DIFIS Deutsches Institut für Interdisziplinäre Sozialpolitikforschung
vernetzen · forschen · beraten

STUDIE
2026 / 2

Juho Alasalmi

Artificial Intelligence in the European Labour Markets

AT A GLANCE

- Adoption of artificial intelligence (AI) in the production of goods and services can automate nonroutine cognitive tasks performed by middle- and high-income workers and so exacerbate job polarisation.
- Adoption of AI in firms and by workers has been rapid since generative AI became widespread. Adoption is, however, uneven among workers and firms.
- AI is changing the demand for labour and the tasks workers do. So far, the new tasks seem to have mostly been created in AI development and implementation, increasing demand for AI skills.
- AI could decrease productivity differences between workers within occupations, but the existing evidence points to the continuation of skill-biased technological change with mainly high-skilled labour benefiting.
- Inclusive distribution of productivity gains requires policies that support labour's bargaining power and labour's ability to productively contribute to the production process.

- Continuous monitoring of AI’s employment effects helps in understanding how to support the reallocation of labour. Understanding workers’ perspectives can help design effective policies.

ABSTRACT

This review surveys the emerging evidence regarding the effects of artificial intelligence technologies in the labour market and on labour market inequality through the lens of the theoretical framework of task-based production and the literature in the field of economics on technological change. The evidence analysed concerns the time period after the early 2010s, with an emphasis on the effects of generative AI after 2022. The focus is on research studying European labour markets. After outlining the context of routine- and skill-biased technological change and job polarisation, the existing evidence regarding AI adoption in production and its effects on productivity and employment is reviewed. The review concludes with a discussion on labour market policy that mediates the effects of AI on the distribution of productivity gains and the direction of technological change and a consideration of the effect of technological change on attitudes toward labour market policy and democracy itself.

GERMAN ABSTRACT

Die vorliegende Studie bietet einen Überblick über neue Erkenntnisse zu den Auswirkungen künstlicher Intelligenz (KI) auf den Arbeitsmarkt und Arbeitsmarkt-Ungleichheiten aus der Perspektive der wirtschaftswissenschaftlichen Literatur zum technologischen Wandel und einer aufgabenbasierten Produktion als theoretischen Rahmen. Die Befunde beziehen sich auf den Zeitraum nach Anfang der 2010er Jahre, wobei der Schwerpunkt auf europäischen Arbeitsmärkten sowie den Auswirkungen der generativen KI nach 2022 liegt. Zunächst wird der Kontext des „routine“- und „skill-biased technological Change“ und der Arbeitsplatzpolarisierung beschrieben. Anschließend werden die bestehenden Erkenntnisse über die Einführung von KI und die Auswirkungen der KI-Technologien auf Produktivität und Beschäftigung besprochen. Die Studie schließt zum einen mit einer Diskussion über arbeitsmarktpolitische Maßnahmen, die KI-Effekte auf die Verteilung von Produktivitätsgewinnen und die Richtung des technologischen Wandels beeinflussen. Zum andern werden die Auswirkungen des technologischen Wandels auf die öffentliche Einstellung zu Arbeitsmarktpolitik und Demokratie behandelt.

1 Introduction

Artificial intelligence (AI), a set of technologies that learn patterns from data to make predictions using new data, is performing more and more tasks that only humans used to be capable of. The adoption of AI in production may lead to an increase in the share of tasks, and even entire jobs, that are performed by machines. Such automation may decrease the value of some workers' skills, or even make them obsolete, while increasing the value of other workers' skills.

This review surveys the emerging evidence on the effects of AI on the labour market and labour market inequality. After innovations such as steam, electricity, machines, computers, and software, AI is the latest technological change to affect the way goods and services are produced. This continuous change has been a subject of a large amount of literature in the field of economics, which will guide this review.

The review focuses on machine learning-based AI and its applications in non-physical tasks. The adoption of such AI in production has been a significant development, which first arose in the early 2010s. Thus, the evidence surveyed concerns the time period after the early 2010s, with an emphasis on the effects of generative AI after the release of ChatGPT in late 2022.

Some findings are particularly relevant to the labour markets of the European Union (EU). European economies are characterised by their ageing populations, labour shortages, high incomes, occupational structures leaning toward cognitively intensive tasks, and pressures to cut public spending, all of which may heighten incentives for automation. However, the EU is also characterised by its will to steer AI by regulation toward human-centric development and use.

This review has benefitted from multiple reviews such as Acemoglu and Restrepo (2018, 2019, 2024b), Agrawal et al. (2019a), Gallego and Kurer (2022), Lane and Saint-Martin (2021), OECD (2023, 2024), and Restrepo (2024).

This review focuses on a field of research that is undergoing rapid development. As such, the author has cited several studies that have been published as working papers or manuscripts that have not yet been peer-reviewed. The literature review began with the studies identified in earlier literature. After this, more recent publications were identified via forward citation searches of those initial sources. After the detailed structure of the review was formulated, additional literature corresponding to this structure was identified and selected. All literature searches were conducted using Google Scholar in May 2025.

The next section lays out the theoretical frameworks of task-based production and wage determination to help consider the effects of AI on labour market inequality. This is followed by an overview of the emerging evidence on the adoption and labour market effects of AI. The focus then moves to a discussion on the distribution of productivity gains, the direction of technological change, and the effect of technological change on attitudes toward labour market policies. The concluding section presents some caveats in the interpretation of the existing evidence and identifies gaps in the existing research.

2 AI and tasks

The labour market concerns the purchase and sale of labour for the production of goods and services. The demand for labour depends on the technology used to convert labour and capital inputs into outputs. This demand, together with the supply of labour, determines wages. As new technologies are adopted in production, the demand for labour changes, with a potential effect on wages. This section describes a framework for considering technological change: the task-based model of production. This framework is then used to discuss the consequences of technological change on labour market inequality and concludes by discussing how AI fits into this framework. The section is based on the reviews of Acemoglu and Restrepo (2019a,b, 2024) and Restrepo (2024).

2.1. TASK-BASED PRODUCTION

The **task-based model of production** is a flexible means of analysing technological change in production. The idea is that producing an output requires the completion of a set of tasks. For instance, producing a research report involves the tasks of stating a research question, reviewing existing literature, ideation, modelling, gathering data, analysing data, drawing figures, drafting, writing, formatting, and proofreading a report, and communicating the research results.

Tasks can be completed by labour or capital. In producing a research report, a researcher may do the writing and software the proofreading. Also, labour's tasks may require different skills and be bundled into occupations. The experienced senior researcher may state the research question and communicate the research results, other research team members may be responsible for handling the data analysis and writing, while the drawing of figures and formatting the research report may be delegated to a research assistant. Likewise, different forms of capital, such as computers, software, furniture, and processes, possess distinct capabilities and are suited to different tasks. A chair supports the posture of a researcher, allowing the researcher to focus on other cognitive work, a text editor helps the researcher in formatting, and an advanced AI tool is able to independently draft a text.

Within this framework, technological development increases the productivity of capital in performing tasks. This may affect production in various ways: More productive capital may better complete tasks already allocated to capital (**augmentation of capital**), complete tasks previously allocated to labour (**automation**) or complement labour in tasks allocated to labour (**augmentation of labour**). Further, new tasks may be created, either for labour or capital (**new task creation**). The consequences for labour depend on the nature of changes in the productivity of labour and capital, the tasks themselves, and the allocation of tasks to capital and labour.

2.1.1 AUTOMATION

Reallocating a task from labour to capital constitutes automation. Automation increases (decreases) the share of tasks performed by capital (labour). This **substitution** creates a **displacement effect***:* less labour is required and demand for labour decreases. When technological change enables capital to perform tasks previously done by labour, it increases the share of tasks that can be automated. For instance, generative AI is increasingly able to produce figures and draft research reports (Korinek 2023), reducing the demand for research assistants.

There are incentives for automation when it decreases input or increases output. In both cases, the amount of output relative to input increases, i.e. productivity increases. If this increase in productivity translates into lower output prices and the demand for the product is sufficiently elastic, the output demanded, and thus produced, may increase. This increases the demand for non-automated tasks and for the labour performing these tasks. This **productivity effect** of automation increases demand for labour. For example, if a code-generating AI tool reduces the cost of statistical analysis and thus lowers the cost of research, buyers who have found research prohibitively expensive may enter the market and increase the demand for research. The demand for tasks such as planning statistical analysis increases, with the demand for senior researchers increasing as a result.

Furthermore, if a decrease in the price of a good does not increase the demand for that good, the money spent on it can be redirected, potentially increasing the demand for goods produced with labour-intensive methods.

2.1.2 AUGMENTATION

New technology may also increase the efficiency at which labour performs its tasks. Such technological change increases the productivity of labour and may even enable people to complete tasks they would not otherwise have had the skills to do. Faster computers run data wrangling and statistical analysis faster. Better data visualisation tools enable researchers to draw graphs beyond their visual design skills. When technology augments labour in this way, labour and capital are **complementary**.

Tasks may also be automated in part, such that capital can handle easy tasks while labour handles more complex ones. A research assistant may delegate the drawing of simple figures to AI, while focusing on drawing more complex figures.

2.1.3 NEW TASK CREATION

If technology automated every task, there would be little left for labour to do. In reality, there is a lot left for labour to do, which is most evident when one considers the new tasks and occupations in our world (Acemoglu and Restrepo 2018; Autor et al. 2024). It could be that the set of tasks, and the tasks where labour has a comparative advantage over capital, may expand. This **reinstatement effect** increases the demand for labour. This may occur as a result of product innovation: creating new products, or new varieties of old products, requires completing new tasks. Faster computers enable researchers to run more computationally demanding models. The reinstatement effect may happen through process innovation: reorganising production creates new tasks, especially in using machines. An AI writing assistant requires the design of prompts. Reinstatement may also happen as the market expands due to the productivity effect: delivering products to new markets requires completing new tasks. Generating research's societal impact requires new kinds of communication and stakeholder engagement.

2.2. LABOUR MARKET INEQUALITY

Technological change affects income distribution in two ways. First, as more tasks are shifted to capital, the labour share falls. This labour share of national income has remained stable in Europe but has been decreasing in the United States (US) (Gutiérrez and Piton 2020; Bastani and Waldenström 2024), particularly in industries with extensive automation such as manufacturing (Restrepo 2024). Second, even if equal displacement and reinstatement effects kept the labour share intact, those effects could still be unevenly distributed across workers, tasks, and occupations (Katz and Murphy 1992; Autor et al. 2003).

2.2.1 AUTOMATION OF ROUTINE TASKS

To obtain an overview of the evolution of task content of production, it is useful to classify tasks into four categories: routine manual, nonroutine manual, routine cognitive, and nonroutine cognitive (Autor et al. 2003). The routine-nonroutine distinction separates tasks into those that can be codified and those that cannot, respectively. The manual-cognitive distinction separates tasks into those dealing with physical objects and those dealing with information, respectively.

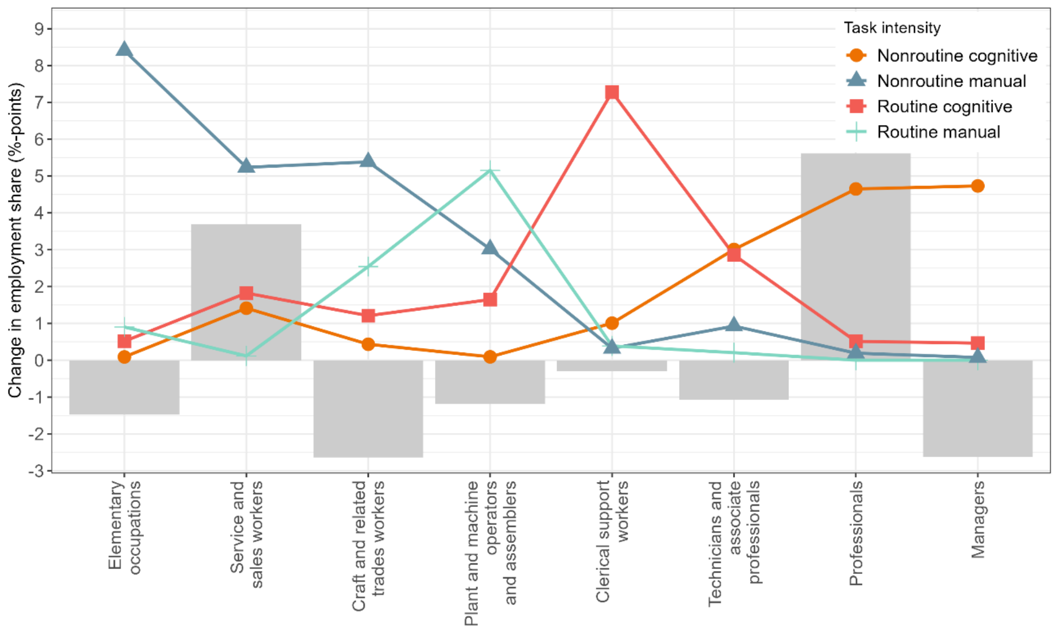
These categories of tasks can be ranked by the compensation paid to labour for doing these tasks (Goos et al. 2014). Workers in jobs mostly consisting of nonroutine manual tasks tend to receive the lowest wages. These workers are followed by the workers in jobs mostly consisting of routine manual tasks, followed by workers in jobs with many routine cognitive tasks. The highest wages are paid to those in jobs that mostly consist of nonroutine cognitive tasks. These nonroutine cognitive tasks are also usually performed by the most skilled and most educated workers while routine tasks and nonroutine manual tasks are performed by less skilled workers.

Codifiable routine tasks are vulnerable to automation. Machines are good at following step-by-step instructions to repeat tasks in stable environments. As machines get better and cheaper, they substitute labour in these tasks: robots take over routine manual tasks and computers take over routine cognitive tasks. The demand for workers in occupations with many routine tasks decreases. Industrial robots, for instance, have reduced production jobs in France (Acemoglu et al. 2020b) and manufacturing jobs in Germany (Dauth et al. 2021).

On the other hand, workers in jobs with mainly nonroutine tasks may need to complete routine tasks to produce output. As machines perform these routine tasks more and more effectively, these workers' productivity, and perhaps the demand for their labour, increases. This **routine-biased technological change** has led to **job polarisation**. Occupations involving many routine tasks in the middle of the income distribution are losing their labour share, while nonroutine manual low-wage occupations and nonroutine cognitive high-wage occupations are increasing their labour shares (Goos et al. 2009, 2014; Kurer and Gallego 2019). Figure 1 shows the job polarisation in the EU, highlighting the changes in employment shares of occupational groups, roughly ranked by their mean wages, between 2008 and 2023, as well as the intensities of different types of tasks in these occupations.

It is clear that not all workers displaced by technology have been able to find new work. While there is certainly structural unemployment due to skills mismatch (Orlandi 2012; Vandeplas and Thum-Thysen 2019), large-scale technological unemployment has not occurred. First, there has been demand for labour elsewhere: reductions in employment in manufacturing due to automation are often compensated by an increase in service sector jobs (Dauth et al. 2021; Mann and Püttmann 2023; Schöll and Kurer 2024). Second, the decline in routine work seems to mostly work through the labour market exits of senior workers to retirement and labour market entries of young workers (Kurer and Gallego 2019; Dauth et al. 2021; Yashiro et al. 2022; Goller et al. 2025).

Figure 1. Change in European Union employment shares 2008-2023 and task group intensities in occupational groups.



Notes: Data on employment from Labour Force Survey (Eurostat 2025a) table lfsa_egised in the EU countries presented also in Figure 2. NACE: All activities (except agriculture, forestry and fishing, and mining and quarrying), excluding financial sector. Task intensities of ISCO-08 one-digit occupations are computed as the mean of Mihaylov and Tijdens (2019) Appendix B four-digit task intensity measures. Nonroutine cognitive task intensity is computed as the average of nonroutine analytic and nonroutine interactive task intensities. The figure presents the task intensities divided by ten for comparability (values not depicted). Occupation groups are ranked from left to right by increasing wage roughly following Goos et al. (2014) Table 1.

2.2.2 WAGES

Wages generally adjust to balance the demand and supply of labour. Given the value of outputs, labour demand is determined by the marginal productivity of labour. The marginal productivity of labour - the amount of output produced by an additional unit of labour - tends to decline as employed labour increases. If the value of this additional output, its market price, exceeds the wage paid for the additional unit of labour, then the producer has an incentive to expand production. Higher wages increase labour supply, allowing the producer to employ more labour. As this mechanism works in both directions, the wage tends to approach the value of the marginal productivity of labour.

Changes in production technology affect the marginal productivity of labour. This causes the value of additional labour input to deviate from its cost, leading companies to adjust labour demand. Such shifts put pressure on wages until labour supply and demand balance again. Therefore, technological changes that decrease the marginal productivity of labour tend to lower wages, while technological changes that increase the marginal productivity of labour tend to increase wages. Importantly, the marginal productivity of labour may diverge from the average productivity of labour. Automation can increase output relative to labour input, simultaneously decreasing the contribution of labour to this output (Acemoglu and Johnson 2024).

As many of the codifiable tasks in the occupations of low- and middle-skilled workers have been automated, the marginal productivity of workers performing these tasks has not kept up with the average productivity of labour (Acemoglu and Autor 2011; Dauth et al. 2021). Instead, the marginal productivity of labour has increased among high-skilled managers and professionals whose jobs depend on the completion of routine tasks, but who themselves do not contribute directly to the completion of these routine tasks. Moreover, while nonroutine manual tasks have mostly evaded automation, there has been more occupational mobility from routine tasks to nonroutine manual tasks than to nonroutine cognitive tasks. This shift in the supply of labour willing to perform nonroutine manual tasks has put downward pressure on wages in nonroutine manual jobs. These developments have contributed to rising wage premiums and stagnating wages among low- and middle-skilled workers.

There are many reasons for increased wage inequality in the US and Europe (Acemoglu and Restrepo 2024). However, automation has been estimated to have played a significant role. Acemoglu and Restrepo (2022) estimate that 50-70 % of changes in the US wage structure can be attributed to automation. While wage inequality has not increased as much in Europe as in the US, a similarly large share of the change can be attributed to job polarisation and automation (Goos and Manning 2007).

Some of the other drivers of income inequality are also created by technology. First, digital goods are nonrival goods sold in winner-takes-all markets where a small number of producers receive a significant share of revenues (Brynjolfsson and McAfee 2014). These revenues may either accrue to the owners or workers of these firms. Second, there may be variation in how workers and firms adopt technologies and thereby realise productivity gains. Third, a decrease in labour share increases the incomes of those who derive their earnings from capital (Rockall et al. 2025).

2.3. ARTIFICIAL INTELLIGENCE

The labour market effects of different technologies are not uniform. Interchangeable parts and assembly lines enabled low-skilled workers with machines to replace high-skilled artisans in the 19th century, while computers and industrial robots automated the work of semi-skilled workers in the 20th century (Acemoglu and Johnson 2023). AI is likely to have yet another unique set of effects.

AI is a field of study concerned with developing technologies capable of completing tasks that, if completed by humans, would require human intelligence. The core of modern AI is machine learning, a branch of computational statistics that develops algorithms able to learn patterns from data and replicate those patterns. AI technologies are often classified by the scope of their capabilities. **Narrow AI** technologies can complete single, well-specified tasks. This was used in the 2010s and early 2020s. **General AI** can perform and learn a wide variety of tasks. **Generative AI**, which captured the public's attention with the release of ChatGPT in late 2022, has been classified as emerging general AI (Morris et al. 2024). For the purposes of this text, it is useful to refer to the technology after 2022 as *generative AI* and reserve the term *narrow AI* for technologies dominant prior to 2022.

AI is a **general-purpose technology** (Goldfarb et al. 2023). General-purpose technologies have economy-wide applications, they evolve, and they facilitate further applied innovation (Lipsey et al. 2005; Breshanan 2010). Together, these three factors create a loop of innovation across many industries where developers improve AI given feedback from downstream applied innovation. A large number of jobs are expected to be exposed to AI (Cazzaniga et al. 2024), and AI is already being used in a wide range of occupations and job tasks (Bick et al. 2024). AI also helps with innovation (Cockburn et al. 2019), is improving quickly, and is outperforming humans in a growing number of tasks (Maslej et al. 2025). AI can thus be expected to have a large and increasing impact across industries and occupations.

The automation of routine tasks has relied on these tasks' codifiability: computers execute instructions, and computer-controlled equipment can be given procedures and rules to follow in each contingency. Such rule-based processing of information has not automated nonroutine tasks. The approach of machine learning is different: statistical learning from vast amounts of data makes it possible for a machine to process far more numerous and more nuanced patterns than a human could instruct. While narrow AI is capable, for instance, of speech and image recognition, recommendations, and fraud detection, in recent years, AI has approached or even exceeded human capabilities, for instance, in image, video and text classification and generation, reasoning, mathematics, coding, and writing (Maslej et al. 2025). US employees surveyed in autumn 2024 reported using AI for writing communications, summarising text, coding software, data analysis and generating ideas (Bick et al. 2024). Fundamentally, AI is capable of prediction, which is crucial for decision-making and at the core of many white-collar jobs (Agrawal et al. 2019b). AI can thus do tasks that were previously considered impossible to automate: nonroutine cognitive tasks.

3 Labour market effects of AI

The effects of AI on labour market inequality depend on the heterogeneity of AI adoption and of the productivity, employment, and wage effects of adopted AI. In this section, we review the emerging evidence on the adoption of AI, the productivity effects of AI, and finally, the employment and wage effects of AI.

3.1. ADOPTION AND DIFFUSION

The effects of AI depend not only on what AI can do, but also whether, how, and by whom AI is used in production. This section reviews the evidence on firms' and workers' adoption of AI.

3.1.1 FIRMS

Firms adopt AI when they expect a positive return on their investment. The returns to AI adoption are expected to be high in firms that have the complementary capital, such as skilled workers and digital data, that have the capacity for co-invention, and in which the interests of employers and employees align (Brynjolfsson et al. 2021; Agrawal et al. 2023).

Prior to the advent of generative AI, AI adoption by firms was rare and concentrated in ICT industries. In 2017, 3 % of Danish firms (Humlum and Meyer 2022) and in 2018, 6-7 % (Rammer et al. 2022; Czarnitzki et al. 2023) of German firms reported using AI. After 2022, the use of AI in firms has rapidly increased. 13 % of German firms reported AI use in June 2023, 27 % in June 2024, and 41 % in May 2025 (Wohlrabe 2025). Figure 2 (left) presents the AI adoption rates in selected EU countries. Adoption has been rapid in the years 2021-2024 and the fastest adoption can be observed in countries where AI use was already prevalent in 2021.

Larger firms adopt narrow AI more often (Acemoglu et al. 2023b; von Maltzan and Zargers 2024; Wohlrabe 2025). However, a 2024 survey of Danish workers about their use of AI chatbots at work found no correlation between AI use and firm size (Humlum and Vestergaard 2025a). This contrast may reflect the worker, rather than firm-level adoption of generative AI. In addition, younger firms (Calvino et al. 2022; Humlum and Vestergaard 2025a) and firms with more educated employees (Babina et al. 2023; Calvino et al. 2022; Fontanelli et al. 2024; Brey and van der Marel 2024) more often adopt AI.

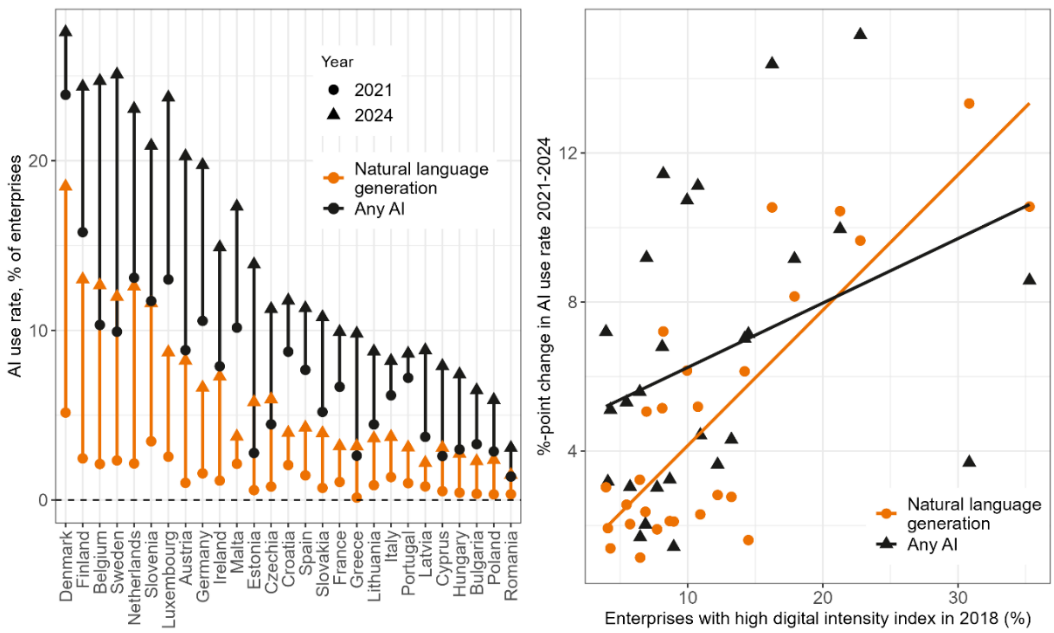
AI does not produce on its own, but requires, in addition to complementary labour with ICT and AI skills, complementary capital including data, digital infrastructure and computing power. In general, firms with these complementary inputs already in place are also those most likely to adopt AI (Calvino et al. 2022). Figure 2 (right) presents changes in AI use across firms between 2021 and 2024 and the digital intensity index in 2018 in EU countries. In countries where more firms were using digital technologies in 2018, AI adoption, especially the adoption of natural language generation, tended to be faster during 2021-2024.

3.1.2 WORKERS

ChatGPT, launched in November 2022, became the fastest-growing consumer application in history, reaching 100 million users in two months, and has 400 million users as of February 2025 (Duarte 2025). In autumn 2024, 39 % of the US adult population reported using AI (Bick et al. 2024). A key factor in this rapid adoption has been these models' accessible natural-language chatbot user-interfaces.

Research on worker adoption of AI began with generative AI. Around 30 % of US employees surveyed in autumn 2024 reported having used AI at work (Bick et al. 2024). Half of Danish employees surveyed between November 2023 and January 2024, and 67 % surveyed in November 2024, reported having used AI at work (Humlum and Vestergaard 2024, 2025a). Cedefop (2025) reports that 31 % of German employees either used AI themselves or knew a colleague using AI in the workplace in spring 2024 (Figure 3). Adoption of generative AI is often worker-initiated: 47 % of Danish employees whose employers had not initiated AI use reported using AI at work (Humlum and Vestergaard 2025a).

Figure 2. AI adoption and use in enterprises in EU countries

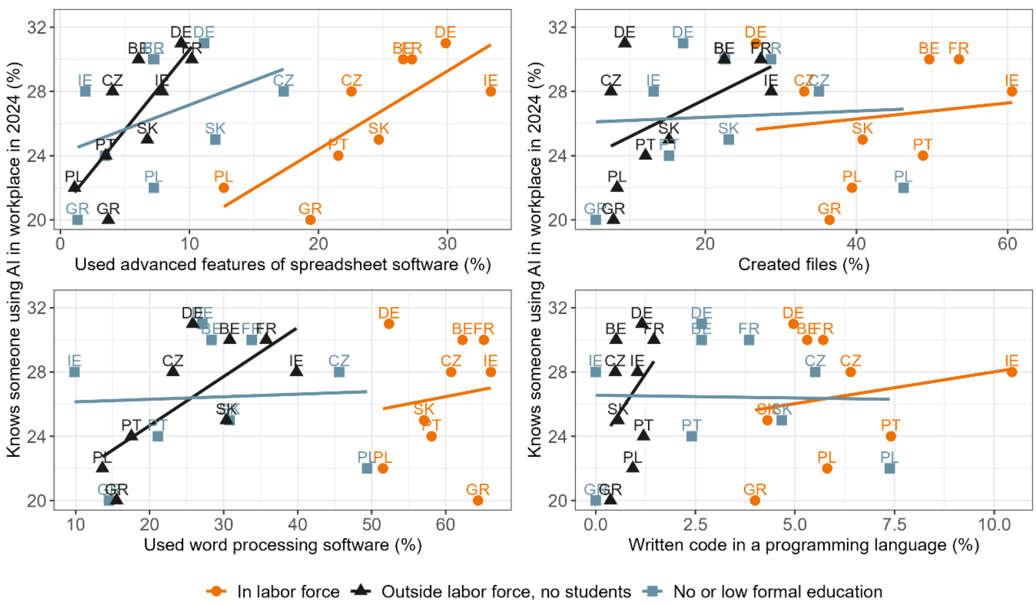


Notes: Natural language generation refers to enterprises using AI technologies generating written or spoken language; Any AI refers to enterprises using at least one of the AI technologies: AI_TTM, AI_TSR, AI_TNLG, AI_TIR, AI_TML, AI_TPA, AI_TAR. NACE includes all activities except agriculture, forestry and fishing, and mining and quarrying, excluding the financial sector. Right: Change in AI adoption rate between 2021 and 2024 (from isoc_eb_ain2) on the y-axis and enterprises with high digital intensity index (DII version 2) (from isoc_e_diin2) on the x-axis. Left: AI use rate (from isoc_eb_ain2). Data source: Data from Eurostat (2025b) table isoc_eb_ain2 and Eurostat (2025c) table isoc_e_diin2.

These studies tend to find that AI is more often adopted by younger, more educated, higher-income, and male workers. These unconditional differences in adoption may reflect differential adoption across tasks, occupations industries, and firms: while AI adoption extends across most industries and occupations, AI is especially adopted in ICT and among software developers. In addition, initiatives taken by the employer to encourage the use, training or deployment of AI, increases adoption among Danish employees (Humlum and Vestergaard 2025a). However, the effects of age, education, and income are observed within occupations as well (Humlum and Vestergaard 2024). Moreover, the clear pattern of higher adoption rates among males (Otis et al. 2024) holds when comparing males and females within occupations and workplaces with similar task structure, age, experience and earnings (Humlum and Vestergaard 2024; Aldasoro et al. 2024). Interestingly, more experienced workers (Humlum and Vestergaard 2024) and top students (Carjaval et al. 2024) are less likely to adopt AI. This may reflect the differential expected productivity gains across different groups of workers (Section 3.2).

AI adoption may also depend on existing digital skills. Figure 3 presents workers' AI use rates in 2024 in different EU countries as measured by the survey of Cedefop (2025) as a function of different measures of computer use in 2021. Workers' AI use in the workplace tends to be higher in countries where people both inside and outside the labour force, including those with no or low education, used computers more in the past. Thus, the prevalence of computer use in the population before wide access to generative AI predicts AI use in workplaces in 2024.

Figure 3. AI use by workers and computer use in EU countries



Notes: NACE: covers all activities (except agriculture, forestry and fishing, and mining and quarrying), excluding the financial sector. The percentage refers to respondents answering answered "Yes" to the question "To the best of your knowledge do you or your colleagues use any AI tools or systems at your workplace?" (Cedefop 2025, p. 15, Luxembourg 43 % and Spain 15 % are removed as outliers for clarity) and activity within the last three months in 2021 (from isco_sk_cskl_i21) on the x-axis. Data source: Eurostat (2025d) table isoc_sk_cskl_i21 and Cedefop (2025).

3.2. PRODUCTIVITY

Firms and workers adopt new technologies to increase their productivity. Some expect AI to generate increasing (Brynjolfsson and McAfee 2014) or even explosive (Nordhaus 2021; Korinek and Suh 2024) productivity growth, while others point to the sluggish productivity growth in the 2010s (Brynjolfsson et al. 2019) and the excessive focus on automation

(Acemoglu 2025) as reasons for caution. This section reviews the existing evidence on AI's effects on workers' and firms' productivity.

3.2.1 WORKERS

A few studies have observed the inputs and outputs of individual workers with (quasi-)randomly allocated access to AI in order to assess whether generative AI increases worker productivity. Brynjolfsson et al. (2025) study customer-support agents assisted with AI-generated replies to customers' questions, Cui et al. (2024), Peng et al. (2023), Hoffmann et al. (2024), and Song et al. (2024) study software developers assisted with code-generating AI, Dell'Acqua et al. (2023) study consultants, and Noy and Zhang (2023) study writers with ChatGPT, Dillon et al. (2025) study general white-collar workers with AI tools integrated in their commonly used office software, and Toner-Rodgers (2024) studies scientists with an AI tool for materials discovery.

These studies generally find that AI increases both the quantity and quality of workers' output. Some productivity gains arise from quicker and higher-quality completion of tasks, while others reflect the reallocation of effort across tasks: writers let AI handle drafting and focused on ideation and editing (Noy and Zhang 2023) and scientists spend less time on ideation and more on evaluating AI output (Toner-Rodgers 2024).

These studies also tend to find that the least productive and least experienced workers gain the largest productivity increases. AI tools appear to perform at a level close to the most productive workers, leaving little room for improvement, while the less productive workers receive useful inputs and increase their performance. AI tools can therefore complement the less-skilled workers and thus decrease productivity differences within occupations. This points to the potential of AI to enable a larger share of workers to perform work that, without AI, would require high skill (Autor 2024).

These tasks and contexts may, however, represent selected use cases of generative AI and thus overstate wider productivity effects. Studying a more representative set of occupations, Humlum and Vestergaard (2025a) combine reported estimates of time savings in individual tasks with the frequency of chatbot use to estimate an average time saving of 3 %.

3.2.2 FIRMS

Firms achieve productivity gains by increasing the value of outputs relative to the cost of inputs. By adopting AI in production without changing outputs (**process innovation**), firms decrease the costs of production. By adopting AI in production to change outputs (**product innovation**), firms increase the value of their outputs. AI can also increase firm productivity by itself being the innovator of products or processes (Cockburn et al. 2019, Aghion et al. 2019).

Firm-level productivity effects cannot be studied in as tightly controlled (quasi-)experimental settings as worker-level effects. Thus, while there is a positive correlation between AI adoption and productivity (Acemoglu et al. 2023b; Calvino et al. 2022; Humlum and Vestergaard 2025a) it is not clear whether AI adoption increases productivity or more productive firms adopt AI.

Studying German firms, Czarnitzki et al. (2023) find, with other inputs kept constant, an (instrumented) association between narrow AI adoption, including both in-house-developed and acquired AI, and increased sales and value-added. Proxying AI investment with AI skill requirements in firms' job postings, Babina et al. (2024) find no productivity increases following narrow AI investments among US firms, while Bäck et al. (2022) find productivity increases among large Finnish firms with a three-year lag. Yang (2022) finds that Taiwanese firms that patent narrow AI technologies are more productive than similar firms that do not.

Evidence on the impact of generative AI is still scarce. Insofar as firm stock valuations proxy expected firm productivity, Eisfeldt et al. (2024) find that the release of ChatGPT increased the valuation of firms which, by the similarity of the tasks performed in the firms and the capacities of generative AI, are exposed to generative AI.

The effects on labour depend on how productivity increases are achieved. Eisfeldt et al. (2024) find that the introduction of ChatGPT especially increased the stock valuations of firms whose workers' core tasks are exposed to AI. They interpret this to mean that the stock market expected the highest productivity increases to occur through cost-cutting process innovation and automation. In contrast, studying investments in narrow AI, Babina et al. (2024) find that AI investments are associated with more trademarks and patents, suggesting that AI investments have generated product innovation. Rammer et al. (2022) find evidence of AI use positively correlating with both product and process innovation among German firms.

The evidence from surveys points to both process and product innovation. In 2023 and 2024, a third of US firms used AI to perform tasks previously done by workers (Bonney et al. 2024). Employers in member countries of the Organisation for Economic Co-operation and Development (OECD) more often report the motivation for AI adoption to be improving worker performance rather than reducing staff costs (Lane et al. 2023). However, they also report AI being more frequently used to automate established tasks rather than create new tasks in their companies.

How and for what purposes firms adopt AI, of course, varies. Some firms are also able to realise substantial productivity gains while others are not, and some focus on cost-cutting while others focus on creating better products. There are, however, reasons to expect an unequal distribution of productivity gains across firms: for instance, larger firms tend to possess existing complementary technologies (Eisfeldt et al. 2024) and greater capacity for complementary investments (Lee et al. 2022; Agrawal et al. 2023). Moreover, the winner-takes-all dynamics of digital goods can concentrate markets (Babina et al. 2024) and generate superstar firms (Autor et al. 2020). These productivity differences may filter through to wage gaps between firms and thus to wage gaps between workers.

3.3. EMPLOYMENT

Having examined the adoption and productivity effects of AI, we now turn to the employment effects. This section reviews the existing evidence on the early employment and wage effects of AI.

3.3.1 EXPOSURE

Ex-ante evaluations of the potential labour market impact of AI break occupations into tasks or skills, identify which of these tasks or skills AI can perform, and compute the share of such tasks or skills in occupations, industries, firms, or regions to construct a measure of **AI exposure** (Felten et al. 2018, 2021; Brynjolfsson et al. 2018). This exposure proxies the usefulness of technological development for these units. Numerical results vary widely depending on the exact method used and the stage of technology studied. Moreover, these measures of exposure are also agnostic as to whether AI adoption is economically viable (Svanberg et al. 2024) or socially acceptable (Pizzinelli et al. 2023). The numerical estimates of AI exposure are thus difficult to interpret.

The results concerning the heterogeneity in AI exposure across groups of workers are more interesting. AI exposure increases with income and education (Pizzinelli et al. 2023, Eloundou et al. 2024; Albanesi et al. 2025) and the occupations most exposed are those requiring routine and nonroutine cognitive analytical skills, while social and manual tasks are relatively shielded (Engberg et al. 2024; Eisfeldt et al. 2024). Women are more exposed than men (Pizzinelli et al. 2023; Gmyrek et al. 2023) due to their concentration in female-dominated service and retail occupations. Advanced economies with a high share of jobs requiring cognitive skills are more exposed than emerging and developing economies (Pizzinelli et al. 2023; Cazzaniga et al. 2024).

These measures of exposure are agnostic as to whether the exposure is labour-displacing or labour-augmenting. In most occupations, only a fraction of tasks can be automated (Brynjolfsson et al. 2018; Gmyrek et al. 2023), suggesting that the displacement of entire occupations should not be expected. However, as AI evolves, a larger share of the core tasks of occupations will become automatable (Auer et al. 2024; Eloundou et al. 2024). Attempts to classify exposure as substituting or complementing (Auer et al. 2024; Rockall et al. 2025; Cazzaniga et al. 2024; Hampole et al. 2025) suggest that while exposure increases with income, so does exposure's complementariness. This points to skill-biased AI displacing workers in low-skill exposed occupations and augmenting workers in high-skill exposed occupations.

3.3.2 VACANCIES

Changes in the demand for labour are often quickly visible in job postings. In the US, job postings requiring AI skills began to appear in the 2010s, with numbers increasing towards the end of the decade, reaching 0.5–0.8 % of all job advertisements (Alekseeva et al. 2021; Acemoglu et al. 2022). Meanwhile, the share of job advertisements requiring computer skills and software skills has been about 25 % of all job postings (Alekseeva et al. 2021). In Germany, the share of job postings requiring AI skills increased from 0.09 % to 0.22 % in the period 2015–2019 (Peede and Stops 2024). In Finland, the share of firms publishing AI-related job postings increased from 2 % in 2013 to 13 % in 2019 and the share of job postings mentioning AI or closely related terms increased from close to zero to around 0.5 % (Bäck et al. 2022). These jobs were mostly in information and communication technologies and, given their explicit AI skill requirements, likely corresponded to positions in developing AI technologies.

Generative AI has further increased the demand for AI skills. In the United Kingdom (UK), the share of job postings requiring AI skills increased from 0.5 % in 2018 to close to 1 % in 2024 (Bone et al. 2025). Eisfeldt et al. (2024) and Chen et al. (2025) aim to identify the effects of generative AI on job postings for occupations with varying degrees of automation potential: Job postings for occupations exposed to AI decrease, while job postings for occupations less exposed to AI decrease less (Eisfeldt et al. 2024), and job postings for occupations likely to benefit from generative AI increase (Chen et al. 2025) following the introduction of ChatGPT.

3.3.3 JOBS

A first step in looking for employment effects is to examine whether AI exposure in regions, industries, occupations or firms predicts changes in employment. The results are mixed: Bonfiglioni et al. (2025) estimate that higher exposure to AI have reduced employment in US commuting zones, while Guarascio et al. (2023) find a positive correlation between AI exposure and employment growth across regions in Europe. At the occupation level, Albanesi et al. (2025) find that occupations exposed to AI increased their employment shares in Europe. Frank et al. (2023) find that occupational AI exposure correlates with job separation and unemployment, and Acemoglu et al. (2022) find no correlation between AI exposure and employment at the industry and occupation level in the United States. Nevertheless, Acemoglu et al. (2022) find that AI-exposed establishments reduce their hiring, especially the hiring of workers without AI skills.

Clearly, the effect of exposure should be interpreted as a net outcome of substitution and complementarity effects. Moreover, since AI may change production in various ways and exposure may be labour-displacing or labour-augmenting, the mixed results are not unexpected. Studying narrow AI in the United States, Hampole et al. (2025) find positive job growth in occupations with substantial variation in task-specific exposure to AI and negative job growth in occupations with little variation but high average task-specific exposure to AI. High variation in task-specific exposure is interpreted as occupation involving many tasks not exposed to AI, making the occupation complementary to AI.

The effects of exposure are expected to operate through firms actually adopting AI in production. However, the research on the consequences of AI adoption on the firm's workforce faces similar challenges to the research studying firm-level productivity effects discussed in the previous section. While there appears to be a correlation between AI adoption and employment growth (Acemoglu et al. 2023b; Babina et al. 2024) and between AI patenting and employment growth (Yang 2022), interpreting these correlations is difficult (Acemoglu et al. 2023b).

There is also early evidence on the effects of generative AI. Kauhanen and Rouvinen (2024) and Kässi (2024) use tax registers to study employment in Finland around the release of ChatGPT and find no employment effects in high-exposure occupations relative to low-exposure occupations. Using a similar setting, Humlum and Vestergaard (2025a) find no effect on working hours in Denmark. Jiang et al. (2025), using US time-use surveys, find that AI exposure is associated with longer working hours and less leisure, especially in contexts where AI increases labour's marginal productivity.

While the evidence on the employment effects of AI exposure and adoption is mixed, differences between the effects on low and high-skilled workers stand out. Firms in Europe (Engberg et al. 2024), occupations in Europe (Fossen and Sorgner 2022; Albanesi et al. 2025) and US commuting zones (Bonfiglioni et al. 2025) that are more exposed to AI employ fewer low-skilled and more high-skilled workers. Likewise, US and German firms adopting AI (Babina et al. 2023; Mühlemann 2024) and Taiwanese firms patenting AI (Yang 2022) are adjusting their workforce compositions toward higher-skilled workers.

3.3.4 TASKS

The essence of the task-based model of production is that tasks, rather than occupations, are automated. Occupations may reorganize around the non-automated tasks. Among surveyed US firms, more reported changes in tasks than in employment (Bonney et al. 2024). German firms exposed to AI reduced the share of nonroutine cognitive tasks, such as information gathering and documenting, and increased the share of tasks involving monitoring and operating machines and technical processes, and, among the high-skilled, tasks in education and training (Gathmann et al. 2024). Swiss stock analysts exposed to AI tools spend more time on complex research and social tasks, such as management and marketing (Grennan and Michaely 2020).

New tasks have primarily been created in developing and adopting AI tools, including training, establishing, explaining, and monitoring AI systems (Milanez 2023; Pimenta Arruda and Pimenta 2024). Generative AI has created new tasks for 8 % of Danish workers (Humlum and Vestergaard 2025a). These tasks mostly relate to the implementation and integration of AI, including ethics and compliance.

Task-level effects may be visible at online freelance work platforms, which are marketplaces for individual work tasks. Teutloff et al. (2025), Liu et al. (2023), Hui et al. (2024), Demirci et al. (2025), Lysyakov and Viswanathan (2023), and Qiao et al. (2025) study the effects of the release of ChatGPT on these platforms. These studies tend to find a significant reduction in the demand for skills overlapping with ChatGPT's capabilities. However, the demand for skills complementary to AI increased (Teutloff et al. 2025; Qiao et al. 2025), and workers using generative AI in their work attracted more jobs (Liu et al. 2023). Low-skilled designers exited the market and high-skilled designers shifted to more complex tasks (Lysyakov and Viswanathan 2023) and novice workers were the most affected (Teutloff et al. 2025). Teutloff et al. (2025) also find that short-term gigs were the most affected, likely due to AI mainly replacing labour in simple tasks.

3.3.5 WAGES

AI-adopting firms tend to pay higher wages than other firms (Acemoglu et al. 2023b). However, AI-adopting firms also have more educated workforces, and they operate more often in ICT. Moreover, these firms may already pay higher wages to start with, which may incentivise the adoption of labour-saving technologies. The evidence on the association between an occupation's exposure to narrow AI and wage growth is mixed (Acemoglu et al. 2022a,e; Fossen and Sorgner 2022; Albanesi et al. 2025, Georgieff 2024; Jiang et al. 2025). Again, education may play a role: Fossen and Sorgner (2022) and Albanesi et al. (2025) find that among the exposed workers, those with higher education experience higher wage growth. Gathmann et al. (2024) find that low-skilled workers in exposed industries experience wage declines. Moreover, exposure does not imply adoption, nor does it reveal whether exposure is augmenting or displacing, and thus these mixed findings may reflect early phases of AI diffusion or substituting and complementing exposures balancing out. This mixed evidence is, however, in line with the mixed evidence on the productivity effects of narrow AI.

Turning to generative AI, Kauhanen and Rouvali (2024), using Finnish tax registers, find wage increases in occupations exposed to generative AI following the introduction of ChatGPT. Eisfeldt et al. (2024), studying job postings in a similar setting, find a small decline in wages in AI-exposed occupations. Comparing Danish chatbot adopters to non-adopters before and after the introduction of ChatGPT, Humlum and Vestergaard (2025a) find no effect on wages or earnings.

AI skills, however, are rewarded. Job postings in the United States, United Kingdom, Australia, New Zealand and Canada requiring AI skills have a wage premium (Alekseeva et al. 2021; Manca 2023; Bone et al. 2025). Applicants with AI skills in the United Kingdom get more job interview invitations (Drydakis 2024). Workers with AI skills in European job markets have higher wages than similar non-AI programmers (Pouliakas et al. 2025). On online job platforms, AI skills (Stephany and Teutloff 2024) and AI tasks (Duch-Brown et al. 2022) earn a premium attributable to high demand relative to their supply. The rewards for AI skills may contribute to skill and gender wage gaps: males and those with higher levels of education are more likely to have AI skills (Green and Lamby 2023).

4 AI and policy

The EU AI Act (2024/1689) defines, in Article 1, its purpose as the promotion of **human-centric** AI. The recitals of the Act specify that human-centric AI should serve as a tool for people with the ultimate aim of increasing well-being. More directly in relation to labour markets, the Artificial Intelligence Strategy of the German Federal Government (German Federal Government 2020) envisions AI development and use aligned with the Sustainable Development Goals. Sustainable Development Goal 8 includes the promotion of inclusive economic growth and full and productive employment for all. This section discusses policies supporting the inclusive distribution of productivity gains and productive employment.

4.1. DISTRIBUTION OF GAINS

A policymaker concerned about the distribution of income may wish for the adoption of AI to benefit all potential labour market participants. Policies affecting the market distribution of income take the form of supporting the bargaining power and the marginal productivity of labour. Taxes, transfers, and social insurance further distribute gains.

4.1.1 BARGAINING

When prices remain constant, productivity gains create profits above costs. As prices change, this surplus is distributed to workers, capital owners, or consumers. For instance, less than 10 % of the productivity gains of chatbots are passed through to workers in Denmark (Humlum and Vestergaard 2025a). In the past, most of the gains of robotics have accrued to owners (Acemoglu and Restrepo 2020).

With surplus to distribute, workers' share of the gains is partly determined by their ability to bargain for wage increases. Parolin (2021) studies whether union membership alleviates the effects of automation in the United States, and finds that more organised labour is shielded from wage declines. However, this comes with a cost: More organised labour also faces stronger negative employment effects. Indeed, bargaining with precarious ability to contribute to production may encourage automation as highlighted by Marx's account on, how, throughout industrialisation, "strikes have regularly given rise to the invention and application of new machines" (Marx 1955, p. 161).

4.1.2 EDUCATION

While AI could complement low-skilled workers by supporting them in high-skilled jobs (Autor 2024), the current evidence points to a continuation of skill-biased technological change. Even if, within tasks, AI can decrease productivity differences (Section 3.2), in general, AI appears to complement high-skilled labour more than low-skilled labour (Section 3.3). Of course, this may partly reflect that production still implements AI through large investments drawing from a scarce pool of AI skills.

Nevertheless, highly educated workers may be more adaptable to new tasks and new technologies. AI adoption seems to positively correlate with education at the individual, firm, and industry level (Section 3.1). In reaction to technological changes, higher-educated workers are also more mobile across tasks (Gathmann et al. 2024), occupations, and workplaces (Cazzaniga et al. 2024; Fossen and Sorgner 2024). Thus, if AI complements highly-educated labour more than less-educated labour, then increasing the education of the labour force may help labour capture productivity gains.

4.1.3 TRAINING

In addition to preparing the next generations of workers with formal qualifications, the displacement and reinstatement effects require re-skilling to support mobility between occupations and tasks. Indeed, in tight labour markets employers may de-emphasise formal qualifications: the emphasis on AI-skills is increasing at the expense of formal qualifications in UK job postings (Bone et al. 2025) and AI developers employed across European countries tend to have less formal education than other software developers (Pouliakas et al. 2025).

Workplace training may also help share productivity gains. The adoption of AI is often left to workers, and gaps in adoption may lead to productivity gaps (Humlum and Vestergaard 2025b). Employer's initiatives in AI adoption, including training, may help alleviate these gaps. Gender differences in AI adoption are smaller in Danish firms that actively encourage adoption (Humlum and Vestergaard 2025a).

4.1.4 REDISTRIBUTION

Productivity gains are also redistributed via taxes and transfers, reaching those not in employment as well. Unemployment insurance and other welfare programmes provide targeted support for those who are eligible. However, fears of widespread technological unemployment have led many to suggest a universal basic income (UBI), an unconditional regular transfer for everyone. While universal basic income faces challenges in financing, resource allocation, and incentives (Goolsbee 2019), more fundamentally, by adapting to decreasing marginal productivity of labour, it may support automation (Acemoglu and

Johnson 2023). Moreover, if labour's economic power decreases with its ability to contribute to production, labour's political power may decrease as well (Brynjolfsson 2022).

4.2. DIRECTION OF TECHNOLOGICAL CHANGE

There are multiple potential paths of technological change. However, market incentives for the development and adoption of new technologies do not necessarily lead down the socially preferable path. Both the development and adoption of new technologies depend on the benefits of these activities for those making the decisions: firms adopt the technologies that increase their profits or cut their costs the most, and innovators work on the technologies that reward them the most. Policies can affect the profitability of these activities and the distribution of power among decision-makers and thus direct technological change in production.

4.2.1 MARKET FAILURES

Generally, research and innovation are undersupplied relative to the efficient level because of their positive externalities: innovators do not take into account the full potential social benefits of their work. The AI strategies of the European Commission (European Commission 2018) and the German Federal Government (German Federal Government 2020) therefore aim for substantial public funding of AI research. As AI is a general-purpose technology, these investments may be warranted (Goldfarb et al. 2023).

However, the issue concerns not only the quantity but also the direction of research. The direction of technological change may be distorted towards excessive automation, that is, toward technologies that substitute rather than complement labour, and towards technologies that cut costs rather than create new products and tasks (Acemoglu 2023a). As the term suggests, AI aims to automate intelligence. Also, common performance benchmarks for AI measure how well human skills are automated (Maslej et al. 2025). However, the set of tasks that humans can do with AI exceeds the set of tasks that AI can do alone (Brynjolfsson 2022). If technological change had only automated production in the past, we would be extremely productive in making clay pottery (Brynjolfsson 2022). Rather, economic growth and rising value creation tend to come from new goods, services, and tasks (Bresnahan and Gordon 1996).

4.2.2 POLICIES

A human-centric direction of technological change focuses on increasing the marginal productivity of labour, for instance, by creating new tasks for workers and by augmenting both low- and high-skilled labour (Acemoglu et al. 2023a). As usual, the policies to influence the amount of externality-creating activity can be categorised as taxes, bargaining and quotas.

The use of labour and capital in production is often taxed at different rates. Employing labour comes with levies such as social security and pension contributions in addition to income taxes, whereas investments in capital may benefit from tax-deductible interest rates and accelerated depreciation schemes. These gaps in effective prices of labour and capital favour automation (Acemoglu et al. 2020a; Brollo et al. 2024). However, taxing capital may be unattractive to countries competing for capital flows and investment. If this is the case, reductions in the effective taxation of labour may be more viable (Acemoglu and Johnson 2023).

The externalities of excessive automation accrue mainly to labour. Incorporating the perspectives of workers helps internalise these externalities. The involvement and bargaining power of labour unions and works councils in the adoption of new technologies may support the adoption of technologies that increase the marginal productivity of labour. According to survey results reported by Lane et al. (2023), both employers and employees in workplaces where workers or their representatives were consulted on AI adoption report larger productivity gains. However, the same survey reports that just over half of AI-using employers have consulted workers or their representatives about AI adoption. AI training is also more common in firms where workers have some form of representation (Cedefop 2025). Such representation is also important in avoiding the adoption of technologies that primarily extract rents. Jiang et al. (2025), using US time-use surveys, find that AI exposure is associated with longer working hours with the effect amplified in contexts where AI enhances labour's marginal productivity and monitoring efficiency. When labour's marginal productivity is high, increased demand for output can foster increased demand for labour. Without the bargaining power to capture the resulting surplus, however, the effects for labour may be detrimental (Acemoglu and Johnson 2023).

While quotas refer to a quantifiable level of required or permitted activity, the relevant concern here is a certain quality of research. The AI strategies of the European Union (European Commission 2018) and the German Federal Government (German Federal Government 2020) envision substantial investments in AI. While governments have a mixed track record when it comes to picking winners, i.e. specific technologies and firms, they can nonetheless influence the direction of technological development by identifying classes of types of technologies with more socially beneficial prospects and by conditioning their funding on the development of those types of technologies (Acemoglu and Johnson 2023).

4.3. POLICY PREFERENCES

In democracies, policies require voters' support. Clearly, the effects of AI on politics are broader than discussed here (see e.g. Acemoglu 2023b). However, this section focuses on how technology-induced changes in labour markets affect views on labour market policy and attitudes towards democracy itself. As research on AI and policy preferences is still scarce, this section draws on the larger literature on automation and policy preferences.

4.3.1 ATTITUDES TOWARD POLICY

Increases in economic inequality and job insecurity raise the share of voters who benefit from redistribution and unemployment insurance and can thus be expected to increase support for such policies (Meltzer and Richard 1981; Wright 1986). The evidence generally points to automation risk increasing demand for redistribution, including unemployment insurance and universal basic income, but the evidence is not strong (Callego and Kurer 2022; Weisstanner 2023).

Preventing or directing technological change is rarely supported (Wu 2022; Heinrich and Witko 2024). One reason is that workers are also consumers and consumers value technological change (Magistro 2025). Moreover, technological change is not always perceived to be the culprit (Callego and Kurer 2022). Nevertheless, surveys and experiments have elicited such preferences when explicitly asked. While the majority of surveyed Spaniards view new technologies in the workplace positively, a concerned minority supports slowing down technological development (Gallego et al. 2022). It is possible that the pace and salience of the latest developments in AI may alter these views.

Expanding the availability of education and training, while holding a prominent place in AI strategies (European Commission 2018; German Federal Government 2020), is not widely supported either. Exposure to automation tends to negatively correlate with demand for active labour market policies (Weisstanner 2023) and does not appear to increase support for expanding access to education (Kurer and Häusermann 2022; Busemeyer et al. 2023). Clearly, education and retraining are costly to individuals.

4.3.2 ATTITUDES TOWARD DEMOCRACY

A robust finding is that those who have perceived increasing economic insecurity due to technological change tend to support radical right and anti-establishment parties (Callego and Kurer 2022; Bekhtiar 2025). It also appears to be those who perceive a decline of relative societal status whilst remaining in employment who are drawn to right-wing policies, while those who actually lose their jobs tend to support redistribution or abstain from politics (Im et al. 2019; Kurer 2020).

While the support for redistribution among the jobless can be understood in terms of their own economic interest, the motivations behind far-right voting among the larger and thus politically more consequential group, those perceiving economic decline, are contested. One interpretation is that middle-skilled routine (male) workers (O'Grady 2019; Dal Bó et al. 2023) and their preferences (Boix 2019) have been underrepresented by the established political parties. Another narrative is a (mis)attribution of the causes of economic insecurity to globalisation, immigration and the delegation of some national powers to the EU (Callego and Kurer 2022; Wu 2022; Kuo et al. 2024). Such (mis)attribution may be reinforced by political rhetoric (Walter 2021; Im et al. 2019; Jeffrey 2019).

If the shift toward the far-right stems from perceived decline in status, redistribution may not be a popular platform (Gingrich 2019, Kurer 2020). Rather, these voters are concerned with the market distribution of income. Inclusive distribution of productivity gains therefore requires policies that support labour's bargaining power and labour's ability to productively contribute to production (Van Overbeke 2024, Acemoglu and Johnson 2023). New opportunities may have at least local effects: In Germany, shifts in employment toward service sectors have attracted workers less supportive of far-right ideologies, dampening the automation-induced changes in the electorate (Schöll and Kurer 2024). Without such opportunities, the young in particular may be drawn towards the far-right (Mitsch 2020).

5 Outlook

The eventual labour market effects of AI are still uncertain, and extrapolating from currently observed effects into the future is not warranted. First, the labour market effects of AI depend on the nature of the technology. The emerging capabilities of AI have surprised even its developers (Wei et al. 2023). Some are predicting technological singularity, in which AI reaches superintelligence, surpassing all human abilities, after which AI can develop at an accelerating rate and the value of all human labour goes to zero (Nordhaus 2021).

Second, the effects take time. The adoption of AI requires investments in and the development of complementarities such as human capital and skills, new production processes and business models, digitalisation and data, and organisational structures (Brynjolfsson et al. 2021). General-purpose technologies also require further downstream innovation (Brynjolfsson et al. 2019).

Finally, it is important to keep in mind that, having taken a narrow focus on AI in non-physical tasks, the labour market effects discussed here are not the only ones to be expected. Technological change continues elsewhere, especially in robotics, as well, and those developments may continue to automate routine manual tasks and, together with AI, also nonroutine manual tasks.

Given the early phase of the implementation of AI technologies in production, the uncertainties surrounding their capabilities, and the need for complementary investments, it is crucial that the employment and wage effects of AI are monitored and continuously researched. It is important to understand early what kinds of labour reallocation are likely to occur. In the past, much of the labour reallocation has taken place through labour market exits of older workers and labour market entries of younger workers. However, if AI affects entry-level jobs, then the young people entering the labour force may require support. If the effects of AI are rapid, then reskilling and occupational mobility may be required.

Any policy, however, requires voters' and participants' support and thus it is important to understand the perspectives of those whose livelihoods are threatened by AI. What do they perceive as the causes of their situation? What is their motivation and willingness for reskilling and occupational mobility? Does income support, public employment services, or job mobility affect their voting behaviour?

Literature

Acemoglu, Daron. 2023a. Distorted innovation: does the market get the direction of technology right? *AEA Papers and Proceedings*, 113, 1-28. DOI: 10.1257/pandp.20231000.

Acemoglu, Daron. 2023b. Harms of AI. In *The Oxford Handbook of AI Governance*, Eds. Justin B. Bullock, Yu-Che Chen, Johannes Himmelreich, Valerie M. Hudson, Anton Korinek, Matthew M. Young and Baobao Zhang, 660-706, Oxford: Oxford University Press. DOI: 10.1093/oxfordhb/9780197579329.013.65.

Acemoglu, Daron. 2025. The simple macroeconomics of AI. *Economic Policy* 40/121: 13-58. DOI: 10.1093/epolic/eiae042.

Acemoglu, Daron and David Autor. 2011. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics Volume 4*, Eds. David Card and Orley Ashenfelter, 1043-1171, Elsevier. DOI: 10.1016/S0169-7218(11)02410-5.

Acemoglu, Daron, Andrea Manera, and Pascual Restrepo. 2020a. Does the US Tax Code Favor Automation? *Brookings Papers on Economic Activity Spring*: 231-300. https://www.brookings.edu/articles/does-the-u-s-tax-code-favor-automation/ (accessed 25 June 2025).

Acemoglu, Daron and Simon Johnson. 2023. *Power and Progress: Our Thousand-Year Struggle Over Technology and Prosperity*. New York: Hachette Book Group.

Acemoglu, Daron and Simon Johnson. 2024. Learning from Ricardo and Thompson: Machinery and labor in the early industrial revolution and in the age of artificial intelligence. *Annual Review of Economics* 16/1: 597-621.DOI: 10.1146/annurev-economics-091823-025129.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo. 2022. Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics* Vol. 40, no. S1: S293-S340. DOI: 10.1086/718327.

Acemoglu, Daron, David Autor, and Simon Johnson. 2023a. Can we have pro-worker AI? Choosing a path of machines in service of minds. *CEPR Policy Insight* no. 123. https://cepr.org/publications/policy-insight-123-can-we-have-pro-worker-ai-choosing-path-machines-service-minds (accessed 25 June 2025).

Acemoglu, Daron, Gary Anderson, David Beede, Catherine Buffington, Eric Childress, Emin Dinlersoz, Lucia Foster, Nathan Goldschlag, John Haltiwanger, Zachary Kroff, Pascual Restrepo, and Nikolas Zolas. 2023b. Advanced Technology Adoption: Selection or Causal Effects? *AEA Papers and Proceedings* 113, 210-214. DOI: 10.1257/pandp.20231037.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020b. Competing with robots: Firm-level evidence from France. *AEA Papers and Proceedings* 110: 383-388. DOI: 10.1257/pandp.20201003.

Acemoglu, Daron and Todd Lensman. 2024. Regulating transformative technologies. *American Economic Review: Insights* 6/3: 359-376. DOI: 10.1257/aeri.20230353.
Acemoglu, Daron and Pascual Restrepo. 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review* 108/6: 1488-1542. DOI: 10.1257/aer.20160696.
Acemoglu, Daron and Pascual Restrepo. 2019a. Artificial intelligence, automation, and work. In *The economics of artificial intelligence: An agenda*, Eds. Ajay Agrawal, Joshua Gans and Avi Goldfarb, 197-236, Chicago: The University of Chicago Press. http://www.nber.org/chapters/c14027 (accessed 25 June 2025).
Acemoglu, Daron and Pascual Restrepo. 2019b. Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives* 33/2: 3-30. DOI: 10.1257/jep.33.2.3.
Acemoglu, Daron and Pascual Restrepo. 2020. Robots and jobs: Evidence from US labor markets. *Journal of Political Economy* 128/6: 2188-2244. DOI: 10.1086/705716.
Acemoglu, Daron and Pascual Restrepo. 2022. Tasks, automation, and the rise in US wage inequality. *Econometrica* 90/5: 1973-2016. DOI: 10.3982/ECTA19815.
Acemoglu, Daron and Pascual Restrepo. 2024. A task-based approach to inequality, *Oxford Open Economics*, Volume 3, Issue Supplement_1, i906–i929. DOI: 10.1093/ooec/odad082.
Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones. 2019. Artificial intelligence and economic growth. In *The Economics of Artificial Intelligence: An Agenda*, Eds. Ajay Agrawal, Joshua Gans and Avi Goldfarb, 237-282. Chicago: The University of Chicago Press. http://www.nber.org/chapters/c14015 (accessed 25 June 2025).
Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2019a. Introduction to "The Economics of Artificial Intelligence: An Agenda". In *The Economics of Artificial Intelligence: An Agenda*, Eds. Ajay Agrawal, Joshua Gans and Avi Goldfarb, 1-19. Chicago: The University of Chicago Press. http://www.nber.org/chapters/c14005 (accessed 25 June 2025).
Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2019b. Artificial intelligence: the ambiguous labor market impact of automating prediction. *Journal of Economic Perspectives*, 33/2, 31-50. DOI: 10.1257/jep.33.2.31.
Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2023. Similarities and differences in the adoption of general purpose technologies. *NBER Working Paper Series* No. w30976. National Bureau of Economic Research. DOI: 10.3386/w30976.
Albanesi, Stefania, António Dias da Silva, Juan F. Jimeno, Ana Lamo, and Alena Wabitsch. 2025. New technologies and jobs in Europe. *Economic Policy* 40/121: 71-139. DOI: 10.1093/epolic/eiae058.
Aldasoro, Iñaki, Olivier Armantier, Sebastian Doerr, Leonardo Gambacorta, and Tommaso Oliviero. 2024. The gen AI gender gap. *Economics Letters* 241/111814. 1-3. DOI: 10.1016/j.econlet.2024.111814.
Alekseeva, Liudmila, José Azar, Mireia Giné, Sampsa Samila, and Bledi Taska. 2021. The demand for AI skills in the labor market. *Labour economics* 71: 102002: 1-27. DOI: 10.1016/j.labeco.2021.102002.
Auer, Raphael, David Köpfer, and Josef Švéda. 2024. The rise of generative AI: modeling exposure, substitution, and inequality effects on the US labour market. *BIS Working Papers* No 1207. Bank for International Settlements. https://www.bis.org/publ/work1207.pdf (accessed 25 June 2025).
Autor, David. 2024. Applying AI to rebuild middle class jobs. *NBER Working Paper Series* No. w32140. National Bureau of Economic Research. DOI: 10.3386/w32140.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2020. The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics* 135/2: 645-709. DOI: 10.1093/qje/qjaa004.

Autor, David, Caroline Chin, Anna Salomons, and Bryan Seegmiller. 2024. New frontiers: The origins and content of new work, 1940–2018. *The Quarterly Journal of Economics* 139/3: 1399-1465. DOI: 10.1093/qje/qjae008.

Autor, David, Frank Levy, and Richard J. Murnane. 2003. The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics* 118/4: 1279-1333. DOI: 10.1162/003355303322552801.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson. 2023. Firm investments in artificial intelligence technologies and changes in workforce composition. *NBER Working Paper* No. w31325. National Bureau of Economic Research. DOI: 10.3386/w31325.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson. 2024. Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics* 151: 103745. DOI: 10.1016/j.jfineco.2023.103745.

Bäck, Asta, Arash Hajikhani, Angela Jäger, Torben Schubert, and Arho Suominen. 2022. *Return of the Solow-paradox in AI?: AI-adoption and firm productivity*. Centre for Innovation Research (CIRCLE), Lund University. https://wp.circle.lu.se/upload/CIRCLE/workingpapers/202201_baeck.pdf (accessed 26 June 2025).

Bastani, Spencer and Daniel Waldenström. 2024. AI, automation and taxation. In *Handbook on Labour Markets in Transition*. Eds. Stéphane Carcillo and Stefano Scarpetta. 354-370. Cheltenham: Edward Elgar Publishing. DOI: 10.4337/9781839106958.00026.

Bekhtiar, Karim. 2025. The decline of manufacturing employment and the rise of the far-right in Austria. *Journal of Public Economics* 242: 1-20. DOI: 10.1016/j.jpubeco.2025.105315.

Bick, Alexander, Adam Blandin, and David J. Deming. 2024. The rapid adoption of generative AI. *NBER Working Paper Series* No. w32966. National Bureau of Economic Research. DOI: 10.3386/w32966.

Boix, Carles. 2019. *Democratic Capitalism at the Crossroads: Technological Change and the Future of Politics*. Princeton, NJ: Princeton University Press.

Bone, Matthew, Eugenia Gonzalez Ehlinger, and Fabian Stephany. 2025. Skills or degree? The rise of skill-based hiring for AI and green jobs. *Technological Forecasting and Social Change* 214: 1-23. DOI: 10.1016/j.techfore.2025.124042.

Bonfiglioli, Alessandra, Rosario Crinò, Gino Gancia, and Ioannis Papadakis. 2025. Artificial intelligence and jobs: evidence from US commuting zones. *Economic Policy* 40/121: 145-194. DOI: 10.1093/epolic/eiae059.

Bonney, Kathryn, Cory Breaux, Catherine Buffington, Emin Dinlersoz, Lucia Foster, Nathan Goldschlag, John Haltiwanger, Zachary Kroff, and Keith Savage. 2024. The impact of AI on the workforce: Tasks versus jobs?. *Economics Letters* 244: 111971. 1-3. DOI: 10.1016/j.econlet.2024.111971.

Bresnahan, Timothy. 2010. General Purpose Technologies. In *Handbook of the Economics of Innovation Volume 2.* Eds. Bronwyn H. Hall and Nathan Rosenberg. 761-791. DOI: 10.1016/S0169-7218(10)02002-2.

Bresnahan, Timothy and Robert J. Gordon. 1996. Introduction to “The economics of new goods”. Eds. Bresnahan, Timothy and Robert J. Gordon. 1-26. Chicago: The University of Chicago Press. https://www.nber.org/system/files/chapters/c6063/c6063.pdf (accessed 25 June 2025).

Brey, Björn and Erik van der Marel. 2024. The role of human-capital in artificial intelligence adoption. *Economics Letters.* 244/111949. 1-5. DOI: 10.1016/j.econlet.2024.111949.

Brollo, Fernanda, Era Dabla-Norris, Ruud de Mooij, Daniel Garcia-Macia, Tibor Hanappi, Li Liu, and Anh DM Nguyen. 2024. Broadening the Gains from Generative AI: The Role of Fiscal Policies. *Staff Discussion Notes* 2024/002: 1-47. International Monetary Fund. DOI: 10.5089/9798400277177.006.

Brynjolfsson, Erik. 2022. The Turing trap: The promise & peril of human-like artificial intelligence. *Daedalus* 151/2: 272-287. DOI: 10.1162/daed_a_01915.

Brynjolfsson, Erik and Andrew McAfee. 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. New York: WW Norton & company.

Brynjolfsson, Erik, Danielle Li, and Lindsey R. Raymond. 2025. Generative AI at Work. *The Quarterly Journal of Economics* 140/2: 889-942. DOI: 10.1093/qje/qjae044.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. 2021. The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics* 13/1: 333-372. DOI: 10.1257/mac.20180386.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. 2019. Artificial intelligence and the modern productivity paradox. In *The Economics of Artificial Intelligence: An Agenda*, Eds. Ajay Agrawal, Joshua Gans and Avi Goldfarb, 23-57. Chicago: The University of Chicago Press. http://www.nber.org/chapters/c14007 (accessed 25 June 2025).

Brynjolfsson, Erik, Tom Mitchell, and Daniel Rock. 2018. What can machines learn and what does it mean for occupations and the economy? *AEA Papers and Proceedings*, 108: 43-47. DOI: 10.1257/pandp.20181019.

Busemeyer, Marius R., Mia Gandenberger, Carlo Knotz, and Tobias Tober. 2023. Preferred policy responses to technological change: Survey evidence from OECD countries. *Socio-Economic Review* 21/1: 593-615. DOI: 10.1093/ser/mwac015.

Calvino, Flavio, Lea Samek, Mariagrazia Squicciarini, and Cody Morris. 2022. Identifying and characterising AI adopters: A novel approach based on big data, *OECD Science, Technology and Industry Working Papers*, No. 2022/06, Paris: OECD Publishing. DOI: 10.1787/154981d7-en.

Carvajal, Daniel, Catalina Franco, and Siri Isaksson. 2024. Will artificial intelligence get in the way of achieving gender equality? Discussion Paper SAM 03/24. Institutt for samfunnsøkonomi, Norges Handelshøyskole. https://openaccess.nhh.no/nhh-xmlui/handle/11250/3122396 (accessed 25 June 2025).

Cazzaniga, Mauro, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J. Panton, Carlo Pizzinelli, Emma Rockall, and Marina M. Tavares. 2024. *Gen-AI: Artificial intelligence and the future of work*. International Monetary Fund. DOI: 10.5089/9798400262548.006.

Cedefop. 2025. Skills empower workers in the AI revolution: First findings from Cedefop's AI skills survey. Policy brief. Luxembourg: Publication Office of the European Union. DOI: 10.2801/6372704.

Chen, Wilbur Xinyuan, Suraj Srinivasan, and Saleh Zakerinia. 2025. Displacement or complementarity? The labor market impact of generative AI. *Harvard Business School Working Paper*. https://www.hbs.edu/faculty/Pages/item.aspx?num=67045.

Cockburn, Iain M., Rebecca Henderson, and Scott Stern. 2019. The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis. In *The Economics of Artificial Intelligence: An Agenda*, Eds. Ajay Agrawal, Joshua Gans and Avi Goldfarb, 115-146. Chicago: The University of Chicago Press. http://www.nber.org/chapters/c14006 (accessed 25 June 2025).

Cui, Kevin Zheyuan, Mert Demirer, Sonia Jaffe, Leon Musolff, Sida Peng, and Tobias Salz. 2024. The Productivity Effects of Generative AI: Evidence from a Field Experiment with GitHub Copilot. *An MIT Exploration of Generative AI.* DOI: 10.21428/e4baedd9.3ad85f1c.

Czarnitzki, Dirk, Gastón P. Fernández, and Christian Rammer. 2023. Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization* 211: 188-205. DOI: 10.1016/j.jebo.2023.05.008.

Dal Bo', Ernesto, Frederico Finan, Olle Folke, Torsten Persson, and Johanna Rickne. 2023. Economic and social outsiders but political insiders: Sweden's populist radical right. *The Review of Economic Studies* 90/2: 675-706. DOI: 10.1093/restud/rdac037.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. 2021. The adjustment of labor markets to robots. *Journal of the European Economic Association* 19/6: 3104-3153. DOI: 10.1093/jeea/jvab012.

Dell'Acqua, Fabrizio, Edward McFowland III, Ethan R. Mollick, Hila Lifshitz-Assaf, Katherine Kellogg, Saran Rajendran, Lisa Krayer, François Candelon, and Karim R. Lakhani. 2023. Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. *Harvard Business School Technology & Operations Mgt. Unit Working Paper*, 24-013. DOI: 10.2139/ssrn.4573321.

Demirci, Ozge, Jonas Hannane, and Xinrong Zhu. 2025. Who is AI replacing? The impact of generative AI on online freelancing platforms. *Management Science* 0/0. DOI: 10.1287/mnsc.2024.05420.

Dillon, Eleanor W., Sonia Jaffe, Nicole Immorlica, and Christopher T. Stanton. 2025. Shifting work patterns with generative AI. *NBER Working Papers* No. w33795. National Bureau of Economic Research. DOI: 10.3386/w33795.

Drydakis, Nick. 2024. Artificial intelligence capital and employment prospects. *Oxford Economic Papers* 76/4: 901-919. DOI: 10.1093/oep/gpae005.

Duarte, Fabio. 2025. Number of ChatGPT Users. Exploding topics. https://explodingtopics.com/blog/chatgpt-users (accessed 25 June 2025).

Duch-Brown, Nestor, Estrella Gomez-Herrera, Frank Mueller-Langer, and Songül Tolan. 2022. Market power and artificial intelligence work on online labour markets. *Research Policy*, 51/3, 104446. DOI: 10.1016/j.respol.2021.104446.

Eisfeldt, Andrea L., Gregor Schubert, and Miao Ben Zhang. 2023. Generative AI and firm values. *NBER Working Paper Series* No. w31222. National Bureau of Economic Research. DOI: 10.3386/w31222.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock. 2024. GPTs are GPTs: Labor market impact potential of LLMs. Science 384/6702: 1306-1308. DOI: 10.1126/science.adj0998.

Engberg, Erik, Holger Görg, Magnus Lodefalk, Farrukh Javed, Martin Längkvist, Natália Monteiro, Kyvik Nordås, Giuseppe Pulito, Sarah Schroeder, and Aili Tang. 2024. AI unboxed and jobs: A novel measure and firm-level evidence from three countries, RF Berlin - CReAM Discussion Paper Series, No. 14/24, Rockwool Foundation Berlin (RF Berlin) and Centre for Research & Analysis of Migration (CReAM). https://hdl.handle.net/10419/304412 (accessed 25 June 2025).

Eurostat. 2025a. Labor force survey. Employment by sex, age, occupation and educational attainment level (1 000) (lfsa_egised). https://ec.europa.eu/eurostat/web/main/data/database (accessed 25 June 2025).

Eurostat. 2025b. ICT usage in Enterprises. Artificial intelligence by NACE Rev. 2 activity (isoc_eb_ain2). https://ec.europa.eu/eurostat/web/main/data/database (accessed 25 June 2025).

Eurostat. 2025c. ICT usage in Enterprises. Digital Intensity by NACE Rev. 2 activity (isoc_e_diin2) https://ec.europa.eu/eurostat/web/main/data/database (accessed 25 June 2025).

Eurostat. 2025d. ICT users. Individuals' level of computer skills (2021 onwards) (isoc_sk_cskl_i21) https://ec.europa.eu/eurostat/web/main/data/database (accessed 25 June 2025).

Felten, Edward W., Manav Raj, and Robert Seamans. 2018. A method to link advances in artificial intelligence to occupational abilities. *AEA Papers and proceedings* 108, 54-57. DOI: 10.1257/pandp.20181021.

Felten, Edward W., Manav Raj, and Robert Seamans. 2021. Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal* 42/12, 2195-2217. DOI: 10.1002/smj.3286.

Fontanelli, Luca, Flavio Calvino, Chiara Criscuolo, Lionel Nesta, and Elena Verdolini. 2024. The role of human capital for AI adoption: evidence from French firms. Discussion Paper No. 2055. Centre for Economic Performance. https://cep.lse.ac.uk/pubs/download/dp2055.pdf (accessed 25 June 2025).

Fossen, Frank M. and Alina 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* 175: 121381. DOI: 10.1016/j.techfore.2021.121381.

Gallego, Aina and Thomas Kurer. 2022. Automation, digitalization, and artificial intelligence in the workplace: implications for political behavior. *Annual Review of Political Science* 25/1: 463-484. DOI: 10.1146/annurev-polisci-051120-104535.

Gallego, Aina, Alexander Kuo, Dulce Manzano, and José Fernández-Albertos. 2022. Technological Risk and Policy Preferences. Comparative Political Studies 55/1, 60-92. DOI: 10.1177/00104140211024290.

Gathmann, Christina, Felix Grimm, and Erwin Winkler. 2024. AI, Task Changes in Jobs, and Worker Reallocation *CESifo Working Paper Series* 11585. DOI: 10.2139/ssrn.5096973.

German Federal Government 2020. Artificial Intelligence Strategy of the German Federal Government. The Federal Government. https://www.ki-strategie-deutschland.de/files/downloads/Fortschreibung_KI-Strategie_engl.pdf (accessed 25 June 2025).

Georgieff, Alexandre. 2024. Artificial intelligence and age inequality. OECD *Artificial Intelligence Papers* No. 13. Paris: OECD Publishing. DOI: 10.1787/bf98a45c-en.

Gingrich, Jane. 2019. Did state responses to automation matter for voters? *Research & Politics* 6/1: 1-9. DOI: 10.1177/2053168019832745.

Gmyrek, Pawel, Janine Berg, and David Bescond. 2023. Generative AI and jobs: A global analysis of potential effects on job quantity and quality. *ILO working paper* 96. Geneva: International Labour Office, 2023. DOI: 10.54394/FHEM8239.

Goldfarb, Avi, Bledi Taska, and Florenta Teodoridis. 2023. Could machine learning be a general purpose technology? A comparison of emerging technologies using data from online job postings. *Research Policy* 52/1:1-25. DOI: 10.1016/j.respol.2022.104653.

Goller, Daniel, Christian Gschwendt, and Stefan C. Wolter. 2025. This time it's different–Generative Artificial Intelligence and Occupational Choice. *Labour Economics*: In Press, 102746. DOI: 10.1016/j.labeco.2025.102746.

Goolsbee, Austan. 2019. Public Policy in an AI Economy. In *The Economics of Artificial Intelligence: An Agenda*, Eds. Ajay Agrawal, Joshua Gans and Avi Goldfarb, 309-316. Chicago: The University of Chicago Press. http://www.nber.org/chapters/c14030 (accessed 25 June 2025).

Goos, Maarten and Alan Manning. 2007. Lousy and lovely jobs: The rising polarization of work in Britain. *The Review of Economics and Statistics* 89/1: 118-133. DOI: 10.1162/rest.89.1.118.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009. Job polarization in Europe. *American Economic Review* 99/2: 58-63. DOI: 10.1257/aer.99.2.58.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review* 104/8: 2509-2526. DOI: 10.1257/aer.104.8.2509.
Green, Andrew and Lucas Lamby. 2023. The supply, demand and characteristics of the AI workforce across OECD countries. *OECD Social, Employment and Migration Working Papers* No. 287. Paris: OECD Publishing. DOI: 10.1787/bb17314a-en.
Grennan, Jillian and Roni Michaely. 2020. Artificial intelligence and high-skilled work: Evidence from analysts. *Swiss Finance Institute Research Paper* 20-84. DOI: 10.2139/ssrn.3681574.
Guarascio, Dario; Reljic, Jelena; Stöllinger, Roman. 2023. Artificial Intelligence and Employment: A Look into the Crystal Ball. *GLO Discussion Paper* No. 1333, Global Labor Organization. https://www.econstor.eu/bitstream/10419/278106/1/GLO-DP-1333.pdf (accessed 25 June 2025).
Gutiérrez, Germán and Sophie Piton. 2020. Revisiting the global decline of the (non-housing) labor share. *American Economic Review: Insights* 2/3: 321-338. DOI: 10.1257/aeri.20190285.
Hampole, Menaka, Dimitris Papanikolaou, Lawrence DW Schmidt, and Bryan Seegmiller. 2025. Artificial intelligence and the labor market. *NBER Working Paper Series* No. w33509. National Bureau of Economic Research. DOI: 10.3386/w33509.
Heinrich, Tobias and Christopher Witko. 2024. Self-interest and preferences for the regulation of artificial intelligence." *Journal of Information Technology & Politics* 22/3: 306-321. DOI: 10.1080/19331681.2024.2370815.
Hoffmann, Manuel, Sam Boysel, Frank Nagle, Sida Peng, and Kevin Xu. 2024. Generative AI and the nature of work. *CESifo Working Papers* No. 11479. https://www.ifo.de/en/cesifo/publications/2024/working-paper/generative-ai-and-nature-work (accessed 25 June 2025).
Hui, Xiang, Oren Reshef, and Luofeng Zhou. 2024. The short-term effects of generative artificial intelligence on employment: Evidence from an online labor market. *Organization Science* 35/6: 1977-1989. DOI: 10.1287/orsc.2023.18441.
Humlum, Anders and Bjørn B. Meyer. 2022. Artificial intelligence and college Majors. Study Paper 172. The Rockwool Foundation Research Unit. https://en.rockwoolfonden.dk/publications/artificial-intelligence-and-college-majors/ (accessed 25 June 2025).
Humlum, Anders and Emilie Vestergaard. 2024. The Adoption of ChatGPT, *IZA Discussion Papers,* No. 16992, Institute of Labor Economics (IZA), Bonn https://hdl.handle.net/10419/299920 (accessed 25 June 2025).
Humlum, Anders and Emilie Vestergaard. 2025a. *Large language models, small labor market effects*. *NBER Working Paper Series* No. w33777. National Bureau of Economic Research. DOI: 10.3386/w33777.
Humlum, Anders and Emilie Vestergaard. 2025b. The unequal adoption of ChatGPT exacerbates existing inequalities among workers. *Proceedings of the National Academy of Sciences* 122/1. DOI: 10.1073/pnas.2414972121.
Im, Zhen Jie, Nonna Mayer, Bruno Palier, and Jan Rovny. 2019. The “losers of automation”: A reservoir of votes for the radical right? *Research & Politics* 6/1: 1-7. DOI: 10.1177/2053168018822395.
Jeffrey, Karen. 2021. Automation and the future of work: How rhetoric shapes the response in policy preferences. *Journal of Economic Behavior & Organization* 192: 417-433. DOI: 10.1016/j.jebo.2021.10.019.
Jiang, Wei, Junyoung Park, Rachel Jiqiu Xiao, and Shen Zhang. 2025. AI and the Extended Workday: Productivity, Contracting Efficiency, and Distribution of Rents. *NBER Working Papers* No. w33536. National Bureau of Economic Research. DOI: 10.3386/w33536.

Kässi, Otto. 2024. Hävittääkö tekoäly työtä? ChatGPT:n vaikutukset työvoiman kysyntään. ETLA Muistio nro 136. https://pub.etla.fi/ETLA-Muistio-Brief-136.pdf (accessed 25 June 2025).

Katz, Lawrence F. and Kevin M. Murphy. 1992. Changes in relative wages, 1963–1987: Supply and demand factors. *The Quarterly Journal of Economics* 107/1: 35-78. DOI: 10.2307/2118323.

Kauhanen, Antti and Petri Rouvinen. 2024. Assessing Early Labor Market Effects of Generative AI: Evidence from Population Data. ETLA Working Papers No 121. https://pub.etla.fi/ETLA-Working-Papers-121.pdf (accessed 25 June 2025).

Korinek, Anton. 2023. Generative AI for economic research: Use cases and implications for economists. *Journal of Economic Literature* 61/4: 1281-1317. DOI: 10.1257/jel.20231736.

Korinek, Anton and Donghyun Suh. 2024. Scenarios for the Transition to AGI. *NBER Working Papers* No. w32255. National Bureau of Economic Research. DOI: 10.3386/w32255.

Kuo, Alexander, Dulce Manzano, and Aina Gallego. 2024. Automation versus openness: support for policies to address job threats. *Journal of Public Policy* 44/1: 1-23. DOI: 10.1017/S0143814X23000260.

Kurer, Thomas. 2020. The declining middle: Occupational change, social status, and the populist right. *Comparative Political Studies* 53/10-11: 1798-1835. DOI: 10.1177/0010414020912283.

Kurer, Thomas and Aina Gallego. 2019. Distributional consequences of technological change: Worker-level evidence. *Research & Politics* 6/1: 1-9. DOI: 10.1177/2053168018822142.

Kurer, Thomas and Silja Häusermann. 2022. Automation risk, social policy preferences, and political participation. In *Digitalization and the welfare state*. Eds. Marius R. Busemeyer, Achim Kemmerling, Kees Van Kersbergen, Paul Marx. 139-156. Oxford: Oxford University Press. DOI: 10.1093/oso/9780192848369.003.0008.

Lane, Marguerita and Anne Saint-Martin. 2021. The impact of Artificial Intelligence on the labour market: What do we know so far? *OECD Social, Employment, and Migration Working Papers* 256, Paris: OECD Publishing. DOI: 10.1787/7c895724-en.

Lane, Marguerita, Morgan Williams, and Stijn 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, Paris: OECD Publishing. DOI: 10.1787/ea0a0fe1-en.

Lee, Yong Suk, Taekyun Kim, Sukwoong Choi, and Wonjoon Kim. 2022. When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy. *Technovation* 118/102590. 1-15. DOI: 10.1016/j.technovation.2022.102590.

Lipsey, Richard G., Kenneth I. Carlaw, and Clifford T. Bekar. 2005. *Economic transformations: general purpose technologies and long-term economic growth*. Oxford: Oxford University Press.

Liu, Jin, Xingchen Xu, Xi Nan, Yongjun Li, and Yong Tan. 2023. Generate" the Future of Work through AI: Empirical Evidence from Online Labor Markets. *arXiv preprint arXiv:2308.05201*. DOI: 10.48550/arXiv.2308.05201.

Lysyakov, Mikhail and Siva Viswanathan. 2023. Threatened by AI: Analyzing users' responses to the introduction of AI in a crowd-sourcing platform. *Information Systems Research* 34/3: 1191-1210. DOI: 10.1287/isre.2022.1184.

Magistro, Beatrice, Sophie Borwein, R. Michael Alvarez, Bart Bonikowski, and Peter John Loewen. 2025. Attitudes toward artificial intelligence (AI) and globalization: Common microfoundations and political implications. *American Journal of Political Science*. 1-18. DOI: 10.1111/ajps.12959.

Manca, Fabio. 2023. Six questions about the demand for artificial intelligence skills in labor markets. *OECD Social, Employment and Migration Working Papers*. No 286. Paris: OECD Publishing. DOI: https://doi.org/10.1787/ac1bebf0-en
Mann, Katja and Lukas Püttmann. 2023. Benign effects of automation: New evidence from patent texts. *Review of Economics and Statistics* 105/3: 562-579. DOI: 10.1162/rest_a_01083.
Marx, Karl. 1955. *The poverty of philosophy*. Moscow: Progress Publishers.
Maslej, Nestor, Loredana Fattorini, Raymond Perrault, Yolanda Gil, Vanessa Parli, Njenga Kariuki, Emily Capstick, Anka Reuel, Erik Brynjolfsson, John Etchemendy, Katrina Ligett, Terah Lyons, James Manyika, Juan Carlos Niebles, Yoav Shoham, Russell Wald, Tobi Walsh, Armin Hamrah, Lapo Santarlasci, Julia Betts Lotufo, Alexandra Rome, Andrew Shi, Sukrut Oak. 2025. The AI Index 2025 Annual Report. AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, Stanford, CA. https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf (accessed 25 June 2025).
Meltzer, Allan H. and Scott F. Richard. 1981. A rational theory of the size of government. *Journal of Political Economy* 89/5: 914-927. DOI: 10.1086/261013.
Milanez, Anna. 2023. The impact of AI on the workplace: Evidence from OECD case studies of AI implementation. *OECD Social, Employment and Migration Working Papers*, No. 289. Paris: OECD Publishing. DOI: 10.1787/2247ce58-en.
Mihaylov, Emil and Kea Tijdens. 2019. Measuring the routine and nonroutine task content of 427 four-digit ISCO-08 occupations. *Tinberger Institute Discussion Paper.* TI 1019-035/V. DOI: 10.2139/ssrn.3389681.
Mitsch Frieder. 2020. Young and vulnerable: automation risk and the AfD in Germany. LSE Working Paper, London School of Economics and Political Science. https://www.momentum-kongress.org/system/files/congress_files/2020/mitsch_momentum_automation_afd_0.pdf (accessed 25 June 2025).
Morris, Meredith Ringel, Jascha Sohl-Dickstein, Noah Fiedel, Tris Warkentin, Allan Dafoe, Aleksandra Faust, Clement Farabet, and Shane Legg. 2024. Position: Levels of AGI for operationalizing progress on the path to AGI. *Proceedings of the 41st International Conference on Machine Learning*, https://openreview.net/forum?id=0ofzEysK2D (accessed 25 June 2025).
Mutz, Diana. 2021. (Mis)Attributing the Causes of American Job Loss: The Consequences of Getting It Wrong. *Public Opinion Quarterly* 85/1: 101–22. DOI: 10.1093/poq/nfab003.
Mühlemann, Samuel. 2024. AI Adoption and Workplace Training, IZA Discussion Papers, No. 17367, Institute of Labor Economics (IZA), Bonn https://hdl.handle.net/10419/307191 (accessed 25 June 2025).
Nordhaus, William D. 2021. Are we approaching an economic singularity? Information technology and the future of economic growth. *American Economic Journal: Macroeconomics* 13/1: 299-332. DOI: 10.1257/mac.20170105.
Noy, Shakked and Whitney Zhang. 2023. Experimental evidence on the productivity effects of generative artificial intelligence. *Science* 381/6654: 187-192. DOI: 10.1126/science.adh2586.
OECD. 2023. OECD Employment Outlook 2023: Artificial intelligence and the labor market, Paris: OECD Publishing. DOI: 10.1787/08785bba-en.
OECD. 2024, *OECD Artificial Intelligence Review of Germany*, OECD Publishing, Paris. DOI: 10.1787/609808d6-en.
O'Grady, Tom. 2019. Careerists versus coal-miners: welfare reforms and the substantive representation of social groups in the British Labour Party. *Comparative Political Studies* 52/4: 544-578. DOI: 10.1177/0010414018784065.

Orlandi, Fabrice. 2012. Structural unemployment and its determinants in the EU countries. *European Economy. Economic Papers 455.* European Commission. DOI: 10.2765/26367.
Otis, Nicholas G., Solène Delecourt, Katelyn Cranney, and Rembrand Koning. 2024. Global evidence on gender gaps and generative AI. Working Paper 25-023. Harvard Business School. https://www.hbs.edu/faculty/Pages/item.aspx?num=66548 (accessed 25 June 2025).
Parolin, Zachary. 2021. Automation, occupational earnings trends, and the moderating role of organized labor. *Social Forces* 99/3: 921-946. DOI: 10.1093/sf/soaa032.
Peede, Lennert and Michael Stops. 2024. *Artificial intelligence technologies, skills demand and employment: evidence from linked job ads data*. No. 15/2024. IAB-Discussion Paper. https://www.econstor.eu/handle/10419/309055 (accessed 25 June 2025).
Peng, Sida, Eirini Kalliamvakou, Peter Cihon, and Mert Demirer. 2023. The impact of AI on developer productivity: Evidence from github copilot. *arXiv preprint arXiv:2302.06590*. DOI: 10.2139/ssrn.4856935.
Pimenta Arruda, Eucidio, and Durcelina Pimenta. 2024. Challenges and implications of microwork in the age of artificial intelligence: A global socioeconomic analysis. *Human Resources Management and Services* 6/2: 3452-3452. DOI: 10.18282/hrms.v6i2.3452.
Pizzinelli, Carlo, Augustus J. Panton, Marina M. Tavares, Mauro Cazzaniga, and Longji Li. 2023. *Labor market exposure to AI: Cross-country differences and distributional implications*. International Monetary Fund. https://www.imf.org/en/Publications/WP/Issues/2023/10/04/Labor-Market-Exposure-to-AI-Cross-country-Differences-and-Distributional-Implications-539656 (accessed 25 June 2025).
Pouliakas, Konstantinos, Giulia Santangelo, and Paul Dupire. 2025. Are artificial intelligence (AI) skills a reward of a gamble? Deconstructing the AI wage premium in Europe. *IZA Discussion Paper* No. 17607. https://www.iza.org/publications/dp/17607 (accessed 25 June 2025).
Qiao, Dandan, Huaxia Rui, and Qian Xiong. 2025. AI and Freelancers: Has the Inflection Point Arrived? Proceedings of the 58th Hawaii International Conference on Systems Sciences. 1804-1813. https://hdl.handle.net/10125/109062 (accessed 25 June 2025).
Raj, Manav, Iain M. and Robert Seamans. 2019. Artificial intelligence, labor, productivity, and the need for firm-level data. In *The Economics of Artificial Intelligence: An Agenda*, Eds. Ajay Agrawal, Joshua Gans and Avi Goldfarb, 553-566. Chicago: The University of Chicago Press. http://www.nber.org/chapters/c14037 (accessed 25 June 2025).
Rammer, Christian, Gastón P. Fernández, and Dirk Czarnitzki. 2022. Artificial intelligence and industrial innovation: Evidence from German firm-level data. *Research Policy* 51/104555. 1-15. DOI: 10.1016/j.respol.2022.104555.
Restrepo, Pascual. 2024. Automation: Theory, evidence, and outlook. *Annual Review of Economics* 16: 1-25. DOI: 10.1146/annurev-economics-090523-113355.
Rockall, Emma, Marina M. Tavares, and Carlo Pizzinelli. 2025. AI Adoption and Inequality. IMF working papers WP/25/68. International Monetary Fund. DOI: 10.5089/9798229006828.001.
Schöll, Nikolas and Thomas Kurer. 2024. How technological change affects regional voting patterns. *Political Science Research and Methods* 12/1: 94-112. DOI: 10.1017/psrm.2022.62.
Song, Fangchen, Ashish Agarwal, and Wen Wen. 2024. The impact of generative AI on collaborative open-source software development: Evidence from GitHub Copilot. *arXiv preprint arXiv:2410.02091*. DOI: 10.48550/arXiv.2410.02091.
Stephany, Fabian and Ole Teutloff. 2024. What is the price of a skill? The value of complementary. *Research Policy* 53/104898. 1-23. DOI: 10.1016/j.respol.2023.104898.

Svanberg, Maja, Wensu Li, Martin Fleming, Brian Goehring, and Neil Thompson. 2024. Beyond AI exposure: which tasks are cost-effective to automate with computer vision? Working Paper. DOI: 10.2139/ssrn.4700751.

Teutloff, Ole, Johanna Einsiedler, Otto Kässi, Fabian Braesemann, Pamela Mishkin, and R. Maria del Rio-Chanona. 2025. Winners and losers of generative AI: Early Evidence of Shifts in Freelancer Demand. *Journal of Economic Behavior & Organization*: 106845. DOI: 10.1016/j.jebo.2024.106845.

Toner-Rodgers, Aidan. 2024. Artificial intelligence, scientific discovery, and product innovation. *arXiv preprint arXiv:2412.17866*. DOI: 10.48550/arXiv.2412.17866.

Vandeplas, Anneleen and Anna Thum-Thysen. 2019. Skills mismatch and productivity in the EU. *Discussion Paper 100.* Luxembourg: Publications Office of the European Union. DOI: 10.2765/954687.

Van Overbeke, Toon. 2024. It's the robots, stupid? Automation risk, labour market resources and incumbent support in Europe. *Research & Politics* 11/1: 1-10. DOI: 10.1177/20531680241228914.

von Maltzan, Annette and Lara Zarges 2024. Unternehmerische Investitionen in Künstliche Intelligenz in Deutschland. *ifo Schnelldienst* 2/77. https://www.ifo.de/DocDL/sd-2024-02-von-maltzan-zarges-kuenstliche-intelligenz-unternehmen.pdf (accessed 25 June 2025).

Walter, Stefanie. 2021. The backlash against globalization." *Annual Review of Political Science* 24/1: 421-442. DOI: 10.1146/annurev-polisci-041719-102405.

Wei, Jason, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. 2022. Emergent abilities of large language models. *arXiv preprint arXiv:2206.07682*. DOI: 10.48550/arXiv.2206.07682.

Weisstanner, David. 2023. Technological change and labour market policy preferences. In *Handbook of labour market policy in advanced democracies.* Eds. Daniel Clegg and Niccolo Durazzi. 132-147. Cheltenham:Edward Elgar Publishing. DOI: 10.4337/9781800880887.00017.

Wohlrabe, Klaus. 2025. Mehr KI, weniger Jobs? Was Unternehmen in Deutschland erwarten. *ifo Schnelldienst digital* 6/12, 1-12. https://www.ifo.de/DocDL/sd-digital-2025-08-wohlrabe-ki-beschaeftigungseffekte.pdf (accessed 25 June 2025).

Wright, Randall. 1986. The redistributive roles of unemployment insurance and the dynamics of voting. *Journal of Public Economics* 31/3: 377-399. DOI: 10.1016/0047-2727(86)90066-6.

Wu, Nicole. 2023. “Restrict foreigners, not robots”: Partisan responses to automation threat. *Economics & Politics* 35/2: 505-528. DOI: 10.1111/ecpo.12225.

Yashiro, Naomitsu, Tomi Kyyrä, Hyunjeong Hwang, and Juha Tuomala. 2022. Technology, labour market institutions and early retirement. *Economic Policy* 37, no. 112: 811-849. DOI: 10.1093/epolic/eiac024.

Yang, Chih-Hai. 2022. How artificial intelligence technology affects productivity and employment: firm-level evidence from Taiwan. *Research Policy* 51/6. 1-12. DOI: 10.1016/j.respol.2022.104536.

About the author

Juho Alasalmi received his game-theory focused doctorate from the University of Konstanz. He currently holds positions at Pellervo Economic Research and VATT Datahuone in Helsinki. Juho Alasalmi's current research spans various topics in education and labour markets and is often directly motivated by political decision-making. He participates in developing procedures and software for the access and management of administrative microdata for research use in Finland.

Imprint

DIFIS - German Institute for Interdisciplinary Social Policy Research
Director: Prof. Dr. Ute Klammer (University of Duisburg-Essen)
Executive Director: Prof. Dr. Frank Nullmeier (University of Bremen)
Duisburg Office: Institute for Work, Skills and Training (IAQ), Forsthausweg 2, 47057 Duisburg
Bremen Office: SOCIUM Research Center on Inequality and Social Policy, Mary-Somerville-Straße 5, 28359 Bremen
Homepage: www.difis.org
Date and place of publication: Duisburg/Bremen, February 2026
Content oversight: Dr. Olexandr Nikolaychuk/ Dr. Achim Schmid
Oversight of the publication series: Dr. Miruna Bacali
ISSN: 2748-7199