, concentrated in few cities, in sectors such as information, healthcare, and manufacturing, and linked with advanced technologies like cloud computing (McElheran et al., 2023[84]). Also, cross-country evidence from a number of OECD countries in 2016-2021 reveals that AI usage is more prevalent in larger firms (Calvino and Fontanelli, 2023[45]). This study also revealed that adoption varies with the firm's age and productivity, with a U-shaped pattern along both dimensions. This indicates higher adoption in younger, more entrepreneurial firms and in older, more established ones. Adoption was also higher among firms at the productivity frontier, highlighting likely synergies with other productivity-boosting technologies or management practices.

Figure 13. AI adoption is still limited compared to the spread of previous General Purpose Technologies

The evolution of technology adoption (as % of firms, United States)



Note: The 2024 value for AI is the expectation (exp.) as reported by firms in the US Census Bureau survey. For more details, see the sources.
Source: For PC and electricity, (Goldman Sachs, 2023[71]); for AI, United States Census Bureau, Business Trends and Outlook Survey, updated on 28 March 2024

Yet, alternative and more real-time sources on consumer-oriented, "user-friendly" AI suggest that adoption is progressing very fast. For instance, the take-up rates for ChatGPT were faster than any internet app to date – 100 million users in two months, compared to two years for Instagram and five years for Twitter (Milmo, 2023[85]; The Economist, 2023[86]). Even though the applied use of AI technologies might benefit from their user-friendliness, fully leveraging AI's productivity potential still requires complementary digital infrastructure and skills, as for earlier digital technologies (Corrado et al., 2021[87]). Indeed, AI adoption challenges can reflect the extent to which obstacles emerge in the access to key tangible and intangible resources. Aside from the digital backbone and storage capacity, modern AI systems require enormous computing power and highly-specialised skills to develop and maintain them and sometimes even to use them.

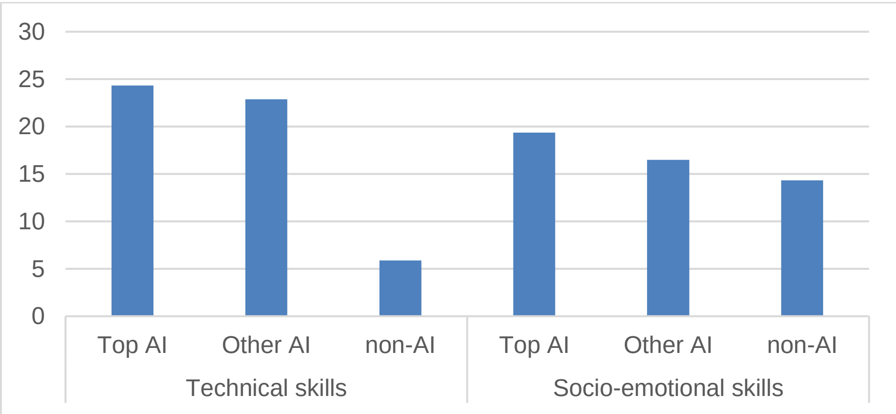
Supply of computing power (especially GPUs) is currently limited due to capacity bottlenecks (related to high R&D and capital intensity requirements and long manufacturing cycles), strong global market concentration and global supply chain vulnerabilities, making access especially difficult for start-ups and small companies ((Mohammad, Elomri and Kerbache, 2022[88]; Griffith, 2023[89]; Global X, 2021[90];

Haramboure et al., 2023[91]). Although many AI developers are making strong investments in this area by building their own chip supply capacity, the market for computing power serving AI is still currently dominated by only a few players.

Regarding skills needs, a crucial issue is how skill demand will evolve with AI's ascent and its impact on labour market shortages and mismatches. This is particularly pressing as the rapid adoption of AI occurs alongside tight labour markets, a situation that might be exacerbated by the ongoing shrinking of the working-age population (Andre, Gal and Schief, 2024[92]). While there is no hard evidence available yet about the extent of AI-related skill shortages (if any)[31], lack of skills is one of the most common barriers to adoption reported by firms in cross-country surveys (OECD, 2023[93]). This is particularly the case given the special needs of AI related jobs: in 2022, US job vacancies requiring technical skills were almost five times higher in top-AI than for non-AI jobs (Figure 14). Socio-emotional and foundational skills are also more likely required in top-AI jobs.[32] With AI necessitating specialised skills, both for its development and utilisation in downstream industries, the demand for certain job roles is likely to intensify, possibly making labour shortages more severe.[33]

Figure 14. AI related vacancies require more advanced technical and complementary skills

The share of online vacancies requiring specific skills, by AI-relatedness (United States, 2022)



Source: (Borgonovi et al., 2023[94]).

AI-related skill usage also appears to be characterized by very high occupational, sectoral and geographical concentration.[34] Moreover, innovation hubs where AI development and deployment thrives often make use of non-compete contractual clauses for highly-qualified professionals, whereby a worker's freedom to seek jobs from competitor firms or start own-account businesses upon termination of the contract with the current employer is (more or less severely) limited. These clauses could not only curb entry of innovative AI-powered startups but also contribute to AI skills bottlenecks (Gibson, 2021[95]).

[31] Ongoing work by the OECD Global Forum on Productivity investigates this issue.

[32] This implies that a skilled traditional worker might only need a bachelor's degree, a proficient AI developer might need to have a diverse set of skills that are usually acquired in post-tertiary education and through workplace training and experience.

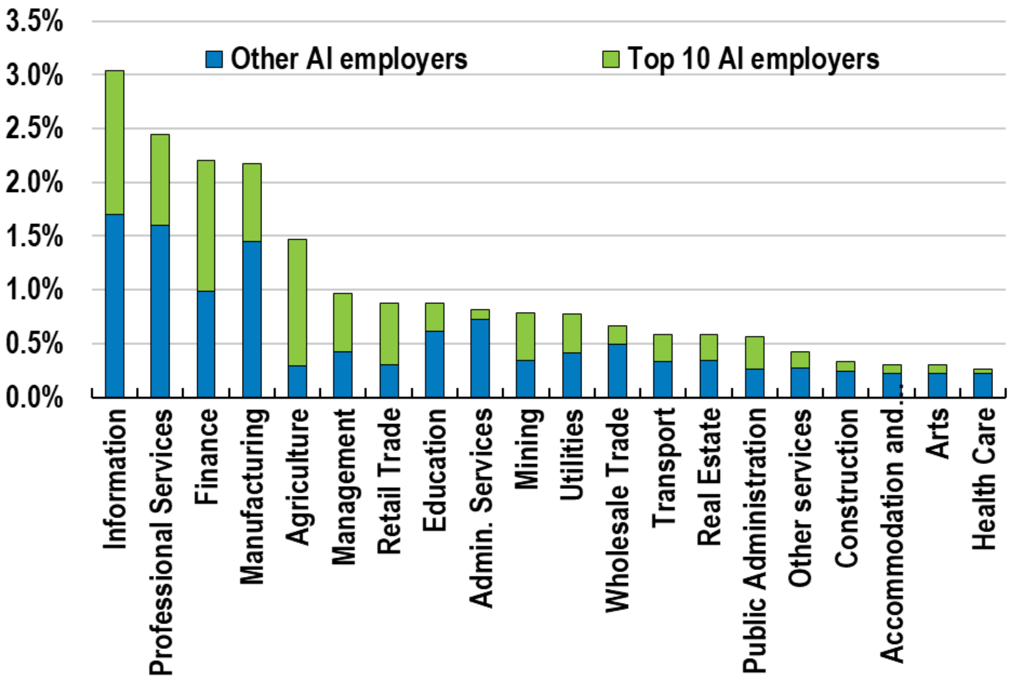
[33] Other factors may act in opposite directions: AI's capacity to replace human workers might ease the demand in some segments of the labour market; and businesses might be more motivated to push for AI-driven automation in sectors where labour shortages are most acute initially.

[34] Occupational and sectoral concentration is documented by (Green and Lamby, 2023[96]) and (Borgonovi et al., 2023[94]), respectively, while evidence of geographical concentration for the US was provided by (McElheran et al., 2023[84]).

Finally, the demand for skills for AI development and adoption can create a concentration of AI expertise within a few large companies, which could hold back the diffusion of AI expertise across businesses and increase performance differences across firms, with negative consequences for aggregate productivity. Although growing fast, OECD estimates suggest that only 0.34% of the workforce possessed AI skills in 2019 (Green and Lamby, 2023[96]). The concentration of AI vacancies in specific industries hides much larger concentration in a few firms within these industries (Figure 15). The share of jobs by top-10 AI employers is often about half of the whole industry. Moreover, the proportion of job listings demanding AI expertise from top employers is greater in sectors where AI job vacancies are relatively low. For instance, in retail, less than 1% of job postings require AI skills, yet almost all of these are from the top ten AI employers (e.g., Amazon). Patterns are similar for utilities and public administration. Thus, in these overall less AI-exposed sectors, a few firms are still very much interested in working with the technology, potentially foreshadowing rising performance differences within these sectors, to the extent that their efforts to turn AI into productivity gains are successful. Data from the OECD.AI Policy Observatory complement the picture by showing that AI skills are concentrated also across countries, with AI skills penetration (the share of workers with AI skills) being twice as high in the US than the OECD average (Figure A.3).

Figure 15. AI skill demand is concentrated in knowledge intensive services and manufacturing

Share of AI vacancies posted by US top AI and other AI employers, by industry (2022)



Source: (Borgonovi et al., 2023[94])

4.3.2. Risks to competition, market functioning and dynamism arising from the characteristics of AI

While widespread AI adoption is necessary for the technology to deliver broad-based productivity gains, AI can also exacerbate competition headwinds in markets that use digital technologies and generate new challenges for competition, market functioning and innovation incens. This in turn may backlash on the diffusion and development of the new technology.

In this respect, two sets of concerns arise. First, AI could exacerbate challenges that have already emerged in digital markets as the role of online platforms has grown in the economy over the past two decades (such as search, retail and booking platforms as well as social media). These include the potentially negative effects on firm demographics and competition of excessive market concentration, barriers to access and abuses of market power (Costa et al., 2021[97]) (Nicoletti, Vitale and Abate, 2023[98]) (OECD, 2023[63]). Second, as AI spreads out in the economy, a number of challenges more specific to the new technology may emerge. These are related to the potential for market distortions (e.g., due to lack of transparency and accountability), new channels for collusion as well as innovation disincentives (e.g., due to property rights uncertainties). [35]

Market concentration and abuses of market power

AI diffusion depends on access to and competition in each of the segments of the "AI value chain": skills and algorithms (e.g., foundation models), data used for training, and infrastructure (computing power and storage) (CMA, 2023[9]). In turn, access and competition would stimulate further AI innovation by developers, facilitate the entry of new AI-using firms and may narrow productivity gaps across firms by fostering AI adoption, for instance via lower prices and broader variety.

Yet, potentially more than with other digital technologies, AI systems embed characteristics that can lead to both early mover advantage and market concentration, tipping and dominance, which could thwart competition and contestability in the provision of AI services. The "scaling laws" affecting AI systems (Kaplan et al., 2020[99]), by which the predictive performance of the models improve with their dimension – requiring larger computing power and pre-training datasets – together with their potential to further (and continuously) improve as they are used thanks to real time feedback loops, heighten the relevance of scale economies and network effects of the AI technology relative to previous digital technologies. Moreover, early experimental evidence suggests that AI-driven recommender systems, which are increasingly used by online platforms, could be inherently conducive to market concentration and higher prices for recommended products in downstream markets, for instance by artificially creating highly-rated "star products" (Calvano et al., 2023[100]).[36,37]

The scale of computing power and data requirements needed to meet competitive AI performance standards provides a huge edge for AI incumbent providers through fixed costs that generate high barriers to access for new entrants, especially if the model pre-training data is proprietary. These features favouring market dominance are compounded by the possibility for incumbent AI providers to suffocate competition at birth by means of "killer" acquisitions that prevent the growth of potential competitors.[38] Lack of

[35] For a recent overview discussing the both the risks and potential upsides from AI in the field of competition, see (Council of Economic Advisers, 2024[8]).

[36] Recommender Systems are software programs providing personalised suggestions to users/consumers about specific items/products. These systems already orient one- to two thirds of consumer choices in leading online platforms (Calvano et al., 2023[100]).

[37] (Calvano et al., 2023[100]) conclusions are less clear cut concerning the effects on consumer surplus, as they depend on the balance between higher prices on the one hand and lower search costs and better matching of consumer to products on the other. The initial positive effects may turn negative as the AI algorithm draws on better and better personalized data. This in turn may provide a further welfare-improving rationale (beyond privacy concerns) for policies aimed at limiting access to personal data.

[38] See https://www.oecd.org/daf/competition/start-ups-killer-acquisitions-and-merger-control.htm. For instance, US competition authorities (FTC and DoJ) and the UK Competition and Markets Authority (CMA) are currently considering whether the close partnership between Microsoft and OpenAI, a major developer of AI systems, should be considered for a merger probe (Bloomberg, 2023). EU antitrust regulators also flagged that MS investment into OpenAI might fall under EU merger scrutiny.

competition in markets for AI services can slow down both AI model development, due to lack of innovation incentives, and AI adoption downstream, due to high prices reflecting market power.

As in markets for online platform services, market dominance by AI incumbents can worsen market outcomes (e.g., via lower output) but also generate abusive behaviour aimed at exploiting or foreclosing competitors in vertically (or horizontally) related markets when AI developers are also AI-powered suppliers in such markets. A typical example would be self-preferencing, where AI-driven recommender systems would orient customers towards products supplied by the incumbent AI-powered provider at the expense of competitors (e.g., a large retail platform developing its own AI to achieve this). Competitors may have little market alternatives if competition in AI development and supply is not thriving and, as for digital platforms, they may find themselves captive due to high switching costs or lack of interoperability that may hinder the move from one AI system to the other.

While barriers to access and the potential for abuses generated by market concentration are a real concern, some features of AI development and use suggest that complex forces are at work in AI markets.[39] For instance, the development of open-source competitors (such as Mistral, in France, and Aleph Alpha, in Germany) to leading commercial Generative AI models and, more generally, the diffusion of such open-source alternatives for more specialized AI tasks could limit in the future the market power of incumbents.

Market distortions

One way in which the impact of AI on growth and welfare could be reduced by distorted market outcomes is through using AI to automate excessively, especially by “so-so automation” (Acemoglu and Restrepo, 2019[101]; Acemoglu and Johnson, 2023[102]). This use of AI may have limited direct effects on productivity (because it typically replaces low-skilled workers) and potentially damaging effects on consumers, either by lowering product quality or by shifting costs onto them. Typical examples are self check-out counters in stores or automated customer services. Too much human-labour focused automation, without considering impacts on consumers, may be driven by herd behaviour (“fads”) in management practices.[40] However, if such automations are well implemented and lead to more reliable and quicker service provision, they may save time and lead to better quality services for consumers thus freeing up their time.

AI also risks reducing aggregate efficiency and welfare outcomes if it is used to influence consumer behaviour in undesirable directions.[41] While the possibility that data intelligence is used to manipulate consumers has been recognised for a long time, machine learning algorithms can bring the impact of these business strategies to another level.

A first such distorting channel is AI’s potential for the exploitation of well-known cognitive biases that cause deviations from consumer rational behaviour. For instance, a study argues that AI-powered marketing can exploit optimism biases, information overload, anchoring, confirmation, and framing highly effectively and at large scale,[42] to twist consumer demand towards low-quality or harmful products (Calo, 2013[103]). The

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[39] In financial markets, risks of herding and one-way markets due to the use of very similar AI models could also have detrimental impacts on stability.

[40] Alternatively, it could be seen as responding to longer term business strategies aimed at boosting collection of personalised data on customers (Brown, 2019[203]).

[41] Related work is being undertaken by the OECD’s Committee on Consumer Policy. In particular, potentially problematic commercial practices will be discussed at the October 2024 Ministerial Meeting of this committee.

[42] See Hanson and Kysar (1999) for a survey of these known biases studied in behavioural economics experiments. Specifically, AI driven by machine learning can identify such consumer vulnerabilities thanks to its ability to predict anomalous consumer behavior and design personalised targeting almost in real time. Calo (2014) reports that so-called “sucker lists” of vulnerable consumers are already traded in the open market.

resulting market manipulation might represent a novel source of market failure possibly leading to inefficient (or otherwise objectionable) economic outcomes.[43] A related source of potential behavioural manipulation is the informational advantage of AI-driven platforms over consumers concerning the "glossiness" (as opposed to the quality) of the products they supply (Acemoglu, Malekian and Ozdaglar, 2023b[104]). Depending on the persistence of such (non-rational) glossiness factors, the use of AI can help platforms to extract consumer surplus and increase profits at the expense of overall welfare.

A second potentially distorting channel is the formidable opportunity that AI-powered companies have to discriminate across consumers by setting close to personalised prices for identical products. While price discrimination in itself can improve both static and dynamic efficiency, it can also lead to exploitative and exclusionary practices when it is coupled with the strong market dominance that characterises many digital markets (OECD, 2018[105]). Particularly, in online markets customers have no information on the way their personalised prices compare to those applied to other customers and this asymmetry of information, coupled with market power, can be used by AI-powered platforms to set prices that penalise certain consumers or foreclose rival suppliers on the same platform (Li, Philipsen and Cauffman, 2023[106]).[44]

Finally, a third channel of market distortions is related to the (as yet unsolved) issue of accountability (and potential liability) for AI-driven business actions. The question is who among AI developers, AI users, and beneficiaries of AI actions should be held accountable and liable for decisions that might be taken autonomously by advanced AI systems with potentially high-risk outcomes (e.g., self-driving vehicles). These decisions can have consequences for market outcomes (e.g., negative effects on competition or on consumers) for which responsibility needs to be attributed in order to find remedies and correct the distortions they might originate. Yet, the more AI acts autonomously, the weaker the links between the agent (the AI system) and its principal(s) (the humans instructing or developing the AI system), putting into question the liability of the individuals or firms who benefit from the algorithm's autonomous decisions (OECD, 2017[107]). Recent research shows that, in the absence of any liability system, AI development with uncertain welfare consequences tends to exceed what would be socially desirable, causing negative externalities (Guerreiro, Rebelo and Teles, 2023[108]). Yet, defining AI accountability goals, processes and enforcement tools is challenging, not least because of the problem of pinpointing individual responsibilities in systems that involve multiple actors and resources (Novelli, Taddeo and Floridi, 2023[109]).[45]

Collusion – and how to prove it

Aside from more traditional channels, risks of collusion among AI developers and users relate especially to (i) algorithmic pricing (AP) and (ii) AI governance arrangements among developers.

The use of AP, whereby firms set prices according to predetermined rules that account for the reaction of competitors, has been quite common in several markets for quite some time already. This was generally done via adaptive mechanisms whose underlying models needed to be coded by humans (Calvano et al., 2020[110]), implying that collusion intent could in principle be detected and sanctioned. Examples of AP use range from air travel, finance, insurance and accommodation to large online retail platforms, where up to two thirds of service providers used such algorithms already in 2017 (OECD, 2017[107])[46]

[43] The economic costs arising from behavioural manipulation have been termed "internalities" to distinguish them from more familiar economic externalities (Herrnstein et al., 1993).

[44] For instance, price discrimination can be used by platforms to implement and sustain exclusionary predatory practices, by reducing the profits foregone during the period in which predated rivals remain in the market.

[45] (OECD, 2023[124]) provides a framework for AI accountability design. An early practical attempt at defining an accountability system is the EU AI Act agreed by EU Council and Parliament in December 2023.

[46] Despite their large use, only a limited number of AP-induced collusion cases have been detected by competition authorities so far (Calvano et al., 2020[110]).

AI-powered AP opens up several new possibilities to collude, including prominently (and safely) by facilitating tacit collusion (OECD, 2021[111]) (OECD, 2023[112]). Under certain conditions, the interaction between AI-driven AP and recommender systems can also further tacit collusive outcomes (Xingchen, Lee and Tan, 2023[113]). This kind of collusive behaviour is pernicious because it cannot be addressed easily by authorities enforcing competition laws that are based on the principle of the "meeting of minds" as a proof of intent.[47] The increasing use of machine-learning algorithms, in which price adjustments are driven autonomously by self-learning AI without building on an explicit economic model, makes collusive outcomes possible even without the explicit intervention of humans (Calvano et al., 2020[110]). AI-powered AP can sustain collusion by facilitating the monitoring of competitors and the implementation of parallel pricing practices as well as by lowering the cost of signaling for cartel members (OECD, 2017[107]).

Under certain conditions, such algorithms may have a comparative advantage over humans in solving coordination issues inherent to collusive behaviour (such as agreement on collusion desired outcomes and punishment mechanisms in case of breaches), though views differ on this (Schwalbe, 2018[114]).[48] Indeed, experimental evidence suggests that tacit collusive outcomes resulting from interactions between AP systems based on machine learning can be quite robust (Calvano et al., 2020[110]; Klein, 2021[115]), even though the extent of supracompetitive pricing still depends on a number of factors, including market structure, algorithm design and heterogeneity in algorithms used by market players (Sanchez-Cartas and Katsamakas, 2022[116]).[49] The little empirical evidence currently available on pricing outcomes under AP, which focuses mostly on markets with many players, provides conflicting results (Musolff, 2022[117]; Assad et al., 2020[118]).

All in all, the diffusion of AI-powered AP poses difficult challenges for policy makers and competition authorities not only because collusive outcomes (if any) are reached tacitly but also because they may have to be examined on a case-by-case basis since their likelihood depends on details such as the degree of heterogeneity of adopted algorithms, the type of algorithms used and the structure of markets. Moreover, the potential harm to consumers caused by higher than competitive prices has to be weighed against the possible benefits consumers may reap from AP, e.g., in terms of better service or product availability (Sanchez-Cartas and Katsamakas, 2022[116]), or cost reductions in sales departments reflected in prices, quicker reactions of firms to improved supply conditions and lower search costs as their willingness to pay is estimated more accurately.

AI governance arrangements, including prominently the establishment of cooperation among large AI developers, are generally deemed to be necessary to ensure that AI systems will develop in a welfare improving direction (G7, 2023[119]). Cooperation among developers can also be used to mitigate the broader societal risks (e.g., related to safety, security, privacy and unbiasedness) that could arise by unfettered development and use of AI systems.[50] Various forms of cooperation have been suggested (Brundage et al., 2020[120])– such as pooling research efforts on socially beneficial AI applications, exchange of information (e.g., about model advances and pitfalls, ways to debias model results, etc.), the setting of common standards (e.g., for internal auditing mechanisms or for ensuring interoperability) or even ways to prevent harmful technological race dynamics via an "Assist Clause" (OpenAI, 2018[121])and

[47] Indeed, aside from exceptional circumstances, tacit collusion generally falls outside the scope of competition laws.

[48] A related, but as yet little explored, issue is to what extent these comparative advantages also make it easier to collude even in markets that do not enjoy the typical conditions that are conducive to collusion: price transparency, homogeneous products and few market players (see OECD, 2017, for a discussion).

[49] Interestingly, other authors show that under fairly general conditions the use of AP in otherwise competitive markets leads to supracompetitive pricing even the absence of tacit collusion (Brown and MacKay, 2023[204]).

[50] For instance, Partnership on AI (PAI), which gathers virtually all the large players in the AI field (including all major developers), explicitly aims at cooperating "so developments in AI advance positive outcomes for people and society", notably by providing a forum for exchanging best practices and setting voluntary standards.

sharing excessive profits in case of extreme market concentration via a “Windfall Clause” (O’Keefe et al., 2020[122]).[51]

However, by allowing and promoting interactions among developers, these arrangements can also facilitate various forms of collusive outcomes, possibly leading to weaker market dynamism, less innovation incentives and lower aggregate productivity growth. For instance, evidence shows that the Assist Clause amounts to commitment from one firm to not compete with another, which may be in contrast with EU competition laws; similarly, various forms of exchanges between competing AI developers (such as mutual monitoring, advance notice of technological advances, etc.) could be used to share sensitive commercial information to enforce collusive agreements; and even standard setting could endanger competition to the extent that it can be used to foreclose competitors (Hua and Belfield, 2020[123]).

Innovation disincentives

While AI can be a powerful source of innovation that holds the potential to durably sustain growth, some features of this technology and the market context that it promotes can limit its innovative drive. Aghion et al. (2015) stressed that thriving competition and protection of intellectual property rights (IPR) are complementary drivers of innovation. As argued above, there are good reasons to expect that AI-driven market outcomes might be inherently characterised by rising market concentration and weak market contestability, which in itself could limit the innovative contribution of new firm entry and competitive pressures.

On the IPR side, the development and use of AI also raises several concerns. First, AI development requires pretraining AI models on massive amounts of data that can be partly found on the web, which are often covered by copyrights and whose use has generally not been authorised by right owners. As expert discussions and legal suits around the concept of AI “fair use” suggest,[52] the legal status of the data used to train AI models is still an unsettled issue and judicial developments concerning copyrights issues could have important repercussions on the type of data barriers faced by AI model developers, providing more or less importance to proprietary data. While it is still unclear whether such pre-training use actually infringes copyrights,[53] it risks lowering incentives for creators and inventors in a range of industries. Research on possible copyrights regimes that might preserve at the same time the welfare benefits of AI development as well as business or innovation incentives for both AI developers and content providers is still scant.[54]

Second, it is yet unclear how possible creations or inventions generated autonomously by AI will be protected (if at all) by IPR. The current approach in major patenting offices is to reject attribution of patents or copyrights to the AI systems that generated them (OECD, 2023[124]). This could discourage either the design of AI for innovative purposes or the licensing of discoveries, limiting AI-driven innovation and the

[51] OpenAI’s “Assist Clause” aims at preventing technological races that could privilege the acquisition of competitive edge over the search for adequate safety precautions: developers would commit to pause their own research and turn to assisting research of any developer that made significant frontier advances towards Artificial General Intelligence (AGI). In the same (but more extreme) spirit a letter undersigned by several AI stakeholders and experts in 2023 proposed to completely pause AI development for six months.

[52] Fair use is a legal principle that allows the use of copyrighted material in certain limited cases without fee or even credit. Recently, the New York Times has sued Microsoft for the alleged infringement of copyrights related to the use of millions of NYT articles for training ChatGPT, claiming that this does not fall under the “fair use” limits.

[53] For instance, OECD work argues that such use might not infringe US laws as long as the AI output is sufficiently different from the copyrighted material on which it was trained (OECD, 2023[33]).

[54] Some scholars argue that an “ex post fair use” regime for large AI models, in which pretraining on copyrighted data is allowed but content providers preserve the right to ask for compensation if they can demonstrate significant commercial damage, could achieve these twin purposes (Gans, 2024[186]).

related knowledge spillovers on the economy. Finally, the use of AI systems could also facilitate the reverse engineering of innovative products and technologies (Aghion, Jones and Jones, 2018[73]). While this could help diffusing frontier knowledge through imitation, it could also discourage innovation due to excessive expropriation of innovators via increased competition. [55]

4.3.3. Upside risks from AI diffusion on competition and market dynamism

Characteristics of AI do not necessarily all entail “downside” risks to competition. A number of “upside risks” may be at work as well with the spread of AI, although they are generally less widely discussed (a very recent brief overview is provided by (Council of Economic Advisers, 2024[8])). For instance, AI may boost productivity-enhancing competitive pressures and innovation via market disruptions by new entrants, for example if they rely to a greater extent on open-source rather than proprietary models. As already mentioned, open-source models are developing fast and may represent soon valid alternatives to commercial models, which would strengthen competition in AI markets. AI models may also improve technologically in the sense of limiting the dependence on scaling laws (e.g., if models are made more parsimonious) and big data (e.g., if pre-training becomes possible on “synthetic” datasets). Finally, and most directly relevant for aggregate productivity, AI may boost knowledge spillovers across the economy and as such help with the catch-up of productivity laggards. Early evidence on the performance-equalising effect of Generative AI in some tasks (see Sections 3 and 5.1) points into this direction.

5. Key challenges and opportunities related to inequality and inclusion

While AI has the potential to significantly raise overall productivity and result in stronger economic growth, such an outcome would not necessarily result in shared prosperity. Indeed, over the past four decades, automation and the resulting increase in productivity – which have moderated recently – have coincided with a decline in the labour share of income, increases in inequality and a polarisation of income distributions within countries across the world (Karabarbounis, 2023[125]; Acemoglu and Loebbing, 2022[126]; OECD, 2019[127]; Autor, Levy and Murnane, 2003[128]).

The ultimate distributional effects of AI will depend on a series of factors. These include (i) the extent to which AI will substitute or complement labour at different points of the income distribution and the resulting effects on wages, (ii) the effect on the level of overall employment, (iii) AI’s potential to improve economic mobility through improvements in education or access to credit, (iv) AI’s effects on market concentration, and (v) whether AI exacerbates the decline in labour’s share of income.

5.1. Inequality in the labour market

AI will affect workers differently depending on their occupational exposure to the technology and the extent to which it will automate or augment their work. The extent and nature of the exposure to AI in different occupations could in turn determine its effects on labour demand and wages. In the case of industrial robots, for example, (Acemoglu and Restrepo, 2020[129]) find negative effects on wages in the occupations most exposed to robotisation. For a given occupation, higher potential for automation by AI is likely to have a negative effect on wages and labour demand, while augmentation may have the opposite effects.

While in the past automation has replaced routine tasks, Generative AI can now perform tasks requiring creativity, oral and written comprehension, and inductive reasoning. Occupations involving high-stakes decisions such as doctors or judges are more likely to be augmented by AI than fully automated (see Section 4.2.2, and Figure 10). Higher-skilled occupations including business professionals, managers,

[55] (Council of Economic Advisers, 2024[8]) also cautions that AI’s anticompetitive effects may materialise not only through price outcomes but also via dampening longer-run innovation and product quality.

science and engineering professionals and legal, social, and cultural professionals are also more exposed (Eloundou et al., 2023[130]) (OECD, 2023[57]).[56] Forthcoming OECD research on exposure by socio-demographic characteristics also suggests that university-educated male, prime-age and native-born workers are among the most exposed to AI (Lane, 2024[131]). Importantly, these initial findings are likely to change because, as AI technology evolves (which has been occurring at a rapid pace), it will likely be able to perform an increasing number of tasks. For example, the coupling of ever more sophisticated robotics technology with AI could result in the technology being able to perform a growing number of physical tasks as well. However, at this stage, initial evidence also suggests that full automation of complete occupations is not yet an immediate risk, especially if the jobs themselves are being redesigned to take advantage of AI capabilities. As stressed by (Brynjolfsson and McAfee, 2014[132]): "AI won't replace managers, but managers who use AI will replace managers who don't use AI".

The few studies that have evaluated the productivity impact of Generative AI suggest that lower-skilled or less-experienced workers receive a stronger productivity boost from AI use than more experienced workers, which could lead to a compression of the income distribution. For example, access to an AI-based conversational tool has been found to increase the productivity of novice or low-skilled customer support agents by 34%, while the impact on more experienced or highly-skilled workers was minimal (Brynjolfsson, Li and Raymond, 2023[50]). Inequality between workers that were assigned professional writing tasks decreased after randomly exposing half of them to ChatGPT, with increases in average productivity and output quality (Noy and Zhang, 2023[52]). Interestingly, both these studies also found that job satisfaction rose after exposure to Generative AI tools. Other studies found similar results among software developers (Peng et al., 2023[51]) and consultants (Dell'Acqua et al., 2023[53]). These results provide evidence of an equalising effect of Generative AI within specific occupations, but such equalising effects may not apply *across* occupations. For instance, using an online experiment with a representative sample of the UK working-age population, (Haslberger, Gingrich and Bhatia, 2023[54]) have shown that while ChatGPT reduced performance inequality *within* occupations, it did not do so *across* occupations or levels of education (Haslberger, Gingrich and Bhatia, 2023[54]). This finding is consistent with forthcoming OECD research suggesting that while AI has not yet affected wage inequality between occupations, it is associated with lower wage inequality within occupations (Georgieff, forthcoming[133]).

The potential for widening inequalities in the aggregate economy as opposed to an equalising effect within occupations is also reflected in studies evaluating the effects of AI (mostly non-Generative, at this point) using machine learning methods. For example, a study documenting the dramatic increase in demand for AI skills (based on the presence in job postings of words associated with knowledge of AI) finds large wage premiums for jobs that require AI skills, with managerial occupations benefiting from the highest wage premiums (Alekseeva et al., 2020[134]), although the proportion of jobs requiring AI skills still remains low overall. (Felten, Raj and Seamans, 2019[135]) also find a stronger positive effect of AI exposure for higher-income occupations, while (Fossen and Sorgner, 2022[136]) find that the link between AI exposure and employment stability is strongest for more educated workers. To the extent that AI widens or narrows performance gaps across firms, this will also have an impact on cross-firm wage inequality, given the strong relationship identified between the two phenomena (Criscuolo et al., 2020[137]). Finally, a cross-country study using aggregate AI investment and income inequality found that investment in AI is

[56] Some recent country-specific analysis in the US confirm that most exposed occupations are not only high skill but also high income ones, even if also mid and low income occupations report high exposure, so that the forecasted net effect on inequality is unclear (Council of Economic Advisers, 2024[8]). A French study also shows that AI can raise employment, on average (complementarity effect), in firms adopting AI but can have negative effects on mid- and low skill professions (Artificial Intelligence Commission of France, 2024[184]).

associated with higher overall income inequality over the 2010-2019 period (Cornelli, Frost and Mishra, 2023[138]).[57] .

An important question when considering the impact of AI on inequality is its ultimate effect on overall employment, given that unemployment is a major contributor to income inequality (see for example (Hacibedel et al., 2020[139]). Dramatic increases in productivity and widespread automation could lead to mass unemployment unless demand rises sufficiently in response to lower prices and higher product quality of the output of AI-exposed activities (Bessen, 2018[140]). Demand may also grow in other, less AI-exposed and human labour intensive activities on the back of rising incomes (see Baumol's disease in Section 4.1). Yet another potential way in which employment may be preserved or increased is the possible creation of new tasks, as has been the case with past technological advances (Acemoglu and Restrepo, 2018[141]; Autor et al., 2022[142]) (Autor, 2024[69]). For example, while the car industry experienced widespread automation starting in the 1910s, the new production methods also introduced a wide range of new design, technical, machine-operation and clerical tasks, leading to higher demand for workers (Acemoglu and Johnson, 2023[102]). A study predating Generative AI suggests that firms adopting AI technologies changed their mix of job skill requirements in jobs not requiring AI technical skills, suggesting an impact of AI adoption on non-AI tasks and ambiguous aggregate employment effects given the technologies limited use so far (Acemoglu et al., 2022[143]).

AI also has the potential to exacerbate a secular trend in the distribution of income between labour and capital. The labour share of income has steadily declined in the United States and most OECD countries, with the headline estimate for the world declining around 6 percentage points between 1980 and 2022, and studies have suggested this was in large part due to technology (Karabarbounis, 2023[125]). AI-driven automation may continue this trend, raising the share of income earned by capital, and, to the extent that capital ownership is concentrated, leading to higher income and wealth inequality as dividends and interest income accrue to owners of capital (Trammell and Korinek, 2023[144]; Piketty, 2014[145]). The potential for an increasing concentration of AI resources (data, hardware and talent, as discussed in the previous sections) could exacerbate these effects on wealth inequality as AI capital becomes increasingly held by a few firms and shareholders. Stronger concentration of resources could also result in widening regional disparities given that AI hubs tend to be geographically concentrated (Muro and Liu, 2021[146]). Finally, if the capital share of income rises further, the erosion of the tax base may become more important, as the effective tax rate on capital has steadily declined in high-income countries (Zucman et al., 2022[147]).

5.2. AI's impact on economic mobility

AI has the potential to improve educational outcomes and advance human learning by helping personalise teaching and training, raising the quality of teaching, and democratising knowledge (Baker, 2021[148]). Given the importance of the quality of education for economic mobility and its impact on future earnings (Chetty, Friedman and Rocko, 2014[149]; Autor, Goldin and Katz, 2020[150]), the rising use of AI in education and training could reduce disparities in economic outcomes and compress the income distribution. However, widespread and affordable access to AI will be necessary for such an outcome to occur, and there are risks that AI may also decrease the inclusiveness of learning systems if appropriate safeguards are not put in place (OECD, 2023[57]).

As reported in the PISA 2022 report (OECD, 2023[124]), socio-economically disadvantaged students are significantly less likely to achieve basic proficiency in mathematics, science and reading. This gap could widen if socio-economically disadvantaged students benefit less from AI due to the lack of digital skills or resources. Socio-economically disadvantaged schools are more likely than advantaged schools to suffer from shortages in material resources, including digital resources (OECD, 2023[124]), with 17% of the

[57] This may not be a causal relationship and could be driven by confounding factors that impact both outcomes and which are challenging to control for in a macroeconomic setting.

variation in student performance accounted for by differences in access to digital resources. An additional concern is that future heavy reliance on AI could prevent students from developing cognitive abilities and the capacity for critical thinking. While it is still too early to find evidence of such an effect, such a risk could inform decisions on educational curricula and modes of teaching.

By augmenting their abilities, AI can help workers perform tasks requiring higher levels of expertise, raising their earnings and improving economic mobility. On the other hand, if it were to replace entire occupations or large segments of entry-level occupations (see again (Brynjolfsson, Li and Raymond, 2023[6])), AI could have the effect of "removing rungs from the professional ladder", negatively impacting mobility.

AI also has the potential to expand access to credit, thereby increasing upward mobility and reducing income inequality (Delis, Fringuellotti and Ongena, 2023[151]). Studies suggest that automated underwriting can lead to higher borrower approval rates, particularly for underserved applicants (Gates, Perry and Zorn, 2002[152]), and that advances in digital financial technology and machine learning can reduce the cost of credit, boost productivity of downstream sectors (Bontadini et al., 2024[153]) and increase financial inclusion (Bazarbash, 2019[154]; Boukherouaa et al., 2021[155]). The potential for expanded access to credit also comes with new challenges, however, including risks of bias and discrimination, data and privacy risks, and the potential for increased volatility and systemic risks in financial markets (Gensler, 2023[156]) (OECD, 2023[63]). For instance, AI-based credit scoring models were found to be 5-10% less accurate for lower income and minority households (Blattner and Nelson, 2021[157]).

5.3. AI and the inclusiveness of disadvantaged groups

AI has the potential to improve the inclusiveness of disadvantaged groups in the labour market and thus partially offset rising demographic challenges due to declining working age populations (Andre, Gal and Schief, 2024[92]), but it also poses risks (OECD, 2023[57]). In an OECD survey conducted in 2022 (before breakthroughs in Generative AI), employers in the manufacturing and finance sectors responded that workers with disabilities are more likely to be helped by AI, while older and lower-skilled workers are more likely to be harmed by it (Lane, Williams and Broecke, 2023[56]). AI could further widen gender inequalities if its benefits are larger in occupations in which men are over-represented, or if existing biases are engrained in AI-assisted hiring processes. In the same survey, men who had used AI at work were more likely than women to respond that it improved their productivity or their working conditions. Further evidence on gender gaps in AI talent – in research, development and use alike – also point to large disparities (Caira et al., 2023[158]).

Assistive AI-powered technologies such as vision-to-language tools and auto-captioning already make work environments more accessible and inclusive for people with disabilities (OECD, 2022[159]; Touzet, 2023[160]), and these technologies will continue improving. AI also has the potential to greatly improve rehabilitation, with large implications for the labour force. Indeed, people with disability represent about 18% of the working age population, while their employment rate is 27 percentage points lower than for people without disability, and they are more than twice as likely to be unemployed than non-disabled people.[58]

However, for the integration of people with disabilities into the labour market to be widely improved, access to AI-powered technologies and the ability to benefit from them must be widespread. Across the OECD, people with disabilities are more likely to lack the prerequisites to use most assistive technologies, such as digital skills or access to digital technology and a stable and fast internet connection, which could limit the extent to which they benefit from AI and further widen disparities. AI technologies may also be less

[58] Data on disability share are for aged 15-69, on average across the OECD and between 2016 and 2019. Data on employment rates are from 2019.

adapted to certain socio-economic groups due to the nature of the training data, which may not properly reflect their experiences, or because AI applications are not designed with their needs and abilities in mind.

AI may also have implications for gender and minority groups discriminations. While commercial use of AI-assisted facial recognition algorithms and AI-assisted recruitment procedures can benefit companies, job-seekers and consumers, they also involve ethical issues and high risks of discrimination that could have consequences for the economic inclusion of disadvantaged groups, including women and minorities (especially people of colour) (Buolamwini, 2023[161]) (Ramos, Squicciarini and Lamm, 2024[162]). For instance, facial recognition algorithms have been shown higher rates of failures for non-white individuals (Buolamwini and Raji, 2019[163]) and image-generating AI have been shown to amplify societal stereotypes on women and minorities (Luccioni et al., 2023[164]; Nicoletti and Bass, 2023[165]). Similarly, AI-assisted recruitment procedures have proved vulnerable to "algorithmic statistical discrimination" (Jackson, 2021[166]; Chen, 2023[167]) against minorities due to inaccuracies in the design of the algorithms or the nature of the datasets on which the AI models are trained. Finally, use of AI screening systems in the provision of financial services (e.g., credit) could also generate or aggravate biases and discriminations (OECD, 2021[168]). These pitfalls of AI systems point to the need to require transparency in their use, to submit them to various forms of internal and external auditing before their real-world application and to continuously monitor their performance in order to avoid unintended negative effects on inclusion.[59]

5.4. AI's impact across countries

There are concerns that AI technologies may have different impacts across countries and have the potential to widen cross-country differences in GDP per capita. On the one hand, there are the direct benefits of national technology development, which are cause for concern given that AI development is heavily concentrated in a few countries, such as the United States and China. This is exemplified, for instance, by the large disparities in the size of cumulative venture capital investments in AI, totalling nearly USD 450 billion in the United States, less than half of that in China, and only around USD 50 billion in the EU (OECD.AI, 2024).[60] On the other hand, to the extent that AI will be a labour- and resource-saving technology, this may devalue the comparative advantage of developing countries and worsen their terms of trade (Korinek, Schindler and Stiglitz, 2021[169]). This phenomenon is developed in a theoretical model by (Alonso et al., 2020[170]), which suggests that higher wages in advanced countries lead to a greater adoption of higher-productivity "robots" or AI. The resulting higher productivity in turn pulls capital from developing to developed countries. As AI replaces unskilled workers, their wages decline and goods and services are produced more cheaply, leading to worsening terms of trade for developing countries.

Relatedly, differences in the extent and nature of labour market exposure to AI across countries will entail different impacts of AI. Studies evaluating the occupational structure of labour markets in advanced economies (including the UK and the US) and emerging markets (including Brazil, Colombia, India and South Africa) find that while the advanced economies exhibit a higher exposure to AI given their higher share of employment in high-skilled jobs that are highly exposed to AI, exposed workers in advanced economies are more likely to be complemented rather than replaced by AI (Cazzaniga et al., 2024[80]). The emerging markets in the study are less exposed to AI, but they also have a smaller proportion of workers with the potential for complementarity. Due to these differences, AI may deliver stronger and more imminent productivity growth in developed rather than developing countries, but labour market disruptions are also likely to be larger.

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[59] These issues have spurred a strand of research on the ethics of AI-based or AI-assisted recruitment (Mujtaba and Mahapatra, 2019[205]; Hunkenschroer and Luetge, 2022[206]).

[60] https://oecd.ai/en/data?selectedArea=investments-in-ai-and-data&selectedVisualization=vc-investments-in-ai-by-country

The adoption of AI technologies may also differ greatly across the world for other reasons, leading to further differences in its impacts. As mentioned above, lower wages in developing countries may reduce the incentives for adopting AI to automate certain tasks, which could slow adoption. More fundamentally, prerequisites for AI adoption such as digital infrastructure (including data storage and computing power (hardware), stable internet connections, digital skills, literacy and numeracy, and general familiarity with data and algorithms may be less prevalent in developing countries, thereby limiting adoption (Björkegren and Blumenstock, 2023[171]). Differences in adoption rates across countries could mean that the productivity benefits of AI will be unequal across countries.

Another reason for which AI may have a different impact across countries is that AI technologies, which are predominantly developed by companies in advanced countries largely using training data from a developed-country context, may not fit the social and institutional context in other countries (Björkegren and Blumenstock, 2023[171]). A straightforward example is that large language models perform better in English, in part due to the large amount of available relevant data, than in other languages for which a smaller corpus of digitised text exists and that may have a very different linguistic structure compared to English (Lai et al., 2023[172]). AI technologies may be less applicable, and their benefits may be smaller in developing countries given the relative lack of training data and the fact that AI developers may not consider applications beyond their own societal and economic context. This effect could be exacerbated by the risks of elevated concentration in the AI service provider market described in section 4.3, with the potential for the market dominance of a few companies in selected developed countries.

Finally, improvements in AI-powered technologies such as instant translation raise the potential for "telemigration" (Baldwin, 2020[173]), allowing more workers in developing countries to work for companies based in higher-income countries despite not speaking the language, for example. While this provides more opportunities for workers in lower-income countries, it could also affect labour markets in higher-income countries where such services "off-shoring" will occur extensively. Nevertheless, results of gravity models suggest that the benefits of telemigration are unlikely to be transformative when it comes to the development paths of most emerging economies (Baldwin and Dingel, 2021[174]).

6. Economic challenges as a result of broader societal risks

Previous sections highlighted several key benefits but also challenges and risks from AI with potentially strong economic repercussions. This contrast is also reflected in the perception of AI by the general public: according to an OECD survey, 35% of adults reported being concerned that AI would primarily harm people in the next two decades, while 42% believed it would primarily benefit people (OECD, 2023[175]). Most widely cited challenges include: concerns related to privacy, misinformation and reaching singularity or AGI, along with the associated existential risks.[61]

First, in many applications, AI relies on a collection, and possibly, a combination, of various data sources. These can lead to – or perceived to be linked to – an increased risk of intrusion to privacy in various fields, such as medical diagnosis, workplace surveillance, public sector applications (Dougherty, 2024[176]) and so on.

Second, the widespread use of AI generated content, and AI assisted decisions provided by an un-safe – that is, either not trustworthy, or biased, or outright malignant – AI can further contribute to misinformation in several domains. If AI generated content is not reliable – as is sometimes the case notably with LLMs given their tendency to "hallucinate" (Lorenz, Perset and Berryhill, 2023[15]) (Perez-Cruz and Shin, 2024[78]) (OECD, 2023[79]) – this makes information collecting and processing ultimately more noisy and costly, negatively impacting knowledge accumulation and sharing in science and research (producing fake studies

[61] Ongoing work by the OECD expert group on AI Futures as well as a forthcoming chapter of the OECD Digital Economy Outlook discuss these ares in more detail.

with fabricated results, see Figure A.4). This may also impact the reliability of marketing information about products and services, and more generally, the nature of public discourse about actual events and news. More generally, an AI-powered further proliferation of distorted information can undermine democracy. These features may exacerbate existing challenges related to the practices of large digital platforms underlying marketplaces and social media. Moreover, as AI generated information gets picked up in the training of the next generation of AI models, such distortions can accumulate over time and make them even more problematic. Distortions in the datasets used for AI training can also have serious repercussions on economic discrimination of disadvantaged social groups (see section 5.3).

Third, a probably longer-term challenge stems from reaching a level of AI that surpasses human capabilities, including the possibility for radical self-improvement (Nordhaus, 2021[177]) (Jones, 2023[39]). Such advanced capabilities may form a technological singularity[62] and could eventually lead to a runaway technological process that humans cannot control or contain. At that point, the alignment problem – whether the ultimate goals of AI are beneficial for humanity – becomes critical (Bostrom, 2014[178]). A very capable AI, that is able to channel resources to its needs but that is not well aligned with the initial goals can lead to existential risks for humanity and may justify slowing down or tightly regulating its development (Jones, 2023[39]; Suleyman and Bhaskar, 2023[179]).

A less threatening but still extreme outcome could be that all – or nearly all – occupations become fully automated and taken over by AI, rendering human labour obsolete and dispensable in economic terms thus leading to mass unemployment (Acemoglu and Lensman, 2023[38]). Even if large-scale redistribution could sustain adequate income levels – despite difficulties in achieving it in a global context –, or an AI powered bounty of freely available services and goods may make incomes unnecessary, such an eventual outcome would still pose enormous challenges during the transition towards such a state.

These risks, directly or indirectly, can also limit AI's economic benefits and welfare gains through various means, such as promoting backlashes which can result in efforts to hold back AI development and adoption even for beneficial uses To address this wide range of looming risks, the impact of AI development and use on these aspects require close monitoring, even from a purely economic standpoint, let alone for broader societal reasons.

7. Policy discussion

The recent rapid evolution of AI and its potential consequences discussed in this paper have spurred a debate on the appropriate policy responses among academics, civil society, and policymakers across the world (Autor et al., 2022[142]; Korinek and Stiglitz, 2021[180]; Lorenz, Perset and Berryhill, 2023[181]; Acemoglu and Johnson, 2023[182]) (Coyle, 2023[183]) (Artificial Intelligence Commission of France, 2024[184]) (Council of Economic Advisers, 2024[8]). The OECD has been at the forefront of shaping the policy discussions around technical, legal and regulatory challenges led in particular by the OECD Policy Observatory (OECD.AI). It culminated in the creation and wide acceptance of the OECD AI Principles (OECD, 2019[1]) adhered to by 46 countries and continuously monitored in the Policy Observatory. They include, as values based principles, i) inclusive growth, sustainable development and wellbeing, ii) human-centred values and fairness, iii) transparency and explicability, iv) robustness, security and safety, and v) accountability; as well as the following recommendations for policy makers: i) investing in AI R&D, ii) fostering a digital ecosystem, iii) shaping and enabling policy environment, iv) building human capacity and preparing for labour market transformation, v) international co-operation for trustworthy AI (see more details in Table A.1).[63]

[62] See definition in footnote 9.

[63] See also https://oecd.ai/en/dashboards/ai-principles/P12

Building on these efforts, further steps are needed to continue the global dialogue and forge a consensus on how to address many of the remaining most important challenges related to AI development and use. This debate is complicated by the rapid pace of the technology's development and the extreme uncertainty over the future capabilities of AI and its implications, highlighting the relevance of developing and promptly updating guiding principles for policy in light of further breakthroughs. Another challenge relates to the possibility that individual countries will not be able to control the global evolution of AI-related technologies, pointing to the need for international cooperation and agreement on these principles.

Since the adoption of the AI Principles, and also informed by them, notable recent progress has been made in this area, including through the Hiroshima AI Process. In that context, G7 leaders agreed on guiding principles and a code of conduct for developing AI systems, in cooperation with the OECD and the Global Partnership for Artificial Intelligence (GPAI). The aims of this Process are "to foster an open and enabling environment where safe, secure, and trustworthy AI systems are designed, developed, deployed, and used to maximise the benefits of the technology while mitigating its risks, for the common good worldwide, including in developing and emerging economies with a view to closing digital divides and achieving digital inclusion."

While an exhaustive discussion of how economic policymakers should respond to AI is beyond the scope of this paper, some areas emerge as priorities from the overview presented here. To ensure the full economic benefits of AI, it is essential to prioritize measures that guarantee market competition and enhance widespread availability of AI technologies. An additional set of policies is crucial to secure equitable and enduring benefits from AI. These policies should centre on addressing the impact of AI on inequality, therefore emphasizing redistributive and educational aspects, as well as developing strategies to adapt to the potentially unpredictable advancements in AI capabilities. Policies can also be distinguished along their *ex ante* or *ex post* nature: the first regards policies to be adopted *ex-ante* for steering research and development in AI and related technologies to maximise their benefits and limit their economic and societal risks (Section 7.1); the second relates to policies aimed at addressing the effects of AI *ex-post* (Section 7.2). (Comunale and Manera, 2024[185]) provide a recent overview of existing AI-related regulations across a range of countries.

7.1. Steering the evolution of AI

The existential risks posed by the development of AGI (Bostrom, 2014[178]) have led some to argue for slowing down its progress. (Jones, 2023[39]) states that self-regulation by a socially-minded entity is unlikely to limit existential risks due to the presence of other for-profit firms, which raises the importance of government policies and global cooperation (Gans, 2024[186]; Suleyman and Bhaskar, 2023[179]). Policies to promote the accountability of AI systems include establishing auditing processes, ethics frameworks, and other regulations (OECD, 2023[124]), as well as policies that make for-profit firms internalise externalities such as product liability laws (Gans, 2024[186]).

More recently, (Sastry et al., 2024[7]) have suggested that an effective way to steer the development and deployment of AI towards socially desirable outcomes is to focus governance efforts on the computing power ("compute") element of AI inputs (see Figure 1 in Section 2) due to its better detectability, excludability and supply traceability relative to other inputs (software, data and skills). They argue that governing computing power could facilitate regulatory visibility of AI, the allocation of AI resources to beneficial uses, and the enforcement of restrictions against irresponsible or malicious AI development and usage.[64] As pointed out by the OECD AI group of experts on AI Futures, the OECD is playing an important role in providing key information and consensus guidelines for steering AI development and deployment –

[64] (Sastry et al., 2024[7]) point out that domestic and international governance of AI computing power ("compute") is already happening in various forms (e.g., via direct investment, subsidisation and export controls). They suggest a framework for steering such governance in ways that minimizes market distortions and maximizes social benefits.

including by monitoring AI compute, reporting AI incidents and helping developing good practices and standards (OECD, 2022[3]).

To limit the risks of increasing inequality, innovation and research could be steered toward more labour-augmenting as opposed to automating AI and related technologies, for example by shifting the relative tax burdens on labour and capital or by increasing government funding for research and development in such technologies (Acemoglu and Johnson, 2023[182]; Korinek, Schindler and Stiglitz, 2021[169]). Using these tools, AI research could be steered toward technologies that create new occupational tasks, complement worker skills and expertise, or that allow for better training or re-training of workers (Acemoglu, Autor and Johnson, 2023[187]; Autor, 2024[69]). Given that appropriate skills reduce the risk of automation and are a pre-requisite for technology adoption, governments should aim to ensure that the workforce is equipped with sufficiently complementary skills to AI via updating and redesigning training and education (Artificial Intelligence Commission of France, 2024[184]). These policies can also favour an effective labour reallocation. Fostering dialogue among the social partners – representing workers and employers – is also crucial to ensure the widespread acceptance of AI and guarding against potential AI misuse that could infringe upon workers' rights.

There is also the possibility to steer AI development in ways that encourage market competition and promote innovation (Council of Economic Advisers, 2024[8]). For example, policies can support open-source ecosystems in order to allow firms of all sizes to develop AI technologies (Brynjolfsson and Unger, 2023[188]) and improve access to finance – potentially from public sources – for AI development (Artificial Intelligence Commission of France, 2024[184]). Additionally, promoting access to training data and system interoperability should be pursued, including via the harmonization of currently heterogeneous international regulations. Currently, the OECD is collaborating with governments and different stakeholders involved in the AI value chain to develop a set of guidelines to enhance interoperability and AI risk management (OECD, 2023[189]). Governments should also consider the ex-ante regulation of certain types of algorithmic pricing.[65] More generally, competition laws and regulatory tools will need to be enforced to prevent anticompetitive mergers and abuses of market power, which could limit AI development to a few selected superstar firms. The innovative potential of AI could also be promoted by reforming intellectual property rights laws to minimise the disincentives to innovation which involves training on IPR protected data.[66] Finally, AI tools can be used by competition authorities to detect and monitor anti-competitive practices.

Policies and regulations should also address other risks posed by AI such as bias, misinformation, consumer manipulation, and issues around privacy. Policies can enhance the transparency of AI model functioning by forcing AI developers to put extra efforts in understanding and stress-testing complex models, eliminate bias from the datasets used to train them, discouraging ad targeting by taxing digital ads, or prohibiting certain forms of price discrimination. Establishing internal auditing standards at the industry level and imposing external auditing (including possibly by public agencies) before full commercialization would seem to be also useful policy tools to consider.

7.2. Addressing the ex-post effects of AI

While the policies discussed above could be used to steer AI development toward more desirable capabilities, another set of policies are also needed to address further undesirable effects such as rising inequality and joblessness or increasing market concentration.

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[65] For instance, some have suggested restricting what actually goes on in the algorithms, such as prohibiting to condition price changes on the past history of a firm prices or on competitors' prices (Klein, 2021[115]).

[66] An example would be to apply an ex post fair use principle to copyrighted material used to train large AI models (Gans, 2024[186]), especially for new entrants.

AI, like most technologies, will create winners and losers. Workers may be impacted differently depending on their skills, experience, occupation, industry, whether they have disabilities or whether AI can automate or augment their tasks. Redistributive policies can help compensate workers that are more negatively impacted by AI, but this may require changes in taxation policies to ensure more progressive taxation, and a shift of taxation from labour towards other factors and rents generated by market power (Korinek, Schindler and Stiglitz, 2021[169]). This may also be harder to achieve in developing countries, where fiscal capacity is lower and where fewer benefits from AI may materialise. Social safety nets can also be reformed to cushion the potential disruptive effects of AI on labour markets. Possible policies include reforming unemployment insurance or increasing public funding for retraining policies.

More and better public spending on investments in education, training or physical and digital infrastructure could also provide broader positive social returns and address some of the concerns relating to access to AI and the potential to be complemented rather replaced by it (Artificial Intelligence Commission of France, 2024[184]). They can also provide additional demand for unskilled labour that may suffer from displacement from AI (Korinek, Schindler and Stiglitz, 2021[169]).

More broadly, existing arrangements that discourage labour mobility, such as employee non-compete agreements, could be prohibited, limited or more closely scrutinized by public authorities in order to facilitate worker transitions to new jobs and locations and limit potential labour market bottlenecks (Bessen et al., 2020[190]). For instance, such clauses have recently come under the review of competition authorities in the US (FTC, 2023[191]), the UK (CMA, 2024[192]) and other OECD countries.[67]

7.3. Adapting policy and governance to the fast pace of AI innovation

Finally, and most crucially, the development of comprehensive policy frameworks is an urgent necessity, as stressed by the OECD AI Principles. While policymakers and international organisations such as the OECD are making concerted efforts to follow the swift and often unpredictable advancements in the technology, both domestically and internationally, the current state of international policy coordination suggests it is challenging to keep the pace in this critical race. The G7 Hiroshima Process on AI exemplifies attempts at fostering deeper international cooperation. Such efforts are vital to ensure that AI technology promotes significant aggregate productivity growth and welfare gains while adhering to the guiding principles set forth by the OECD.

The unpredictable nature of AI development necessitates governance frameworks that can quickly adapt to changing circumstances. Adopting a "portfolio approach" to planning – anticipating a spectrum of scenarios from "business as usual" to the potential emergence of AGI – is crucial for developing adaptable contingency plans (Korinek and Su, 2023[193]). This strategy represents a critical area where organizations like the OECD can offer increased support and guidance. Given the rapid advancements in AI, the importance of establishing agile policy mechanisms that can effectively respond to and capitalize on these changes cannot be overstated. Without significant progress in this area, policy risks remaining significantly outpaced by technology, missing crucial opportunities to shape the development and impact of AI on society.

[67] Proposals to address the possible negative effects of such clauses currently range from a complete ban to limiting their duration, imposing mandatory worker compensations or increasing their transparency.

References

Acemoglu, D. et al. (2022), “Artificial Intelligence and Jobs: Evidence from Online Vacancies”, *Journal of Labor Economic*, Vol. 40/1. [143]

Acemoglu, D., D. Autor and S. Johnson (2023), *Can we Have Pro-Worker AI? Choosing a path of machines in service of minds,* MIT Shaping the Future of Work Initiative, Policy Memo.. [187]

Acemoglu, D. and S. Johnson (2023), *Power and Progress: Our Thousand-Year Struggle Over Technology and Prosperity*, PublicAffairs/Hachette Book Group, New York, NY. [102]

Acemoglu, D. and S. Johnson (2023), *Rebalancing AI*. IMF Finance & Development. [182]

Acemoglu, D. and T. Lensman (2023), “Regulating Transformative Technologies”, *National Bureau of Economic Research Working Papers* No. 31461. [38]

Acemoglu, D. and J. Loebbing (2022), “Automation and polarization”, *National Bureau of Economic Research Working Papers* No. 30528., https://doi.org/10.3386/w30528. [126]

Acemoglu, D., A. Malekian and A. Ozdaglar (2023b), “A model of behavioral manipulation”, *National Bureau of Economic Research Working Papers* No. 31872. [104]

Acemoglu, D. and P. Restrepo (2020), “Robots and Jobs: Evidence from US Labor Markets”, *Journal of Political Economy*, Vol. 128/6. [129]

Acemoglu, D. and P. Restrepo (2019), “Automation and New Tasks: How Technology Displaces and Reinstates Labor”, *Journal of Economic Perspectives*, Vol. 33/2, pp. 3-30. [101]

Acemoglu, D. and P. Restrepo (2018), “The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment”, *American Economic Review*, Vol. 108/6, pp. 1488–1542. [141]

Acemoglul, D. (2024), *The Simple Macreconomics of AI*. forthcoming [72]

Aghion, P., B. Jones and C. Jones (2018), “Artificial Intelligence and Economic Growth”, NBER Chapter in *The Economics of Artificial Intelligence: An Agenda*, p. 237-28 [73]

Agrawal, A., J. Gans and A. Goldfarb (2023), *Similarities and Differences in the Adoption of General Purpose Technologies*, NBER Chapters, in: *Technology, Productivity, and Economic Growth* [22]

Agrawal, A., J. Gans and A. Goldfarb (2023), "The Turing Transformation: Artificial intelligence, intelligence augmentation, and skill premiums". *National Bureau of Economic Research Working Papers* No. *31767.* [13]

Agrawal, A., J. Gans and A. Goldfarb (2019), "Economic Policy for Artificial Intelligence", *Innovation Policy and the Economy*, Vol. 19. [19]

Alderucci, D. et al. (2020), *Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata*, https://www.aeaweb.org/conference/2020/preliminary/paper/Tz2HdRna. [47]

Alekseeva, L. et al. (2020), "The Demand for AI Skills in the Labour Market", *CEPR Discussion Paper*, Vol. DP14320. [134]

Alonso, C. et al. (2020), "Will the AI revolution cause a great divergence?", *IMF Working Paper*, Vol. 20/104. [170]

Andre, C. and P. Gal (2024), "Reviving productivity growth: A review of policies", *OECD Economics Department Policy Paper, forthcoming*. [36]

Andre, C., P. Gal and M. Schief (2024), "Enhancing Productivity and Growth in an Ageing Society: Key Mechanisms and Policy Options", *OECD Economics Department Working Paper*, *forthcoming.* [92]

Anyoha, R. (2017), *The History of Artificial Intelligence. Science in the News*, https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/. [82]

Artificial Intelligence Commission of France (2024), *IA : Notre Ambition pour la France*, https://www.gouvernement.fr/actualite/25-recommandations-pour-lia-en-france. [184]

Assad, S. et al. (2020), *Algorithmic pricing and competition: Empirical evidence from the German retail gasoline market*. CESifo Working Paper No. 8521. [118]

Autor, D. (2024), "Applying AI to Rebuild Middle Class Jobs", *National Bureau of Economic Research Working Papers* No. *32140* [69]

Autor, D. et al. (2022), "New Frontiers: The Origins and Content of New Work, 1940–2018", *National Bureau of Economic Research Working Papers* No. 30389. [142]

Autor, D., C. Goldin and L. Katz (2020), "Extending the Race between Education and Technology", *AEA Papers and Proceedings*, Vol. 110, pp. 347–51. [150]

Autor, D., F. Levy and R. Murnane (2003), "The Skill Content of Recent Technological Change: An Empirical Exploration", *The Quarterly Journal of Economics*, Vol. 118/4, pp. 1279–1333. [128]

Babina, T. et al. (2024), "Artificial intelligence, firm growth, and product innovation", *Journal of Financial Economics*, Vol. 151/103745. [30]

Baily, M., E. Brynjolfsson and A. Korinek (2023), *Machines of mind: The case for an AI-powered productivity boom*. Brookings, https://www.brookings.edu/articles/machines-of-mind-the-case-for-an-ai-powered-productivity-boo [37]

Baker, R. (2021), "Artificial intelligence in education: Bringing it all together", in *OECD Digital Education Outlook 2021: Pushing the Frontiers with Artificial Intelligence, Blockchain and Robots*, OECD Publishing, Paris, https://doi.org/10.1787/f54ea644-en. [148]

Baldwin, R. (2020), *The Globotics Upheaval*, Oxford University Press. [173]

Baldwin, R. and J. Dingel (2021), “Telemigration and Development: on the Offshorability of Teleworkable Jobs”, *National Bureau of Economics Research Working Papers* No. 29387. [174]

BarclayHedge (2018), *BarclayHedge Survey: Majority of Hedge Fund Pros Use AI/Machine Learning in Investment Strategies*, https://www.barclayhedge.com/insider/barclayhedge-survey-majority-of-hedge-fund-pros-use-ai-machine-learning-in-investment-strategies. [62]

Barro, R. (1999), “Notes on Growth Accounting”, *Journal of Economic Growth*, Vol. 4, pp. 119–137. [201]

Baruffaldi, S. et al. (2020), “Identifying and measuring developments in artificial intelligence: Making the impossible possible”, *OECD Science, Technology and Industry Working Papers, No. 2020/05,* https://doi.org/10.1787/5f65ff7e-en. [83]

Basu, S. et al. (eds.) (2023), *Data, Intangible Capital, and Productivity*, University of Chicago Press. [70]

Bazarbash, M. (2019), “FinTech in Financial Inclusion: Machine Learning Applications in Assessing Credit Risk”, *IMF Working Paper*, Vol. WP/2019/109. [154]

Berryhill, J. et al. (2019), *Hello, World: Artificial intelligence and its use in the public sector*, http://oe.cd/helloworld. [64]

Bessen, J. (2018), “AI and Jobs: The Role of Demand”, *National Bureau of Economic Research Working Papers* No. 24235. [140]

Bessen, J. et al. (2020), *Automation: A guide for policymakers*. Brookings Economic Studies, January 2020. [190]

Bianchini, S., M. Müller and P. Pelletier (2022), “Artificial intelligence in science: An emerging general method of invention”, *Research Policy*, Vol. 51/10. [27]

Björkegren, D. and J. Blumenstock (2023), “Technology for Development”, *IMF Finance & Development*. [171]

Blattner, L. and S. Nelson (2021), “How Costly is Noise? Data and Disparities in Consumer Credit”, arXiv:2105.07554. [157]

Bloom, N. et al. (2020), “Are ideas getting harder to find?”, *American Economic Review*, Vol. 110/4, pp. 1104-1144. [26]

Bontadini, F. et al. (2024), *Digitalization of financial services, access to finance, and aggregate economic performance*. OECD Economics Department Working Papers, forthcoming. [153]

Borgonovi, F. et al. (2023), "Emerging trends in AI skill demand across 14 OECD countries", OECD Artificial Intelligence Papers, No. 2, OECD Publishing, Paris, https://doi.org/10.1787/7c691b9a-en. [94]

Bostrom, N. (2014), *Superintelligence: Paths, dangers, strategies*. Oxford University Press [178]

Boukherouaa, E. et al. (2021), “Powering the Digital Economy: Opportunities and Risks of Artificial Intelligence in Finance”, IMF Departmental Paper No 2021/024. [155]

Bresnahan, T. and M. Trajtenberg (1995), “General purpose technologies ‘Engines of growth’?”, *Journal of Econometrics*, Vol. 65, pp. 83-108. [17]

Brown, S. (2019), *The lure of "so-so technology," and how to avoid it*, https://mitsloan.mit.edu/ideas-made-to-matter/lure-so-so-technology-and-how-to-avoid-it. [203]

Brown, Z. and A. MacKay (2023), "Competition in pricing algorithms", *American Economic Journal: Microeconomics*, Vol. 15/2, pp. 109-156. [204]

Brundage, M. et al. (2020), *Toward trustworthy AI development: mechanisms for supporting verifiable claims*, arXiv:2004.07213. [120]

Brynjolfsson, E. (2022), "The Turing Trap: The Promise & Peril of Human-Like Artificial Intelligence", *Dædalus (2022) 151 (2): 272–287.* [196]

Brynjolfsson, E., D. Li and L. Raymond (2023), "Generative AI at Work", *National Bureau of Economic Research Working Papers* No. 31161. [6]

Brynjolfsson, E. and L. M. Hitt (2003), "Computing Productivity: Firm-Level Evidence", *The Review of Economics and Statistics*, Vol. 85/4, pp. 793–808,. [43]

Brynjolfsson, E. and A. McAfee (2014), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, W. W. Norton & Company. [132]

Brynjolfsson, E., D. Rock and C. Syverson (2021), "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies", *American Economic Journal: Macroeconomics*, Vol. 13/1, pp. 333-372, [68]

Brynjolfsson, E. and G. Unger (2023), *The Macroeconomics of AI*, IMF Finance & Development. [188]

Buolamwini, J. (2023), *Unmasking AI: My Mission to Protect What Is Human In a World of Machines*, Penguin Random House. [161]

Buolamwini, J. and I. Raji (2019), *Actionable Auditing: Investigating the Impact of Publicly Naming Biased Performance Results of Commercial AI Products*. MIT Media Lab. [163]

Caira, C. et al. (2023), "Artificially Inequitable? AI and closing the gender gap", *The AI Wonk*, https://oecd.ai/en/wonk/closing-the-gender-gap. [158]

Calo, R. (2013), "Digital market manipulation", *Geo. Wash. L. Rev.*, Vol. 82/995. [103]

Calvano, E. et al. (2020), "Artificial intelligence, algorithmic pricing, and collusion", *American Economic Review*, Vol. 110/10, pp. 3267-3297. [110]

Calvano, E. et al. (2023), *Artificial Intelligence, Algorithmic Recommendations and Competition*. http://dx.doi.org/10.2139/ssrn.4448010. [100]

Calvino, F. et al. (2023), *What technologies are at the core of AI? An exploration based on patent data*, OECD Artificial Intelligence Papers, No. 6, OECD Publishing, Paris. https://doi.org/10.1787/32406765-en. [34]

Calvino, F. and L. Fontanelli (2023), "A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity", *OECD Science, Technology and Industry Working Papers*, No. 2023/02, OECD Publishing, Paris, https://doi.org/10.1787/0fb79bb9-en. [45]

Calvino, F. and L. Fontanelli (2023), *Artificial intelligence, complementary assets and productivity: evidence from French firms*. LEM Working Paper Series 2023/35. [46]

Cazzaniga, M. et al. (2024), “Gen-AI: Artificial Intelligence and the Future of Work”, *IMF Staff Discussion Notes No. 2024/001* [80]

Chen, Z. (2023), “Ethics and discrimination in artificial intelligence-enabled recruitment practices”, *Humanities and Social Sciences Communications*, Vol. 10. [167]

Chetty, R., J. Friedman and J. Rocko (2014), “Measuring the Impact of Teachers II: The Long-Term Impacts of Teachers.”, *American Economic Review*, Vol. 104/9, pp. 2633-2679. [149]

CMA (2024), “Competition and market power in UK labour markets”, *Competition and Markets Authority*. [192]

CMA (2023), “IA Foundation Models Initial Report.”, *Competition and Markets Authority (CMA),*. [9]

Cockburn, I., R. Henderson and S. Stern (2018), *The impact of artificial intelligence on innovation: An exploratory analysis.*, University of Chicago Press. [20]

Comunale, M. and A. Manera (2024), “The Economic Impacts and the Regulation of AI: A Review of the Academic Literature and Policy Actions”, *IMF Working Papers*, Vol. 2024/065, p. 1, https://doi.org/10.5089/9798400268588.001. [185]

Cook, L. (2023), *Generative AI, Productivity, the Labor Market, and Choice Behavior*, https://www.federalreserve.gov/newsevents/speech/cook20230922a.htm. [208]

Cornelli, G., J. Frost and S. Mishra (2023), “Artificial intelligence, services globalisation and income inequality”, *BIS Working Papers*, Vol. 1135. [138]

Corrado, C. et al. (2021), *New evidence on intangibles, diffusion and productivity*. OECD Science, Technology and Industry Working Papers, No. 2021/10, OECD Publishing, Paris. [87]

Corrado, C., J. Haskel and C. Jona-Lasinio (2021), “Artificial intelligence and productivity: an intangible assets approach”, *Oxford Review of Economic Policy*, pp. 435-458. [11]

Costa, H. et al. (2021), “Welcome to the (digital) jungle: Measuring online platform diffusion”, *OECD Economics Department Working Papers*, No. 1683, OECD Publishing, Paris, https://doi.org/10.1787/b4e771d7-en. [97]

Council of Economic Advisers (2024), *Economic Report of the President*, https://www.whitehouse.gov/wp-content/uploads/2024/03/ERP-2024.pdf. [8]

Coyle, D. (2023), “The Promise and Peril of Generative AI”, *Project Syndicate*, https://www.project-syndicate.org/commentary/generative-ai-tools-could-displace-millions-of-workers-but-also-boost-productivity-growth-by-diane-coyle-2023-04. [183]

Criscuolo, C. et al. (2020), “Workforce composition, productivity and pay: The role of firms in wage inequality”, *OECD Social, Employment and Migration Working Papers*, Vol. 241. https://doi.org/10.1787/52ab4e26-en. [137]

Czarnitzki, D., G. Fernández and C. Rammer (2023), “Artificial intelligence and firm-level productivity”, *Journal of Economic Behavior & Organization*, Vol. 211, pp. 188-205. [49]

Damioli, G., V. Van Roy and D. Vertesy (2021), “The impact of artificial intelligence on labor productivity”, *Eurasian Business Review*, Vol. 11, pp. 1-25. [48]

Delis, M., F. Fringuellotti and S. Ongena (2023), “Credit and Income Inequality”, *Federal Reserve Bank of New York Staff Reports*. [151]

Dell’Acqua, F. et al. (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 No. 24-013. [53]

Dougherty, S. (2024), “Deploying artificial intelligence and data analytics to support intergovernmental fiscal relations”, *Policy Brief, OECD Network on Fiscal Relations across Levels of Government*, https://www.oecd.org/tax/federalism/deploying-artificial-intelligence-and-data-analytics.pdf. [176]

Durlauf, P. (ed.) (2005), *General Purpose Technologies*, Amsterdam: Elsevier. [198]

Eisfeldt, A., G. Schubert and M. Zhang (2023), "Generative AI and Firm Values", National Bureau of Economic Research Working Papers No. 31222 [66]

Eloundou, T. et al. (2023), “GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models”, https://arxiv.org/abs/2303.10130. [130]

Felten, E., M. Raj and R. Seamans (2023), *Occupational Heterogeneity in Exposure to Generative AI*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4414065. [202]

Felten, E., M. Raj and R. Seamans (2021), “Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses”, *Strategic Management Journal*, Vol. 42/12, pp. 2195-2217 [40]

Felten, E., M. Raj and R. Seamans (2019), “The Variable Impact of Artificial Intelligence on Labor: The Role of Complementary Skills and Technologies”, *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.3368605. [135]

Fossen, F. and A. Sorgner (2022), “New digital technologies and heterogeneous wage and employment dynamics in the United States: Evidence from individual-level data”, *Technological Forecasting and Social Change*, Vol. 175, p. 121381, [136]

FTC (2023), “FTC proposes rule to ban non-compete clauses which hurt workers and harm competition”, *Federal Trade Commission (FTC)*. [191]

Furman, J. (2016), *Is This Time Different? The Opportunities and Challenges*, https:// obamawhitehouse .archives .gov /sites. [41]

Furman, J. and R. Seamans (2019), “AI and the Economy”, *Innovation Policy and the Economy*, Vol. 19, pp. 161-191 [5]

G7 (2023), *Hiroshima Principles*. [119]

Gal, P. et al. (2019), “Digitalization and Productivity: In Search of the Holy Grail - Firm-level Empirical Evidence from European Countries”, *International Productivity Monitor*, Vol. 37, pp. 39-71. [44]

Gans, J. (2024), “Copyright Policy Options for Generative Artificial Intelligence.”, *National Bureau of Economic Research Working Papers* No. 32106. [186]

Gates, S., V. Perry and P. Zorn (2002), “Automated underwriting in mortgage lending: Good news for the underserved?”, *Housing Policy Debate*, Vol. 13. [152]

Gensler, G. (2023), “Remarks before the Financial Stability Oversight Council: 2023 Annual Report”, https://www.sec.gov/news/speech/gensler-remarks-fsoc-121423. [156]

Georgieff, A. (2024), “Artificial Intelligence and Wage Inequality”, *OECD Artificial Intelligence Papers* No. 15 https://doi.org/10.1787/bf98a45c-en. [133]

Georgieff, A. and R. Hyee (2021), “Artificial intelligence and employment: New cross-country evidence”, *OECD Social, Employment and Migration Working Papers*, Vol. 265, p. 60, https://doi.org/10.1787/c2c1d276-en. [81]

Gibson, M. (2021), “Employer market power in Silicon Valley”, *IZA Discussion Paper No. 14843*. [95]

Global X (2021), *Putting chip shortage in context.*, https://www.globalxetfs.com/putting-the-chip-shortage-into-the-context-of-long-term-trends/. [90]

Goldfarb, A., B. Taska and F. Teodoridis (2023), “Could machine learning be a general purpose technology? a comparison of emerging technologies using data from online job postings”, *Research Policy*, Vol. 52/1. [199]

Goldin, I. et al. (2024), “Why is productivity slowing down?”, *Journal of Economic Literature*, Vol. 62/1, pp. 196-268, [35]

Goldman Sachs (2023), *Upgrading Our Longer-Run Global Growth Forecasts to Reflect the Impact of Generative AI*, https://www.goldmansachs.com/intelligence/pages/generative-ai-could-raise-global-gdp-by-7-percent.html. [71]

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*, https://doi.org/10.1787/bb17314a-en. [96]

Griffith, E. (2023), *The Desperate Hunt for the AI Boom’s Most Indispensable Prize,* International New York Times, 18 Aug. 2023. [89]

Guerreiro, J., S. Rebelo and P. Teles (2023), “Regulating Artificial Intelligence”, *National Bureau of Economic Research Working Paper 31921*. [108]

Hacibedel, B. et al. (2020), “Inequality in Good and Bad Times: A Cross-Country Approach”, *IMF Working Paper*, Vol. WP/19/20. [139]

Haramboure, A. et al. (2023), "Vulnerabilities in the semiconductor supply chain", OECD Science, Technology and Industry Working Papers, No. 2023/05, OECD Publishing, Paris, https://doi.org/10.1787/6bed616f-en. [91]

Haslberger, M., J. Gingrich and J. Bhatia (2023), *No great equalizer: experimental evidence on AI in the UK labor market*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4594466. [54]

Hua, S. and H. Belfield (2020), “AI & Antitrust: Reconciling Tensions between Competition Law and Cooperative AI Development”, *Yale JL & Tech.*. [123]

Hunkenschroer, L. and C. Luetge (2022), “Ethics of AI-enabled recruiting and selection: A review and research agenda.”, *Journal of Business Ethics*. 178, 977–1007 (2022). [206]

Ing, L. and G. Grossman (2022), *Robots and AI: A New Economic Era*, Routledge, [21] Jackson, M. (2021), “Artificial Intelligence & Algorithmic Bias: The Issues With Technology Reflecting History & Humans”, *Journal of Business Technology & Law*, Vol. 16/2. [166]

Jones, C. (2023), “The A.I. Dilemma: Growth versus Existential Risk”, National Bureau of Economic Research Working Papers No. 31837,. [39]

Jones, C. (2023), “The Outlook For Long-Term Economic Growth”, National Bureau of Economic Research Working Papers No. 31648. [24]

Jumper, J. et al. (2021), “Highly accurate protein structure prediction with AlphaFold”, *Nature*, Vol. 596/7873, pp. 583-589,. [31]

Kanazawa, K. et al. (2022), *AI, Skill, and Productivity: The Case of Taxi Drivers*, National Bureau of Economic Research Working Papers No. 30612. [65]

Kaplan, J. et al. (2020), *Scaling laws for neural language models*, arXiv:2001.08361. [99]

Karabarbounis, L. (2023), “Perspectives on the labor share”, National Bureau of Economic Research Working Papers No. 31854. [125]

Klein, T. (2021), “Autonomous algorithmic collusion: Q-learning under sequential pricing”, *Amsterdam Law School Research Paper No. 2018-15.* [115]

Korinek, A. (2023), *Scenario Planning for an A(G)I Future*, IMF Finance & Development, December 2023. [16]

Korinek, A., M. Schindler and J. Stiglitz (2021), “Technological Progress, Artificial Intelligence, and Inclusive Growth”, *IMF Working Paper*, Vol. WP/21/166. [169]

Korinek, A. and J. Stiglitz (2021), “Steering technological progress” , *http://rcea.org/wp-content/uploads/2021/04/Future-of-growth/Korinek.pdf* [180]

Korinek, A. and D. Su (2023), "Scenarios for the Transition to AGI", *National Bureau of Economic Research Working Papers* No.32255 [193]

Kotlikoff, L. (2022), “Does Prediction Machines Predict Our AI Future? A Review”, *Journal of Economic Literature*, Vol. 60/3, pp. 1052-57, https://doi.org/10.1257/jel.20191519. [200]

Kurzweil, R. (2005), *The Singularity is Near: When HUmans Transcend Biology*, Penguin Group. [197]

Lai, V. et al. (2023), “ChatGPT Beyond English: Towards a Comprehensive Evaluation of Large Language Models in Multilingual Learning”, *arXiv:2304.05613*. [172]

Lane, M. (2024), “Who will be the workers most affected by AI? A closer look at the impact of AI on women, low-skilled and other vulnerable groups”, *OECD Artificial Intelligence Papers, forthcoming*. [131]

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* 288, https://doi.org/https://doi.org/10.1787/ea0a0fe1-en. [56]

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*, Vol. 282, p. 66, https://doi.org/10.1787/646aad77-en. [77]

Lipsey, R., K. Carlaw and C. Bekar (2005), *Economic Transformations: General Purpose Technologies and Economic Growth*, Oxford University Press, Oxford UK. [2]

Li, Q., N. Philipsen and C. Cauffman (2023), "AI-enabled price discrimination as an abuse of dominance: a law and economics analysis", *China-EU Law Journal*. [106]

Lorenz, P., K. Perset and J. Berryhill (2023), "Initial policy considerations for generative artificial intelligence", *OECD Artificial Intelligence Papers*, No. 1, OECD Publishing, Paris, https://doi.org/10.1787/fae2d1e6-en. [15]

Luccioni, A. et al. (2023), "Stable Bias: Analyzing Societal Representations in Diffusion Models", arXiv:2303.11408. [164]

Ludwig, J. and S. Mullainathan (2024), "Machine Learning as a Tool for Hypothesis Generation", *The Quarterly Journal of Economics*, Vol. 139/2, pp. 751-827, [29]

McElheran, K. et al. (2023), *AI Adoption in America: Who, What, and Where*, National Bureau of Economic Research Working Papers No. 31788. [84]

McKinsey (2023), *The economic potential of generative AI*. McKinsey Report January 2023. [60]

Merchant, A. et al. (2023), "Scaling deep learning for materials discovery", *Nature*, Vol. 624/7990, pp. 80-85 [58]

Microsoft Research, A. (2023), *The Impact of Large Language Models on Scientific Discovery: a Preliminary Study using GPT-4*, arXiv:2311.07361. [32]

Milanez, A. (2023), "The impact of AI on the workplace: Evidence from OECD case studies of AI implementation", *OECD Social, Employment and Migration Working Papers*, Vol. 289, p. 114, https://doi.org/10.1787/2247ce58-en. [55]

Milmo, D. (2023), *ChatGPT reaches 100 million users two months after launch*, https://www.theguardian.com/technology/2023/feb/02/chatgpt-100-million-users-open-ai-fastest-growing-app. [85]

Mohammad, W., A. Elomri and L. Kerbache (2022), "The Global Semiconductor Chip Shortage: Causes, Implications, and Potential Remedies", *IFAC-PapersOnLine*, Vol. 55/10, pp. 476-483. [88]

Mokyr, J. (2018), *Building Taller Ladders*, IMF Finance & Development, June 2018. [25]

Mujtaba, D. and N. Mahapatra (2019), *Ethical considerations in AI-based recruitment*, *2019 IEEE International Symposium on Technology and Society (ISTAS)*, Medford, MA, USA, 2019, pp. 1-7, [205]

Muro, M. and S. Liu (2021), "The geography of AI: which cities will drive the artificial evolution?", *Brookings Metropolitan Policy Program*. [146]

Musolff, L. (2022), *Algorithmic pricing facilitates tacit collusion: Evidence from e-commerce*. Proceedings of the 23rd ACM Conference on Economics and Computation, July 2022, Pages 32–33. [117]

Nicoletti, G., C. Vitale and C. Abate (2023), “Competition, regulation and growth in a digitized world: Dealing with emerging competition issues in digital markets”, *OECD Economics Department Working Papers*, No. 1752, OECD Publishing, Paris, https://doi.org/10.1787/1b143a37-en. [98]

Nicoletti, L. and D. Bass (2023), *Humans are biased, Generative AI is even worse*, https://www.bloomberg.com/graphics/2023-generative-ai-bias/. [165]

Nordhaus, W. (2021), “Are We Approaching an Economic Singularity? Information Technology and the Future of Economic Growth”, *American Economic Journal: Macroeconomics*, Vol. 13/1, pp. 299–332 [177]

Novelli, C., M. Taddeo and L. Floridi (2023), “Accountability in artificial intelligence: what it is and how it works”, *AI & SOCIETY*, pp. 1-12. [109]

Noy, S. and W. Zhang (2023), *Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence*. Science 381,187-92(2023). [52]

OECD (2023), *Artificial Intelligence in Science: Challenges, Opportunities and the Future of Research*, https://doi.org/10.1787/a8d820bd-en. [33]

OECD (2023), “A blueprint for building national compute capacity for artificial intelligence”, *OECD Digital Economy Papers, No. 350*, https://doi.org/10.1787/876367e3-en. [10]

OECD (2023), “Advancing accountability in AI: Governing and managing risks throughout the lifecycle for trustworthy AI”, *OECD Digital Economy Papers*, No. 349, OECD Publishing, Paris, https://doi.org/10.1787/2448f04b-en. [124]

OECD (2023), “AI language models: Technological, socio-economic and policy considerations”, *OECD Digital Economy Papers*, No. 352, OECD Publishing, Paris, https://doi.org/10.1787/13d38f92-en. [79]

OECD (2023), *Algorithmic Competition, OECD Competition Policy Roundtable Background Note*, https://www.oecd.org/daf/competition/algorithmic-competition-2023.pdf. [112]

OECD (2023), “Common guideposts to promote interoperability in AI risk management”, *OECD Artificial Intelligence Papers, No. 5*, https://doi.org/10.1787/ba602d18-en. [189]

OECD (2023), *Employment Outlook*, https://doi.org/10.1787/08785bba-en. [93]

OECD (2023), “Generative artificial intelligence in finance”, *OECD Artificial Intelligence Papers*, OECD Publishing, Paris, https://doi.org/10.1787/ac7149cc-en. [63]

OECD (2023), *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris, https://doi.org/10.1787/08785bba-en. [57]

OECD (2023), *Recommendation of the Council on Artificial Intelligence*, https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449. [4]

OECD (2023), *The human behind the machine: Skills and attitudes towards the future of artificial intelligence*, OECD Publishing, Paris, https://doi.org/10.1787/fc36a980-en. [175]

OECD (2022), “Disability, Work and Inclusion: Mainstreaming in All Policies and Practices”, *OECD Publishing, Paris,* https://doi.org/10.1787/1eaa5e9c-en. [159]

OECD (2022), "OECD Framework for the Classification of AI systems", *OECD Digital Economy Papers, No. 323, OECD Publishing, Paris*, https://doi.org/10.1787/cb6d9eca-en. [12]

OECD (2022), *Summary of OECD expert discussion on future risks from artificial intelligence of 20 October 2022*. [3]

OECD (2021), *AI in Business and Finance*, OECD Business and Finance Outlook 2021. [61]

OECD (2021), *Artificial Intelligence, Machine Learning and Big Data in Finance: Opportunities, Challenges and Implications for Policy Makers*, https://www.oecd.org/finance/financial-markets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf. [168]

OECD (2021), *Competition issues in AI*, https://read.oecd-ilibrary.org/finance-and-investment/oecd-business-and-finance-outlook-2021_ba. [111]

OECD (2020), *The Digitalisation of Science, Technology and Innovation: Key Developments and Policies*, OECD Publishing, Paris, https://doi.org/10.1787/b9e4a2c0-en. [59]

OECD (2019), *Recommendation of the Council on Artificial Intelligence*, https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449. [1]

OECD (2019), *Scoping the OECD AI principles: Deliberations of the Expert Group on Artificial*, https://doi.org/10.1787/d62f618a-en. [194]

OECD (2019), "Under Pressure: The Squeezed Middle Class", *OECD Publishing*, Paris, https://doi.org/10.1787/689afed1-en [127]

OECD (2018), *Personalised Pricing in the Digital Era*. OECD Publishing, Paris, https://www.oecd.org/competition/personalised-pricing-in-the-digital-era.htm [105]

OECD (2017), *Algorithms and Collusion: Competition Policy in the Digital Age*. OECD Publishing, Paris. [107]

O'Keefe, C. et al. (2020), *The windfall clause: Distributing the benefits of AI for the common good*, arXiv:1912.11595. [122]

OpenAI (2018), , https://openai.com/charter. [121]

Peng, S. et al. (2023), *The Impact of AI on Developer Productivity: Evidence from GitHub Copilot*. arXiv:2302.06590 [51]

Perez-Cruz, F. and H. Shin (2024), "Testing the cognitive limits of large language models", *BIS Bulletin* 83, [78]

Piketty, T. (2014), *Capital in the Twenty-First Century*, Harvard University Press. [145]

Ramos, G., M. Squicciarini and E. Lamm (2024), "Making AI Ethical by Design: The UNESCO Perspective", *Computer*, Vol. 57/2, pp. 33-43 [162]

Sanchez-Cartas, J. and E. Katsamakas (2022), *Artificial Intelligence, algorithmic competition and market structures*. IEEE Access PP(99):1-1. [116]

Sastry, G. et al. (2024), "Computing Power and the Governance of Artificial Intelligence", *arXiv:2402.08797* [7]

Schwalbe, U. (2018), “Algorithms, machine learning, and collusion”, *Journal of Competition Law & Economics*. http://dx.doi.org/10.2139/ssrn.3232631. [114]

Sorbe, S., P. Gal and V. Millot (2018), “Can productivity still grow in service-based economies? Literature overview and preliminary evidence from OECD countries”, *OECD Economics Department Working Papers No 1531*. [74]

Suleyman, M. and M. Bhaskar (2023), *The Coming Wave: Technology, Power, and the Twenty-first Century’s Greatest Dilemma*, Crown. [179]

Susskind, D. (2020), “A Model of Task Encroachment in the Labour Market”, *Oxford University Working Paper*, https://www. danielsusskind. com/s/SUSSKIND-Task-Encroachment-April-2020. pdf. [75]

Svanberg, M. et al. (2024), *Beyond AI Exposure: Which Tasks are Cost-Effective to Automate with Computer Vision?* http://dx.doi.org/10.2139/ssrn.4700751. [207]

The Economist (2023), *ChatGPT mania may be cooling, but a serious new industry is taking shape*, https://www.economist.com/leaders/2023/09/21/chatgpt-mania-may-be-cooling-but-a-serious-new-industry-is-taking-shape. [86]

Touzet, C. (2023), “Using AI to support people with disability in the labour market: Opportunities and challenges”, *OECD Artificial Intelligence Papers No.7*, OECD Publishing, Paris,, https://doi.org/10.1787/008b32b7-en. [160]

Trammell, P. and A. Korinek (2023), “Economic Growth under Transformative AI”, National Bureau of Economic Research Working Papers No. 31815. [144]

Van Noorden, R. and J. Perkel (2023), “AI and science: what 1,600 researchers think.”, Nature, Vol. 621/7980, pp. 672-675. [28]

Varian, H. (2019), *Artificial Intelligence, Economics, and Industrial Organization*, NBER Chapter in *The Economics of Artificial Intelligence: An Agenda,* pp 399 – 422. [18]

Vollrath, D. (2020), *Fully grown: Why a stagnant economy is a sign of success*, University of Chicago Press. [67]

WEF (2023), *Jobs of Tomorrow: Large Language Models and Jobs*. WEF White Papers, September 2023. [76]

Wei, J. and et al (2022), “Emergent Abilities of Large Language Models”, *Transactions on Machine Learning Research*, arXiv:2206.07682. [23]

Xingchen, X., S. Lee and Y. Tan (2023), *Algorithmic Collusion or Competition: the Role of Platforms’ Recommender Systems, arXiv:2309.14548.* [113]

Zucman, G. et al. (2022), “Globalisation and the effective taxation of capital versus labour”, *VoxEU Column, Taxation, 2022*. [147]

Annex A. Additional Tables and Figures

Table A.1. OECD AI Principles

Values based principles	Recommendations for policy makers
1.1 Inclusive growth, sustainable development and well-being Stakeholders should proactively engage in responsible stewardship of trustworthy AI in pursuit of beneficial outcomes for people and the planet, such as augmenting human capabilities and enhancing creativity, advancing inclusion of underrepresented populations, reducing economic, social, gender and other inequalities, and protecting natural environments, thus invigorating inclusive growth, sustainable development and well-being.	**2.1.Investing in AI research and development** a) Governments should consider long-term public investment, and encourage private investment, in research and development, including interdisciplinary efforts, to spur innovation in trustworthy AI that focus on challenging technical issues and on AI-related social, legal and ethical implications and policy issues. b) Governments should also consider public investment and encourage private investment in open datasets that are representative and respect privacy and data protection to support an environment for AI research and development that is free of inappropriate bias and to improve interoperability and use of standards
1.2 Human-centred values and fairness a) AI actors should respect the rule of law, human rights and democratic values, throughout the AI system lifecycle. These include freedom, dignity and autonomy, privacy and data protection, non-discrimination and equality, diversity, fairness, social justice, and internationally recognised labour rights. b) To this end, AI actors should implement mechanisms and safeguards, such as capacity for human determination, that are appropriate to the context and consistent with the state of art.	**2.2.Fostering a digital ecosystem for AI** Governments should foster the development of, and access to, a digital ecosystem for trustworthy AI. Such an ecosystem includes in particular digital technologies and infrastructure, and mechanisms for sharing AI knowledge, as appropriate. In this regard, governments should consider promoting mechanisms, such as data trusts, to support the safe, fair, legal and ethical sharing of data.
1.3 Transparency and explainability AI Actors should commit to transparency and responsible disclosure regarding AI systems. To this end, they should provide meaningful information, appropriate to the context, and consistent with the state of art: i.to foster a general understanding of AI systems, ii.to make stakeholders aware of their interactions with AI systems, including in the workplace, iii.to enable those affected by an AI system to understand the outcome, and, iv.to enable those adversely affected by an AI system to challenge its outcome based on plain and easy-to-understand information on the factors, and the logic that served as the basis for the prediction, recommendation or decision.	**2.3.Shaping an enabling policy environment for AI** a) Governments should promote a policy environment that supports an agile transition from the research and development stage to the deployment and operation stage for trustworthy AI systems. To this effect, they should consider using experimentation to provide a controlled environment in which AI systems can be tested, and scaled-up, as appropriate. b) Governments should review and adapt, as appropriate, their policy and regulatory frameworks and assessment mechanisms as they apply to AI systems to encourage innovation and competition for trustworthy AI.
1.4 Robustness, security and safety a) AI systems should be robust, secure and safe throughout their entire lifecycle so that, in conditions of normal use, foreseeable use or misuse, or other adverse conditions, they function appropriately and do not pose unreasonable safety risk. b) To this end, AI actors should ensure traceability, including in relation to datasets, processes and decisions made during the AI system lifecycle, to enable analysis of the AI system's outcomes and responses to inquiry, appropriate to the context and consistent with the state of art. c)AI actors should, based on their roles, the context, and their ability to act, apply a systematic risk management approach to each phase of the AI system lifecycle on a continuous basis to address risks related to AI systems, including privacy, digital security, safety and bias.	**2.4.Building human capacity and preparing for labour market transformation** a) Governments should work closely with stakeholders to prepare for the transformation of the world of work and of society. They should empower people to effectively use and interact with AI systems across the breadth of applications, including by equipping them with the necessary skills. b) Governments should take steps, including through social dialogue, to ensure a fair transition for workers as AI is deployed, such as through training programmes along the working life, support for those affected by displacement, and access to new opportunities in the labour market. c) Governments should also work closely with stakeholders to promote the responsible use of AI at work, to enhance the safety of workers and the quality of jobs, to foster entrepreneurship and productivity, and aim to ensure that the benefits from AI are broadly and fairly shared.

1.5 Accountability AI actors should be accountable for the proper functioning of AI systems and for the respect of the above principles, based on their roles, the context, and consistent with the state of art.	**2.5 .International co-operation for trustworthy AI** a) Governments, including developing countries and with stakeholders, should actively co-operate to advance these principles and to progress on responsible stewardship of trustworthy AI. b) Governments should work together in the OECD and other global and regional fora to foster the sharing of AI knowledge, as appropriate. They should encourage international, cross-sectoral and open multi-stakeholder initiatives to garner long-term expertise on AI. c) Governments should promote the development of multi-stakeholder, consensus-driven global technical standards for interoperable and trustworthy AI. d) Governments should also encourage the development, and their own use, of internationally comparable metrics to measure AI research, development and deployment, and gather the evidence base to assess progress in the implementation of these principles.

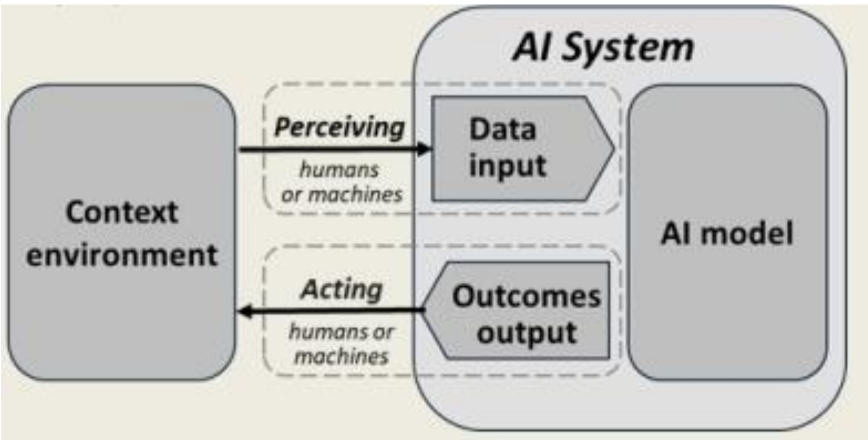
Source: OECD.AI, AI Principles overview. For more details, see (OECD, 2019[1])

Table A.2. Estimates on the effect of AI on firm productivity and worker performance

Paper	Treatment	Outcome	Sample	Method	Effect	SE
Calvino and Fontanelli (2023a)	AI use	Turnover/employment	9 OECD countries	OLS without firm FE	0.087	0.027
Alderucci et al. (2019)	AI patents	Log revenues per worker	US, 2000-2018	Event study	0.068	0.004
Damioli et al. (2021)	AI patents	Log revenues per worker	Orbis, 2000-2016	GMM estimation of prd. Function - one step	0.032	0.011
Czarnitzki et al. (2023)	AI use	Log sales	Germany, 2018	IV with FE and entropy balancing	0.044	0.020
Calvino and Fontanelli (2023b)	AI use	Log VA per worker	French firms, 2019	OLS with control for initial productivity and ICT	0.027	0.028
Calvino and Fontanelli (2023a)	AI use	Turnover/employment	9 OECD countries	OLS without firm FE but including other digital tech.	0.021	0.052
Calvino and Fontanelli (2023b)	AI developer	Log VA per worker	French firms, 2020	OLS with control for initial productivity and ICT	0.106	0.053
Brynjolfsson et al. (2023)	AI-based assistant	Log resolution per hours	Call centers employees, 2020-2021	Event study	0.138	0.020
Peng et al. (2023)	GitHub Copilot	% number of tasks completed	Software developers, 2022	Experiment	0.558	0.169
Noy and Zhang (2023)	ChatGPT	Average effect	Professional writing, 2022	Online experiment	0.479	0.053
Dell'Acqua et al. (2023)	ChatGPT-4	Performance (quality, inside frontier, GPT only)	Consultants, 2023	Experiment	0.388	0.019
Haslberger et al. (2023)	ChatGPT	Average overall effect	UK working-age population, 2023	Experiment	0.481	0.022

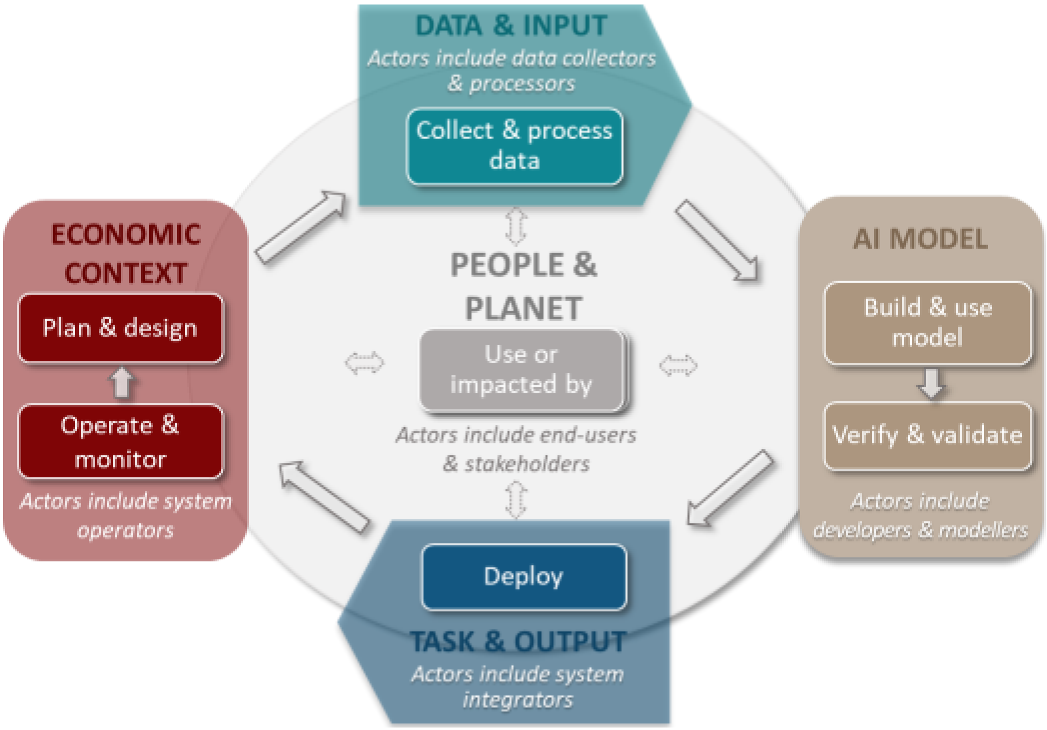
Notes: SEs for Peng et al. (2023) are calculated indirectly using the 95% confidence interval reported in the paper. Estimates for Noy and Zhang (2023) average the gain in terms of quality and the gain in terms of time needed to complete the task. For Dell'Acqua et al. (2023) effect and SE in % obtained by dividing the estimated figures by the control mean reported in the article. The estimate for Haslberger et al. (2023) is obtained as a simple average of the effect on email writing, assessment and comprehension. The effect for each of these tasks are estimated as an average of the gain in terms of quality and the gain in terms of time needed to complete each of the three tasks.

Figure A.1. Stylised conceptual view of an AI system (per OECD AI Principles)



Source: (OECD, 2019[194])

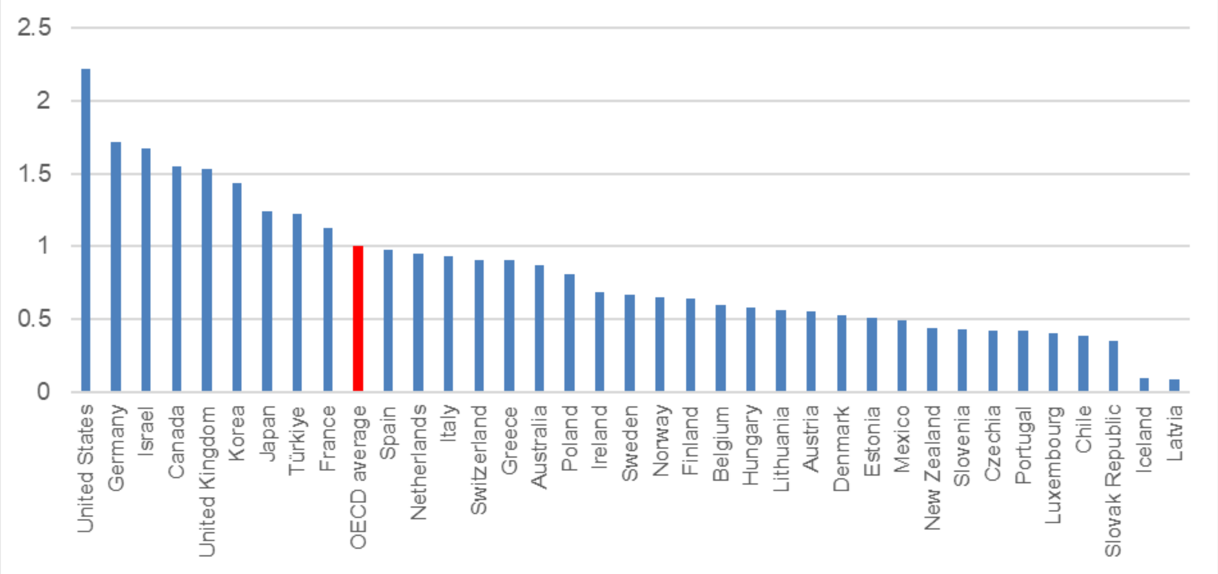
Figure A.2. The AI system lifecycle



Notes: Actors are illustrative and not exhaustive and based on previous OECD work on the AI system lifecycle.
Source: (OECD, 2022[12])

Figure A.3. AI Skills are Concentrated in Specific Countries

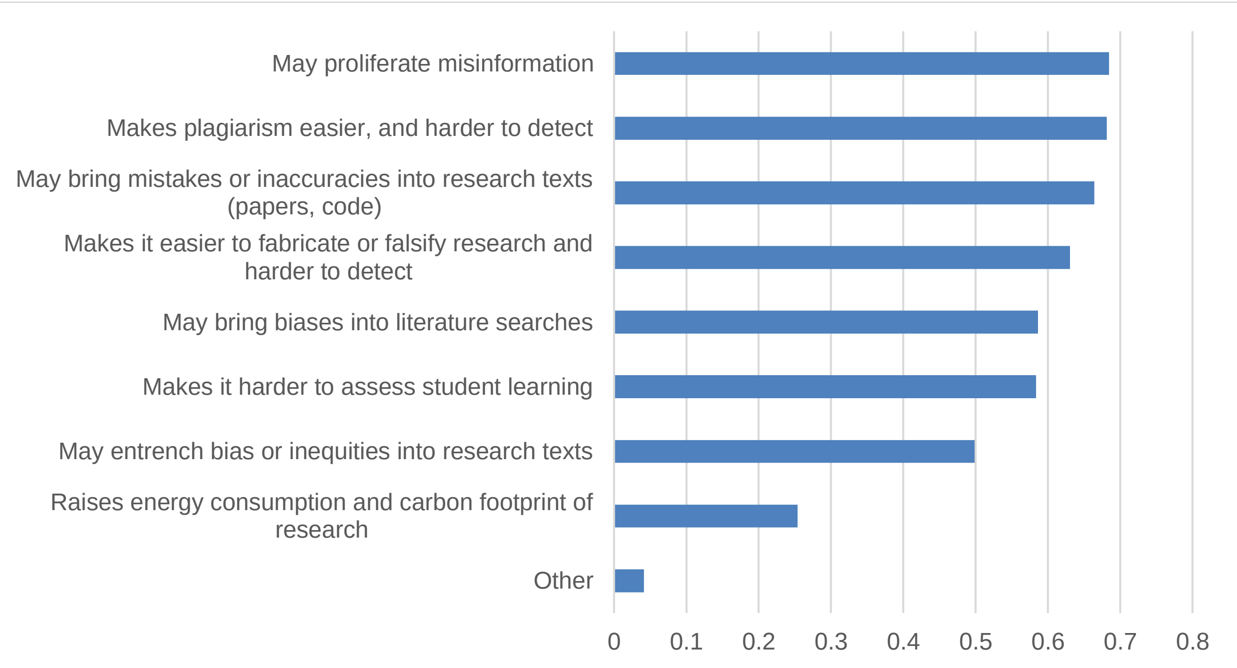
AI Skills Penetration



Notes: This chart shows the prevalence of workers with AI skills – as self-reported by LinkedIn members from 2015-2022 – by country and against a benchmark. A country's AI skills penetration of 1.5 means that workers in that country are 1.5X more likely to report AI skills than workers in the benchmark. Average from 2015 to 2022 for a selection of countries with 100 000 LinkedIn members or more. The value represents the ratio between a country's and the benchmark's AI skills penetrations, controlling for occupations. Data downloads provide a snapshot in time. Caution is advised when comparing different versions of the data, as the AI-related concepts identified by the machine learning algorithm may evolve in time. Please see methodological note for more information.
Source: LinkedIn Economic Graph, OECD AI Policy Observatory (OECD.AI).

Figure A.4. Risks from adopting AI as seen by scientists

Question: "Where do you think generative AI may have negative impacts on research?"



Source: (Van Noorden and Perkel, 2023[28]), Nature.