



OECD Employment Outlook 2023

ARTIFICIAL INTELLIGENCE AND THE LABOUR MARKET



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MARKET**

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Foreword

The *OECD Employment Outlook* provides an annual assessment of key labour market developments and prospects in OECD member countries. Each edition also contains several chapters focusing on specific aspects of how labour markets function and the implications for policy in order to promote more and better jobs. The 2023 edition of the *OECD Employment Outlook* examines the recent evolution of labour demand and widespread shortages, as well as wage developments in times of high inflation and related policies. It also takes stock of the current evidence on the impact of artificial intelligence (AI) on the labour market and investigates how to get the balance right in addressing the possible negative effects of AI on labour market outcomes while not stifling its benefits.

The *OECD Employment Outlook* 2023 is the joint work of staff of the Directorate for Employment, Labour and Social Affairs (ELS). It has also greatly benefited from comments from other OECD directorates and contributions from national government delegates and national institutions. However, its assessments of each country's labour market prospects do not necessarily correspond to those made by the national authorities and institutions concerned.

This report was edited by Andrea Bassanini and Stijn Broecke. Lead authors for individual chapters were Satoshi Araki, Sandrine Cazes, Andrea Garnero and Andrea Salvatori (Chapter 1), Stijn Broecke (Chapter 2), Andrew Green (Chapter 3), Andrew Green, Angelica Salvi Del Pero and Annelore Verhagen (Chapter 4), Julie Lassébie (Chapter 5), Angelica Salvi Del Pero and Annelore Verhagen (Chapter 6) and Sandrine Cazes (Chapter 7). All chapters also benefitted from specific contributions from other ELS staff members. The report also benefitted from extensive comments from Stefano Scarpetta (Director of ELS), Mark Pearson (Deputy Director of ELS), Stéphane Carcillo (Head of the Jobs and Income Division of ELS) and Mark Keese (Head of the Skills and Employability Division of ELS). The infographic is based on contributions from Alastair Wood. Pascal Marianna was responsible for the statistical annex. Statistical support was provided by Sébastien Martin, Agnès Puymoyen, Dana Blumin and Isac Olave Cruz. Editorial assistance was provided by Marie-Aurélie Elkurd, Hagai Glebocki, Lucy Hulett and Niamh Kinane.

Editorial: Beyond the hype on AI – early signs of divides in the labour market

The release of ChatGPT on 30 November 2022 was a revelation in the advance of artificial intelligence (AI). Developed with large language models, the easy-to-use tool demonstrated a remarkable ability to automatically perform a wide range of prompted tasks, from writing to graphics to computer programming. ChatGPT is just one of many such tools now open to the public, and part of a continuum of AI development that dates back decades.

Yet the past seven months mark a technological watershed, triggering an unprecedented awareness of AI's potential to change our lives and economies, leading some to even question the meaning and purpose of our lives. Inevitably such a breakthrough technology has sparked a mix of wonder and worry among users and experts alike. A recent open letter by prominent technologists called for an immediate pause on giant AI experiments like ChatGPT, citing "profound risks to society and humanity". Meanwhile, private investment continues to multiply as AI is seen as general-purpose technology like electricity, the internal combustion engine and the internet.

There is unease over the speed at which AI is developing, far faster than previous technologies, while the implications for the economy and society remain uncertain. Also, and unlike robots for instance, whose risks were most concentrated in certain sectors, AI may have the capacity to affect all industries and occupations. With so much at stake, it is crucial for policy makers to seek clarity on the coming impact of AI and take action.

To this end, the OECD has launched its first-ever study of one area where we know that AI will have a significant impact: the labour market, by focusing on the manufacturing and financial sectors that have been integrating AI into work processes for several years. This research is the first cross-country empirical look into the effects that AI is having on the labour market; these early findings offer important clues of what will become more widespread with the vast new awareness and capabilities spawned in the post-ChatGPT context.

This study was part of our wider research programme on *AI in Work, Innovation, Productivity and Skills* (AI-WIPS), which offers some of the first robust evidence to a debate that is still often based on anecdotes.

Employees say AI can improve work, but fear it will threaten jobs and wages

In 2022, we surveyed over 2 000 employers and 5 300 workers in the manufacturing and finance sectors of seven OECD countries. We also spoke directly to stakeholders in these sectors and asked them about their experience as early adopters of tools like computer vision and natural language processing, amongst others.

What emerged was a nuanced picture of the early impact of AI which – even before the more recent wave of generative AI – showed strong opinions and sharp divisions on the benefits and risks.

Despite the renewed worries about a jobless future, the impact of AI on job levels has been limited so far. We are at a very early stage of AI adoption that is generally concentrated in the largest firms that are often still experimenting with these new technologies. Among these early adopters, many appear reluctant to dismiss staff, preferring to adjust the workforce through slowed hiring, voluntary quits and retirement. Some companies even told us that, in the face of an ageing population and labour shortages, AI could help relieve some skills needs.

However, it is also clear that the potential for substitution remains significant, raising fears of decreasing wages and job losses. Taking the effect of AI into account, occupations at highest risk of automation account for about 27% of employment. **And a significant share of workers (three in five) is worried about losing their jobs entirely to AI in the next ten years, particularly those who actually work with AI.** The advent of the latest generative AI technologies is sure to heighten such concerns across a wide range of job categories.

Although AI is not currently tied to any major changes in wages, positive or negative, across the labour market, **the OECD surveys showed that two in five workers in manufacturing and finance expressed worries that wages in their sector would decrease due to AI adoption in the next 10 years.**

For the time being, more than replacing jobs, AI is changing them and the skills that are required to carry them out. According to employers, AI has increased the importance of specialised AI skills but it has increased the importance of human skills even more. Two out of five employers consider that the lack of adequate AI-related skills is a barrier to using AI at work.

An equally interesting finding from our research is that, despite some widespread anxiety about the future, many say AI is having a positive impact on job quality. **Nearly two-thirds (63%) of workers reported that AI had improved their enjoyment at work: by automating dangerous or tedious tasks, AI is allowing them to focus on more complex and interesting ones.** In one of the case studies we conducted, an aerospace firm had introduced an AI-led visual inspection tool to check newly manufactured turbine blades for jet engines. AI technology had a positive impact on the work environment of inspectors who, prior to the introduction of AI, would sit in a darkened room for long periods inspecting blades through a magnifying eyepiece.

Despite the generally positive feedback on AI's impact on job quality, our study also found some tangible concerns: for example, creating work intensification. And workers who are managed by AI are often less positive about the impact of AI than those who work alongside it. **The use of AI also comes with serious ethical challenges around data protection and privacy, transparency and explainability, bias and discrimination, automatic decision making and accountability.** There are many real-world examples of AI hiring tools that have baked in human **biases against women, people with disabilities, and ethnic or racial minorities.** In our survey, many workers expressed concerns about AI collecting data on them as individuals or how they do their work.

An urgent need to act

How AI will ultimately impact workers and the workplace, and whether the benefits will outweigh the risks, will also depend on the policy action that we take. The advance of AI in the workplace, in itself, should not be halted because there are many benefits to be reaped. Yet we should also avoid falling into the trap of “technological determinism”, where technology shapes social and cultural changes, rather than the other way around. To paraphrase labour economist David Autor, instead of asking what AI *can* do, we must ask what we *want it to do for us*.

Urgent action is required to make sure AI is used responsibly and in a trustworthy way in the workplace.

On the one hand, there is a need to enable workers and employers in reaping the benefits of AI while adapting to it, notably through training and social dialogue.

Countries have taken some action to prepare their workforce for AI-induced job changes, but initiatives remain limited to date. Some countries have invested in expanding formal education programs (e.g. Ireland), or launched initiatives to raise the level of AI skills in the population through vocational training and lifelong learning (e.g. Germany, Finland and Spain). The OECD's research also shows that outcomes are better where workers have been trained to interact with AI, and where the adoption of technologies is discussed with them.

On the other hand, there is an urgent need for policy action to address the risks that AI can pose when used in the workplace – in terms of privacy, safety, fairness and labour rights – and to ensure accountability, transparency and explainability for employment-related decisions supported by AI.

Governments, international organisations and regulators must provide a framework for how to work with AI. This includes setting standards, enforcing appropriate regulations or guidelines, and promoting proper oversight of these new technologies. The OECD has played a pioneering role in this area by developing the OECD AI Principles for responsible stewardship of trustworthy AI, adopted in May 2019 by OECD member countries – forming the basis also for the G20 AI Principles – and since then also by Argentina, Brazil, Egypt, Malta, Peru, Romania, Singapore and Ukraine.

Many countries already have regulations relevant to enforce some of the key principles of trustworthy use of AI in the workplace. Existing legislation, including on data protection, includes provisions relevant to AI. However, a major development in recent years has been the proposal of specific-AI regulatory frameworks that address AI high-risk systems or impacts, albeit with key differences in approach across countries.

Anti-discrimination legislation, occupational safety and health regulation, worker privacy regulation, freedom of association all need to be respected when AI systems are used in the workplace. For instance, all OECD member countries have in place laws that aim to protect data and privacy. Examples include the requirement to prior agreement with workers' representatives on the monitoring of workers using digital technologies (e.g. Germany, France and Italy), and regulations requiring employers to notify employees about electronic employee monitoring policies. In some countries, such as Italy, existing anti-discrimination legislation has been successfully applied in court cases related to AI use in the workplace. But regulations that were not designed specifically for AI will, in all likelihood, need to be adapted.

Using AI to support decisions that affect workers' opportunities and rights should also come with accessible and understandable information and clearly defined responsibilities. The ambition to achieve accountability, transparency and explainability is prompting AI-specific policy action with direct implications for uses in the workplace.

A notable example is the proposed EU AI Act, which takes a risk-based approach to ensure that AI systems are overseen by people, are safe, transparent, traceable and non-discriminatory. In the United States in October 2022, the White House Office of Science and Technology Policy published a Blueprint for an AI Bill of Rights, which laid out a roadmap for the responsible use of AI. In June 2022, Canada introduced in Parliament the Artificial Intelligence and Data Act (AIDA) which requires "plain language explanations" of how AI systems reach their outcomes. Many countries, organisations and businesses are also developing frameworks, guidelines, technical standards, and codes of conduct for trustworthy AI.

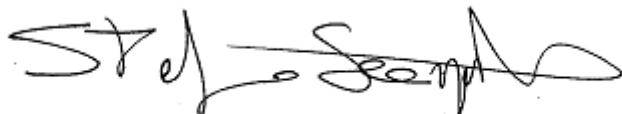
When it comes to using AI to make decisions that affect workers' opportunities and rights, there are some avenues that policy makers are already considering: adapting workplace legislation to the use of AI; encouraging the use of robust auditing and certification tools; using a human-in-the-loop approach; developing mechanisms to explain in understandable ways the logic behind AI-powered decisions.

A general concern by many experts is that the pace of the policy response is not keeping up with the very rapid developments in generative AI and that the policy response still lacks specificity and enforceability.

Indeed, there have been many calls to act on generative AI. The European Union announced plans to introduce a voluntary code of conduct on AI to be adopted rapidly. The US-EU Joint Statement of the Trade and Technology Council in May 2023 decided to add special emphasis on generative AI to the work on the Roadmap on Evaluation and Measurement Tools for Trustworthy AI and Risk Management, and the UK Prime Minister announced a summit on AI safety to be held late 2023. AI-related regulation also raises new challenges in relation to their international interoperability, which calls for international action to promote alignment of key definitions and of their technical implementation where appropriate.

Many of these calls are addressed by the “Hiroshima AI Process” launched by G7 Leaders in May 2023 with the objective of aligning countries (including the EU) to an agreed approach to generative AI. The OECD has been convoked to support this process that is underway.

Such action will need to be quickly complemented by concrete, actionable and enforceable implementation plans to ensure AI is trustworthy. International co-operation on these issues will be critical to ensure a common approach that will avoid a fragmentation of efforts that would unnecessarily harm innovation and create a regulatory gap that might lead to a race to the bottom.



Stefano Scarpetta,

Director for Employment, Labour and Social Affairs,

OECD

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Executive summary

Labour markets remain tight despite some signs of easing

The robust recovery from the COVID-19 recession lost momentum since 2022 while a cost of living crisis took hold as Russia's war of aggression against Ukraine contributed to decades-high inflation in many countries. However, employment has held its ground, while unemployment rates have reached their lowest levels in decades. With few exceptions, inactivity rates are below pre-pandemic levels, including among older adults. Labour markets remain tight in most countries, yet there are some signs of easing as the number of vacancies per unemployed has decreased slightly from historically high peaks.

Real wages are falling in almost all OECD countries amid a cost of living crisis

Despite a pick-up in nominal wage growth, real wages are falling in virtually all OECD countries. In many countries, profits have increased more than labour costs, making an unusually large contribution to domestic price pressures, and leading to a fall in the labour share. While public transfers and fiscal support have provided some relief, the loss of purchasing power is particularly challenging for workers in low-income households who have less leeway to deal with price increases through savings or borrowings and often face higher effective inflation rates because a higher proportion of their spending goes to energy and food.

With little sign of a price-wage spiral, minimum wages and collective bargaining can help cushion losses in purchasing power

Several policy levers can be activated to limit the impact of inflation on workers and ensure a fair share of the costs between governments, companies, and workers. The most direct way to help workers is via an increase in their wages, including statutory minima, which are under government control. On average across OECD countries, nominal statutory minimum wages have kept pace with inflation thanks to discretionary increases or indexation mechanisms. In contrast, wages negotiated in collective agreements have declined in real terms, as they are reacting with some delays due to the staggered and rather infrequent nature of wage bargaining.

AI is likely to have a significant impact on the labour market

To guide policy makers in developing an appropriate response, this edition of the *Employment Outlook* reviews the emerging evidence on the impact of artificial intelligence (AI) on the labour market, while highlighting the significant level of uncertainty that surrounds the current and especially future impact of AI in the labour market, as well as the most suitable policy actions to promote a trustworthy use of AI.

AI appears to be different from previous digital technological changes in several ways: i) it significantly expands the range of tasks that can be automated beyond just routine, non-cognitive tasks; ii) AI is a general-purpose technology, meaning that nearly every sector and occupation will be affected; and iii) the speed of development is unprecedented.

So far, job quality has been impacted more than job quantity

Based on the current literature (which mostly predates the latest wave of generative AI), there is little evidence of significant negative employment effects due to AI so far. This may be because AI adoption is still relatively low and/or because firms so far prefer to rely on voluntary workforce adjustments. Any negative employment effects of AI may therefore take time to materialise. At the same time, AI creates new tasks and jobs, particularly for high-skilled workers who have the right competencies to work with AI. Monitoring the distribution of job loss and creation will be important with an eye on inclusiveness.

The biggest impact highlighted by the literature so far has been on job quality. Workers and employers report that AI can reduce tedious and dangerous tasks, leading to greater worker engagement and physical safety. However, there are risks too. There are reported cases of AI automating simple tasks and leaving workers with a more intense, higher-paced work environment. AI can also change the way work is monitored or managed, which may increase perceived fairness, but also poses risks to workers' privacy and autonomy to execute tasks. AI can also introduce or perpetuate biases.

Policies and social dialogue will play a key role

The risks of using AI in the workplace, coupled with the rapid pace of AI development and deployment (including the latest generative AI models), underscore the need for decisive action to develop policies to reap the benefits AI can bring to the workplace while addressing risks for workers' fundamental rights and well-being. Existing legislation – e.g. on discrimination, data protection or workers' rights to organise – is an important foundation for managing AI use in the workplace, but it is still uncertain to what extent it can be applied to AI because relevant case law remains limited. As a result, countries are also developing AI-specific legislation and soft law (e.g. AI strategies, ethical principles, standards).

The impact of AI on tasks and jobs will engender changing skills needs. While companies using AI say they provide training for AI, a lack of skills remains a major barrier to adoption. Public policies will therefore have an important role to play, not only to incentivise employer training, but also because a significant proportion of required training takes place in formal education. AI itself may present opportunities to improve the design, targeting and delivery of training, notably the opportunity of providing tailored training solutions at scale. Yet the use of AI in training could exacerbate inequalities and perpetrate human biases and these challenges must be addressed.

Collective bargaining and social dialogue also have an important role to play in supporting workers and businesses in the AI transition. AI adoption tends to result in better outcomes for workers when their representatives are consulted on the matter. Yet, the specific characteristics of AI and the way it is implemented, such as its rapid speed of diffusion, its ability to learn and the greater power imbalance it can create, put further pressure on labour relations. While AI technologies have the potential to assist social partners to pursue their goals and strategies, the lack of AI-related expertise among social partners is a major challenge.

Infographic 1. Key facts and figures

Employment rates are now above pre-pandemic levels

Employment rate index, 100 = December 2019

Euro area OECD average United States



Employment in the OECD area stabilised in April 2023 at a rate about 3% higher than its pre-crisis level.

High-skill jobs are the most exposed to advances in artificial intelligence

Exposure to AI (the extent that AI capabilities can match tasks performed by workers in various occupations, min = 0 max = 1)



Lack of relevant skills is a barrier to using artificial intelligence

2 out of 5 companies declare that the lack of relevant skills is a barrier to using AI at work.



Social partners, such as trade unions and business associations, can facilitate the use of AI by helping to decide which AI technologies are adopted, securing key worker rights as well as helping them to develop new skills.

Profits have outpaced labour costs in many countries

% cumulative change of unit labour costs and unit profits, Q4 2019 - Q1 2023

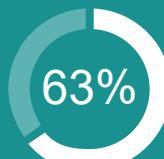


Company profits have increased more than labour costs, suggesting the cost-of-living crisis has not been shared equally by everyone.

Workers are divided about the impact of artificial intelligence on jobs

Almost two-thirds of workers using AI in finance and manufacturing (63%) said that it had improved enjoyment in their job.

However, 60% of workers are also worried about losing their jobs to AI in the next ten years.



Enjoy their job more because of AI



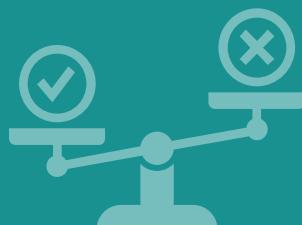
Worried about losing their job to AI

Urgent action is needed to ensure trustworthy AI in the workplace

57% of workers in finance and manufacturing whose employer uses AI worry about their privacy.



Worried about losing their privacy



Many countries have developed principles and some are introducing AI specific regulations, but much remains to be done to ensure trustworthy use of AI in the workplace.

1

Under pressure: Labour market and wage developments in OECD countries

Satoshi Araki, Sandrine Cazes, Andrea Garnero and Andrea Salvatori

The recovery from the COVID-19 pandemic lost momentum in 2022, with employment and unemployment stabilising. Labour markets remain tight, despite signs of easing. In this context, the quality of jobs on offer has improved in some dimensions, but real wages are falling significantly in almost all OECD countries despite a pick-up in nominal wage growth. In most countries, profits have grown robustly, often more than nominal wages. Nominal minimum wages are keeping pace with inflation, but any real gains may fade rapidly if inflation remains high. In contrast, wages negotiated in collective agreements between employers or employers' organisations and trade unions are reacting with some delay even in countries where the majority of workers are covered by a collective agreement, although a catch-up phase is expected in the coming quarters.

In Brief

Amid a cost-of-living crisis, the robust recovery from the COVID-19 recession lost momentum since 2022. The energy shock caused by Russia's war of aggression against Ukraine put a drag on global growth and contributed to propelling price inflation in many countries to levels not seen in decades. However, OECD labour markets have proved resilient. Employment and unemployment have held their ground, and the labour market remains tight in most countries, despite some signs of easing. The past quarters have shown signs of improvements, with global GDP growth picking up slightly.

The latest available evidence at the time of writing suggests that:

- **After stabilising in the second half of 2022, employment in the OECD area picked-up slightly in the first months of 2023.** In May 2023, OECD-wide employment was about 3% higher than in December 2019. Unemployment rates across the OECD mostly remained below pre-crisis levels. A recent pick-up in growth has led to an improvement of the economic projections for the near future, but GDP growth is likely to remain subdued in 2023 and 2024. Over the same period of time, OECD-wide employment is projected to continue to expand and the unemployment rate to increase slightly.
- **Inactivity rates have declined relative to the pre- COVID-19 crisis in most countries.** Early concerns that the pandemic might permanently increase inactivity rates have not come to pass, including among older adults. On average across all OECD countries, inactivity rates for 55 to 64 years old have decreased more than for the younger age groups. Inactivity rates for the whole working age population, however, are higher than before the crisis in seven OECD countries, with the largest increases found in Latin American member states.
- **Labour markets remain tight even as pressures are easing.** Labour market tightness (i.e. the number of vacancies per unemployed person) eased in the second half of 2022 but remained well above pre-crisis levels. Online job postings data for selected countries suggest that labour demand has continued to ease in the first half of 2023.
- **Amid tight labour markets, nominal wage growth has picked up and some non-monetary aspects of job quality have improved.** In Q1 2023, nominal year-on-year wage growth exceeded its pre-crisis level in nearly all OECD countries, reaching 5.6% on average across the 34 countries with available data. Among new hires, the share of temporary contracts and involuntary part-time has declined in most OECD countries. In addition, data on online job postings in Canada, the United Kingdom and the United States show an increase in the share of vacancies offering employee benefits, especially health-related benefits, retirement programs/schemes and paid time off.
- **As inflation reached levels not seen in decades in many countries, real hourly wages have fallen – often substantially – in virtually every industry and OECD country, contributing to the cost-of-living crisis.** In Q1 2023, despite the pick-up in nominal wages, the difference between nominal annual wage growth and inflation was -3.8% on average across the 34 OECD countries with available data, with a negative difference observed in 30 countries. The loss of purchasing power is particularly challenging for workers in low-income households, who have less leeway to deal with increases in the cost of living through savings or borrowing and often face higher actual inflation rates because a higher proportion of their spending goes to energy and food.

- **Nominal wage growth has not significantly accelerated in the first half of 2023, but the gap with declining inflation is narrowing in some countries.** Recent wage data from five countries point to stable nominal wage growth in most in April and May 2023. Similarly, growth in wages posted on the online platform *Indeed* has been steady or declining in the first five months of 2023 in France, Germany, Ireland, Italy and the United States. In Spain, the Netherlands, and – more markedly – the United Kingdom nominal growth of posted wages has increased. In general, the gap between inflation and nominal wage growth in posted wages has become smaller. However, wages posted on *Indeed* have grown in real terms only in Spain and the United States in recent months.
- **In many countries, real wages are falling across all industries, but less so in low-pay industries.** Among the 31 countries with available data, in Q1 2023, real wages in low-pay industries performed better than those in mid-pay industries in 18 countries, and better than those in high-pay industries in 22 countries. Real wages in low-pay industries had a worse performance than real wages in both mid- and high-pay industries only in six countries.
- **In most countries, profits have increased more than labour costs, making an unusually large contribution to domestic price pressures, and leading to a fall in the labour share.** Data from Europe and Australia indicate that this has occurred not only in energy sectors, but also in other parts of the economy, including in accommodation and food and manufacturing. As economies re-opened, pent-up demand and large recovery plans bolstered aggregate demand, helping profits grow quickly while supply bottlenecks limited the speed of adjustment of output. With strong consumer demand and rapidly evolving inflation driven by external factors, many producers were likely able to adjust prices quickly, while wage increases typically involve longer renegotiations periods.

Several policy levers can be activated to limit the impact of inflation on workers and ensure a fair sharing of the cost-of-living crisis between taxpayers (through government taxes), companies, and workers. The most direct way to help workers is via an increase in their wages. Wage setting institutions – including minimum wages and collective bargaining – can help mitigate losses in purchasing power and ensure a fair distribution of the cost of inflation between firms and workers, while avoiding a price-wage spiral. The latest available evidence and information from a policy questionnaire addressed to Labour Ministries and social partners across OECD countries suggests that:

- **Between December 2020 and May 2023, on average across OECD countries, nominal statutory minimum wages have increased by 29%.** This trend has allowed minimum wages to keep pace with inflation (prices increased by 24.6%, on average, over the same time period), even if real gains tend to be quickly eroded as inflation remains high. Going forward, it is important to ensure that statutory minimum wages continue to adjust regularly through the different national institutional settings and uprating mechanisms. There is a concern that increases in the minimum wage contribute to fuel inflation. However, the effect of minimum wage increase to the growth in aggregate wages is limited, even accounting for spillover effects on wages above the minimum.
- **In most OECD countries, increases in the minimum wage are the result of a discretionary policy decision that is typically taken once a year at most, while in six countries the national statutory minimum wage is automatically indexed to inflation.** Automatic indexation helps to safeguard the purchasing power of minimum wage earners and improve the predictability of future increases. However, it also reduces the scope for governments, social partners or commissions to exercise judgement on future increases and could lead to an excessive compression of the wage distribution if other wages are not raised, with consequences both for individual careers, and for the design of redistribution policies.

- **Wages negotiated in collective agreements between firms and workers have declined in real terms and are reacting with longer delays.** Several factors can explain why negotiated wages, on average, have not managed to keep up with inflation. Most importantly, the staggered and rather infrequent nature of wage agreements means that negotiated wages rarely adjust immediately to unexpected price inflation. However, in some OECD countries, unions, employers' organisations and governments have found innovative ways to cushion the effects of inflation while limiting the costs for firms by using tax-free lump-sum bonuses or non-wage benefits.
- **Faster growth in negotiated wages is likely in the coming quarters as the most recent bargaining rounds have tried to recoup some of the losses in purchasing power.** However, the available evidence suggests that, after a catch-up phase, nominal negotiated wage growth are likely to go back to previous trends without generating a price-wage spiral. Overall, aggregate nominal wage growth is projected to be just over 4% in the OECD area in 2023, before moderating to around 3.5% in 2024 while inflation is projected to be at 6.6% in 2023 and 4.3% in 2024.

Minimum wages and collective bargaining can help achieve a fair distribution of the cost of inflation between workers and employers, as well as across workers of different pay levels. A fair sharing of the cost of inflation can prevent further increases in inequality and support effective monetary policy by averting feedback loops between profits, wages and prices. The analysis of this chapter suggests that, in several sectors and countries, there is room for profits to absorb some further increases in wages to mitigate the loss of purchasing power at least for the low paid without generating significant additional price pressures. Given the downward rigidity of prices, the recent decline in input costs will also likely provide further room to absorb some wage increases without generating inflationary pressures. Collective bargaining can also help identify solutions tailored to firms' varying ability to sustain increase in wages – for instance for small and medium firms that may face more significant constraints.

Introduction

This chapter offers a detailed overview of recent labour market developments across the OECD countries with a particular focus on wage dynamics and discusses the policy measures that countries have at their disposal to help address the ongoing cost-of-living crisis, focusing on wage policies. This includes a discussion on the role that minimum wages and collective bargaining have played so far in cushioning the costs of inflation, drawing on a policy questionnaire that was addressed to OECD countries as well as employers' organisations and trade unions through, respectively, the Business@OECD (BIAC) and the Trade Union Advisory Committee (TUAC) networks.

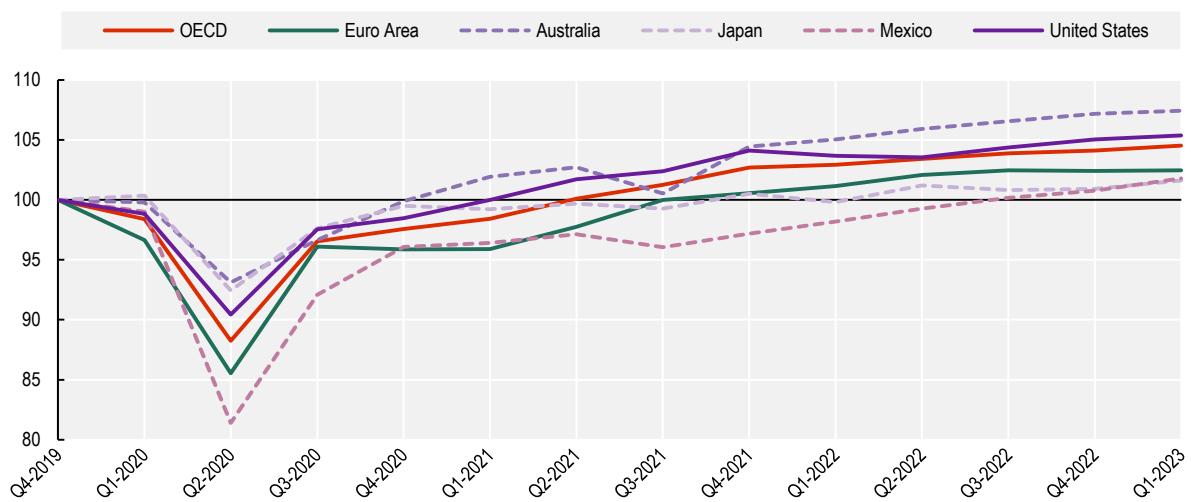
The chapter is organised as follows: Section 1.1 reviews recent labour market developments across the OECD; Section 1.2 reports on recent wage developments; and finally Section 1.3 discusses the role of statutory minimum wages and collective bargaining as a policy lever to support workers and ensure a fair burden-sharing of the cost of inflation among governments, firms and workers. Section 1.4 concludes with policy recommendations.

1.1. As economic growth lost momentum in 2022, labour market indicators across the OECD stabilised

Growth across the OECD slowed substantially over the course of 2022, but there are signs of improvement in 2023 (Figure 1.1). Russia's war of aggression against Ukraine pushed up prices substantially, especially for energy and food, adding to inflationary pressures at a time when the cost of living was already rising rapidly around the world. Inflation eroded household incomes and monetary policy tightened considerably amidst the unusually vigorous and widespread steps to raise policy interest rates by central banks in recent months (OECD, 2022^[1]). By the fourth quarter of 2022, global growth had slowed to an annualised rate of just 2%, with growth over the year falling to 2.3%, just over half the pace seen through 2021. Output declined in 15 OECD economies in the fourth quarter, with most of these in Europe. The recent decline in energy prices and the improving prospects for China have contributed to an uptake in economic indicators in the first half of 2023, with global GDP growth picking up to an annualised rate of just over 3% in the first quarter, despite mixed outcomes across countries and particularly weak growth in the Euro Area (OECD, 2023^[2]). In the first quarter of 2023, GDP for the OECD area stood 5% above its level at the end of 2019, after a year-on-year growth of 1.5% (Figure 1.1).

Figure 1.1. GDP growth slowed down over the course in the past year

Real GDP indexed to 100 in Q4 2019, seasonally adjusted, selected OECD countries



Note: Euro Area refers to the averages of 20 Eurozone countries.

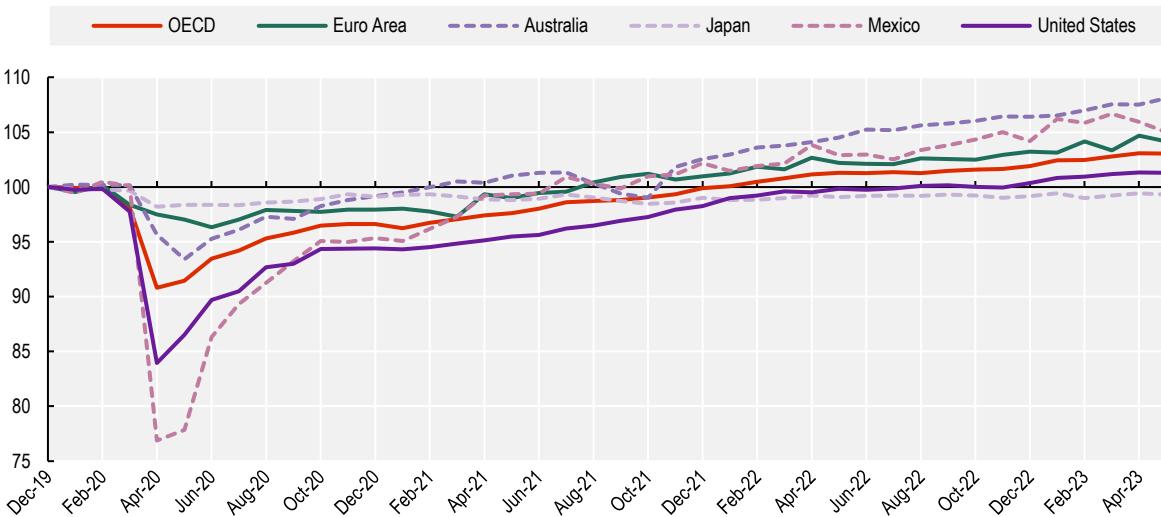
Source: OECD (2023), "Quarterly National Accounts", OECD National Accounts Statistics (database), <https://doi.org/10.1787/data-00017-en> (accessed on 23 June 2023).

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Amid the slowdown in economic growth, employment growth also lost momentum over the course of 2022 but continued to grow in the first months of 2023 (Figure 1.2). In May 2023, total employment for the OECD, was about 3% higher than in December 2019. Overall, employment growth since the start of the pandemic was slightly stronger for women than men (see Box 1.1). Employment rates across most OECD countries also stabilised above pre-crisis levels by the first quarter of 2023 (Annex Figure 1.A.1).

Figure 1.2. Total employment has recovered in most countries after COVID-19

Total employment indexed to 100 in December 2019, seasonally adjusted, selected OECD countries



Note: Euro Area refers to the averages of 20 Eurozone countries. The OECD average, the Euro Area and Mexico are derived from the OECD Monthly Unemployment Statistics estimated as the unemployment level times one minus the unemployment rate and rescaled on the LFS-based quarterly employment figures.

Source: OECD (2023), "Labour: Labour market statistics", *Main Economic Indicators* (database), <https://doi.org/10.1787/data-00046-en> (accessed on 3 July 2023).

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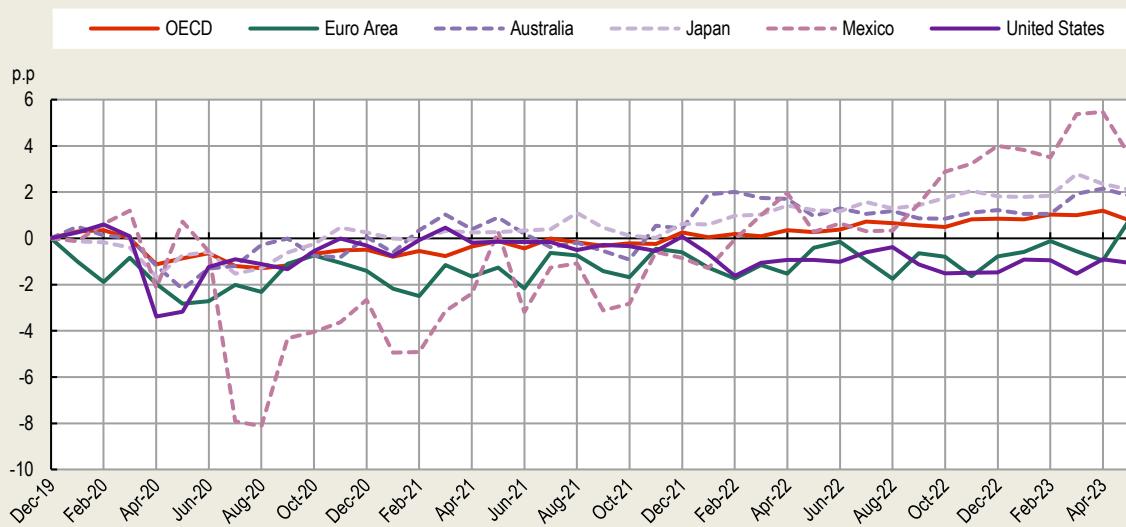
Box 1.1. In most countries, employment has grown more for women than for men since the onset of the pandemic

The initial labour market impact of the pandemic was stronger among women than men in most OECD countries, raising the concern that the pandemic-induced recession might be a “shecession” (OECD, 2020^[3]). However, as economies reopened, in most OECD countries women benefitted more than men from the rebound in economic activity. Indeed, in early 2022 – two years after the onset of the pandemic – the employment rate gap between men and women had declined in most of the OECD countries relative to its pre-pandemic level (Salvatori, 2022^[4]).

Over the course of 2022 and the first half of 2023, employment levels for both women and men stabilised above pre-pandemic levels (Figure 1.3). By May 2023, on average across the OECD, women’s total employment had grown about 1 percentage point more than men’s, reaching 3.5% above its pre-crisis level.

Figure 1.3. Employment has grown more for women than for men since the onset of the pandemic

Percentage point difference in employment growth since December 2019 between women and men, seasonally adjusted



Note: Women’s and men’s employment are indexed to 100 in December 2019. Euro Area refers to the averages of 20 Eurozone countries. The OECD average and the Euro Area are estimates derived from the OECD Unemployment statistics estimated as the unemployment level times one minus the unemployment rate and rescaled on the LFS-based quarterly employment figures.

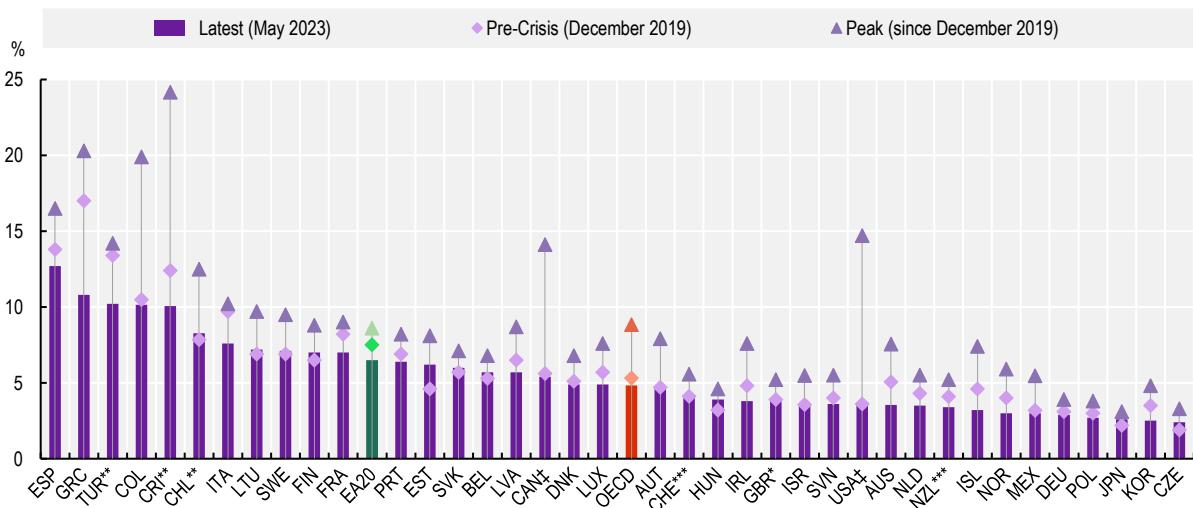
Source: OECD (2023), “Labour: Labour market statistics”, *Main Economic Indicators* (database), <https://doi.org/10.1787/data-00046-en> (accessed on 3 July 2023).

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Similarly, unemployment rates across the OECD held their ground as the year ended, mostly remaining below pre-crisis levels (Figure 1.4). The average unemployment rate for the OECD stood at 4.8% in May 2023 – or half a percentage point below its pre-crisis levels. In May 2023, the unemployment rate indeed exceeded its pre-crisis levels by at least half a percentage point only in four countries – with the maximum difference of 1.6 percentage points recorded in Estonia.

Figure 1.4. Unemployment rates remain low across the OECD countries

Unemployment rate (percentage of labour force), seasonally adjusted



Note: The labour force population includes all those aged 15 or more. Euro Area refers to the averages of 20 Eurozone countries. For countries marked with * the latest data refer to March 2023, those marked ** to April 2023; those marked *** to Q1 2023; and those marked ‡ to June 2023.

Source: OECD (2023), “Unemployment rate” (indicator), <https://doi.org/10.1787/52570002-en> (accessed on 11 July 2023).

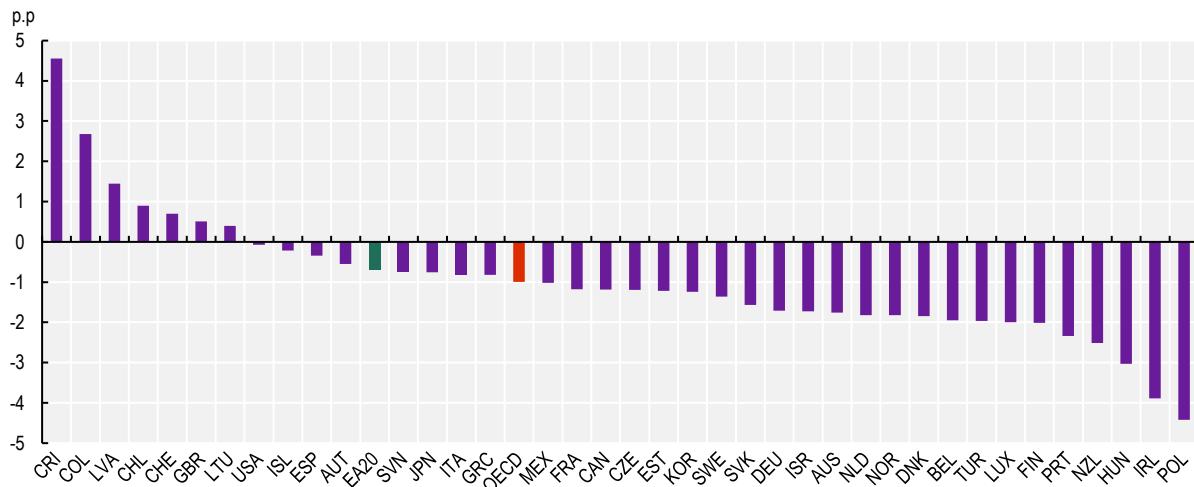
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1.1.1. Inactivity rates have generally declined but average hours worked are slightly below pre-crisis levels in several countries

Inactivity rates among the working age population are below pre-crisis levels in most countries, pointing to a recovery of labour supply from the initial decline at the start of the COVID-19 crisis. As of Q1 2023, inactivity rates were at or below pre-crisis levels in 31 countries, with an average decline across all countries of just under 1 percentage point. Inactivity rates were at least 1 percentage point above pre-crisis levels only in Colombia, Costa Rica and Latvia.¹

Figure 1.5. Inactivity rates are below pre-crisis levels in most OECD countries

Percentage point change in inactivity rates among the working age population from Q4 2019 to Q1 2023, seasonally adjusted



Note: The working age population includes all those aged 15 to 64. OECD is an unweighted average of the countries shown above. Euro Area refers to 20 Eurozone countries. p.p: percentage point.

Source: OECD (2023), "Labour: Labour market statistics", *Main Economic Indicators* (database), <https://doi.org/10.1787/data-00046-en> (accessed on 28 June 2023).

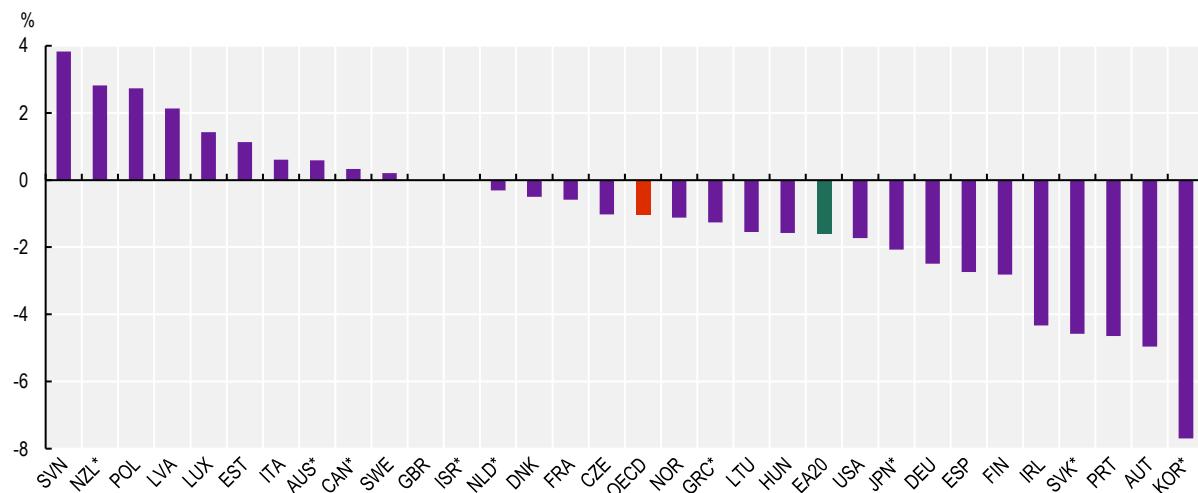
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Inactivity rates have generally decreased among older adults as well, despite earlier concerns that the pandemic might induce a permanent reduction in the labour supply of this group. In fact, on average across all OECD countries, by Q1 2023, the inactivity rate for individuals aged 55 to 64 had decreased relative to pre-crisis levels more than for those aged 25 to 54 (-2.5 vs -0.6 percentage points) (Annex Figure 1.A.2). More broadly, there is little indication that the pandemic induced an increase in retirement of older workers across countries. While some earlier evidence for the United States suggested that this might have been the case (Faria-e-Castro, 2021^[5]), more recent data point to a limited impact (Thompson, 2022^[6]). In addition, there is no indication of significant increases in retirement in the United Kingdom (Murphy and Thwaites, 2023^[7]), the Euro Area (Botelho and Weïller, 2022^[8]) or Australia (Agarwal and Bishop, 2022^[9]).

Hours worked per employed person are below pre-crisis levels in most countries with recent data available (Figure 1.6). The persistence of lower hours worked in tight labour markets does raise the question as to whether the COVID-19 crisis might have led to some structural changes, for example in workers' preferences over work-life balance. However, the differences are generally small. In Q4 2022, hours worked per employed person were above pre-crisis levels or below that level by less than 2% in 22 of the 30 countries with recent data available. On average, hours worked per employed person were down by just under -1%. In Latvia, New Zealand, Slovenia and Poland they had increased by more than 2%, while they had decreased by more than 4% in Ireland, the Slovak Republic, Portugal, Austria and Korea. The relatively large decline in hours per employed in Korea is due to the progressive lowering of the statutory limit on total weekly working hours from 68 to 52 (Carcillo, Hijzen and Thewissen, 2023^[10]).

Figure 1.6. Average hours worked are close to pre-pandemic levels in most OECD countries

Percentage change between Q4 2019 and Q1 2023, seasonally adjusted



Notes: The figure reports total hours worked divided by total employment. OECD is an unweighted average of the countries shown above. Euro Area refers to 20 Eurozone countries. For New Zealand, it refers to total paid hours divided by filled jobs. *The latest quarter is Q4 2022.

Source: OECD (2023), "Quarterly National Accounts", *OECD National Accounts Statistics* (database), <https://doi.org/10.1787/data-00017-en> (accessed on 23 June 2023) for the Euro Area and the United Kingdom, Labour Force Survey (Australian Bureau of Statistics), Labour Force Survey (Statistics Bureau of Japan), Economically Active Population Survey (Statistics Korea), Household Labour Force Survey – Tables QEM034AA and QEM025AA (Statistics New Zealand), and Current Population Survey (U.S. Bureau of Labor Statistics).

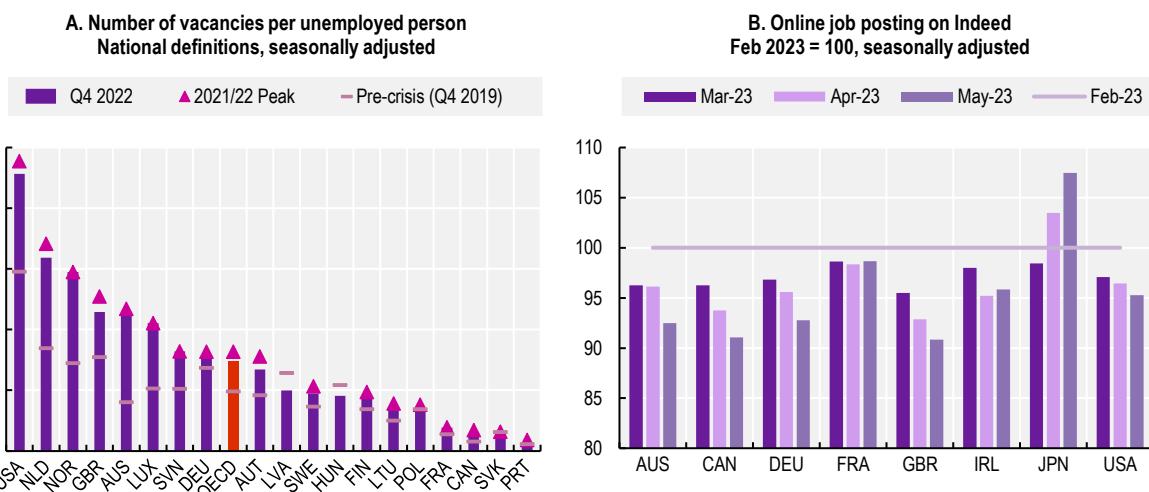
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1.1.2. Labour markets remain tight even as there are signs that pressure is easing

After the sharp increase in vacancies in 2021 amid the unprecedented rebound of economic activity, labour market tightness (i.e. the number of vacancies per unemployed person) peaked in the first half of 2022 in many OECD countries (Figure 1.7, Panel A). Among the 19 countries with data available, the increase in tightness in 2021 was particularly large in English speaking countries, but also in Norway and the Netherlands.² By the end of 2022, labour market tightness was mostly below its peak levels but generally remained significantly higher than before the COVID-19 crisis.

Data on job postings on the online platform *Indeed* suggest a continued easing over more recent months in the majority of countries (Figure 1.7, Panel B). Online job postings declined in the first five months of 2023 in Australia, Canada, Germany, the United Kingdom and the United States. The largest decline occurred in the United Kingdom (-10% in May 2023 relative to February 2023). In France, online job postings declined at the start of the year and stabilised in the three months leading to May 2023. Japan is the only country among those with available data where online job postings increased steadily in the first half of 2023. In New Zealand, the official index of online job vacancies fell 9.9% in the year to March 2023.³

Figure 1.7. Labour markets remain tight in many countries even as pressure is easing



Note: OECD is an unweighted average of the countries shown above. In Panel A, the definition of vacancies is not harmonised across countries. For European countries (except Austria, France, Germany, Hungary and Portugal – see below), a vacancy is defined as a paid post that is newly created, unoccupied, or about to become vacant for which the employer is taking active steps and is prepared to take further steps to find a suitable candidate from outside the enterprise concerned; and which the employer intends to fill either immediately or within a specific period. For Australia, a vacancy is defined as a job available for immediate filling and for which recruitment action has been taken by the employer. For Austria, a vacancy is defined as a job notified by firms to employment agencies which remain unfilled at the end of the month. For Canada, a vacancy is defined as a job meeting the following conditions: it is vacant on the reference date (first day of the month) or will become vacant during the month; there are tasks to be carried out during the month for the job in question; and the employer is actively seeking a worker outside the organisation to fill the job. The jobs could be full-time, part-time, permanent, temporary, casual, or seasonal. Jobs reserved for subcontractors, external consultants, or other workers who are not considered employees, are excluded. For France, a vacancy is defined as the monthly number of vacancies posted by companies in Pôle emploi. For Germany, a vacancy is defined as a job of seven days' duration or more reported by employers to employment agencies to be filled within three months and remaining unfilled at the end of the month. For Hungary, a vacancy is defined as the number of vacancies notified to local labour offices and then to the Ministry of Labour. For Portugal, a vacancy is defined as the number of vacancies reported by employers to be still vacant at the end of the month. For the United Kingdom, a vacancy is defined as a position for which employers are actively seeking recruits from outside their business or organisation (excluding agriculture, forestry and fishing) based on the estimates from the Vacancy Survey. For the United States, a vacancy is defined as a job that is not filled on the last business day of the month and a job is considered open if a specific position exists and there is work available for it, the job can be started within 30 days, and there is active recruiting for the position.

Source: OECD (2020), “Labour: Registered unemployed and job vacancies (Edition 2019)”, Main Economic Indicators (database), <https://doi.org/10.1787/190bb5bc-en> (accessed on 23 June 2023) for Australia, Austria, Germany, Hungary, Portugal, the United Kingdom, Job vacancy statistics by NACE Rev.2 activity for Finland, Luxembourg, Latvia, Lithuania, the Netherlands, Norway, Poland, the Slovak Republic, Slovenia and Sweden (Eurostat), Job vacancies, payroll employees, and job vacancy rate (Statistics Canada), Les demandeurs d’emploi inscrits à Pôle emploi (Dares, France), Posti vacanti (Italian National Institute of Statistics), Job Openings and Labor Turnover Survey (U.S. Bureau of Labor Statistics, retrieved from FRED); Online job posting on Indeed.

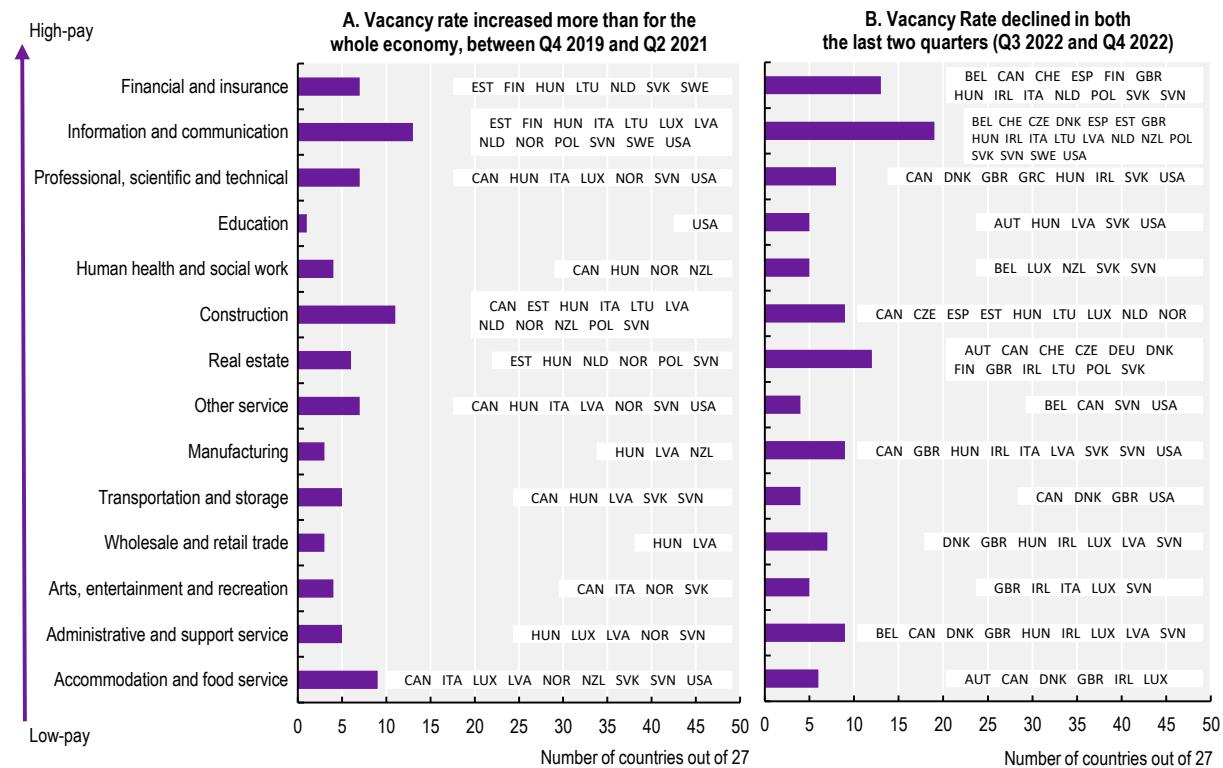
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Imbalances between labour demand and supply have been widespread across industries. Vacancy rates capture the fraction of all available jobs that are unfilled and for which employers state that they are actively trying to recruit. Panel A of Figure 1.8 provides an overview of the number of countries (out of the 27 with available data) in which a specific industry experienced an increase in vacancy rates larger than the country average. The three industries most likely to have seen relatively larger increases in vacancy rates cut across the pay ranking are “Information and Communication” (13 countries), Construction (11 countries), and “Accommodation and Food Services” (9 countries).

Vacancy rates declined in the last two quarters of 2022 in many industries across countries (Panel B of Figure 1.8). Declines in vacancy rates have been particularly frequent across countries in “Finance and insurance” (13 countries) and “Information and communication” (19 countries) – two high-pay service sectors. Other industries with frequent declines in vacancy rates across countries are found across the pay rank, and include construction, manufacturing and “administrative and support services” (9 countries each).

Figure 1.8. Tightness increased across industries, but is often decreasing in high-pay industries

Number of countries where the vacancy rate for a given industry increased more than that for the whole economy in 2021/22 or declined consecutively in the last two available quarters



Note: Countries where a given industry has increased more than for the whole economy (resp. has declined for the last two quarters) are indicated in white background in the chart. The countries included are Austria, Belgium, Canada, the Czech Republic, Denmark, Estonia, Finland, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Latvia, Lithuania, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Slovenia, Spain, Sweden, Switzerland, the United Kingdom and the United States. The definition of vacancies and vacancy rate is not harmonised across countries. For Italy, it refers to paid jobs (new or existing, if they are vacant or about to become vacant) for which the employer is looking (actively and outside the company) for a suitable candidate and is willing to make additional efforts to find one. The vacancy rate is the percentage ratio of the number of vacancies to the sum of vacancies with filled job positions. For the United States, it refers to all jobs that are not filled on the last business day of the month. A job is considered open if a specific position exists and there is work available for it, the job can be started within 30 days, and there is active recruiting for the position. For Canada, a job is considered vacant if it meets the following conditions: it is vacant on the reference date (first day of the month) or will become vacant during the month; there are tasks to be carried out during the month for the job in question; and the employer is actively seeking a worker outside the organisation to fill the job. The jobs could be full-time, part-time, permanent, temporary, casual, or seasonal. Jobs reserved for subcontractors, external consultants, or other workers who are not considered employees, are excluded. The job vacancy rate is the number of job vacancies expressed as a percentage of labour demand; that is, all occupied and vacant jobs. For the United Kingdom, vacancies are defined as positions for which employers are actively seeking recruits from outside their business or organisation. The estimates are based on the Vacancy Survey, this is a survey of employers designed to provide estimates of the stock of vacancies across the economy, excluding agriculture, forestry, and fishing. The vacancy rate is calculated as the number of vacancies per 100 jobs. For countries from Eurostat, a vacancy is defined as a paid post that is newly created, unoccupied, or about to become vacant for which the employer is taking active steps and is prepared to take further steps to find a suitable candidate from outside the enterprise concerned; and which the employer intends to fill either immediately or within a specific period. The job vacancy rate is the number of job vacancies expresses as a percentage of the sum of the number of occupied posts and the number of job vacancies. For New Zealand, Jobs Online measures changes in online job advertisements from 4 internet job boards – SEEK, Trade Me Jobs, Education Gazette and Kiwi Health Jobs (Index August 2010 = 100). For Austria, a vacancy is defined as a job notified by firms to employment agencies which remain unfilled at the end of the month.

Source: Job vacancy statistics by NACE Rev.2 activity (Eurostat), Job vacancies, payroll employees, and job vacancy rate by industry (Statistics Canada), Jobs Online (Ministry of Business, Innovation & Employment, New Zealand), Vacancies by industry (UK Office for National Statistics), Job Openings and Labor Turnover Survey (U.S. Bureau of Labor Statistics, retrieved from FRED).

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Numerous factors contribute to differences in the dynamics of labour market tightness between countries. On the demand side, the initial strength of the economic rebound and the intensity of the slowdown differed depending on the composition of the economy, exposure to the energy crisis, and timing of the tightening of monetary policy. On the supply side, while labour market participation is back to pre-crisis levels in most countries (see above), the speed of its recovery varied. Notably, labour force participation lagged behind in two of the largest OECD economies – the United States and the United Kingdom – which also experienced some of the largest increases in labour market tightness. The European Central Bank (2023^[11]) attributes part of the higher labour market tightness in the United States relative to the Euro Area to the slower recovery of labour supply.

As the COVID-19 crisis began, there was a concern that the crisis would create mismatches between labour supply and demand due to its differential impact across industries (Salvatori, 2022^[4]). However, studies have found that the initial increase in mismatch was short-lived and smaller than during the Global Financial Crisis (Pizzinelli and Shibata, 2023^[12]; Duval et al., 2022^[13]). During the recovery, labour demand increased across sectors and countries, with no significant changes in sectoral composition. Some evidence suggests that workers redirected job searches away from affected occupations but not industries (Carrillo-Tudela et al., 2023^[14]; Hensvik, Le Barbanchon and Rathelot, 2021^[15]).

In some countries, quits increased as workers reaped the benefits of tight labour markets

Workers have taken advantage of tight labour markets to improve their working conditions, leading to an uptake in quits and job mobility in several countries. In the United States, quits in non-farm employment increased to their highest levels since the start of series in 2000. After a peak in December 2021, the quit rate (i.e. quits as percentage of total employment) returned to pre-crisis levels in April 2023.⁴ Initial concerns that this wave of resignations might be eroding the labour force have not come to pass as participation rates in the United States have continued to increase. Instead, the increase in quits is linked to an improvement in working conditions especially for younger and less-educated workers (Autor, Dube and McGrew, 2023^[16]). In addition, historical evidence from manufacturing indicate that the recent surge in quits was not unprecedented since waves of job quits have occurred during all fast recoveries in the post-war period in the United States (Hobijn, 2022^[17]).

Similarly, evidence from France indicates that the increase in quits in 2022 was large but not unprecedented and did not erode the labour force, as over 80% of those who quit were employed within six months. Evidence from early 2022, indicates that amid the recruiting difficulties and the increase in workers' mobility, some firms have made attempts to improve working conditions or allow more flexibility in the organisation of work (Lagouge, Ramajo and Barry, 2022^[18]). Similar results also hold for Italy (Armillei, 2023^[19]). In the United Kingdom, job-to-job transitions reached a record high at the end of 2021, and then declined slightly over the course of 2022, but in Q4 2022 they were still 10% higher than in the same quarter of 2019.⁵ By contrast, there is little indication of an increase in quits in Australia, as the proportion of businesses with open vacancies reporting the need to replace leaving employees was stable just under 80% over the course of 2021 and 2022.⁶

Amid tight labour markets, online job postings have offered benefits more frequently while temporary contracts and involuntary part-time have decreased among new hires

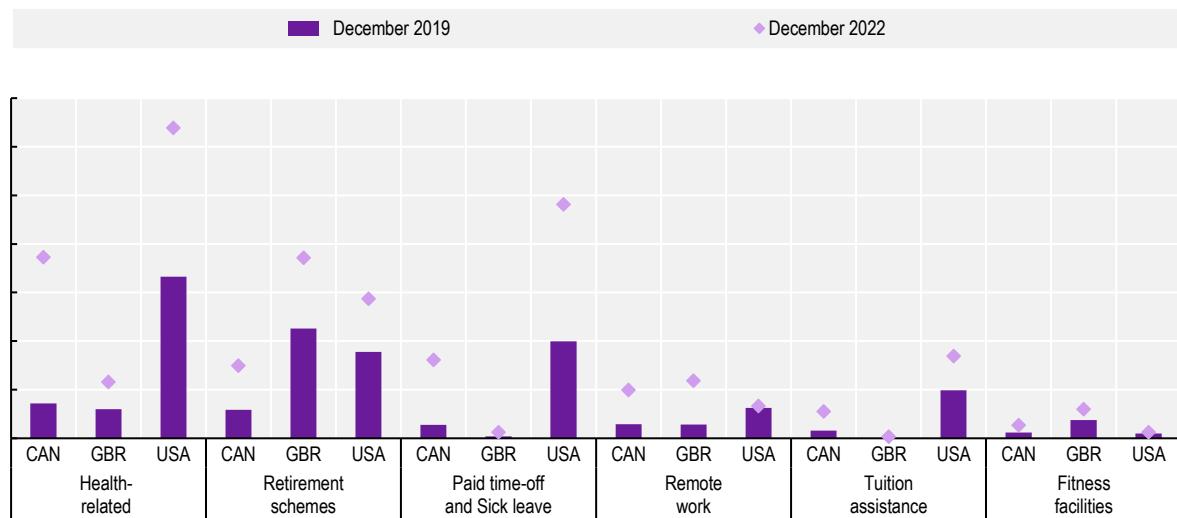
Amid tight labour markets, the share of online job postings offering job benefits has increased in several countries.⁷ Between December 2019 and December 2022, the United States, Canada and the United Kingdom saw an increase in the share of online job postings offering employee benefits, especially health-related benefits (including dental, vision and life insurance), retirement programs/schemes and paid time off (Figure 1.9).⁸ The fraction of job postings offering health-related benefits increased in particular in the United States and Canada, by 24 and 11 percentage points respectively. The mention of retirement

benefits increased the most in the United Kingdom (+15 percentage points), while the share of job postings offering paid time off or sick leave increased by 17 percentage points in the United States. There were also significant increases in the mention of tuition assistance in Canada and the United States, and small increases in the mention of fitness facilities in all three countries analysed.

The increase in benefit offerings coincided with the sharp increase in labour market tightness described above. While this suggests that workers overall might have benefitted from the tight labour markets of the last year, additional analysis find no indication that benefit offerings increased more in industries where the growth in labour demand (as proxied by the growth in the number of job postings) was stronger (see Annex 1.B).⁹ The increase in benefit offers also appear to affect industries regardless of their pay level.

Figure 1.9. In some OECD countries, employers are offering more benefits in job postings amid tight labour markets

Percentage share of online job postings offering each benefit in Canada, the United Kingdom and the United States



Note: An online job posting offers a benefit if it includes in the text at least one of the keywords listed in Annex 1.B.

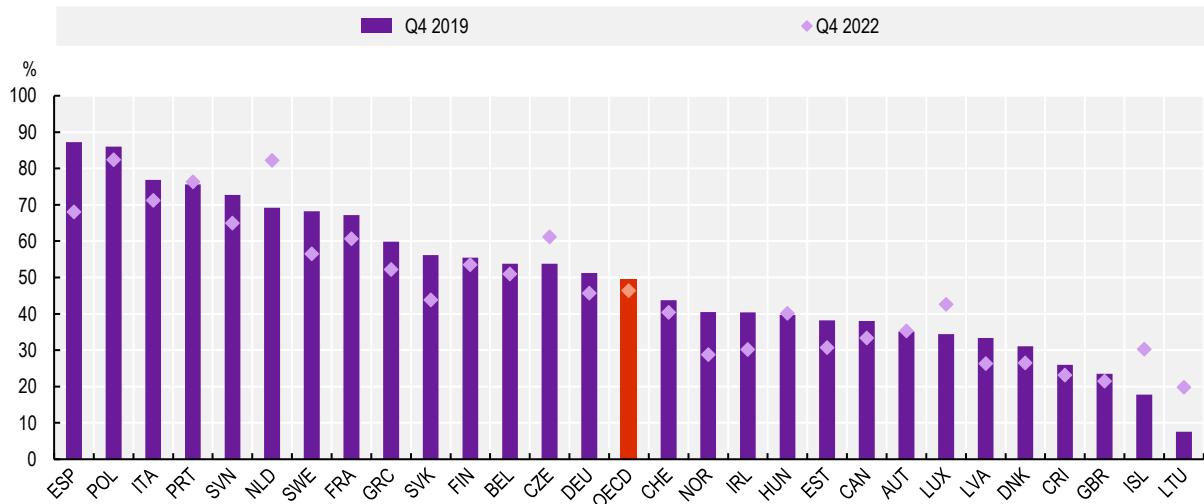
Source: OECD calculations based on Lightcast data.

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Amid the tight labour markets, the number of temporary contracts and of workers in involuntary part-time jobs have declined among new hires, suggesting an improvement in the working conditions of this group.¹⁰ In Q4 2022, the share of new hires on temporary contracts was lower than in Q4 2019 in 20 of the 28 countries with data available – despite the strong economic cycle in both periods (Figure 1.10). On average, the share of new hires on temporary contracts declined from 49% to 46%. The largest proportional declines were recorded in Norway, Spain, Sweden, the Slovak Republic and Ireland, while Lithuania and Iceland saw an increase in the share of new hires on temporary contracts although from initially low levels. Involuntary part-time among new hires declined between Q4 2019 and Q4 2022 in Canada, Costa Rica, the United Kingdom and the United States (Figure 1.11, Panel A). Similarly, in European countries, involuntary part-time among new hires declined in 18 of the 21 countries with data available between Q1 2021 and Q1 2022 (Figure 1.11, Panel B).¹¹

Figure 1.10. Temporary employment has declined among new hires

Percentage share of new hires with a temporary contract



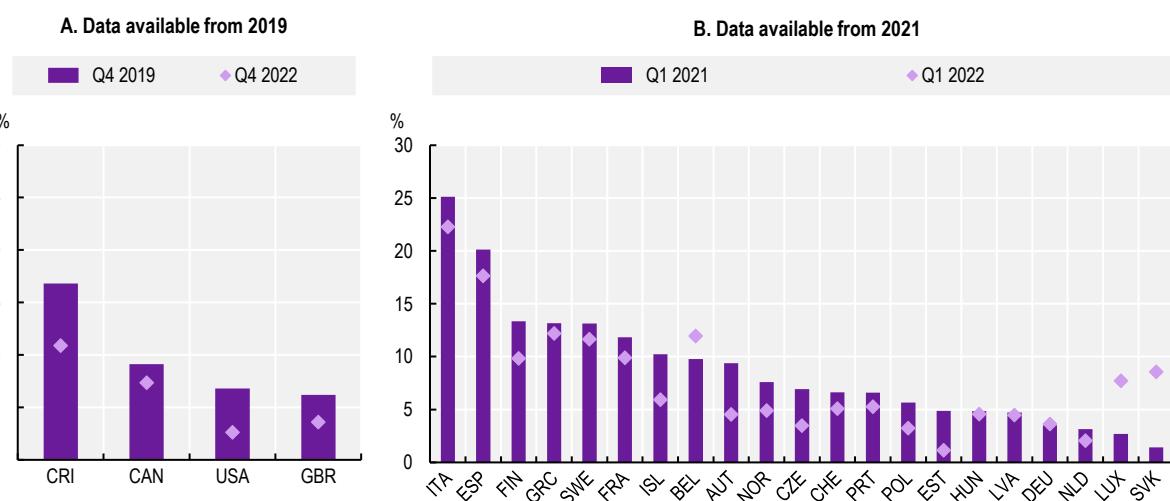
Note: OECD is the unweighted average of the countries shown. New hires are defined as employees with a tenure of at most three months.

Source: OECD calculations based on the Canadian Labour Force Survey (Statistics Canada), the Labour Force Survey (UK Office for National Statistics), Encuesta Continua de Empleo (Costa Rica) and EU labour force survey (EU-LFS) for European countries.

StatLink <https://stat.link/pzrqe7>

Figure 1.11. Involuntary part-time has declined among new hires

Percentage share of new hires in involuntary part-time



Note: Denmark, Ireland and Lithuania are not included due to anomalies in the data. Data on the share of new hires in involuntary part-time in Panel B are only available from Eurostat from Q1 2021 to Q4 2022. The figure focuses on the comparison between Q1 2021 and Q1 2022 to account for possible seasonality effects. New hires are defined as employees with tenure of at most three months.

Source: OECD calculations based on the Canadian Labour Force Survey (Statistics Canada), the Labour Force Survey (UK Office for National Statistics), Encuesta Continua de Empleo (Costa Rica), Current Population Survey (U.S. Bureau of Labor Statistics) and EU labour force survey (EU-LFS) for European countries.

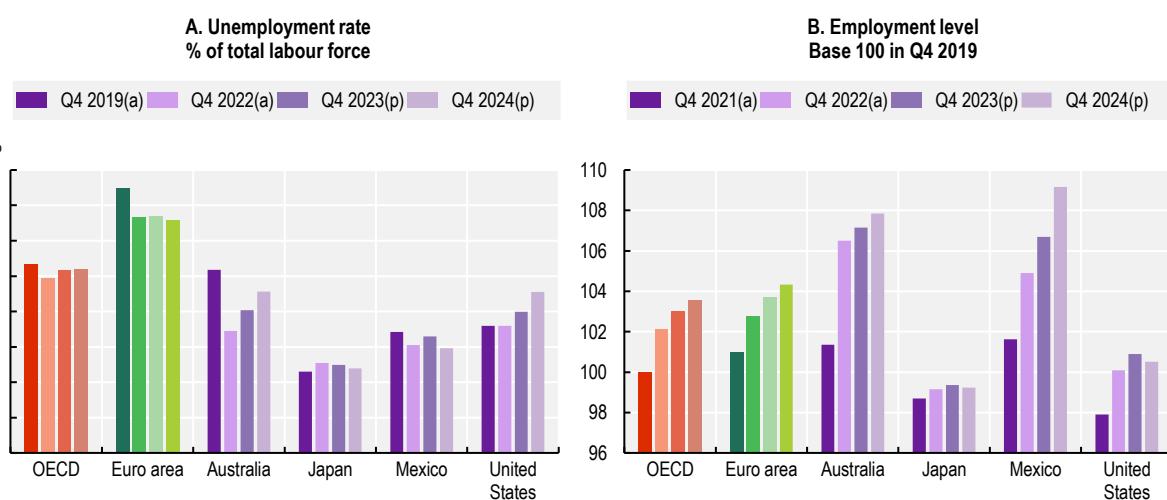
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1.1.3. Economic growth in the OECD is expected to remain subdued in 2023 and 2024, with moderate employment growth and a small increase in unemployment

Despite the signs of improvement seen in the early months of 2023, the outlook is for a period of subdued growth and persisting inflation.¹² The full effects of the tightening of monetary policy since the start of 2022 are likely to appear over the course of 2023 and early 2024, particularly on private investment. Annual OECD GDP growth is projected to be below trend at 1.4% in both 2023 and 2024, although it will gradually pick up on a quarterly basis through 2024 as inflation moderates and real income growth strengthens. Helped by the decline in energy prices over the past few months, average annual headline inflation in the OECD as a whole is now projected to fall relatively quickly from 9.4% in 2022 to 6.6% in 2023 and 4.3% in 2024, with year-on-year inflation in the last quarter of 2024 down to 3.8%.

OECD-wide employment is projected to keep expanding in 2023-24 (Figure 1.12) and the unemployment rate to rise only marginally, especially in the Euro Area. The OECD-wide unemployment rate is expected to increase from 4.9% at the end of 2022 to 5.2% in the fourth quarter of 2024 (Figure 1.12), though with relatively large rises of around 0.75 percentage point or more in Australia, New Zealand, the United Kingdom and the United States.

Figure 1.12. Employment in the OECD is projected to continue to grow in 2023 and 2024, with the unemployment rate also inching up slightly



Note: (a) Actual value. (p) OECD projection. Euro Area refers to the 17 EU member states using the euro as their currency which are also OECD Member States.

Source: OECD (2023[2]), *OECD Economic Outlook, Volume 2023 Issue 1: Preliminary version*, <https://doi.org/10.1787/ce188438-en>.

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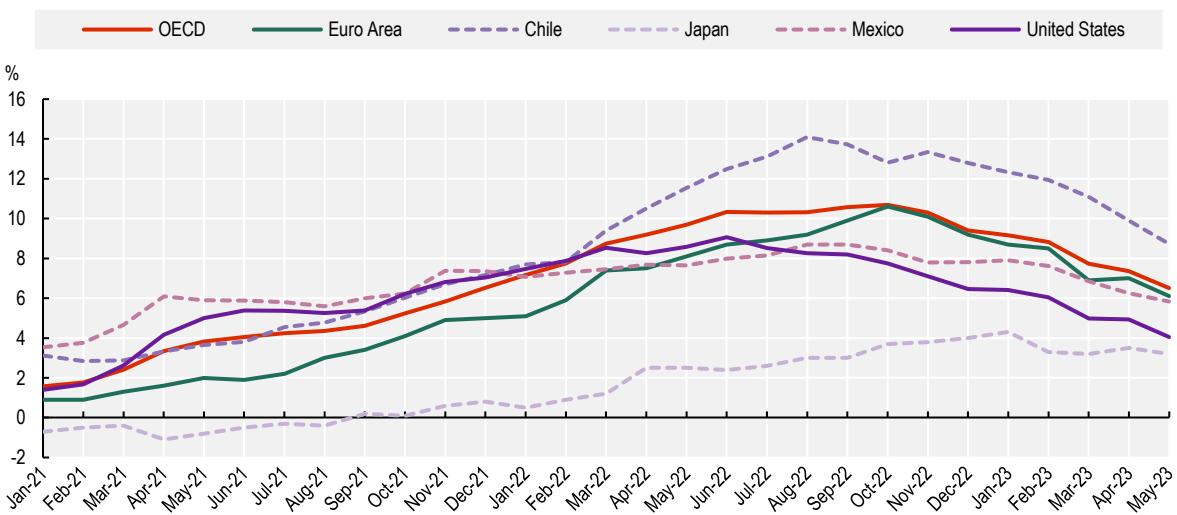
Significant uncertainty about economic prospects remains, and the major risks to the projections are on the downside. One key concern is that inflation could continue to be more persistent than expected requiring tighter monetary policy for longer. In addition, the impact on economic growth could be stronger than expected if tighter financial conditions were to trigger stress in the financial system and undermine financial stability. Another key downside risk to the outlook relates to the uncertain course of Russia's war of aggression against Ukraine and the associated risks of renewed disruptions in global energy and food markets. On the upside, reduced uncertainty from an early end to the war, easier-than-expected financial conditions, more robust labour force growth, and greater use of accumulated savings by households and businesses would all improve growth and investment prospects.

1.2. Inflation reached levels not seen in decades, causing real wages to fall across the OECD

The COVID-19 crisis was followed by a large surge in prices. Prices began to increase in 2021 due to the rapid rebound from the pandemic and related supply chain bottlenecks (Figure 1.13). Then, over the course of 2022, the impact on energy prices of Russia's war of aggression against Ukraine pushed inflation to levels not seen for decades in most countries. Inflation was initially mostly imported and driven by input and energy prices (OECD, 2022^[1]), but, over the course of 2022, it became more broad-based with higher costs increasingly being passed through into the prices of goods and services (OECD, 2022^[1]).¹³

Figure 1.13. Inflation is slowly declining after reaching decades-high levels in many countries

Inflation defined as the annual growth rate of Consumer Price Index (CPI) including all items



Note: Euro Area refers to the 20 EU member states using the euro as their currency.

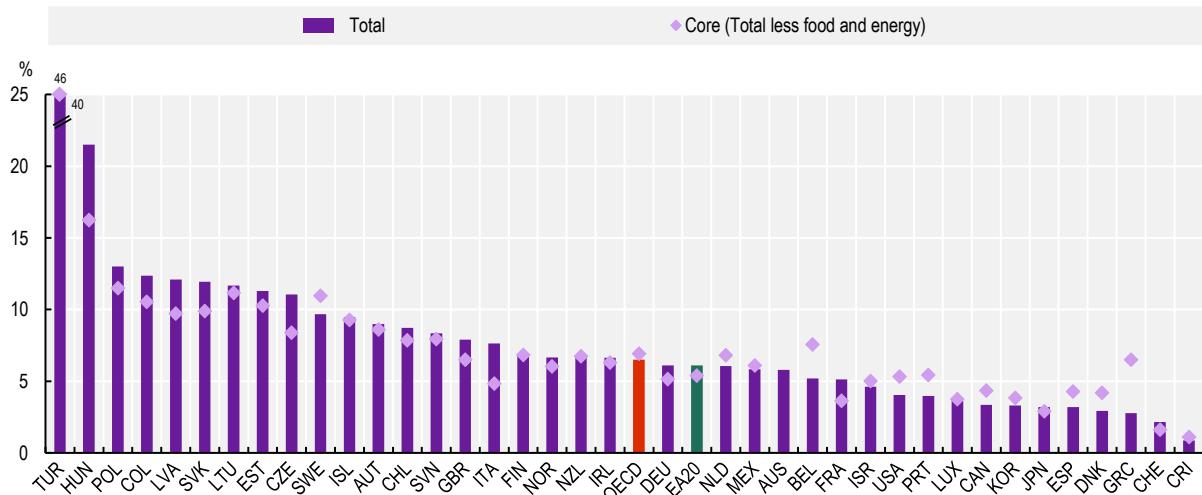
Source: OECD (2023), "Prices: Consumer prices", *Main Economic Indicators* (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 4 July 2023).

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Inflation for the OECD area increased rapidly from below 2% at the start of 2021 to a peak of 10.7% in October 2022 and then fell to 6.5% in May 2023 – the last observation available at the time of writing. As of May 2023, inflation remained above 10% in nine OECD countries. Differences in total inflation across countries tended to be larger than differences in core inflation (see Figure 1.14), reflecting the differential exposure of countries to the increases in energy prices. Because of their higher vulnerability to the increase of energy prices, total inflation was particularly high in countries in Central and Eastern Europe. In general, however, amongst OECD countries, inflation was higher in Europe and South America, while it remained at relatively low levels in Korea and Japan (3.3% and 3.2% respectively).

Figure 1.14. Core inflation has grown in many countries recently, as inflation has become more broad-based

Inflation defined as annual percentage change in the Consumer price index (CPI), May 2023 or latest observation



Note: Core inflation represents price changes excluding energy and food items, not available for Australia. Euro Area refers to 20 Eurozone countries. * For New Zealand, the data refer to year-on-year changes from Q1 2022 to Q1 2023.

Source: OECD (2023), "Prices: Consumer prices", *Main Economic Indicators* (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 4 July 2023), and Monthly CPI Indicator (Australian Bureau of Statistics).

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1.2.1. Low-income households often face higher effective inflation rates and have less leeway to absorb increases in the cost of living

In most countries, low-income households have faced a higher effective inflation rate because a higher proportion of their spending goes towards energy and food which drove most of the initial increase in inflation.¹⁴ Similarly, there is evidence that rural households have suffered more in several countries because energy and fuel account for a larger share of their total expenditures (Causa et al., 2022^[20]). In general, however, as inflation becomes more broad-based, differences in effective inflation rates across different households or groups with different consumption patterns become less pronounced.

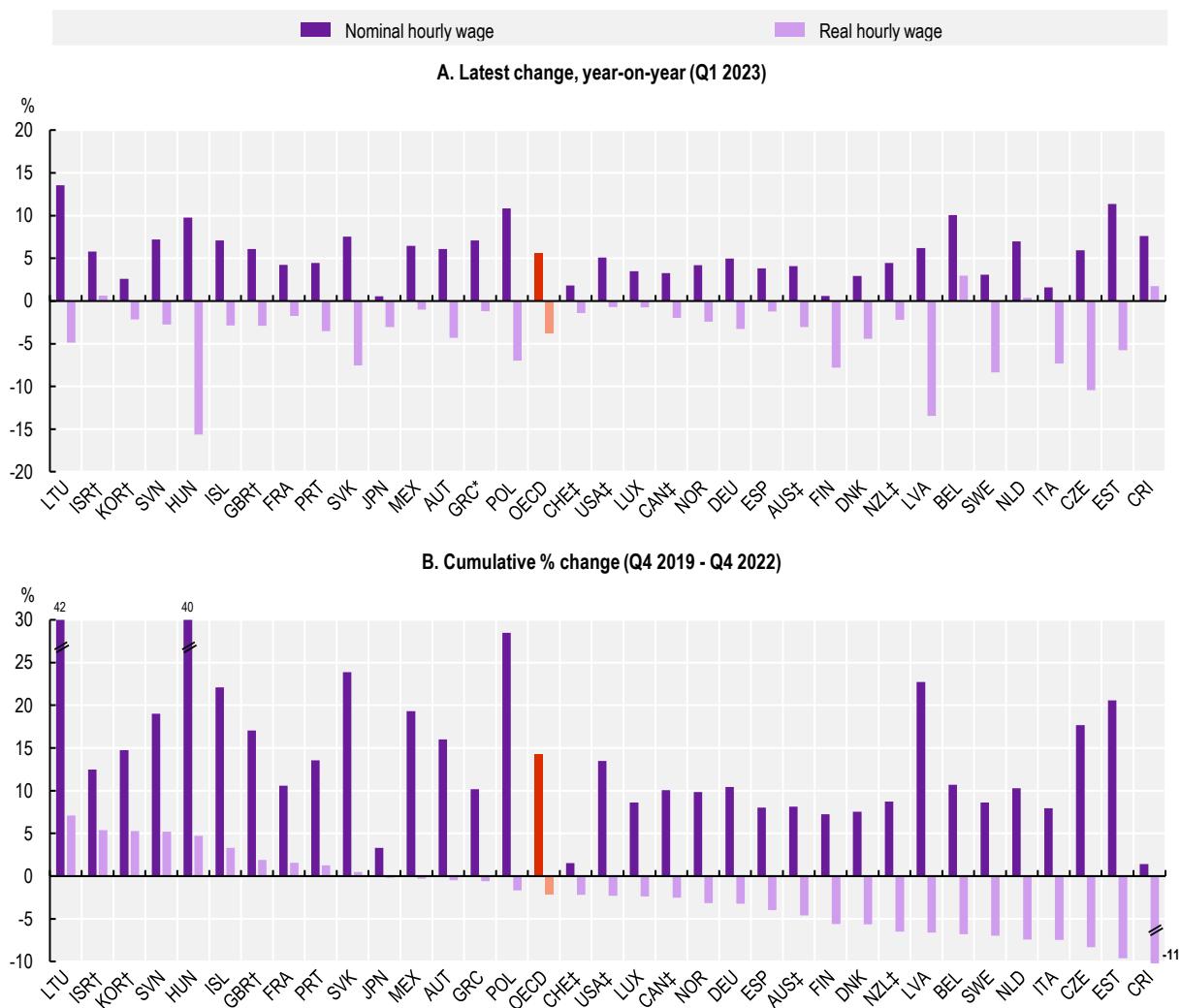
However, low-income households have less leeway to absorb increases in cost of living even when facing effective inflation rates like those of other households. First, low-income households might have less room to substitute for lower-price alternatives if they are already buying cheaper versions of a given item.¹⁵ Second, low-income households typically can rely less on savings or borrowing to buffer the increase in cost of living (Charalampakis et al., 2022^[21]; The German Council of Economic Experts, 2022^[22]).¹⁶

1.2.2. Despite a pickup in nominal wage growth, real wages are falling in all OECD countries

Year-on-year nominal growth in hourly wages generally picked up in 2022, but by less than the rise in inflation, leading to widespread falls in real wages. In Q1 2023, nominal year-on-year wage growth exceeded its pre-crisis level in nearly all OECD countries, reaching 5.6% on average across the 34 countries with data available (Figure 1.15, Panel A).¹⁷ However, nominal wage growth fell short of inflation by -3.8%, on average, with negative differences observed in 30 countries.^{18 19}

Figure 1.15. Real wages are below pre-pandemic levels, despite the recent nominal wage growth

Changes in nominal and real hourly wages



Note: Real wage growth is calculated by subtracting consumer price index (CPI) inflation (all items) from nominal wage growth. OECD is an unweighted average of the countries shown above. *The latest year-on-year change refers to Q4 2022 (Greece). †The composition of industries is not fixed for Israel, Korea and the United Kingdom, and thus comparing these results with the others requires caution. ‡Additional sources of compositional shifts, such as regions (Australia, Canada, New Zealand), job characteristics and workers' characteristics (Australia, New Zealand), gender (Switzerland) and occupations (United States) are controlled for. For Israel, the average monthly wages per employee job are used. For the United Kingdom, average weekly earnings are used. Moreover, wages in the public sector are excluded for Australia, Canada, Costa Rica, Japan, Korea, Mexico, New Zealand, the United Kingdom and the United States.

Source: The wages and salaries component of the labour cost index by NACE Rev. 2 activity (Eurostat), Wage Price Index (Australian Bureau of Statistics), Fixed weighted index of average hourly earnings for all employees (Statistics Canada), OECD calculations based on Encuesta Continua de Empleo (Instituto Nacional de Estadística y Censos, Costa Rica), Wages and Employment Monthly Statistics (Israeli Central Bureau of Statistics), OECD calculations based on Monthly Labour Survey (Japanese Ministry of Health, Labour and Welfare), Labour Force Survey at Establishments (Korean Ministry of Employment and Labour), OECD calculations based on Encuesta Nacional de Ocupación y Empleo, Encuesta Telefónica de Ocupación y Empleo, Encuesta Nacional de Ocupación y Empleo Nueva Edición (Instituto Nacional de Estadística y Geografía, Mexico), Labour Cost Index (Statistics New Zealand), Swiss Wage Index (Swiss Federal Statistical Office), Monthly Wages and Salaries Survey (UK Office for National Statistics), and Employment Cost Index (U.S. Bureau of Labor Statistics, retrieved from FRED); OECD (2023), "Prices: Consumer prices", Main Economic Indicators (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 23 June 2023).

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Inflation has now exceeded nominal wage growth for several quarters in most countries. As a result, at the end of 2022, real wages were below their Q4 2019 level by an average of -2.2% in 24 of the 34 OECD countries with available data (Figure 1.15, Panel B).²⁰ Even in the remaining 10 countries, however, inflation had eroded most of the nominal wage growth.

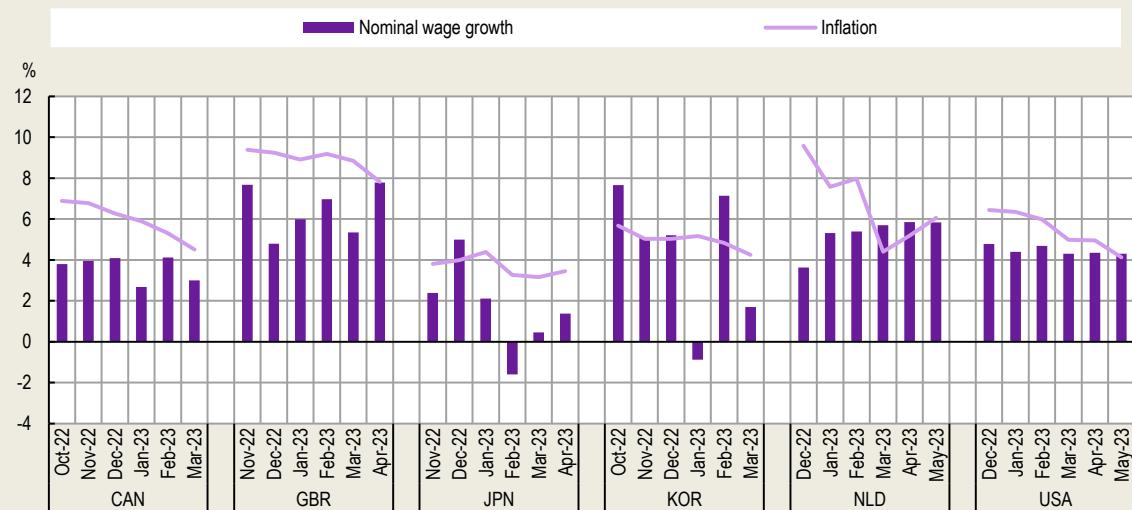
The evolution over the past year (leading up to Q1 2023) shows no clear sign of substantial acceleration of nominal wage growth across countries – with the dynamics of real wages still largely driven by inflation instead (Annex Figure 1.A.3). Data for April or May 2023 are only available for a limited number of OECD countries and, along with data from wages advertised in online job postings, point to a narrowing (or even closing in some countries) of the gap between nominal wage growth and inflation. This is mostly because of steady nominal wage growth and declining inflation (see Box 1.2).

Box 1.2. Recent data from selected OECD countries point to a narrowing of the gap between nominal wage growth and inflation

Recent data on wages for five OECD countries mostly point to a narrowing of the gap between nominal wage growth and inflation (Figure 1.16). In fact, the latest data suggest that the fall in real wages might have come to an end in the United Kingdom, the United States and the Netherlands. This is mostly driven by a deceleration of inflation rather than an acceleration of nominal wage growth. In the United Kingdom, however, nominal wage growth was particularly robust in April 2023, reaching a high of just under 8%. In Canada and Japan, however, the latest year-on-year nominal wage growth remains below inflation, while in Korea it exhibits considerable short-term variation.

Figure 1.16. The gap between nominal wage growth and inflation is narrowing in some countries

Year-on-year percentage change, over the latest six months



Note: The wage measures used above do not include the public sector and are not harmonised across countries: fixed weighted index of average hourly earnings for Canada; average weekly earnings – private sector level – seasonally adjusted total pay excluding arrears for the United Kingdom; total hourly cash earnings (seasonally adjusted) for Japan; average hourly wages (seasonally adjusted) for Korea; collective labour agreement wages per hour including special remunerations for the Netherlands; and average hourly earnings of all employees (Total Private, seasonally adjusted) for the United States.

Source: Fixed weighted index of average hourly earnings for all employees (Statistics Canada), Monthly Wages and Salaries Survey (UK Office for National Statistics), Monthly Labour Survey (Japanese Ministry of Health, Labour and Welfare), Labour Force Survey at Establishments (Korean Ministry of Employment and Labour), and Current Employment Statistics (U.S. Bureau of Labor Statistics, retrieved from FRED); OECD (2023), "Prices: Consumer prices", *Main Economic Indicators* (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 23 June 2023).

Nominal wage growth in online job postings is mostly steady in Europe and the United States, while inflation is slowly declining

Evidence from wages advertised in job posting on the online platform *Indeed* suggests a steady or declining nominal wage growth over the first five months of 2023 in Germany, France, Ireland, Italy and the United States (Figure 1.17). In Spain, the Netherlands, and – more markedly – the United Kingdom, nominal growth of posted wages has increased slightly. In general, the gap between inflation and nominal wage growth in posted wages (both measured here as 3-month moving averages) has becomes smaller. However, real growth in posted wages has turned positive only in Spain and the United States in recent months. In Italy, the gap between inflation and growth in posted wages increased again in May 2023, after declining for the first four months of the year.

Figure 1.17. Nominal growth in posted wages has mostly been stable in 2023

Year-on-year percentage change, 3-month moving averages, from December 2022 to May 2023



Note: The posted wages are the average year-on-year percentage changes in wages and salaries advertised by job postings on Indeed.
Source: Indeed Wage Tracker (<https://github.com/hiring-lab/indeed-wage-tracker>); OECD (2023), “Prices: Consumer prices”, *Main Economic Indicators* (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 23 June 2023).

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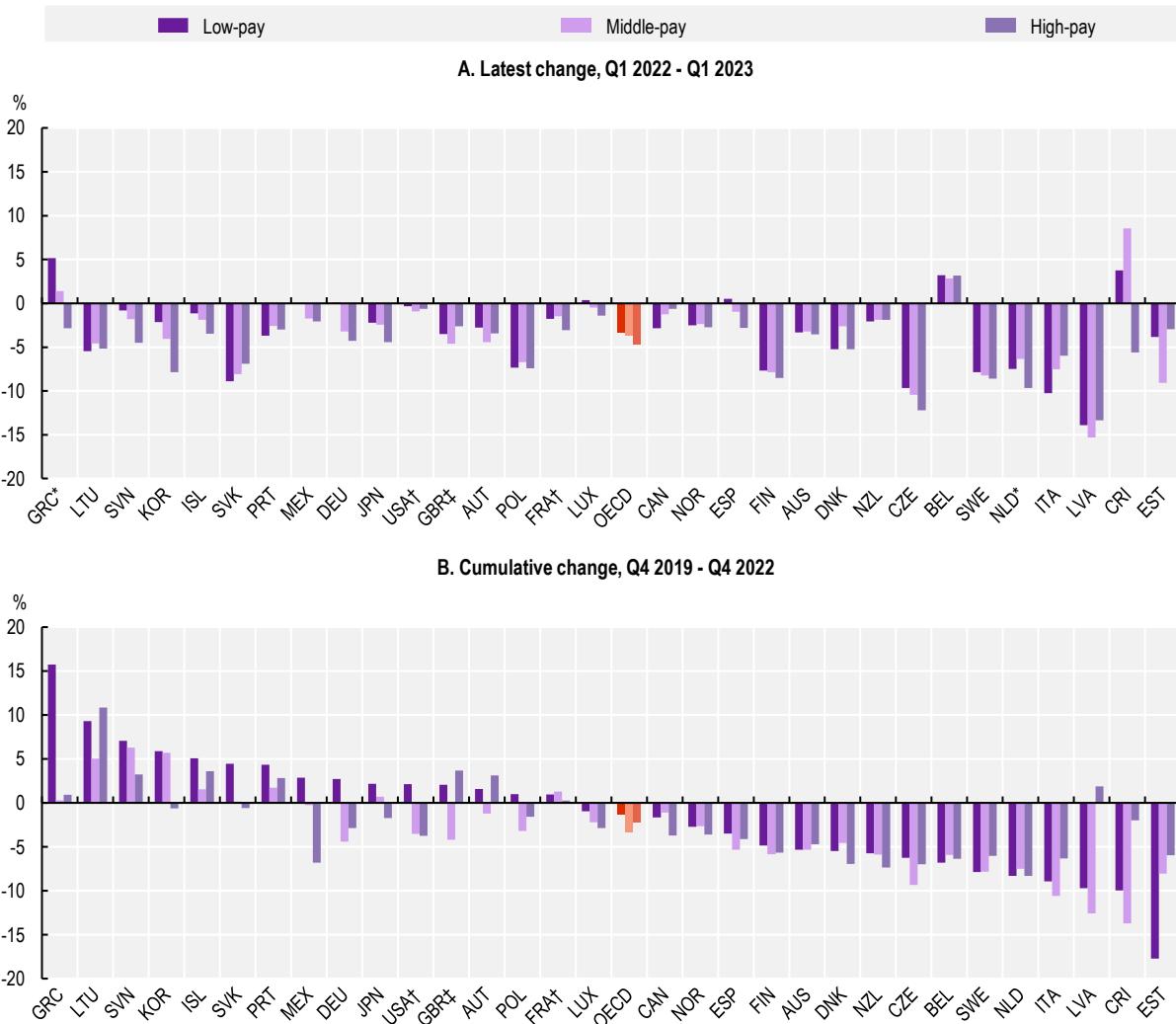
Real wages are falling across industries, but they are faring relatively better in low-pay industries in many countries

Wage dynamics could vary across the wage distribution due to factors such as labour demand, minimum wage laws, collective bargaining, and employer monopsony power. Since data on individual wages become available only with a significant lag for most countries, this section relies on wages by industry to provide some initial insights on how workers of different pay levels have fared in many OECD countries.

To offer an overview of wage developments by industry across countries, Figure 1.18 reports changes in real wages by industries aggregated in three broad groups: low-pay industries (accommodation and food services, administrative & support services, arts, entertainment and recreation, wholesale & retail trade); mid-pay industries (transportation and storage, manufacturing, other services, real estate activities, and construction); and high-pay industries (human health and social work, education, professional activities, information and communication, and finance and insurance). Industries are weighted by employment shares within each group.

Figure 1.18. Changes in real wages by industry and country

Percentage change in real hourly wages



Note: Real wage growth is calculated by subtracting consumer price index (CPI) inflation (all items) from nominal wage growth. OECD is an unweighted average of the countries shown. Low-pay industries include Accommodation & food service, Administrative & support service, Arts, entertainment & recreation and Wholesale & retail trade. Middle-pay industries include Transportation & storage, Manufacturing, Other service, Real estate activities and Construction. High-pay industries include Human health & social work, Education, Professional activities, Information & communication and Finance & insurance. Average employment shares by industry over the four quarters of 2019 are used for aggregation and thus small inconsistencies between changes in wages by industry and changes in average wages are possible. *The latest year-on-year change refers to Q4 2022 (Greece and the Netherlands). †There are missing industries: Arts, entertainment & recreation is not included for the United States; Human health & social work and Education are not included for France. ‡Average weekly earnings are used for the United Kingdom. Moreover, wages in the public sector are excluded for Australia, Japan, Korea, New Zealand, the United Kingdom and the United States.

Source: The wages and salaries component of labour cost index by NACE Rev. 2 activity (Eurostat), Wage Price Index (Australian Bureau of Statistics), Fixed weighted index of average hourly earnings for all employees (Statistics Canada), OECD calculations based on Encuesta Continua de Empleo (Instituto Nacional de Estadística y Censos, Costa Rica), Wages and Employment Monthly Statistics (Israeli Central Bureau of Statistics), OECD calculations based on Monthly Labour Survey (Japanese Ministry of Health, Labour and Welfare), Labour Force Survey at Establishments (Korean Ministry of Employment and Labour), OECD calculations based on Encuesta Nacional de Ocupación y Empleo, Encuesta Telefónica de Ocupación y Empleo, Encuesta Nacional de Ocupación y Empleo Nueva Edición (Instituto Nacional de Estadística y Geografía, Mexico), Labour Cost Index (Statistics New Zealand), Swiss Wage Index (Swiss Federal Statistical Office), Monthly Wages and Salaries Survey (UK Office for National Statistics), and Employment Cost Index (U.S. Bureau of Labor Statistics, retrieved from FRED); OECD (2023), "Prices: Consumer prices", *Main Economic Indicators* (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 23 June 2023).

Real wages have declined across industries in almost all OECD countries, but workers in low-pay industries have often fared relatively better (Figure 1.18, Panel A).²¹ The latest year-on-year changes for Q1 2023 show that real wages performed better in low-pay industries than in both mid- and high-pay industries in 15 of the 31 countries with data available. Conversely, wages in low-pay industries had the worst performance only in six countries, losing more than 1 percentage point relative to both mid- and high-pay industries only in Canada and Italy. In the pair-wise comparison, real wages performed better in low-pay industries than in mid-pay ones in 18 countries, and better than in high-pay industries in 22 countries.

The pattern of relatively better wage performance in low-pay industries also holds when considering changes relative to pre-crisis levels – even if over this longer time horizon real wages declined in fewer countries and industries (Figure 1.18, Panel B). Between Q4 2019 and Q4 2022, real wages performed better in low-pay industries than in both high- and mid-pay ones in 16 of the 31 OECD countries with available data. Conversely, wages in low-pay industries fared worse than both the other two groups of industries only in four countries (Belgium, Estonia, the Netherlands and Sweden). In the pair-wise comparison, real wages performed better in low pay industries than in mid-pay ones in 23 countries, and better than in high-pay industries in 20 countries.

Tight labour markets have contributed to stronger nominal wage growth

Tentative evidence suggests that labour markets tightening has been associated with stronger wage growth at the industry level. A simple analysis correlating changes in real wages with changes in vacancy rates for 14 industries in 15 OECD countries suggests that – on a year-on-year basis – a 1% increase in the vacancy rates was associated with a 0.03% increase in real wages. The analysis provides some indication that the correlation between tightness and real wage growth might have been slightly stronger in low-pay industries, but the differences are not statistically significant. In addition, a simple extension of the exercise does not support the conclusion that differences in either the level of tightness or in its impact across (broad) industries can explain the relatively better performance of real wages in low-pay industries. Similarly, another extension of the analysis finds that increases in statutory minimum wages are associated with larger increases in average wages particularly in low-pay industries, but this difference does not explain the differentials in wage growth across industries (see Section 1.3. for a detailed discussion of minimum wage policies and adjustments across OECD countries in recent times).²²

These findings might be at least in part the result of averaging across countries with very different institutional settings. Using more granular data from before the pandemic, Duval et al. (2022^[13]) find that in the United Kingdom and the United States, the impact of a given increase in tightness on wage growth is at least twice as large in low-pay sectors as in the average industry. However, they acknowledge that the gap might be smaller in continental Europe because of binding and stickier statutory or collectively bargained minimum wages. Consistent with this observation, Hentzgen et al. (2023^[23]) find no correlation across industries between recent changes in tightness and nominal wage growth in France, a country where both collective bargaining and the minimum wage play a significant role in wage setting (see Section 1.3). As for the effect of the minimum wage, Hentzgen et al. (2023^[23]) find a clear correlation between recent increases in wages in an industry and the proportion of workers affected by increases in minimum wages in France, but Autor et al. (2023^[16]) find no indication in the United States that wages at the bottom of the distribution increased more in states that increased their minimum wages recently.

The developments of wages by industry suggest a compression of wages across pay levels, but more granular data are needed to assess the impact of the real wage crisis on inequality

The results presented in this section indicate a trend of compression of wages across workers of different pay levels, as proxied by industry wages. For the few countries for which data on wages by education and occupations are already available, the picture is mixed, with an indication of compression of wages across both education and occupation groups in Costa Rica, Mexico and the United States, but not in Canada and in the United Kingdom (see Box 1.3).

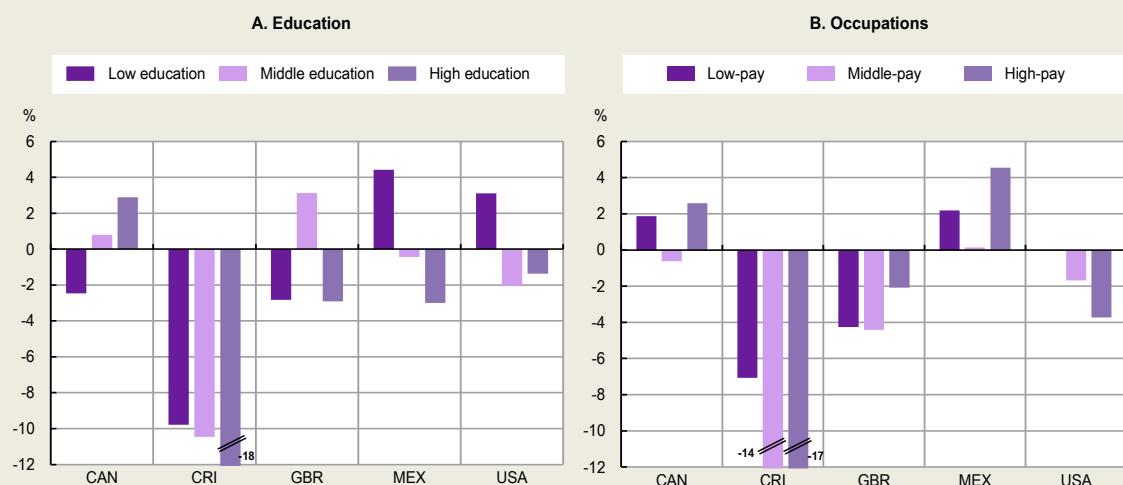
Box 1.3. Real wage developments by education and occupation vary across the countries with timely data

The main analysis in the chapter looks at wages by industry to provide evidence on wage dynamics across workers of different pay levels. For five countries, the analysis can be extended to look at changes in wages by education and occupation thanks to the timely availability of Labour Force Survey data. Figure 1.19 reports changes in real wages (calculated as the difference between nominal wage growth and inflation) for various groups between the end of 2019 and that of 2022. The results suggest a compression of wages across workers of different pay levels (as proxied by education and occupation) in Costa Rica, Mexico and the United States, but not in Canada and in the United Kingdom.

In Costa Rica and the United States, wages performed better among the low educated and workers in low-pay occupations (Figure 1.19). In Costa Rica, real wages fell across the board but much less among workers of low education and workers in low-pay jobs. In the United States, workers with low education and those in low-pay occupations were the only ones that avoided a real wage contraction between Q4 2019 and Q4 2022.

Figure 1.19. Changes in real wages by education and occupation vary across countries

Cumulative percentage change in real hourly wages between Q4 2019 and Q4 2022



Note: The classification of pay levels by occupation is determined by identifying the top/middle/bottom tercile of employed population based on the ranking of average hourly wages according to a national classification of occupations in each country. The level of education is classified as follows: low (ISCED 0-2), middle (ISCED 3-4) and high (ISCED 5-8). Real wage growth is calculated by subtracting consumer price index (CPI) inflation (all items) from nominal wage growth.

Source: OECD calculations based on the Labour Force Survey (Statistics Canada), Encuesta Continua de Empleo (Instituto Nacional de Estadística y Censos, Costa Rica), Labour Force Survey (UK Office for National Statistics), Encuesta Nacional de Ocupación y Empleo, Encuesta Telefónica de Ocupación y Empleo, Encuesta Nacional de Ocupación y Empleo Nueva Edición (Instituto Nacional de Estadística y Geografía, Mexico) and Current Population Survey (U.S. Bureau of Labor Statistics). OECD (2023), "Prices: Consumer prices", *Main Economic Indicators* (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 23 June 2023).

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In Canada, Mexico and the United Kingdom, however, there is no clear sign of a compression of wages across groups of different pay levels, with results varying depending on whether education or occupations are considered. In Canada, workers with low education are the only ones to have experienced a fall in real wages since the start of the crisis (by -2.5%), but workers in low-pay occupations have seen better wage performance than those in middle-pay occupations (Figure 1.19). In Mexico, wage differentials by education have compressed, as the low-educated are the only group that experienced real wage growth. However, at the same time, wages have grown more for workers in high-pay occupations than in low-pay occupations. In the United Kingdom, the low-educated saw a decline in real wages of -3%, similar to that of high-educated workers, while real wages of mid-educated workers increased by 3%. Workers in low-pay occupations experienced a decline in real wages like those in mid-pay ones, while workers in high-pay occupations saw a smaller fall in real wages.

While informative of a widespread trend across OECD countries, these results do not allow strong conclusions on how the current wage crisis is affecting wage inequality more broadly. More granular data on wages are necessary to assess changes across the wage distribution and conduct a more reliable analysis of their determinants. Because of the paucity and the delay of this type of data, however, there is currently very limited evidence even on individual countries, with data pointing to a compression of the wage distribution in the United States but not in the United Kingdom.

For the United States, Autor et al. (2023^[16]) document a remarkable compression of the wage distribution in 2021-22 which counteracted one-quarter of the four-decade increase in aggregate inequality between the 10th and 90th percentile. They find that the pandemic increased the elasticity of labour supply to firms in the low-wage labour market, reducing employer market power and spurring rapid wage growth at the bottom. Among the factors they discuss that might have contributed to this change is a decrease in work-firm attachment spurred by the large number of separations that occurred during the pandemic. By contrast, in the United Kingdom, gross hourly earnings of employees at the bottom and at the top of the distribution have grown in similar ways between the last quarter of 2019 and the last quarter of 2022, with slightly larger growth in the top decile than in the bottom one over the last year.²³

Box 1.4. Changes in real wages by gender vary across countries

The cost-of-living crisis could affect men and women in different ways if wage dynamics differ substantially across industries and occupations with different gender composition. However, the limited data currently available show no systematic gender differences in the evolution in real wages across countries (Figure 1.20). In four of the 11 countries with data available for Q4 2022, men experienced larger year-on-year declines in real wages than women, with the largest differential in Australia and the United Kingdom where real wages for men fell by at least 3%. In four other countries, men fared better than women on average – with the largest difference in Mexico, where real wages for women fell by more than 3% against less than 1% for men. In the remaining three countries (Lithuania, Norway and New Zealand), year-on-year changes in real wages were similar between the two genders.

Figure 1.20. Both men and women have been affected by the cost-of-living crisis

Percentage change between Q4 2019 and Q4 2022



Note: Gross monthly earnings for Lithuania and Norway. Gross weekly earnings for New Zealand. Net monthly wages for Portugal. Quarterly cumulative gross earnings for Hungary. Real wage growth is calculated by subtracting consumer price index (CPI) inflation (all items) from nominal wage growth.

Source: OECD calculations based on the Labour Force Survey (Statistics Canada), Encuesta Continua de Empleo (Instituto Nacional de Estadística y Censos, Costa Rica), Labour Force Survey (UK Office for National Statistics), Encuesta Nacional de Ocupación y Empleo, Encuesta Telefónica de Ocupación y Empleo, Encuesta Nacional de Ocupación y Empleo Nueva Edición (Instituto Nacional de Estadística y Geografía, Mexico) and Current Population Survey (U.S. Bureau of Labor Statistics). Average gross earnings of full-time employees (Hungarian Central Statistical Office), Average Weekly Earnings (Australian Bureau of Statistics), Average monthly earnings (Statistic Lithuania, Official Statistics Portal), Average monthly earnings (Statistics Norway), Average Weekly Earnings (Statistics New Zealand), Net monthly mean wages (Statistics Portugal). OECD (2023), "Prices: Consumer prices", *Main Economic Indicators* (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 23 June 2023).

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1.2.3. In many OECD countries, profits have grown faster than wages, making an unusually large contribution to price pressures and reducing the labour share

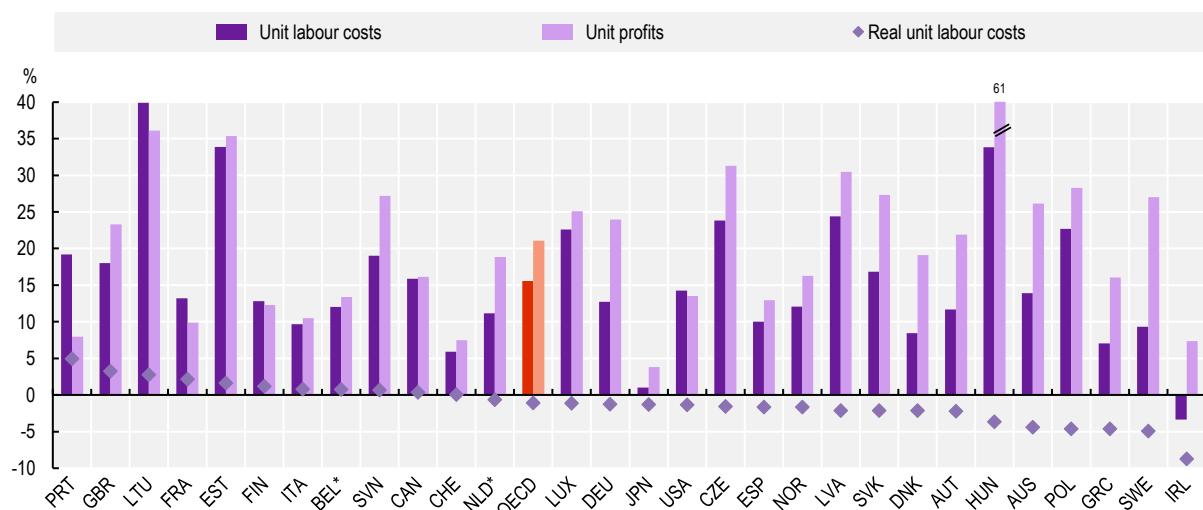
Over the last three years, labour costs per unit of real output (or unit labour costs) have increased in most OECD countries as growth in nominal wages has exceeded productivity growth (Figure 1.21).²⁴ Profit margins, as measured by profits per unit of real output (or unit profits), also grew in most countries, indicating that – on aggregate – firms were able to increase prices beyond the increase in the cost of labour and other inputs.

In fact, in most countries, unit profits rose more than unit labour costs in 2021 and 2022. As a result, over the last two years, profits have made an unusually large contribution to domestic price pressures (Box 1.5) and the labour share (i.e. the part of national income allocated to wages and other labour-related compensation) has fallen in many OECD countries.²⁵ Changes in real unit labour costs, i.e. the difference between changes in unit labour costs and changes in producers prices (i.e. GDP deflator) – offers a visualisation of the labour share changes. Real unit labour costs declined in 18 out of 29 countries with available data. Among the remaining countries, the largest increases in real unit labour costs took place in Portugal, the United Kingdom and Lithuania (Figure 1.21).²⁶

The combination of rising unit labour costs and unit profits is relatively unusual as increases in one are often absorbed by a fall in the other (OECD, 2023^[2]). Looking at historic evidence, one could have expected that the worsening of the terms of trade would have reduced profits (Arce and Koester, 2023^[24]). The specific nature of the recovery from the COVID-19 crisis likely provided conditions particularly favourable to the expansion of profits margins.²⁷ At the height of the COVID-19 crisis, in many countries, the fall in profit margins was mitigated by various forms of public support, including job retention schemes which subsidised labour hoarding to an unprecedented extent (European Central Bank, 2021^[25]; OECD, 2021^[26]). Unlike in previous recessions, production capacity was largely preserved during the pandemic-induced freezing of the economy. As economies re-opened, pent-up demand and large recovery plans bolstered aggregate demand and helped profits pick up quickly as supply-chain bottlenecks slowed down the expansion of supply. In a context with strong consumer demand and rapidly evolving inflation driven by external factors, firms might have had more room to increase prices simultaneously as they expected competitors to behave in the same way, while consumers might have been more prone to accept price increases given the inflationary context (Weber and Wasner, 2023^[27]). In addition, some of the increases in prices might have also been in anticipation of future increases in input and labour costs (Glover, Mustre-del-Río and von Ende-Becker, 2023^[28]). However, the recent decline in the cost of energy and other inputs along with downward price rigidity is likely to sustain profit margins at least in the near future (INSEE, 2023^[29]; European Commission, 2023^[30]).

Figure 1.21. Profits have increased more than labour costs in many OECD countries

Percentage changes, seasonally adjusted, from Q4 2019 to Q1 2023



Note: OECD is an unweighted average of the countries shown above. *For Belgium and the Netherlands, changes refer to the period from Q4 2019 to Q4 2022. For Norway, the data are based on mainland Norway. Unit labour costs and unit profits are calculated by dividing compensation of employees, gross operating surplus, respectively, by real GDP. Real unit labour costs are calculated by dividing compensation of employees by nominal GDP, indicating the share of national income going to labour. For Japan and Norway, gross operating surplus is approximated by deducting nominal GDP from compensation of employees. Compensation of employees, gross operating surplus, gross domestic products and GDP deflators are denominated in local currencies.

Source: OECD Quarterly National Accounts: Volume and price indices – GDP Expenditure Approach, <http://dotstat.oecd.org/Index.aspx?QueryId=120521>; Quarterly National Accounts – Income Approach, <http://dotstat.oecd.org/Index.aspx?QueryId=120186>; National Accounts – Quarterly Estimates (The Cabinet Office of Japan); National Accounts – Tables 09190 and 09175 (Statistics Norway).

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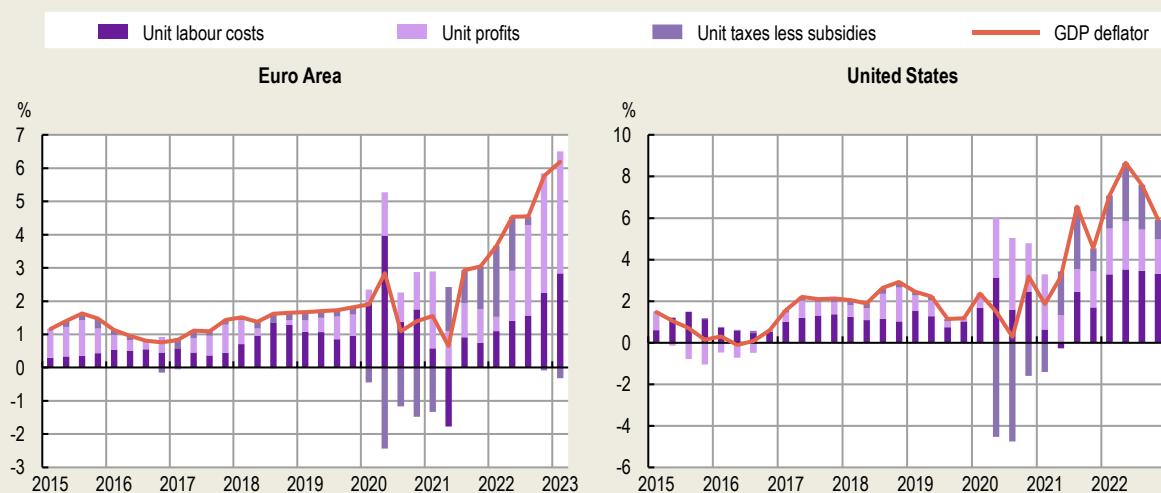
Box 1.5. The role of wages and profits in domestic price formation

The initial surge in inflation was largely imported in many OECD countries and driven by commodity and energy prices. However, over the course of 2022, inflation became more broad-based with higher costs increasingly being passed through into the prices of domestic goods and services (OECD, 2022^[11]). In addition to the increase in the costs of intermediate inputs, price dynamics are also influenced by changes in wages, profits, and taxes and subsidies. The analysis of this section shows that in recent quarters, both profits and labour costs have increased, with growth in profits exceeding growth in labour costs in many countries and sectors.

Figure 1.22 presents a decomposition of changes in the GDP deflator to gauge the contribution of wages, profits, and taxes to domestic price changes. Changes in the GDP deflator differ from consumer price inflation discussed in this section because the composition of household consumption underlying CPI-based measures of inflation is different from the composition of domestic output measured by GDP. Nevertheless, domestic price pressures are one of the main drivers of core inflation, i.e. inflation excluding energy and food (Arce and Koester, 2023^[24]).

Figure 1.22. Profits contributed more to domestic price pressures

Contribution to the GDP deflator, year-on-year percentage changes, seasonally adjusted data



Note: Euro Area represents the average of 20 Eurozone countries. Unit labour costs, unit profits and unit taxes less subsidies are calculated by dividing compensation of employees, gross operating surplus and taxes less subsidies on production and imports, respectively, by real GDP. For the United States, changes in the GDP deflator are reported net of statistical discrepancies. Data for Q1 2023 are not shown due to unusually large statistical discrepancies in the data available at the time of writing. Compensation of employees, gross operating surplus, taxes less subsidies on production and imports, gross domestic products and deflators are denominated in local currencies.

Source: OECD Quarterly National Accounts: Volume and price indices – GDP Expenditure Approach, <http://dotstat.oecd.org/Index.aspx?QueryId=120521>; Quarterly National Accounts – Income Approach, <http://dotstat.oecd.org/Index.aspx?QueryId=120186>.

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In the Euro Area and in the United States, both wages and profits have contributed to recent increases in domestic prices. In the Euro Area, the contribution of profits has been particularly large, accounting for most of the increase in domestic prices in the second half of 2022 and first quarter of 2023. This is in contrast with previous energy shocks, when increases in GDP deflator were mostly accounted for by changes in labour costs (Hansen, Toscani and Zhou, 2023^[31]). In the United States, amid particularly tight labour markets, wages have generally contributed to increases in domestic prices more than profits in recent quarters. The recent contribution of profit margins was much larger than in the years before the crisis but has decreased in the most recent quarters. The differences between the Euro Area and the United States might in part reflect the fact that price dynamics have been more demand-driven in the latter (Hansen, Toscani and Zhou, 2023^[31]). The contribution of unit taxes and subsidies has been particularly volatile over the period considered due to the introduction and withdrawal of pandemic-related subsidies as well as changes in the composition of household consumption (OECD, 2023^[2]).

Data from Europe and Australia show that in the last year unit profits increased more than unit labour costs in several sectors beyond the energy one

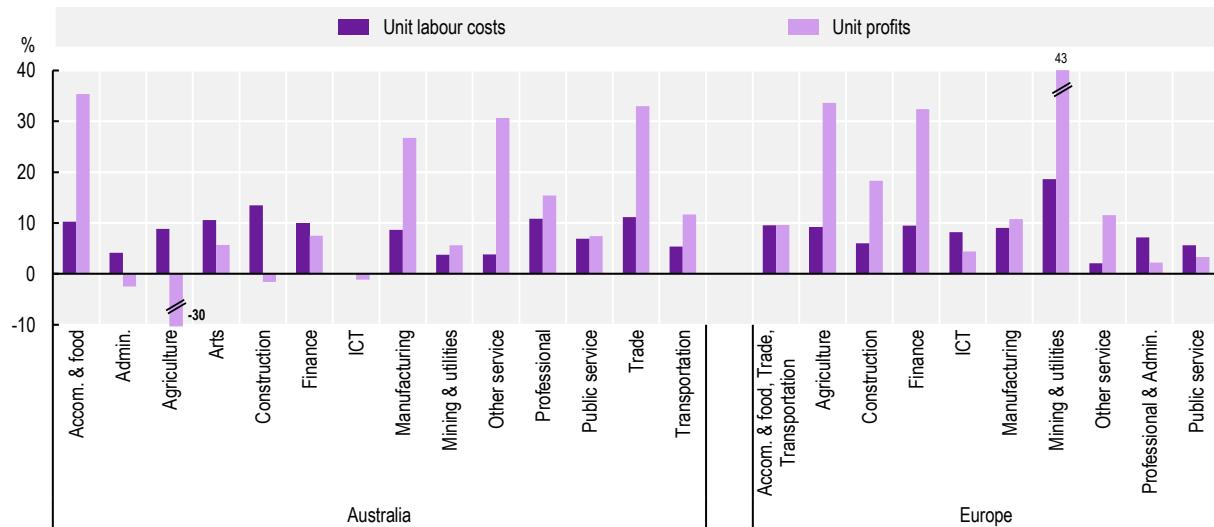
Data from Europe and Australia show that the strong performance of profits in 2022 was not limited to the energy sector. In the year to Q1 2023, in Europe, unit profits increased more than unit labour costs in manufacturing, construction and finance, and grew at the same rate as unit labour cost in “accommodation food and transportation” (Figure 1.23). Similarly, unit profits increased more than unit labour costs in several sectors in Australia, including “accommodation and food”, manufacturing, trade, and transportation.

Going forward, this evidence suggests some room for profits to absorb further partial adjustments in wages without generating significant price pressures or resulting in a fall in labour demand. However, the implications of further increases in labour costs for prices, profits and labour demand can vary across firms depending on the competitiveness of the output market, the cost structure of the firm and the evolution of the business cycle. These factors can vary significantly even within the broad sectors referenced in Figure 1.23. Firms that have more market power or operate in non-tradable sectors are more likely to be able to increase prices.²⁸ In contrast, firms operating in more competitive markets may have to absorb wage increases by reducing profits.

Rising costs of other inputs, such as energy, can also eat into profits and limit the ability to absorb some wage increases. Indeed, some of the increases in prices might have been in anticipation of further increases in input costs, as the energy shock works its way through the supply chain. Energy-intensive manufacturing may be particularly vulnerable to these cost pressures, but some service sectors – such as accommodation and food – are also relatively energy-intensive (European Commission, 2022^[32]). The impact of the increase in input prices is likely to be more significant on small and medium firms in these sectors. However, given the downward rigidity of prices, the recent decline in input costs will also likely provide further room to absorb some wage increases without generating inflationary pressures. More broadly, firm profitability may be undermined in the short term by a fall in the demand due to the tightening of monetary policy and the erosion of purchasing power. In this context, rising labour costs might be more likely to translate into a reduction in labour demand and potential employment losses. All in all, while the evidence suggests room for profits to absorb some adjustments in wages in several sectors and countries, the exact room of manoeuvre will likely vary across sectors and type of firms.

Figure 1.23. Profits outpace labour costs in many industries in Australia and Europe

Percentage changes, seasonally adjusted, from Q1 2022 to Q1 2023



Note: Europe represents the unweighted averages of 19 European OECD countries: Austria, Belgium, the Czech Republic, Denmark, Spain, Estonia, Finland, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, the Netherlands, Portugal, the Slovak Republic, Slovenia and Sweden. Unit labour costs are calculated as the share of compensation of employees in gross value added (chain volume measures). For Australia, unit profits are calculated as the share of gross operating surplus and gross mixed income in gross value added (chain volume measures). For Europe, unit profits are calculated from the sum of gross operating surplus and taxes less subsidies on production and imports, which are the deduction of compensation of employees from gross value added (current prices). Compensation of employees, gross operating surplus, taxes less subsidies on production and imports, gross value added are based on local currencies.

Source: Australian National Accounts: National Income, Expenditure and Product – Table 6 & Table 45 (Australian Bureau of Statistics); Gross value added and income – A*10 industry breakdowns (Eurostat).

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With no indication of a price-wage spiral in recent data, there is room to adjust wages at least for the most vulnerable

The quick rise of inflation over the past two years – that largely originated outside the labour market – raised the concern that it might set-off a price-wage spiral which could further undermine the purchasing power of those employed and even lead to significant employment losses. The evidence presented in this section, however, offers no indication of signs of a price-wage spiral so far. Nominal growth has picked up but it exhibits no clear signs of significant further acceleration across countries. The gap with inflation appears to be narrowing in recent months mostly because of a slow decline in inflation, but the erosion of real wages has not halted yet in the vast majority of OECD countries.

On balance therefore, the main problem going forward is a deepening of the cost-of-living crisis across the OECD. A gradual recovery of at least some of the recent losses in purchasing power is essential to prevent widespread increases in economic hardship especially among workers with low earnings. The analysis of this chapter suggests that, in several sectors and countries, there is room for profits to absorb some further increases in wages to mitigate the loss of purchasing power at least for the low paid without generating significant additional price pressures. Given the downward rigidity of prices, the recent decline in input costs will also likely provide further room to absorb some wage increases without generating inflationary pressures. A fair sharing of the cost of inflation can prevent further increases in inequality and support effective monetary policy by averting feedback loops between profits, wages and prices. The next section discusses policy options to tackle the cost-of living crisis while avoiding a price-wage spiral, focusing on wage setting institutions.

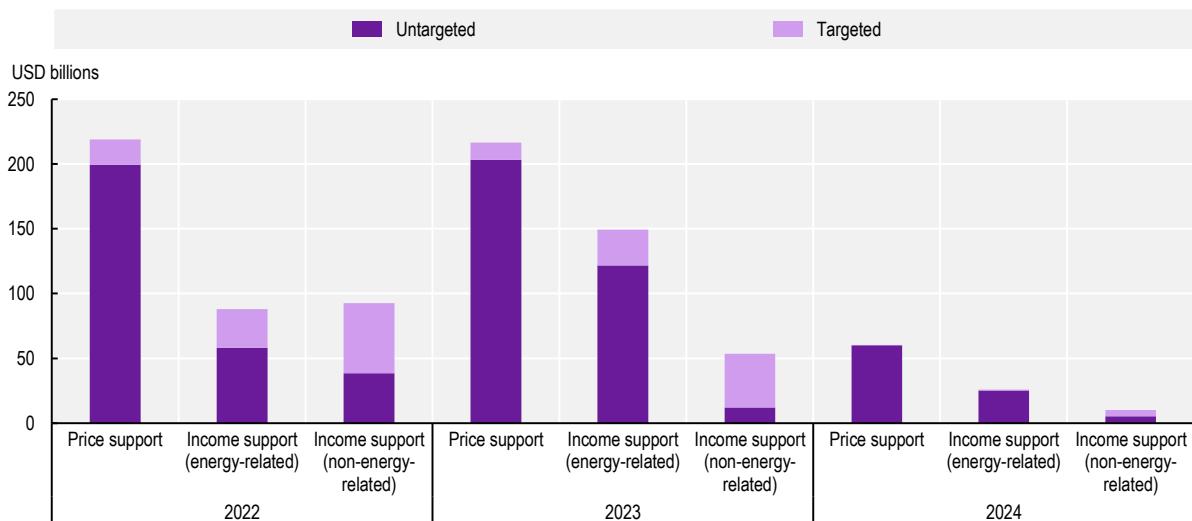
1.3. Wage setting in a high inflation environment

Several policy levers can be mobilised to limit the impact of inflation on workers and ensure a fair share of the costs between governments, companies, and workers. The most direct way to help workers is via an increase in their wages. Governments can take measures to increase their national statutory minimum wage to ensure that they maintain purchasing power for low-paid workers. They can also promote regular renegotiations of collective agreements – given the critical role of wage settings institutions in ensuring adequate wage increases, while avoiding a price-wage spiral – via a suitable regulatory framework as well as tailored fiscal incentives.

Beyond facilitating suitable adjustments of gross wages, governments can also provide direct support to net income more generally. Households and businesses can be compensated for the increase in prices via temporary price measures or via direct government transfers. Most OECD countries have for instance taken energy support measures between the end of 2021 and 2022, through price regulations, income support or tax reductions. Support to energy consumers was about 0.7% of GDP in the median OECD economy in 2022 but above 2% of GDP in some countries, especially in Europe. For the OECD area, similar levels of support are foreseen for 2023 (OECD, 2023^[33]). However, only a fraction of the measures adopted in the last two years appears to be targeted to the most affected households and businesses (Figure 1.24). Ensuring that support measures are targeted and temporary is important to concentrate the support on those who need it most, preserve incentives for energy savings and avoid a persistent stimulus to demand at a time of high inflation (Hemmerlé et al., 2023^[34]).

Figure 1.24. Price and income support policies remain sizeable but largely untargeted

Cost of energy-related fiscal support by type of measure, USD billion, calculated using 2022 bilateral exchange rates



Note: Based on an aggregation of support measures in 41 countries, of which 35 are OECD economies (all members except Hungary, Iceland and Switzerland) and 6 are non-OECD economies (Brazil, Bulgaria, Croatia, India, Romania and South Africa). Support measures are taken in gross terms, i.e. not accounting for the effect of possible accompanying energy-related revenue-increasing measures, such as windfall profit taxes on energy companies. Where government plans have been announced but not legislated, they are incorporated if it is deemed clear that they will be implemented in a shape close to that announced. Measures classified as credit and equity support are not included. When a given measure spans more than one year, its total fiscal costs are assumed to be uniformly spread across months. For measures without an officially announced end-date, an expiry date is assumed and the fraction of the gross fiscal cost that pertains to 2022–24 has been retained. For Japan and Spain, it has been assumed that some existing measures will be extended further into 2023 or 2024, even though that extension has not been decided or announced by the authorities.

Source: OECD (2023^[2]), *OECD Economic Outlook, Volume 2023 Issue 1: Preliminary version*, <https://www.doi.org/10.1787/ce188438-en>, based on the OECD Energy Support Measures Tracker.

Finally, on top of *ad hoc* measures to mitigate energy costs, the existing tax and benefits systems can also be used to cushion the shock on the most vulnerable workers through in-work benefits and other social transfers.

On the tax side, some governments, for instance, have taken measures to limit the effects of the so-called “fiscal drag” (i.e. when increases in wages result in larger tax burdens) – see Box 1.6 – and reduce the tax wedge as to increase net wages without affecting labour costs for firms. Austria and Germany, for instance, introduced the possibility for firms to pay tax-free inflation-compensation bonuses (i.e. lump-sum payments) up to EUR 3 000. France detaxed profit-sharing bonuses in 2022 and 2023 for workers earning less than three times the minimum wage. Italy increased the threshold for tax-free “fringe benefits”²⁹ to EUR 3 000, up from EUR 600, for all workers.

On the benefit side, several targeted cash benefits that provide a safety net in case of turbulence, including high inflation, were already in place prior to the cost-of-living crisis (OECD, 2022^[35]). Unlike price regulation and subsidies, income support maintains price signals that are needed for easing supply bottlenecks and rebalancing consumption towards greener energy sources. However, except for some forms of in-kind transfers and “social tariffs” for housing or other forms of committed expenditures, such as utilities or public transport, most transfers are not immediately responsive to price shocks (e.g. social benefits do not increase when recipients face higher energy or food prices) as experienced by individual households. It is important therefore to ensure an effective and predictable support and that, despite rapidly changing price levels, transfers keep operating as they were intended to (OECD, 2022^[35]).

Box 1.6. Labour tax policy and inflation

Inflation not only erodes wages in real terms but can also increase the tax burden of workers via the so-called “fiscal drag” – i.e. the phenomenon whereby increases in wages result in larger tax burdens – meaning that workers could be doubly disadvantaged by inflation – see OECD (2022^[35]) and OECD (2023^[36]).

“Nominal” fiscal drag¹ occurs when thresholds and tax brackets fail to fully adjust for inflation, resulting in workers being pushed into higher tax brackets. Inflation also reduces the real value of tax-free allowances, tax credits, and benefits. To the extent that these instruments target low-income workers, nominal fiscal drag can have a disproportionately large impact at the middle-to-lower end of the income distribution. Social security contributions are also affected by nominal fiscal drag, with impacts varying by income level. At the bottom end, fiscal drag will increase public revenues by lowering the real minimum earnings threshold for paying social security contributions. At the upper end, it will reduce revenues by reducing the value of contribution ceilings.

To mitigate “nominal” fiscal drag, countries can adjust personal income tax (PIT) systems, social security contributions (SSCs), and cash benefits in response to inflation. Some countries automatically adjust these parameters, while others use discretionary approaches. In 2022, in just under half of OECD countries, the PIT system is adjusted automatically, while for 21 countries the adjustments are discretionary (see Table 1.1). The majority of countries index SSCs and cash benefits². Twelve countries adjust each of PIT, SSCs and benefits automatically, while ten adopt a discretionary approach to all three categories. The timing and modality of adjustment vary across countries: some use prices (CPI or other indices) while others use wages. Long delays in adjusting parameters and incomplete adjustments can contribute to discretionary measures, including pressures for untargeted solutions, and be particularly challenging for the most disadvantaged individuals (OECD, 2022^[35]).

Table 1.1. Adjustment of labour taxation and benefits in OECD countries, 2022

Number of countries, percentage of countries in brackets

	Personal income tax	Social security contributions	Cash benefits
Automatic indexation	17 (45%)	21 (55%)	19 (50%)
Discretionary adjustment	21 (55%)	14 (37%)	17 (45%)
Not applicable	0	3 (8%)	2 (5%)

Note: In two countries, the automatic adjustment only takes effect if the benchmark indicator increases by a pre-specified rate. Due to rounding, percentages may not sum to 100%.

Source: OECD (2023)^[36], *Taxing Wages 2023: Indexation of Labour Taxation and Benefits in OECD Countries*, <https://www.doi.org/10.1787/8c99fa4d-en>, based on a policy questionnaire circulated by the OECD Center for Tax Policy in July 2022.

1. As opposed to “real” fiscal drag which occurs when wages grow in real terms, resulting in a worker’s tax burden increasing with the progressivity of the tax system.
2. The cash benefits analysed in this box are limited to those transfers that are contained in the OECD Taxing Wages models; the analysis may not cover all social protection benefits that a given country might provide.

The remainder of this section focuses on the role that minimum wages and collective bargaining have played so far in cushioning the costs of inflation partially drawing on a policy questionnaire that was addressed to OECD countries as well as trade unions and employers’ organisations through the Business@OECD (BIAC) and Trade Union Advisory Committee (TUAC) networks – see Box 1.7.

Box 1.7. OECD Questionnaire on recent measures to deal with inflation pressure on wages

The analysis on minimum wages and collective bargaining in this chapter partially draws on the information provided by the responses to an OECD policy questionnaire that was circulated in January and February 2023 to Labour Ministries as well as to employer organisations and trade unions through the Business@OECD and TUAC networks across OECD countries. The information collected via the policy questionnaires has been complemented and cross-checked with other data sources at national and international level.

The questionnaire focused on i) the minimum wage uprating procedures (e.g. the frequency of updating, the use of indexation, etc.); ii) the special measures taken to speed up the increase of minimum wages since January 2022; iii) the renegotiation of collective agreements (e.g. frequency, indexation, ultra-activity, etc.); iv) the measures taken by governments to promote the renegotiation of collective agreements and protect wages from the increase in prices.

36 out of the 38 OECD countries have filled in the questionnaire as well as 18 employers’ organisations and 18 trade unions. If the rules change across geographical areas (states, provinces, prefectures, cantons, etc.), the information was reported using the largest area as a reference. Moreover, in the case of collective bargaining, if there are differences across sectors, the answers focused on what is applicable in the agreement that prevails for the manufacturing sector.

1.3.1. Minimum wages have kept pace with inflation

Currently, 30 out of 38 OECD countries have a national statutory minimum wage in place³⁰ and minimum wages also exist in most non-OECD emerging economies. Statutory wage floors are the most direct policy lever governments have for influencing wage levels at the bottom of the distribution. Historically, minimum wages have been justified as a measure for: i) ensuring fair pay, ii) counterbalancing the negative effects of firms' labour market power; iii) making work pay; iv) boosting tax revenue and/or tax compliance by limiting the scope of wage under-reporting.³¹

With the sharp rise in prices in most OECD countries hitting particularly the most vulnerable, low-income households, minimum wages have become an even more important tool to protect the standard of living of low-paid workers.³²

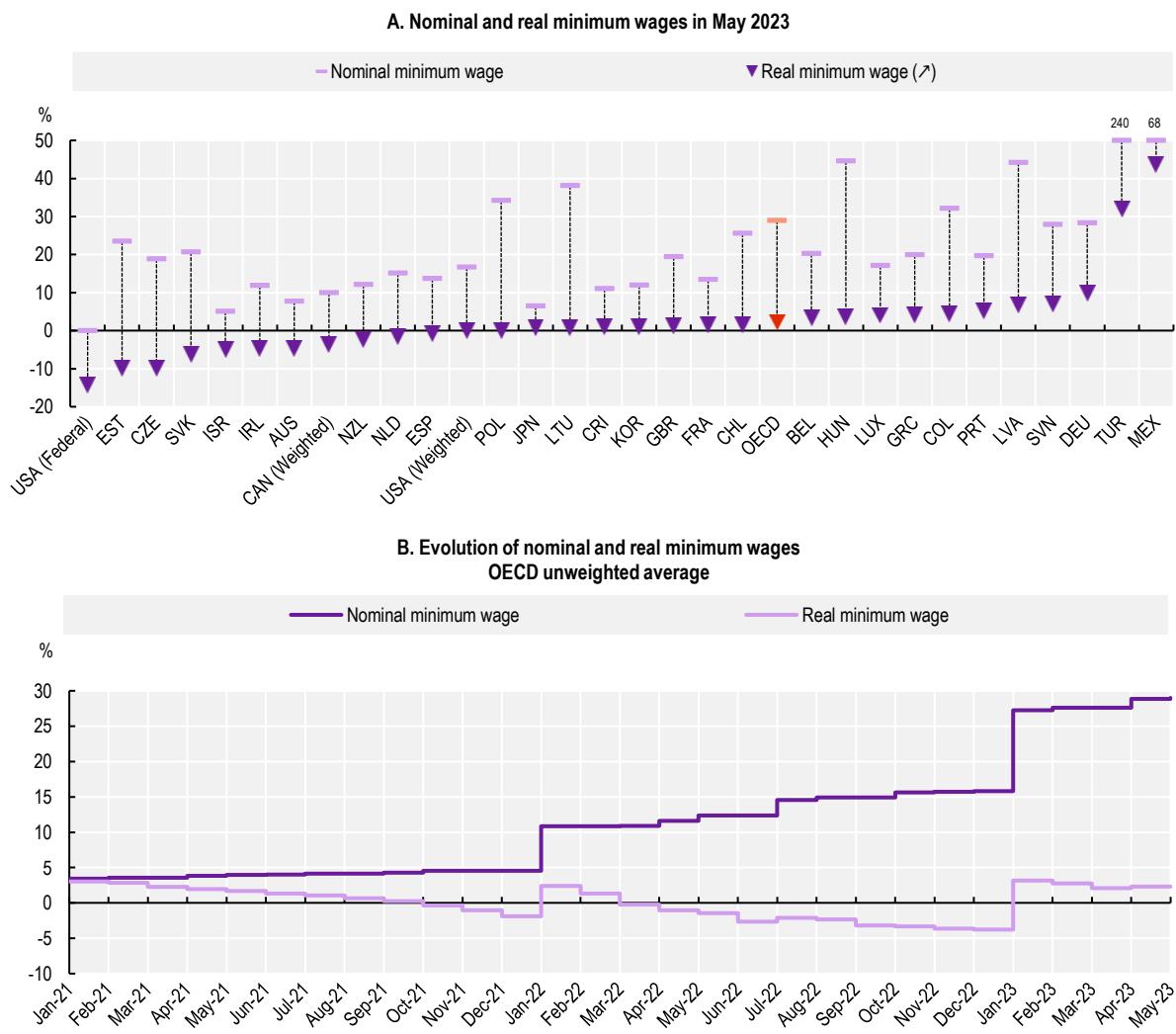
Almost all OECD countries have taken measures to increase their minimum wages between January 2021 and May 2023, including special measures to speed up minimum wage adjustments in the current cost-of-living crisis (see below). If minimum wages are keeping pace so far with inflation in many OECD countries, real wage gains may actually quickly vanish over time as inflation remains high as it happened in 2022 – see Figure 1.25 and trends for all OECD countries with a statutory minimum wage in Annex 1.C.

Some of the differences across OECD countries in the timing, frequency, and size of the nominal increases are linked to different uprating procedures (see Table 1.2). In most OECD countries, the minimum wage is adjusted annually with a usually short delay between the decision and the application. In other countries, the minimum wage is adjusted annually or biannually but with a slightly longer delay which may make a difference in times of high and/or rising inflation. Finally, in some countries, there is no regular adjustment, which may result in long delays and major losses in purchase power. In the United States, for instance, the federal minimum wage has not been increased since 2009 (while minimum wages at state and local level have been updated much more regularly).

The revision of minimum wages may be subject to government discretion or can take place automatically in case of indexation. In some OECD countries – notably, Belgium, Canada (since April 2022), Costa Rica, France, Israel, Luxembourg, the Netherlands and Poland – there is a form of automatic indexation mechanism for the minimum wage at national level (Table 1.3). But automatic indexation also exists for minimum wages at subnational level (e.g. in Canada, Switzerland and the United States). Indexation may then be anchored to wages or prices. Minimum wages are for instance indexed to negotiated wages (i.e. wages defined in collective agreements) in the Netherlands, and to average wages in Israel. Indexation to (past) prices is in places, instead, in Belgium, Canada, France³³ and Luxembourg³⁴ as well as nine provinces and territories in Canada, four cantons in Switzerland and 19 states and the District of Columbia in the United States.³⁵ Furthermore, multiple increases can also take place in years of high inflation, as in Belgium, France and Luxembourg.³⁶ Poland links its minimum wage to future price developments and corrects it *ex post* in case of differences between the forecasts and the realised rates. Finally, a few countries have a form of indexation that kicks in only if social partners fail to find an agreement (Colombia and the Slovak Republic).

Figure 1.25. Minimum wages are keeping pace with inflation, but real gains may vanish over time if inflation remains high

Cumulative percentage change since December 2020



Note: Statistics refer to the cumulative percentage change in March 2023 relative to December 2020 for New Zealand. At date, statistics in Panel A, do not include planned increases in the minimum wage for Australia, the Netherlands, Poland and Türkiye in July 2023 (+8.7%, +3.1%, +3.2% and +34%, respectively). OECD is the unweighted average of all countries shown except the United States (weighted). Canada (weighted) is a Laspeyres index based on minimum wage of provinces and territories (excluding the Federal Jurisdiction) weighted by the share of employees of provinces and territories in 2019. United States (weighted) is a Laspeyres index based on minimum wage of states (not including territories like Puerto Rico or Guam) weighted by the share of nonfarm private employees by state in 2019. For further details on minimum wage series used in this Chart and evolution by country, see Annex Table 1.C.2 and Annex Figure 1.C.1.

Source: OECD Employment database, <https://www.oecd.org/employment/emp/onlineoecdemploymentdatabase.htm>, OECD (2023), "Prices: Consumer prices", Main Economic Indicators (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 4 July 2023), and Monthly CPI Indicator (Australian Bureau of Statistics).

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Table 1.2. Uprating procedures of the minimum wage (timing and frequency of adjustments)

	Delay between the decision and application lower or equal to two months	Delay between the decision and application higher than two months
Regular adjustment on a fixed date	Australia Canada (Federal) Colombia Costa Rica France Hungary Japan Luxembourg Mexico Poland Portugal Slovenia Switzerland (5 Cantons) Türkiye	Estonia Germany Ireland Korea Lithuania Netherlands New Zealand Slovak Republic Spain United Kingdom
No regular adjustment	Belgium Chile Czech Republic Greece United States (Federal)	Latvia

Note: Switzerland (5 Cantons) refers to the five cantons with a statutory minimum wage: Canton of Basel-Stadt, Canton of Geneva, Canton of Jura, Canton of Neuchâtel, and Canton of Ticino.

Source: OECD Questionnaire on recent measures to deal with inflation pressure on wages (February 2023).

Table 1.3. Automatic minimum wage indexation in OECD countries, 2022

Country	Indexation mechanism
Belgium	The minimum wage is indexed to the so-called “health index”, i.e. past CPI excluding alcohol and tobacco and petrol but including heating fuel, gas, and electricity (every time the index increases by 2% or more since last increase)
Canada	The minimum wage at the federal level is indexed to the Consumer Price Index for the previous calendar year. Also, nine provinces and territories have a form of indexation.
Costa Rica	The minimum wage is indexed on the living cost; and the Gross Domestic Product (GDP) growth.
France	The minimum wage is indexed to past CPI for the bottom quintile and revised annually or as soon as the CPI increases by 2% or more since last minimum wage increase). Annual revisions also incorporate half real salary increase of blue-collar workers (only if positive).
Israel	The minimum wage is anchored to 47.5% of the average wage.
Luxembourg	All wages are indexed to past CPI (every time CPI increases by 2.5% or more since the last semester)
Netherlands	The minimum wage is indexed to the predicted wage developments for the next six months using a basket of collectively agreed wages.
Poland	The minimum wage is indexed to future inflation + 2/3 of future GDP growth if, in the first quarter of the year, the amount of the minimum wage is lower than half of the average wage. If the inflation forecasts differ from the realised evolution of the price index, a correction takes place in the following year.
Switzerland	In the canton of Neuchâtel, the cantonal minimum wage is automatically adjusted each year to the consumer price index. In the canton of Basel-Stadt, the minimum wage is adjusted (only upwards) according to a mixed index (average of nominal wage and consumer price index). In the canton of Geneva, the minimum wage is indexed to the consumer price index (only upwards). In the canton of Ticino, the government adjusts the lower and upper limits of the cantonal minimum wage annually according to the development of the national price index.
United States	The federal minimum wage is not indexed. Currently, 13 states and the District of Columbia index state minimum wages to a measure of inflation. In addition, another 6 states are scheduled in a future year to index state minimum wage rates to a measure of inflation.

Note: In Belgium, it is important to note that all wages are indexed but rules may vary across sectors depending on the collective agreement. Moreover, wage increases in general are capped by a “wage norm” (a ceiling which takes into account weighted wage developments in France, Germany and the Netherlands). In addition, in Colombia, the minimum wage is indexed to prices if social partners fail to find an agreement. In the Slovak Republic, the minimum wage is set at 57% of the average wage of two years before if social partners fail to find an agreement.

Source: OECD Questionnaire on recent measures to deal with inflation pressure on wages (February 2023).

In other countries, discretionary measures have been taken over the last months to speed up the increase of minimum wages. In Chile, for instance, the minimum wage was increased three times in 2022 reflecting the increases in inflation. In Greece, after postponing the increase during the early phase of the COVID-19 pandemic, the government increased the minimum wage in January 2022 and then again in May 2022. In Türkiye, the minimum wage was increased by around 40% in January 2022 and nearly 30% in June 2022. In October 2022, Germany increased its minimum wage by 15%, from EUR 10.45 to EUR 12 per hour.³⁷ Similarly, in the Netherlands, in October 2022, the government decided, for the first time since the introduction of the minimum wage in 1969, to go beyond the formula displayed above and exceptionally increase the minimum wage by 10% in January 2023. Ireland also announced in 2022 its intention to raise the minimum wage to 60% of the median by 2026, which would correspond to an increase of 16% compared to the current level. In Hungary, the social partners agreed to further increase the minimum wage mid-year if inflation rises to 18% and GDP growth is positive (Eurofound, 2023^[37]).

These minimum wage increases, especially when linked to a formula that automatically indexed them to past inflation, are raising two main concerns: a squeezing of the wage distribution and the risk of a price-wage spiral, especially in case of high inflation and uncertainty. In fact, increases in minimum wages often have spillover effects higher in the wage distribution and can, therefore, have an aggregate effect on wage growth that goes well beyond the direct beneficiaries. This happens because minimum wages are used, formally or informally, as a benchmark in the negotiation of collective and individual wages as well as a reference for certain social minima.

Figure 1.26 estimates the impact of minimum wage increase to the growth in aggregate wages, accounting for both its direct effect (on those at or below the minimum wage) and its spillover effect (on those above the minimum wage). The impact of a 1% increase in the minimum wage is simulated using estimates of spillover effects from the literature and taking the share of the minimum wage earners in a baseline year (2018 for France and Germany, an average of 2019, 2021 and 2022 for the United Kingdom and 2022 for the United States) – see Box 1.8 for more details. This exercise suggests that a minimum wage increase of 1% can be expected to have an effect on aggregate wage growth between 0.03% (in the United States, using the share of minimum wage earners of state-level minimum wages) and 0.2% (in France). These estimates are in line with those of Koester and Wittekopf (2022^[38]) who conducted a similar analysis with another data source and only including the direct effects.

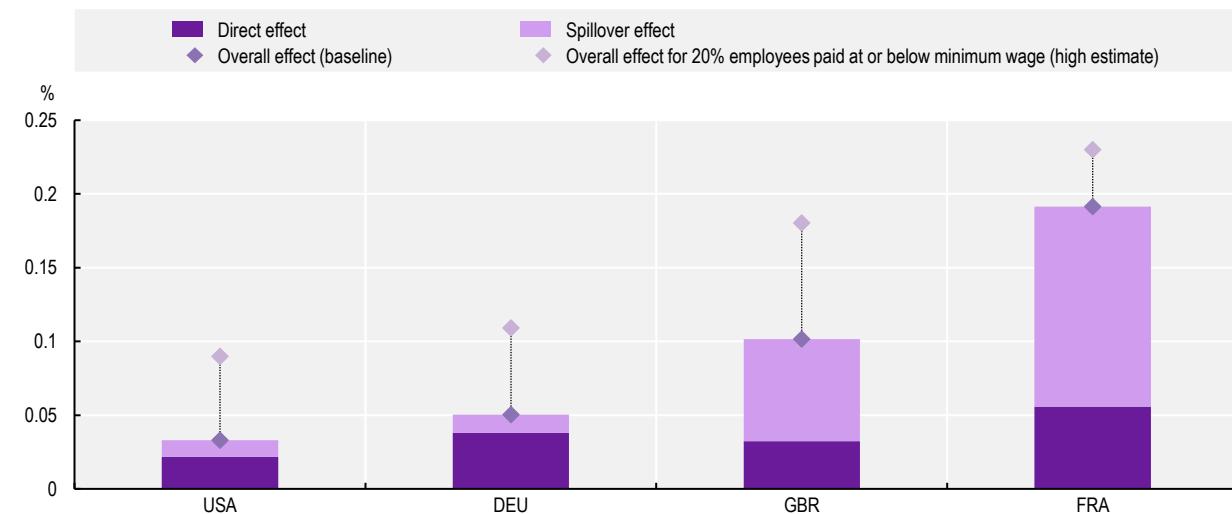
These cross-country variations can be explained by the difference in the share of minimum wage earners, the magnitude of the spillover effects and the shape of the wage distribution. In France, where a relatively high proportion of workers earns the minimum wage (the share of minimum wage earners even increased since 2018 to 14% in 2022), a double automatic indexation of the minimum wage is in place and the wage distribution is relatively compressed, most of the aggregate wage effects come from wage increases higher up in the wage distribution (i.e. spillovers). On the opposite, in a country like the United States where the share of minimum wage earners is low (around 6% in 2022), spillovers are quite limited and the wage distribution is less compressed, most of the aggregate wage effects come from the increase in minimum wage earners (i.e. direct effects). Between these two polar cases, there are Germany where the share of minimum wage earners is relatively high (8.4% at the baseline in 2018) but the wage distribution is less compressed and the United Kingdom where the share of minimum wage earners (5.9% at the baseline) is similar to the United States but the wage distribution is more compressed.

These effects could be, nonetheless, somewhat underestimated. First, spillover effects could be stronger in a high inflation environment when minimum wage increases are larger and more frequent. Second, these estimates do not account for possible feedback loop on the minimum wage, notably in a country like France where the minimum wage is also indexed to half of the past increase of the real wage of blue-collar workers.³⁸ However, the overall impact is likely to remain relatively limited in magnitude: even assuming a higher share of minimum wage earners (20%), Figure 1.26 shows that the aggregate wage effects range between 0.09% (in the United States) and 0.23% (in France) suggesting a rather limited risk of major impact on wage inflation of minimum wage increases.

On top of the effect of a minimum wage increase on aggregate wages, a second issue is how firms which employ minimum wage workers respond to increases in the minimum wage, and, in particular, if and how much these firms are able to pass higher wages onto prices. Most empirical studies agree that part of minimum wage increases is passed on to consumers – see e.g. Harasztsosi and Lindner (2019^[39]). However, Lindner (2022^[40]) calculates that in the United Kingdom, an increase in the minimum wage of 20% would still only lead to an increase in inflation of 0.2% – which compared to the inflation rates observed in the last quarters is small.

Figure 1.26. Impact of a 1% increase in the minimum wage on aggregate wages

Percentage change in aggregate wages



Note: The estimated impact of a minimum wage increase on aggregate wages is based on the share of employees paid at or below the minimum wage in 2018 for France and Germany (11% and 8.4% of employees, respectively), in 2019 and 2021-22 for the United Kingdom (5.9% of employees) and in 2022 for the United States (6% of employees). The high estimate corresponds to the estimated impact of raising the proportion of employees paid at or below the minimum wage to 20%.

The direct effect refers to the impact of a 1% increase in the minimum wage of employees paid at or below the minimum wage on the aggregate wage growth. The spillover effect estimates the impact of this increase for employees paid above the minimum wage on total wage bill through the estimated spillover coefficients based on empirical evidence for various academic studies – see Box 1.8. Note that these estimates do not account for possible feedback loop on the minimum wage, notably in a country like France where the minimum wage is also indexed to half of the past increase of the real wage of blue-collar workers.

Reading: In France, assuming the share of employees paid at or below the minimum wage at its 2018 level (11%), a 1% increase in the minimum wage would lead to a 0.06% increase in the total wage bill (direct effect). This increase in the minimum wage would also have a spillover effect on all earnings above the minimum wage, but in a lesser proportion (+0.2% for employees paid 1.2 times the minimum wage and +0.1% from 1.5 times the minimum wage onwards) through the adaptation of conventional wage scales, resulting in an increase of 0.14% of the total wage bill (spillover effect). In total, this increase would increase the total wage bill by 0.19%.

Source: OECD estimations based on the European Union Structure of Earnings Survey (EU-SES) scientific-use files (SUFs) for France and Germany, the UK Labour Force Survey for the United Kingdom and the Current Population Survey (CPS) for the United States.

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Box 1.8. Estimating the aggregate effects of minimum wage increases

In order to estimate the impact of an increase in the minimum wage on the total wage bill (henceforth, the “aggregate effect of minimum wage increases”), both the *direct* effect of a minimum wage increase, i.e. the wage increase for minimum wage earners, and the *spillover* effects, i.e. the wage increase for those employees earning more than the minimum wage as firms may have to readapt pay scales to maintain wage differentials, is calculated.

The direct effect is estimated by a 1% increase in hourly wages at, below or slightly above the minimum wage (threshold set at 105% of the minimum wage). For the employees at or below the threshold, the average hourly wage and the average number of hours worked are calculated using EU-SES (2018) for France and Germany, the UK-LFS (2019 and 2021-22) for the United Kingdom and the CPS (2022) for the United States. Using the information on hourly wages and hours, the total wage bill of the employees affected by an increase in the minimum wage is computed.

For the spillover effects, the same calculation is made for four wage bands expressed as a fraction of the minimum wage MW ($1.05 < MW \leq 1.2$; $1.2 < MW \leq 1.5$; $1.5 < MW \leq 2$; $MW > 2$) using spillover estimates from the literature (pre-dating the surge in inflation):

- In France, building on the work by Gautier, Roux and Suarez Castillo (2022^[41]) and Aeberhardt, Givord and Marbot (2012^[42]), an increase in the minimum wage of 1% is assumed to lead to an increase of 0.2% in wages up to 1.2 times the minimum wage level; 0.1% between 1.2 and 1.5 times the minimum wage; 0.1% between 1.5 and 2 times the minimum wage, and 0 above.
- In Germany, building on the work by Biewen, Fitzenberger and Rümmel (2022^[43]), an increase in the minimum wage of 1% is assumed to lead to an increase of 0.02% in wages up to 1.2 times the minimum wage level, and 0 above.
- In the United Kingdom, building on the work by Giupponi et al. (2022^[44]), an increase in the minimum wage of 1% is assumed to lead to an increase of 0.02% in wages up to 1.2 times the minimum wage level, and 0 above.
- In the United States, building on the work by Gopalan et al. (2021^[45]), an increase in the minimum wage of 1% is assumed to lead to an increase of 0.03% in wages up to 1.2 times the minimum wage level; 0.03% between 1.2 and 1.5 the minimum wage, and 0 above.

Beyond the risk of a price-wage spiral, which is likely to be limited as just illustrated before, there are other aspects to consider in assessing the merits and pitfalls of regular and sustained minimum wage increases in times of high inflation, especially when linked to an automatic indexation to past price developments. On the one hand, these increases contribute to safeguard the purchasing power of minimum wage earners and may help to reduce in-work inequality (or at least limit its increase, in cases where high-wage workers are able to negotiate wage increases that keep pace with inflation while low-wage workers are not). Automatic indexation, more specifically, may also increase visibility and transparency for firms, which can more easily anticipate future increases,³⁹ as opposed to discretionary increases. On the other hand, automatic indexation mechanisms may reduce the margins of judgement that governments, social partners or commissions have in deciding future increases (e.g. in a period of stagflation, decision-makers may have to weigh the risk of loss of purchasing power against the risk of job losses), limit the role of social partners in setting wages, and may also lead to an excessive compression of the wage distribution if the rest of the wage structure does not move, with consequences on individual careers, as well as on the design of redistribution policies.

While keeping these potential pitfalls in mind, in a context of high inflation, it remains important to ensure regular adjustments of statutory minimum wages to maintain their usefulness as a policy instrument and protect, at least partially, the most vulnerable workers from rising prices.

1.3.2. Negotiated wages: falling in real terms even in countries with high collective bargaining coverage

Collective bargaining: A tool to ensure fair and tailored responses to inflation cost

Statutory minimum wages only determine the wage floor. Above that floor, collective bargaining can play an important role in ensuring a fair share of the cost of inflation for a large share of the employees, in particular at the bottom and the middle of the wage distribution. Collective agreements can help companies and workers find tailored and ad hoc solutions to avoid a price-wage spiral, for instance by limiting (permanent) wage increases in exchange for lump-sums and/or non-wage benefits. Blanchard and Pisani-Ferry (2022^[46]), for instance, argue that a forum in which trade unions, employers' organisations and the government agree on how to share the burden of inflation would likely allow a fairer outcome and lower risk of second-round inflation (e.g. a pass-through of inflationary shocks on wages and prices, thereby triggering a price-wage spiral), making the job of monetary policy easier. Tripartite agreements, including on wages, were relatively common in the heydays of collective bargaining, but they are now very rare. However, the 2022 tripartite agreement on wages and competitiveness in Portugal shows how tripartite social dialogue can be revived to help ensuring a fair share of the costs of high inflation (see Box 1.9).

Box 1.9. The 2022 tripartite agreement in Portugal

In October 2022, the government, four employer associations and the trade union UGT in Portugal signed a tripartite agreement on wages and competitiveness. The General Confederation of Portuguese Workers (CGTP-IN) did not sign the agreement, taking the view that wages should be subject of collective agreements alone.

The key goals of the pact are to increase the labour share (i.e. the part of national income allocated to wages and other labour-related compensation) by 3 percentage points compared to the pre-crisis value, to converge with the European average and to raise productivity growth to 2% by 2026.

To achieve these objectives the minimum wage will increase from EUR 760 in 2023 to EUR 900 in 2026. In parallel, several measures will be taken to boost workers' income via the tax and benefit system. In particular, the personal income tax (IRS) brackets will be revised to avoid that pay rises to compensate for inflation lead to higher taxes – a phenomenon known as fiscal drag. In addition, the incentives to return to the labour market will be strengthened by allowing the partial accumulation of unemployment benefits with the wage. Moreover, overtime pay will be increased, and the severance pay in case of dismissal for economic reason (individual or collective) will increase to 14 days per year of tenure from 12 now.

Companies will be accompanied in this process: specific fiscal incentives are foreseen for those companies which have "dynamic" collective bargaining (i.e. they have a collective agreement less than three years old), which increase wages in line with or above the values set in the agreement and narrow the gap between the 10% best-paid workers and the 10% least-paid workers. Incentives are foreseen also for companies which increase R&D expenditure and on-the-job training and those who invest in the green transition.

The agreement also dedicates a section to youth employment, with provisions that span from a reduction in taxes to incentives to return from abroad. A new hiring incentive scheme for young workers to support open-ended contracts with wages above EUR 1 330 (and an additional "autonomisation" top-up) is included.

Finally, the last section of the tripartite agreement focuses on a simplification of the tax system and the licensing process.

The implementation of the agreement will be subject to a regular assessment by a dedicated working group which will be tasked notably to monitor the implementation of the measures, the progress towards the targets and the development in collective bargaining.

However, over the past decades, collective bargaining has been weakening (OECD, 2019^[47]). On average, 15.8% of employees were members of a trade union in 2019, down from 33% in 1975. While this decline characterises a majority of countries, union density has been relatively stable since the mid-1970s in Canada, Korea and Norway, and has increased in Iceland and Belgium.

Declining union density has been accompanied by a reduction in the share of workers covered by a collective agreement, which has shrunk to 32.1% in 2020 from 46% in 1985 on average in OECD countries. This decline was strongest in Central and Eastern European countries, with steep decreases also observed in Australia, New Zealand (where, however, a recent reform has reintroduced a form of sectoral bargaining, see Box 1.10), the United Kingdom, and, more recently, Greece. Coverage has been relatively stable in most other European countries, except for Germany where it has decreased significantly since the reunification in 1990.

However, Figure 1.27 shows that wages negotiated in collective agreements between firms and workers have declined in real terms over the last quarters even in countries such as Austria, Finland, Italy, the Netherlands and Sweden where the large majority of employees is covered by a collective agreement.

Box 1.10. The new Fair Pay Agreements in New Zealand

New Zealand is the first OECD country to reintroduce a form of sectoral bargaining after eliminating it in 1990. In 2022, it passed the Fair Pay Agreements Act which allows unions and employers to bargain for minimum terms and conditions for all employees in that industry or occupation.

The process to negotiate a Fair Pay Agreement must start from a request of a union which has to demonstrate support from 1 000 workers, or 10% of workers, under potential coverage of an agreement. Workers can also request a Fair Pay Agreement by invoking the public interest, showing that employees in the sector are low paid and have little bargaining power at work or have a lack of pay progression at work or are not paid well enough when factors like working long hours, night shift, weekends or employment uncertainty (like short-term or seasonal work) are considered.

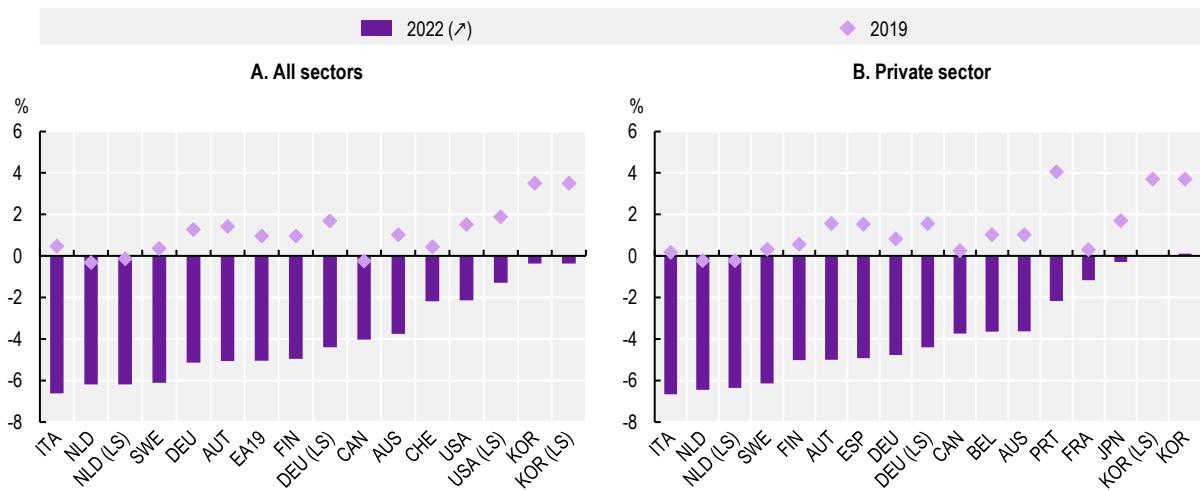
If the Ministry of Business, Innovation and Employment (MBIE) approves a union's application to initiate bargaining for a proposed Fair Pay Agreement, an eligible employer association can apply to become an employer bargaining party. In case no employers' representative has stepped forward after three months, the national employers' association, BusinessNZ, has one further month to decide whether it will bargain on the employer side. If it does not choose to be an employer bargaining party, the MBIE will let the workers bargaining side know and the workers' side has three months to apply for the Employment Relations Authority to set the terms of the Fair Pay Agreement. If this happens, the Employment Relations Authority will set terms without any bargaining.

The agreements must include specific topics, such as wages and overtime, while others such as safety and flexible working must be discussed but not necessarily included. Other employment terms can be included if the bargaining sides agree. The Fair Pay Agreements, as in all countries with a two-tier bargaining system, set a floor and bargaining at the firm/establishment level can set higher standards.

Once the bargaining sides agree, covered employees and employers can vote on whether they support the employment terms proposed and, if there is a majority (from both bargaining sides), the Fair Pay Agreement will be finalised and set as law, and noncompliance is a criminal act.

Figure 1.27. Negotiated wages in OECD countries have declined in real terms

Year-on-year percentage change in negotiated wages (i.e. resulting from collective agreements)



Note: LS: wages including lump sums and/or special payments.

International comparability of data on negotiated wages is affected by differences in definitions and measurement. For further details, see Annex Table 1.C.3. and Annex Table 1.C.4. Statistics are representative of all employees covered by a collective wage agreement for Austria, Belgium, the Euro Area (19), Finland, France, Germany, Italy, the Netherlands, and Sweden. In Canada, statistics refer to collective bargaining settlements of all bargaining units covering 500 or more employees (units of 100 or more employees for the Federal Jurisdiction). In Japan, figures refer to wage increase in major enterprises defined as those with a capital of 1 billion yen or more, 1 000 or more employees, and with a trade union, and, to workplaces with 100 or more full-time workers in Korea. In Switzerland, statistics refer to collective agreements containing wage provisions and with at least 1 500 employees subject to the collective bargaining agreement. For Australia, Canada, Korea, Portugal, Spain, Switzerland and the United States, statistics refer only to employees affected by an increase of the negotiated wage at date. Wage increases in Austria, Belgium, the Euro Area (19), Finland, Germany, Italy, the Netherlands and Sweden refers to the average increase in negotiated wages weighted by the employment composition for a reference year (Laspeyres index). The reference year of the employment composition used is 2005 for Finland, 2009 for Sweden, 2010 for Belgium and the Netherlands, January 2015 for the Euro Area, 2015 for Germany and Italy, and 2016 for Austria. For Australia, Canada, France, Japan, Korea, Portugal, Spain, Switzerland and the United States, wage increases refer to the average increase in negotiated wages weighted by the number of employees affected of the period considered. Statistics for 2022 are provisional for Spain. Negotiated wage increases in Spain in 2022 refer only to the agreed wages not accounting for (retroactive) revisions from "wage guarantee clauses" expressed in the text of the agreements. Private sector in Germany refers to all industries excluding agriculture, public administration, education, health, and other personal services (Sections B to N of the NACE rev. 2).

Source: OECD calculations based on national data on negotiated wages and OECD (2023), "Prices: Consumer prices", Main Economic Indicators (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 22 May 2023).

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Negotiated wages are reacting with longer delay

Several factors may explain why negotiated wages have not kept up with inflation, even in countries where large shares of workers remain covered by collective bargaining.

First, the staggered and rather infrequent nature of wage bargaining means that negotiated wages do not adjust immediately and fully to unexpected price inflation. Across OECD countries, collective agreements are renewed on average every 12-24 months, in some cases more. Therefore, several collective agreements still reflect a pre-high inflation scenario.

Table 1.4. Frequency of renegotiation of collective agreements

Agreements usually renegotiated every year	Agreements usually renegotiated every two years	Agreements usually renegotiated every three years or more
Austria	Belgium	Australia
Czech Republic	Colombia	Canada (Ontario)
Estonia	Costa Rica	Chile
France	Finland	Denmark
Hungary	Germany	Greece
Ireland	Israel	Iceland
Japan	Korea	Italy
Latvia	New Zealand	Luxembourg
Lithuania	Norway (whole agreements)	Sweden
Mexico	Switzerland	
Netherlands		
Norway (wage agreements)		
Portugal		
Slovak Republic		
Slovenia		
Türkiye		

Source: OECD Questionnaire on recent measures to deal with inflation pressure on wages (February 2023).

In a few countries (e.g. Portugal, the Slovak Republic, Slovenia and Spain), the negotiations in certain sectors have been advanced in light of the sudden increase in prices. In others, in the face of very high economic uncertainty, social partners have opted to postpone the conclusion of the agreement to a later stage and reach a “bridge agreement” instead or to combine permanent wage increases with one-off payments. In some cases, one-off payments have been incentivised by the government. The first and most prominent of such “bridge agreements” is the one in the German chemical industry between the trade union IGBCE and the employer federation *Bundesarbeitgeberverband Chemie* (BAVC) which, in April 2022, agreed on a one-time payment of EUR 1 400 (USD 1 393) postponing talks on a formal wage increase until the autumn (Global Deal, 2022^[48]).⁴⁰ In 2022, the model of “bridge agreements” has been followed by several other companies in Europe, without necessarily involving the unions. These one-off payments have provided a first answer to the fall in real wages. Moreover, if high inflation eases over the coming years, they help to mitigate the risk of feedback loop of increasing wages on inflation. However, they do not constitute a structural solution since the loss of purchasing power due to the marked increase in inflation rates will be permanent unless future inflation rates become negative.

Second, while high bargaining coverage is often considered as a key indicator of social partners’ strength, it may not necessarily fully reflect workers’ bargaining power. In some countries, high coverage is reached through administrative extensions while unions do not systematically have the power to negotiate strong wage increases in all sectors. Moreover, in some countries, like Germany or Italy, the (*de facto* or *de jure*) possibility for companies to circumvent the sectoral agreement is a threat that weighs on the final outcomes. Finally, in some cases, workers are covered by collective agreements that have expired (the so called “ultra-activity”). While most provisions remain binding in such cases, wages are eroded in real terms.⁴¹

Third, while in a minority of countries and sectors, pay scales in collective agreements are indexed to inflation,⁴² for most employees the inflation measure retained for wage adjustment is generally forward-looking (i.e. based on forecasts), and excludes energy without any in-built catch-up phase (i.e. the catch-up must be negotiated and agreed with the employers) – see Table 1.5. In particular:

- In Luxembourg, all wages are indexed (see previous section).

- In Belgium, 98% of private-sector workers have their wages automatically indexed to inflation. The social partners freely determine on a sector-by-sector basis the regularity (quarterly, annually, etc.) and method of indexation (but still using the “health index” as a reference).
- In Italy, collective agreements are indexed to the forecast harmonised consumer price index (HICP) net of the contribution of imported energy goods.⁴³ Before the COVID-19 crisis, the forecasts were almost systematically above the realised value. In principle, this should have led to an ex-post reduction in negotiated wages, but it rarely occurred. However, wage increases were limited by the prolonged delays in the renewal of collective agreements. In the coming months, in the sectors with ex-post renegotiation clauses, which cover about 30% of the total wage bill (among the main ones, banking, wood industry and the metal sector), workers will see more significant wage increases in 2023 to compensate for the 4 percentage point difference between the forecast and realised HICP excluding energy (Banca d’Italia, 2022^[49]).
- In Spain, collective agreements can include indexation clauses. According to the Bank of Spain (Banco de España, 2022^[50]), 45% of workers covered by a collective agreement had their negotiated wages indexed to inflation in 2023, up from 16.6% on average in 2014-21, but still lower than at the beginning of the 2000s, when 70% of workers with a collective agreement had such clause. There is no general rule, but according to the preliminary analysis of the Bank of Spain, collective agreements are indexed to the headline inflation index, therefore including energy.⁴⁴ Most workers are covered by annual indexation clauses, but in some cases, there are multi-year indexation clauses. In that case, wage adjustments would be determined based on inflation dynamics over the full term of the collective agreement (which would help to smooth the impact of a temporary spike in inflation). Seventy-five percent of the clauses currently in force includes some caps or thresholds, i.e. the increase in inflation is not fully passed on to wages.
- In other countries, such as Denmark, Germany or Sweden negotiated wages are generally not indexed to inflation, but collective agreements are regularly renegotiated and inflation dynamics are (at least, partially) accounted for even without a formal indexation mechanism.

Table 1.5. Automatic wage indexation in collective agreements, 2022

Country	Are pay scales indexed (on inflation or other indicator)?	Formula	Is there any automatic correction?
Belgium	Yes, in all sectors.	The exact formula varies across sectors depending on the collective agreement but in general it refers to past CPI.	No
Germany	Yes, but only in few sectors	The agreement is renegotiated if inflation exceeds a specific rate.	No
Italy	Yes, in all sectors	Forecast HICP index without imported energy goods.	Yes, both upwards and (but rarely or never applied) downwards <i>ex post</i> correction
Luxembourg	Yes, in all sectors	Same as for the minimum wage. See Table 1.3	No
Netherlands	Yes, but only about 5% of the agreements	Past CPI in period t-1	n.a.
Spain	Yes, but only in some sectors	No general rule, but usually CPI in past	Yes, wage increases can be corrected during the validity of the agreement but only upwards (if realised inflation is higher than the indicator of reference) with a maximum ceiling imposed.
Switzerland	Yes, but only in few sectors	It varies depending on the agreement	Yes, in some sectors wage increases can be revised upwards (if realised inflation is higher than the indicator of reference) during the validity of the agreement

Note: n.a.: not available.

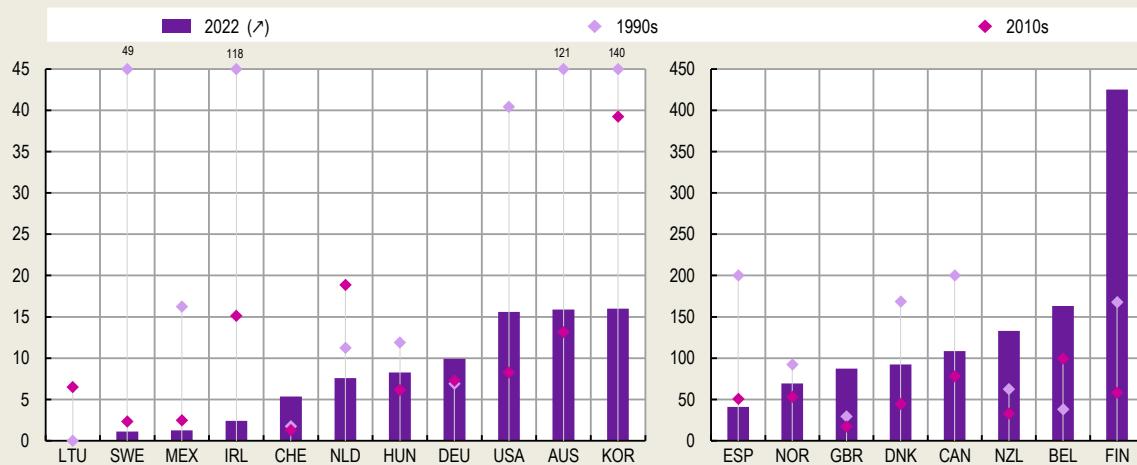
Source: OECD Questionnaire on recent measures to deal with inflation pressure on wages (February 2023).

Box 1.11. Despite the major fall in real wages, industrial disputes have increased only in few OECD countries

In the OECD countries for which timely data are available, Figure 1.28 shows that, in 2022, despite the significant losses in purchasing power, there has not been a general increase in industrial disputes (strikes and lockouts) compared to the historically low levels observed in the decade before COVID-19. While data on strikes are not entirely comparable and should be interpreted with caution,¹ they show that industrial disputes have increased significantly in Finland (an 8-fold increase compared to the average in 2010-19), in the United Kingdom (a quadruple increase compared to the average in 2010-19), in Denmark (work days lost doubled in 2022 compared to the average in 2010-19), in Belgium (one-third increase) and less so but still significantly in Australia (however, latest data shows industrial disputes in Australia have returned to near historic lows), Canada, Germany, Switzerland and the United States. On the opposite, in Ireland, Mexico and Spain the number of industrial disputes in 2022 has been lower than in the period 2010-19. More generally, apart from Belgium, Finland and the United Kingdom, industrial disputes in 2022 were far below the levels recorded in the 1990s. The large transfer put in place by governments as well as some restraint from trade union and concerns over job security may have contributed to limit strife and wage increases in the recent negotiations (European Commission, 2022[32]).

Figure 1.28. Recent trends in industrial disputes

Annual averages of work days lost per 1 000 salaried employees



Note: International comparability of data on strikes is affected by differences in definitions and measurement. Belgium: Strikes in the public sector are excluded until 2002. Since 2003 strikes in the public sector are included except for strikes in the local and county administration and similar institutions and for sailors in the merchant marine and shipping industry. Since 2013 strikes in the local and county administration and similar institutions are also included. Mexico: The statistics concern strikes at establishments and enterprises covered by federal jurisdiction. As a result, strikes at enterprises under local jurisdiction are not included. The latest year available refers to June-Dec 2022 for the United Kingdom. 1990s and 2010s refer to the unweighted averages of workdays lost per 1 000 employees in 1990-99 and 2010-19, respectively.

Source: ILOSTAT and national statistical offices for working days not worked and OECD (2023), "Labour Force Statistics: Employment by activities and status", OECD Employment and Labour Market Statistics (database), <https://doi.org/10.1787/data-00289-en> (accessed on 15 June 2023), and national statistical offices for total number of employees.

StatLink <https://stat.link/zjab9d>

1. Data on industrial disputes should be interpreted with caution because differences in definitions and measurement severely limit the comparability of the data across countries (see for more information: <https://www.oecd.org/els/emp/Industrial-disputes.pdf>). Moreover, the number of strikes also reflects regulations at the national level and may thus not reflect the actual level of strife. For instance, in some countries, typically in the Nordic countries, it is not possible to strike in the presence of a valid agreement and, therefore, strikes and lockouts are possible only at the time moment of renegotiating the agreements.

Finally, and more generally, higher bargaining coverage is not necessarily associated with stronger aggregate wage growth, especially in times of crisis. As discussed in previous OECD work on collective bargaining (OECD, 2019^[47]), collective bargaining can also serve as an instrument for wage adjustment and, hence, stabilisation over the business cycle. In countries where wage co-ordination is still strong (notably the Nordic countries as well as Austria, Belgium, Germany and the Netherlands) and to a lesser extent also in the other OECD countries with multi-employer bargaining, wages are negotiated taking into account the general macroeconomic situation, not just inflation, as well as the impact on competitiveness.

Recent bargaining rounds suggests that, after a catch-up phase, negotiated wage growth should go back to previous trends

Looking forward, the staggered nature of wage bargaining means that the adjustment of nominal wages to a sudden increase in inflation takes place over several years. Hence, as external pressures from energy prices and supply bottlenecks are decreasing, increases in negotiated wages may weigh more on price increases. A forward-looking experimental tracker of negotiated wage growth in Austria, France, Germany, Greece, Italy, the Netherlands and Spain developed by the ECB in co-operation with euro-area national central banks shows that collective agreements during 2022 have typically delivered a 4.7% increase for 2023, up from 4.4% in 2022 (Lane, 2023^[51]). Outside the Euro Area, negotiated wages also increased in various countries:

- In Denmark, a sectoral agreement was reached in the manufacturing sector in February granting an increase of 3.5% in 2023 and 3.4% in 2024 for minimum wage floors. The agreement, which serve as a reference for the rest of the economy, is valid for two years and extends until 1 March 2025, covering approximately 230 000 employees and around 6 000 companies.
- In Norway, an agreement for a 5.2% increase for the frontline trade areas (exporting industry and manufacturing which set the benchmark for the rest of the economy) was reached in April after four days of strike.
- In Sweden, industry unions and employers agreed on new collective agreements for two years, that include salary increases of 4.1% in the first year and 3.3% in the second year. This agreement sets the reference for the others (the so-called “cost mark”).

These higher-than-normal nominal wage increases largely reflect the catch-up process after the decline in real wages since mid-2021. Meanwhile, as global energy and food prices decline, inflation is expected to continue to decline (OECD, 2023^[33]). Mechanically, wages can be expected to become an increasingly dominant factor in underlying inflation in the near future.⁴⁵ However, most agreements already foresee a deceleration in 2024 suggesting that after a catch-up phase of relatively higher nominal negotiated wage increases nominal negotiated wage growth should go back to previous trends without generating a price-wage spiral. Overall, nominal wage growth is projected to be just over 4% in the OECD area in 2023, before moderating to around 3.5% in 2024 (OECD, 2023^[33]).

1.4. Concluding remarks

Labour markets in the OECD area have largely proved resilient to the slowdown in economic growth that took place since the onset of Russia’s war of aggression against Ukraine, as total employment stabilised and unemployment rates generally remained below their pre-pandemic levels. The first months of 2023 have shown signs of improvement in economic growth which is however projected to remain subdued over the next two years.

Against this backdrop, a cost-of-living crisis has taken hold, as the energy shock caused by the war in Ukraine contributed to propelling price inflation to levels not seen in decades in many countries. Despite a

pick-up in nominal wage growth amid tight labour markets, real wages have fallen in virtually every industry and OECD country, often considerably.

Overall, there is no indication of a price-wage spiral, while the main risk going forward is a deepening of the cost-of-living crisis across the OECD. Indeed, even as inflation has been decelerating in most OECD countries, nominal wage growth is still trailing behind and thus real wages continue to fall.

Monetary policy should continue to pursue price stabilisation to bring inflation under control and prevent further erosion of real wages and living standards. Fiscal and wage policies can support monetary policy to achieve these objectives and ensure a fair distribution of the cost of inflation. Through fiscal support, most OECD governments have helped cushion the immediate impact of the cost-of-living crisis on household finances often at a sizeable cost for public finances (OECD, 2023^[2]). This support should now become more targeted to vulnerable households to avoid turning into a permanent stimulus to demand and further fuelling price increases. In addition, wage setting institutions – minimum wage and collective bargaining – are key to achieve sustainable wages increases and ensure a fair distribution of the cost of inflation between firms and workers, as well as among different groups of workers.

Fairly sharing the cost of inflation is essential to prevent further increases in income inequality and can support monetary policy in taming inflation. In fact, as argued by the President of the European Central Bank (Lagarde, 2023^[52]), a fair split of the cost of inflation can prevent a “tit-for-tat” between profits and wages that can feed upward price spirals. From this perspective, the evidence of this chapter suggests that, in several sectors and countries, there are margins for profits to absorb wage increases to help recover some of the losses in purchasing power. Indeed, in many cases, profits have increased more than labour costs in recent quarters, making an unusually large contribution to domestic price pressures and leading to a fall in the labour share. Given the downward rigidity of prices, the recent decline in input costs will also likely provide further room to absorb some wage increases without generating inflationary pressures. However, firm’s ability to absorb wage increases varies, with small and medium firms, in particular, likely to face more significant constraints. Collective bargaining can help identify solutions tailored to sectors and firms’ varying ability to sustain further increase in wages.

Adjustments in nominal minimum wages have helped contain the impact of inflation on the purchasing power of low-paid workers. Going forward, statutory minimum wages should continue to adjust regularly. The analysis shown in this chapter suggests that the risk of further fuelling inflation by increasing minimum wages is limited. However, countries will need to assess carefully the risk that the sole increase of minimum wage – without increases higher up in the wage distribution – may lead to excessive compression of the wage distribution, with negative impact on individual careers and implications for designing redistribution policies.

Collective bargaining can play an important role in allowing some wage adjustment that ensure an equitable distribution of the cost of inflation between workers and employers and across workers of different pay levels. As new bargaining rounds take place, wages negotiated between trade unions and employers are now starting to adjust. Where renegotiations are not taking place, governments can help promote regular renegotiation of collective agreements. In addition, social dialogue and tripartite agreements between governments, workers, and firms, may also offer a platform for a fair sharing of the cost of inflation, and facilitate the job of monetary policy.

Going forward, the focus should be on wages regaining some of the lost purchasing power gradually over an extended period of time, as quick and full recoveries of past inflation would most likely feed further inflation.

In the long run, sustained real wage gains can only be ensured through sustained productivity growth. It is therefore essential for OECD countries to deploy a wide range of labour market, skill, and competition policies to make the most of the opportunities afforded by new technological developments, such as Artificial Intelligence – whose potential impact on the labour market is discussed in the remainder of this volume.

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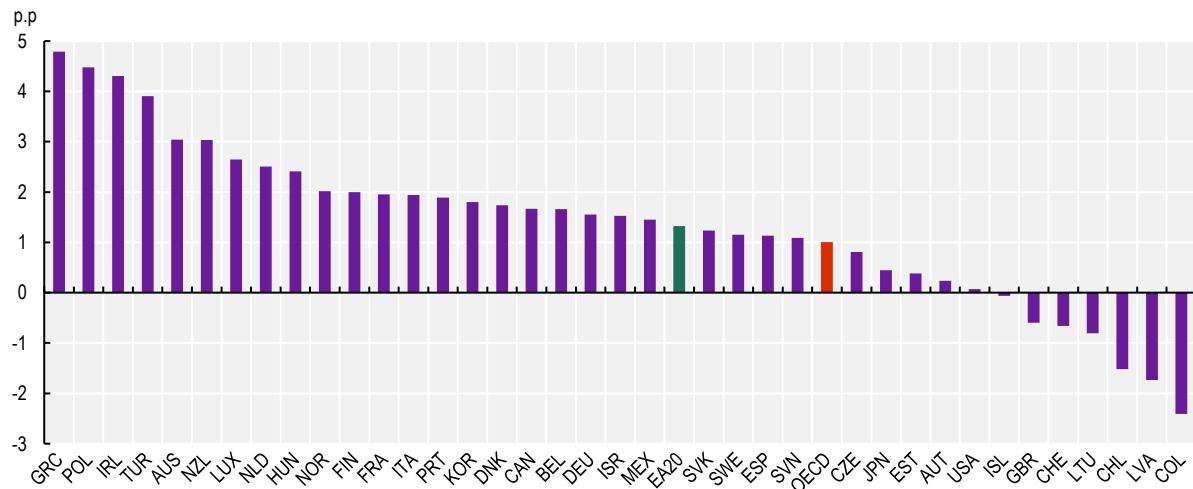
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Annex 1.A. Additional results

Annex Figure 1.A.1. Employment rates have improved in most countries

Percentage point change in employment rates among the working age population from Q4 2019 to Q1 2023, seasonally adjusted



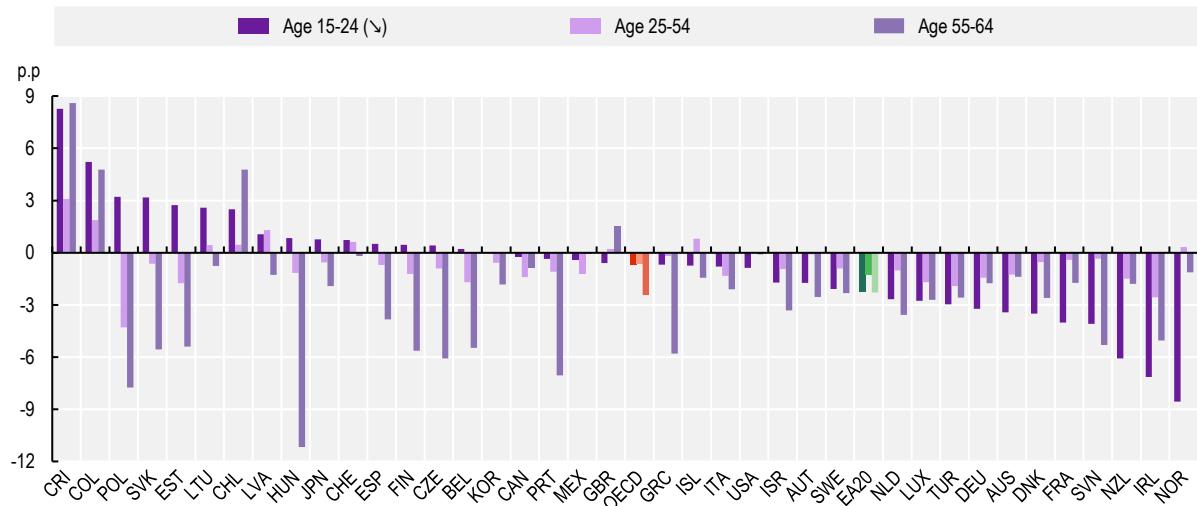
Note: Working age population includes all those aged 15 to 64. OECD is an unweighted average of the countries shown above. Euro Area refers to 20 Eurozone countries. p.p: percentage point.

Source: OECD (2023), "Labour: Labour market statistics", Main Economic Indicators (database), <https://doi.org/10.1787/data-00046-en> (accessed on 28 June 2023).

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Annex Figure 1.A.2. Changes in inactivity rates by age

Percentage point change in inactivity rates among the working age population from Q4 2019 to Q1 2023, seasonally adjusted



Note: OECD is an unweighted average of the countries shown above. Euro Area refers to 20 Eurozone countries. p.p: percentage point.

Source: OECD (2023), "Labour: Labour market statistics", *Main Economic Indicators* (database), <https://doi.org/10.1787/data-00046-en> (accessed on 28 June 2023).

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Annex Figure 1.A.3. Nominal wage growth has picked up but does not seem to be accelerating significantly

Year-on-year percentage changes, from Q2 2022 to Q1 2023



Note: Real wage growth is calculated by subtracting CPI inflation (all items) from nominal wage growth. OECD represents the unweighted average of 34 OECD countries. Euro Area represents the averages of 20 Eurozone countries. The composition of industries is not fixed for Korea, and thus comparing these results with the others requires caution. Additional sources of compositional shifts, such as regions (Australia), job characteristics and workers' characteristics (Australia) and occupations (United States) are controlled for. Moreover, wages in the public sector are excluded for Australia, Japan, Korea, Mexico and the United States..

Source: The wages and salaries component of labour cost index by NACE Rev. 2 activity (Eurostat), Wage Price Index (Australian Bureau of Statistics), Fixed weighted index of average hourly earnings for all employees (Statistics Canada), OECD calculations based on Encuesta Continua de Empleo (Instituto Nacional de Estadística y Censos, Costa Rica), Wages and Employment Monthly Statistics (Israeli Central Bureau of Statistics), OECD calculations based on Monthly Labour Survey (Japanese Ministry of Health, Labour and Welfare), Labour Force Survey at Establishments (Korean Ministry of Employment and Labour), OECD calculations based on Encuesta Nacional de Ocupación y Empleo, Encuesta Telefónica de Ocupación y Empleo, Encuesta Nacional de Ocupación y Empleo Nueva Edición (Instituto Nacional de Estadística y Geografía, Mexico), Labour Cost Index (Statistics New Zealand), Swiss Wage Index (Swiss Federal Statistical Office), Monthly Wages and Salaries Survey (UK Office for National Statistics), and Employment Cost Index (U.S. Bureau of Labor Statistics, retrieved from FRED); OECD (2023), "Prices: Consumer prices", Main Economic Indicators (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 23 June 2023).

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Annex 1.B. Identifying employee benefits in online job postings

Within the key information contained in online job postings (OJPs), employers often include different discretionary benefits for employees that help attract the best talent by making their companies stand out from others offering similar positions. Employee benefits widely varies from health-related and retirement benefits to student loan support and workplace amenities (on-site gym, snacks/food provided, etc).

Using nearly 8 million OJPs advertised in Canada, the United Kingdom and the United States, this annex explores how mentions of different types of benefits changed between two specific months: December 2019 and December 2022. The first month represents the period right before the COVID-19 pandemic, which significantly affected labour markets across the world, while the latter is the month with the most updated data available. For this purpose, this section leverages the texts included in the OJPs and, since this data is not generally structured, it uses text mining techniques to identify and classify job postings in different categories of employee benefits.

The first step comprises the analysis of the texts available from OJPs advertised in the United Kingdom in December 2022 – more than 900 000 texts – to extract all possible combinations of two and three contiguous words (often called bigrams and trigrams), excluding stop words, numbers and punctuation. These combinations mitigate the risk of misclassifying OJPs when using single keywords that can be used in different contexts not related to employee benefits. For instance, the word “gym” can be located in the job title of postings seeking for gym trainers but also in the benefits section when a company is offering a “gym membership”. Typical words used in employee benefits, such as insurance, gym, pension, among others, worked as an additional filter to select relevant bigrams and trigrams from a list of nearly 700 000. A complementary strategy includes to review random texts from OJPs including the word “benefits” in the three countries analysed to manually identify specific keywords used to offer employee benefits, including specific programs such as the 401(k)-retirement account in the United States or the Registered Retirement Savings Plan (RRSP) matching contribution in Canada. Annex Table 1.B.1 summarises the combinations that were likely to signal an employee benefit and grouped them in ten different types.

The second step involves tagging each OJP with a 1 if it includes at least one of the keywords defined for each type of benefit in Annex Table 1.B.1. Annex Figure 1.B.1 shows the share of OJPs including the six more frequent benefits per month and type of benefit, excluding the groups “more vacations”, “free/subsidised food”, “social activities” and “parental leave”, since they were not typically used by employers in job postings advertised in these months. Results show significant increases in the mentions of health-related benefits, retirement schemes and paid time-off (in Canada and the United States).

Following the evidence suggesting the increase in the use of employee benefits, a final step aims to assess if the change on the share of employee benefits mentions between the two months analysed was correlated with an increase in the demand for workers at the sectoral level. Annex Figure 1.B.2 compares, by sector, the average change in mentions of employee benefits (weighted average across the different types of benefits using as weights the share of each benefit in the total number of mentions per sector) and the growth observed in the number of job postings. The latter can signal, to some extent, how tight is the labour market for each economic sector. However, results are not conclusive since correlations are weak – as depicted by the weighted trendlines – and the sign of the relation varies across countries.

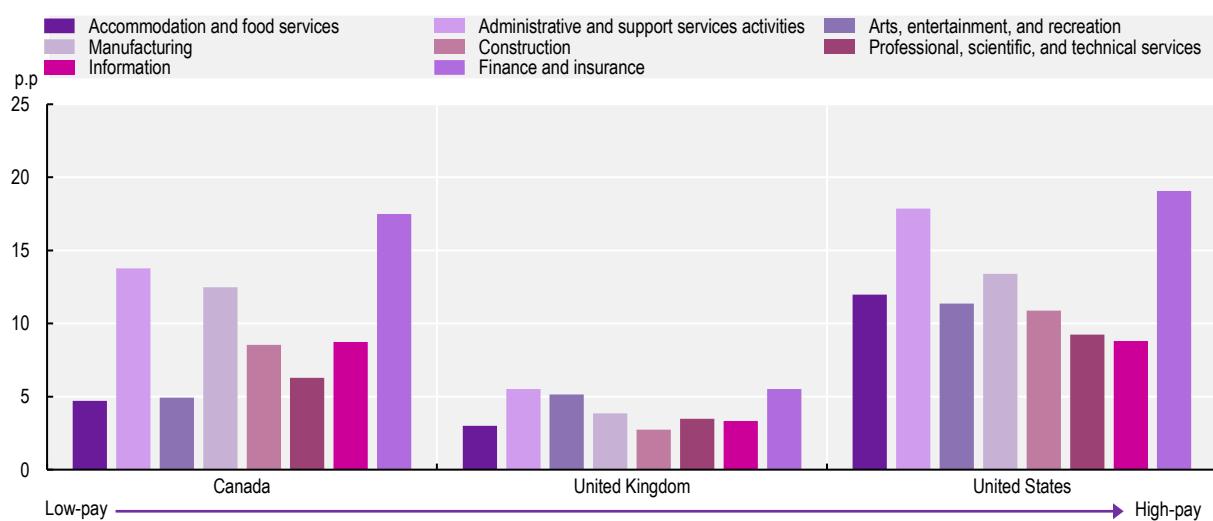
Annex Table 1.B.1. Keywords for identifying employee benefits in online job postings

Benefit	Keywords
Fitness facilities	Gym membership, gym discounts, discounted gym, gym subsidised, gym subsidised, fitness classes, yoga classes, subsidised fitness, subsidised fitness, on-site gym, equipped company gym, on-site fitness centre.
Free/subsidised food	Subsidised food, free snacks, snacks provided, free healthy snacks, free coffee, discount on food, discounts on food, free food.
Health-related	Dental insurance, vision insurance, medical Insurance, health & welfare, health insurance, life insurance, disability insurance, dental care, wellness programme, wellness programme, flexible spending account.
More vacations	More vacation, annual leave increased, additional vacation, generous holiday, generous holidays, holiday package, holiday entitlement, holiday entitlements, unlimited vacation.
Paid time off	Paid time off, sick leave, sick days, paid week off.
Parental leave	Paid maternity leave, pay maternity leave, paid paternity leave, pay paternity leave, adoption leave, full pay maternity, paternity pay, paid parental leave.
Remote work	Work from home, teleworking, home office, remote working, work remotely.
Retirement schemes	Pension contribution, pension scheme, pension benefits, pension bonus, pension plan, pension package, pension rewards, pension arrangements, 401(k), Company pension, RRSP matching.
Social activities	Company retreats, company outings, team outings, social outings, outings, team bonding events.
Tuition assistance	Student loan assistance, tuition assistance, tuition discount, tuition reimbursement.

Note: Some keywords refer to country-specific benefits: Flexible spending accounts are special savings accounts where employees and employers in the United States can contribute to pay for certain healthcare costs; 401(k) is a personal pension account in which employees and employers in the United States contribute to retirement plans with tax benefits; and the Registered Retirement Savings Plan (RRSP) matching refers to Canadian employers' choice to contribute a percentage of employees' salaries, to a pension account with similar benefits of 401(k).

Annex Figure 1.B.1. Mentions of employment benefits increased

Average of the change of online job postings offering selected benefits by industry, percentage points



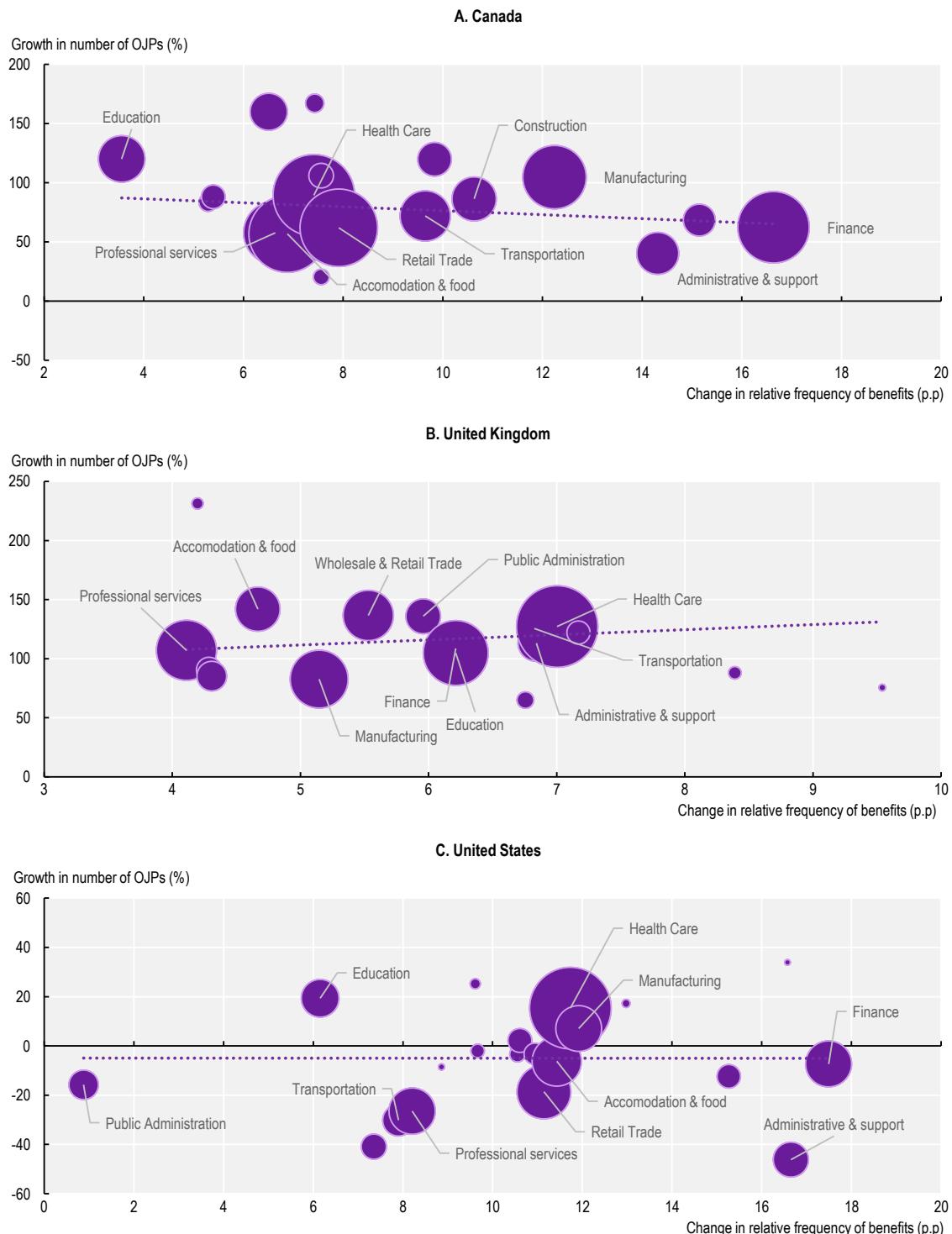
Note: The chart reports the unweighted average of the change (in percentage points) of online job postings offering health-related benefits, retirement schemes, or paid time-off/sick leave. Industries are ordered by low-pay to high-pay from left to right. p.p: percentage point.

Source: OECD calculations based on Lightcast data.

StatLink <https://stat.link/19dmex>

Annex Figure 1.B.2. Employee benefits and demand per economic sector in online job postings

Average change in mentions of employee benefits and growth in online job postings (OJPs) per sector between December 2019 and December 2022. Bubbles' size represents the sector's share in total OJPs in both months



Note: The average change in mentions of employee benefits is weighted by the share of each benefit in the total number of mentions per sector. The trend line is weighted by the share of each sector in the total number of OJPs in both months (bubbles' size).

Source: OECD calculations based on Lightcast data.

StatLink <https://stat.link/yeof46>

Annex 1.C. Latest developments on minimum wages and negotiated wages

Annex Table 1.C.1. Minimum wage setting mechanisms

Country	Minimum wage uprating procedures	Usual date of uprating	Delay between the decision and the application
Australia	The Fair Work Commission formulates binding advice.	Every year on a fixed date: 1 July	Less than one month
Belgium	Minimum wage set by a national collective agreement negotiated by unions and employers.	No regular increase in the minimum wage but increased each time inflation exceeds 2% from the last revision).	Between 1 and 2 months
Canada (Federal)	Set by the federal government based on inflation developments	Every year on a fixed date: 1 April	Between 1 and 2 months
Chile	Minimum wage revision decided after discussion between the Ministries of Labor and Social Security and of Finance with the Central Unitaria de Trabajadores (CUT). The final decision must be approved by the National Congress.	No regular increase in the minimum wage	Less than one month
Colombia	The minimum wage is set by the Permanent Commission on the Harmonization of Wage and Labour Policies (Commission) through an Executive Decree. If the Commission cannot reach a consensus each year as of 30 December, the government shall fix the minimum wage.	Every year on a fixed date: 1 January	Less than one month
Costa Rica	The National Wage Council fixes minimum wages (by sector and occupation) through executive decrees.	Every year on a fixed date: 1 January	Between 1 and 2 months
Czech Republic	The government sets the national minimum wage rate in an official decree, after consultation with trade unions and employer organisations, similarly to any regulations or bills concerning employees' interests.	No regular increase in the minimum wage	Between 1 and 2 months
Estonia	Minimum wage set by a national collective agreement negotiated by unions and employers.	Every year on a fixed date: 1 January	More than 2 months
France	An expert group formulates non-binding advice. Minimum wage increases must at least cover inflation plus half of real wage increases among blue-collar workers (rules fixed by law). Minimum wage is revised accordingly by decree.	Every year on a fixed date: 1 January, or each time inflation exceeds 2% from the last revision	Less than one month
Germany	The Minimum Wage Commission (<i>Mindestlohnkommission</i>) formulates binding advice	Every two years	More than 2 months

Country	Minimum wage uprating procedures	Usual date of uprating	Delay between the decision and the application
Greece	Law provides for a certain process of consultation, co-ordinated by an ad hoc Commission, the reports of which are submitted to a state supervised Institute (KEPE) to form, under another process, the final report of the consultation. After this report is submitted to the Ministers of Labour and Finance, the Minister of Labour submits it to the Council of Ministers for further discussion, which yields the final guidance for the issuance of Minister of Labour's decision on the definition and the amount of the minimum wage.	No regular increase in the minimum wage	Less than one month
Hungary	Minimum wage is determined by the government following consultations of the National Economic and Social Council.	Every year on a fixed date: 1 January	Less than one month
Ireland	Minimum wage determined by the government following consultations of the Low pay Commission.	Every year on a fixed date: 1 January	More than 2 months
Japan	Minimum wage is determined by the government following consultations of the Minimum Wages Council.	At regular intervals, once a year: around October.	Between 1 and 2 months
Korea	The Minimum Wage Council formulates binding advice.	Every year on a fixed date: 1 January	More than 2 months
Latvia	Set by the government following recommendations of the National Tripartite Co-operation Council (NTCC).	No regular increase in the minimum wage	More than 2 months
Lithuania	The government, upon the recommendation of the Tripartite Council, determines the minimum wage.	Every year on a fixed date: 1 January	More than 2 months
Luxembourg	The minimum wage is fixed legally by law. Every second year the government must submit a report on the general situation of the economy and wages to the parliament, together with a draft bill aiming at adapting the legal minimum wage, if deemed necessary.	At regular intervals, less than once a year: 1 January, or each time inflation exceeds 2.5% from the last revision.	Less than one month
Mexico	The National Commission of Minimum Wages (CONASAMI) formulates binding advice.	Every year on a fixed date: 1 January	Less than one month
Netherlands	Minimum wage increases are automatically indexed to estimated increases in average negotiated wage rates in both the public and private sectors in the current year and revised accordingly by the Ministry of Social Affairs and Employment	At regular intervals, more than once a year: 1 January and 1 July	More than 2 months
New Zealand	The government sets the minimum wage by Order in Council, following consultations with social partners and annual review by, and recommendations from, the Ministry of Labour.	Every year on a fixed date: 1 April	More than 2 months

Country	Minimum wage uprating procedures	Usual date of uprating	Delay between the decision and the application
Poland	The minimum wage for the following year is negotiated within the Tripartite Commission based on a proposal of level and date of changing of the minimum wage put forward by the government. In case the Commission does not reach a consensus, the government shall set the minimum wage by its own resolution.	Every year on a fixed date: 1 January	Less than one month
Portugal	The government sets the national minimum wage after consultation with the Committee for Social Consultation of the Economic and Social Council (Comissão Permanente de Concertação Social do Conselho Económico e Social).	Every year on a fixed date: 1 January	Less than one month
Slovak Republic	The adjustment of the minimum wage is set by Law based on an agreement between the social partners (representatives of employers and representatives of employees). If the social partners are unable to agree on its level, the government decides on it unilaterally, by taking into consideration the growth rate of the average monthly nominal wage in the previous year.	Every year on a fixed date: 1 January	More than 2 months
Slovenia	Amount of the minimum wage is determined by the Ministry of Labour, Family, Social Affairs and Equal Opportunities (MOLFSA) after consultation with the social partners.	Every year on a fixed date: 1 January	Less than one month
Spain	The government sets the minimum wage following recommendations of the permanent commission of experts.	Every year on a fixed date: 1 January	More than 2 months
Switzerland (5 Cantons)	It varies by cantons.	Every year on a fixed date: 1 January	Less than one month
Türkiye	The minimum wage is determined by Minimum Wage Determination Commission annually. The Commission consist of 15 members (five representatives each from government, employees' and, employers' representatives). The Commission's decisions are taken by majority.	Every year on a fixed date: 1 January	Less than one month
United Kingdom	Determination of the minimum wage rate by the Secretary of State is made following the Low Pay Commission's recommendation on the minimum wage rate.	Every year on a fixed date: 1 April	More than 2 months
United States (Federal)	Federal minimum wage increase is determined and voted by the Congress and signed into law by the US President.	No regular increase in the Federal minimum wage:	Between 1 and 2 months

Note: Canada (Federal): the federal minimum wage set for the federally regulated private sector, there are also separate minimum wages set at the level of the provinces and territories. Switzerland (5 cantons): Only the five cantons with a statutory minimum wage: Basel-Stadt, Geneva, Jura, Neuchâtel, and Ticino; United States (Federal): there are also separate minimum wages set at the State level.

Source: OECD Questionnaire on recent measures to deal with inflation pressure on wages (February 2023).

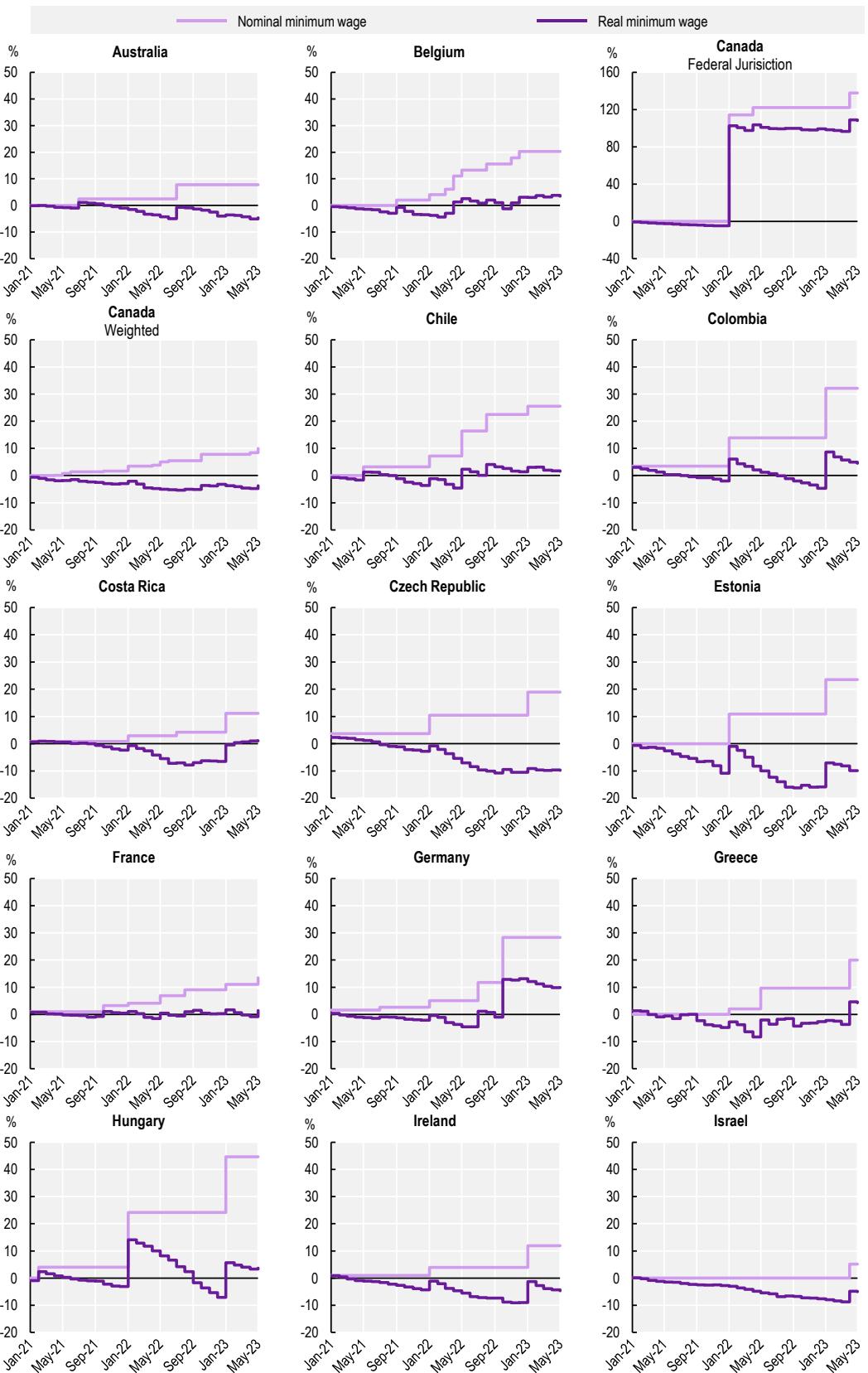
Annex Table 1.C.2. Reference minimum wage series

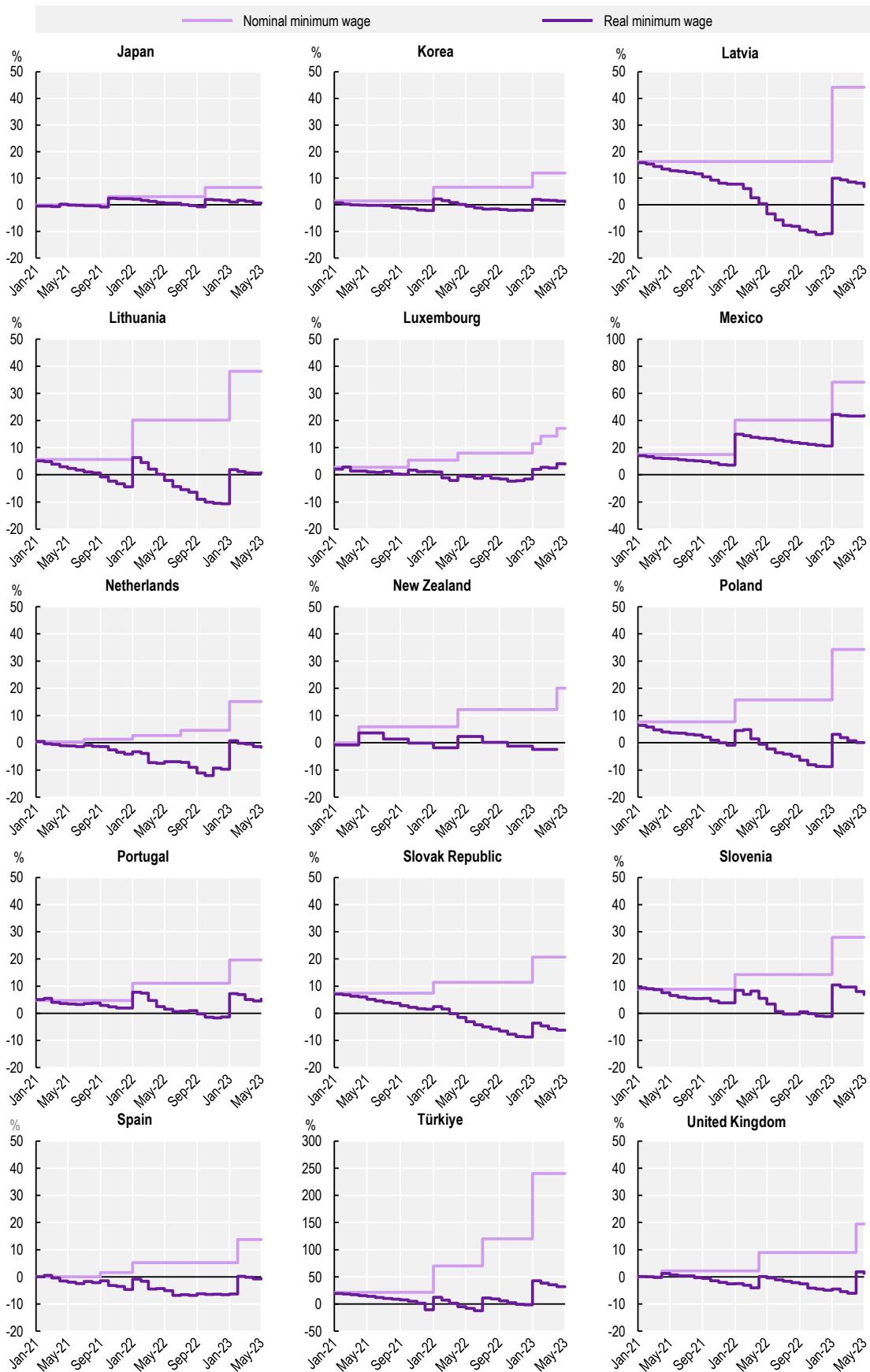
Country	Rate	Definition
Australia	Hourly	Employees aged 21 and over
Belgium	Monthly	Employees aged 18 and over
Canada (Weighted)	Hourly	Laspeyres index based on minimum wage of provinces and territories (excluding the Federal Jurisdiction) weighted by the share of employees of provinces and territories in 2019.
Chile	Monthly	Employees aged 18-65 for a 45 hours week
Colombia	Monthly	Excluding transport allowance
Costa Rica	Monthly	Generic unskilled workers
Czech Republic	Hourly	Individual work of the same kind (private sector)
Estonia	Hourly	
France	Hourly	
Germany	Hourly	
Greece	Daily	
Hungary	Hourly	
Ireland	Hourly	Employees aged 20 and over
Israel	Monthly	
Japan	Hourly	
Korea	Hourly	
Latvia	Monthly	
Lithuania	Hourly	
Luxembourg	Hourly	Unskilled workers aged 18 and over
Mexico	Daily	Generic workers (excluding the Free Trade Zone)
Netherlands	Daily	Employees aged 21 and over
New Zealand	Hourly	Adult minimum wage for all employees aged 16 and over who are not starting-out workers or trainees, and all employees who are involved in supervising or training other employees.
Poland	Monthly	Employees with more than one year of services
Portugal	Monthly	Employees in continental Portugal (excluding Azores and Madeira) including the 13th and 14th months
Slovak Republic	Hourly	
Slovenia	Monthly	
Spain	Daily	General employees aged 18 and over including the 13th and 14th months
Türkiye	Monthly	
United Kingdom	Hourly	Employees aged 21 and over (aged 25 and over before April 2021)
United States (Federal)	Hourly	
United States (Weighted)	Hourly	Laspeyres index based on minimum wage of states (not including territories like Puerto Rico or Guam) weighted by the share of nonfarm private employees by state in 2019

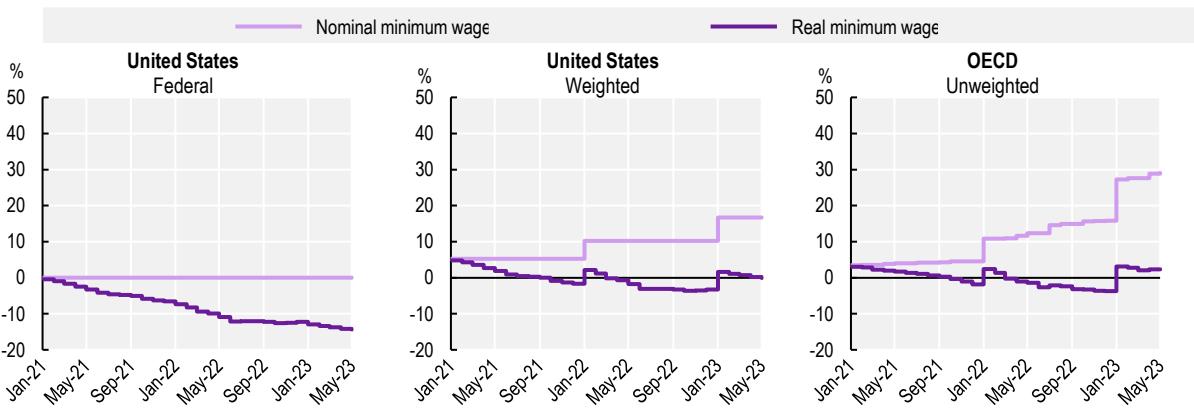
Note: Canada (weighted) and the United States (Weighted) are OECD estimates used to illustrate the aggregate evolution of minimum wage rates based on the minimum wage rates at the sub-national level. These estimates do not, however, consider special exemptions and rates in force in the provinces and states of the countries concerned. In particular, the minimum wage applying to the employees working under the federal Jurisdiction in Canada are excluded. The estimation for Canadian are based on the minimum wage of province and territories weighted by the number of employees in provinces and territories in 2019 from the Survey of Employment, Payrolls and Hours (SEPH); and those for the United States, on the minimum wage of states weighted by the number of nonfarm private employees by state in 2019 from the State and Metro Area Employment, Hours, & Earnings published by the BLS. For the five States where no minimum wage is required (i.e. Alabama, Louisiana, Mississippi, South Carolina and Tennessee), the federal minimum wage is included in the estimate.

Annex Figure 1.C.1. Minimum wage evolution, January 2021 to May 2023

Nominal and real minimum wage, cumulative percentage change since December 2020, January 2021 to May 2023







Note: Canada (weighted) is a Laspeyres index based on minimum wage of provinces and territories (excluding the Federal Jurisdiction) weighted by the share of employees of provinces and territories in 2019. United States (weighted) is a Laspeyres index based on minimum wage of states (not including territories like Puerto Rico or Guam) weighted by the share of nonfarm private employees by state in 2019. At date, statistics do not include planned increases in the minimum wage for Australia, the Netherlands, Poland and Türkiye in July 2023 (+8.7%, +3.1%, +3.2% and +34%, respectively). Changes in nominal minimum wage in Belgium in April and May 2022 relate to the transition to a single rate for workers aged 18 and over. OECD is the unweighted average of 30 OECD countries with statutory minimum wage (not including Canada Federal Jurisdiction and the weighted average for the United States).

Source: OECD Employment database, <https://www.oecd.org/employment/emp/onlineoecdemploymentdatabase.htm>, OECD (2023), "Prices: Consumer prices", Main Economic Indicators (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 4 July 2023), and Monthly CPI Indicator (Australian Bureau of Statistics).

StatLink <https://stat.link/0kg6xu>

Annex Table 1.C.3. Negotiated wages in OECD countries: Data sources

Country	Title of the indicator	Provider	Sampling	Source data	Statistical population	Sector coverage
Australia	Average annualised wage increases (AAWI)	Department of Employment and Workplace Relations (DEWR)	Enterprise agreements for which average percentage wage increases could not be quantified (e.g. those with inconsistent increases) are excluded from these estimates.	Workplace Agreements Database (WAD)	All employees whose pay are set by collective agreements (federally or state registered and unregistered).	All sectors (private and public)
Austria	Index of collectively agreed minimum wages (Tariflohnindex)	Statistics Austria	The TLI does not consist of all KV or statutory salary regulations, but of a representative selection of the same. The complex selection process was based on the one hand on the affected employees of a KV or a statutory salary regulation, but also on other criteria (job groups, biennial levels).	ÖGB databases ("KV system") and RIS (Federal legal information system)	All employees	NACE Rev. 2. Codes A-S (Foreign companies which are not registered to the commercial register are not included).
Belgium	Index of the Collectively Agreed Wages	Ministry of Labour (NL: FOD Werkgelegenheid, arbeid en sociaal overleg/FR: SPF Emploi, travail et concertation)	No sampling method is used; by definition the average wage in the wage classification scheme is used for each sector committee as the base wage for calculation	Collective agreements filed at the ministry (mandatory by law)	All private sector blue- and white-collar workers (i.e. all people with an employment contract and no civil service employment status)	Private sector
Canada	Annual percentage adjustment in major wage settlements	Employment and Social Development Canada (ESDC), Strategic Policy, Analysis, and Workplace Information Directorate	Selection of major collective bargaining settlements	Collective agreements encompassing all industrial sectors and jurisdictions in Canada	collective bargaining settlements of all bargaining units covering 500 or more employees (units of 100 or more employees for the Federal Jurisdiction).	All sectors (private and public)

Country	Title of the indicator	Provider	Sampling	Source data	Statistical population	Sector coverage
Euro area	Indicator of negotiated wage rates	European Central Bank	-	Non-harmonised negotiated wage indicators for 10 countries.	-	All sectors
Finland	The Index of Negotiated Wages and Salaries	Statistics Finland	Selection of major and representative sector-level collective agreements (70)	Collective agreements signed by social partners	All private and public sector workers (blue- and white-collar workers) covered by collective agreements (coverage rate approx. 90%)	Four employer sectors: private, local government, central government and others.
France	Wage floor growth	Banque de France	Selection of 367 sector-level collective agreements	Sector-level collective agreements (LegiFrance)	Private sector employees	Private sector
Germany	Quarterly index of negotiated wages and hours worked (EVAS No. 62 221)	Federal Ministry of Labor and Social Affairs (BMAS)	Selection of major and representative sector-level collective agreements. These CAs should represent at least 75% of the sector.	BMAS receives information on wage agreements from trade unions and employers (mandatory by law, Collective Bargaining Agreement Act – TVG).	All employees including civil servants but excluding trainees.	NACE Rev. 2. Codes A-S
Italy	Index numbers of the collectively agreed wages (Indici delle retribuzioni contrattuali)	Istat	Selection of major and representative sector-level collective agreements	Collective agreements register (CCNL)	Employees excluding apprentices and managers	All sectors (private and public)
Japan	Wage-increase related to Spring Wage Increase (Shunto) in major enterprises	Ministry of Health, Labour and Welfare (MHLW)	Status of wage increase demands and settlements at major private-sector enterprises	Survey from the MHLW	"Major" enterprises with a capital of 1 billion yen or more, 1 000 or more employees, and a labor union	Private sector
Korea	Agreed wage increase rate	Ministry of Employment and Labor	No	Survey on Wage Determination Status (formerly Survey on Wage Bargaining Settlement)	All workplaces with 100 or more full-time workers who determine the national wage increase rate	All sectors (private and public)

Country	Title of the indicator	Provider	Sampling	Source data	Statistical population	Sector coverage
Netherlands	Collective Labour Agreement Wage Indexes (CAO-lonen indexcijfers)	Statistics the Netherlands (Centraal Bureau voor Statistiek, CBS)	CBS samples 250 of the approximately 900 collective agreements, including all agreements covering at least 2 500 employees.	Collective agreements filed at the ministry (mandatory by law)	Full-time employees, i.e. persons working for a wage or a salary.	All branches of economic activity, except private households with employed persons (SBI95) and extra-territorial organisations and bodies (SBI99). All types and sizes of establishments taking part in collective agreements.
Portugal	Annualised weighted average variation between wage tables (Variação salarial nominal média ponderada intertabelas anualizada, VMPI)	Ministry of Labour (DGERT)	No. All published Collective agreements (IRCT) that contain minimum wages.	Collective agreements (IRCT) registered	Private sector employees (Continental Portugal) excluding domestic workers.	Private sector excluding agriculture and households as employers.
Spain	Revised wage variations (include revisions by "wage guarantee clause")	Ministry of Labour and Social Economy (MITES)	No. All published Collective agreements	Collective agreement register (REGCON)	Private sector employees	Private sector
Sweden	Change in negotiated wages (central agreements)	Mediation Office	Selection of major and representative sector-level collective agreements (70)	Collective agreements registered at the Mediation Office	All employees	All sectors (private and public)
Switzerland	Salary adjustments in Agreements on nominal adjustments of minimum wages	Federal Statistical Office	Collective agreements containing wage provisions and with at least 1 500 employees subject to them (around 90% of employees covered).	Wage Agreements Survey (WAS)	All employees	All sectors (private and public)
United States	Average first-year wage increases in union contracts	Bloomberg Law	No	Bloomberg's Law's database of wage settlements	All employees	All sectors (private and public)

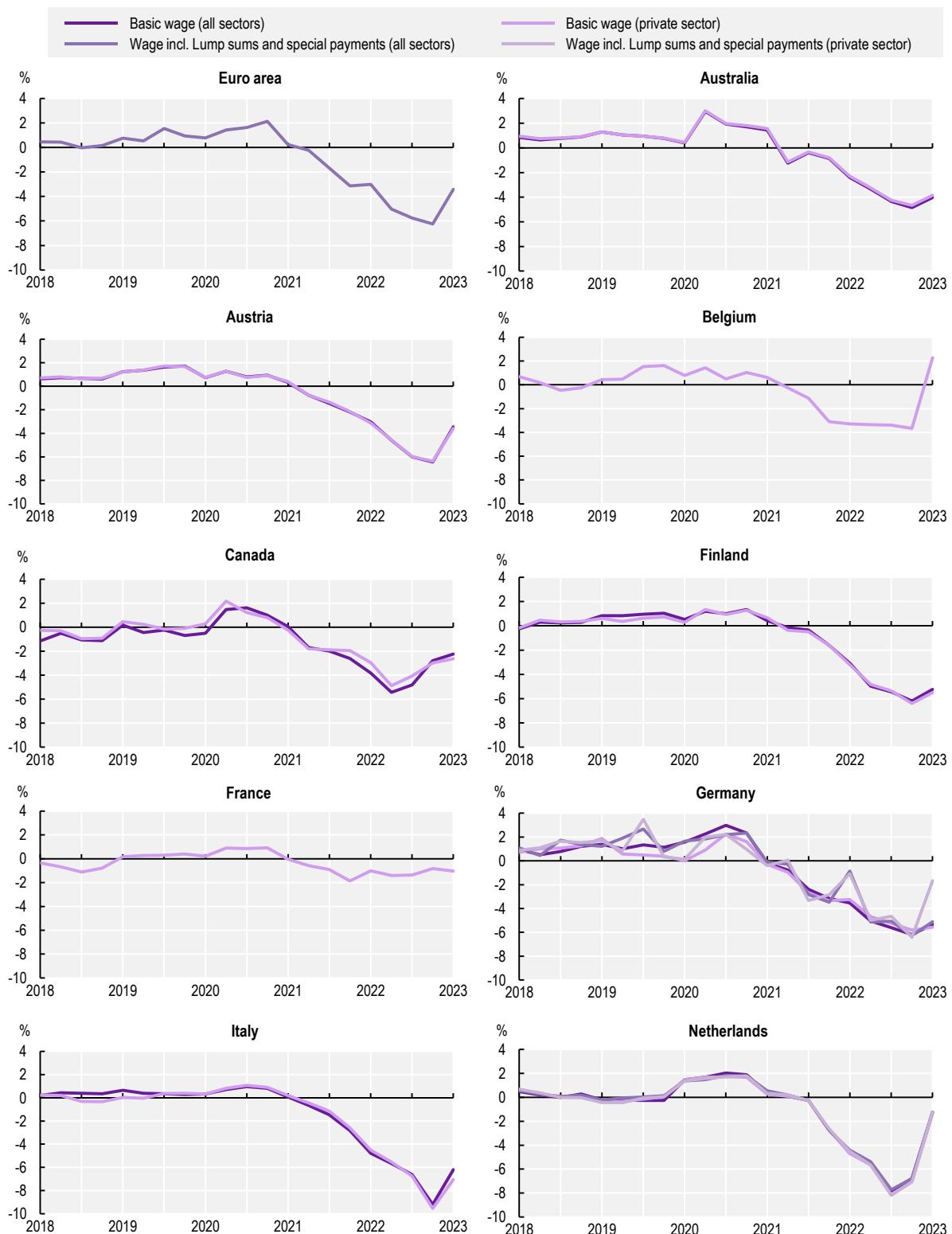
Annex Table 1.C.4. Negotiated wages in OECD countries: Measurement issues

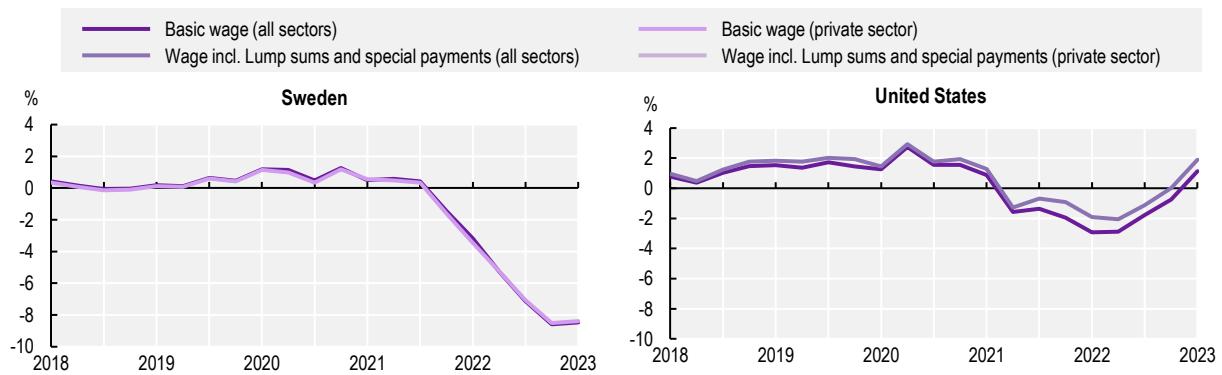
Country	Wage definition	Measurement
Australia	Basic rate of pay. Estimates of AAWI generally exclude increases paid in the form of conditional performance pay, one off bonuses, profit sharing or share acquisition, as these data cannot readily be either quantified or annualised.	Employee-weighted estimates of average wage increases calculated for those federal enterprise agreements that provide quantifiable wage increases over the life of the agreement.
Austria	All regular payments that are conditional on the job the person holds, not including payments conditional on personal circumstances of a particular person, such as special payments for parents, payments for special occasions, jubilee premia and so on. The wage also does not include wages paid in kind.	Laspeyres index of increase in wage index weighted by the corresponding number of employees in the base year (2016).
Belgium	Basic salary only; currently limited to sector agreements Excluded: bonuses, deferred compensation	Fixed employment composition (Laspeyres index) of median value of wage scales within joint industrial committees, calculation of relative increases. Absolute conventional wage increases are described relative to the average effective wage in 2010.
Canada	The base wage rate is the lowest paid classification used for qualified employees in the bargaining unit. In most instances, the base rate is the rate of pay for an unskilled or semi-skilled classification of workers. However, this may not apply in the case of contracts covering skilled workers and professional employees. In some cases, the base rate occupation may not be representative of the general group within the bargaining unit and another classification that is more representative will be chosen.	The effective wage adjustment is the increase or reduction in rates of pay, including estimated cost-of-living allowance (COLA) payments. Estimates of the yield of COLA clauses are obtained by quantifying the characteristics of these clauses in each agreement and applying a combination of actual Consumer Price Index (CPI) increases available to date plus a specified projected inflation rate for the remainder of the contract duration. In succeeding quarters, these estimates are revised using actual CPI values as they become available.
Euro Area	Wages including one-off payments and bonuses	Weighted average of national year-on-year growth rates of collectively agreed wages for most Euro Area countries. Euro Area 19 (fixed composition) as of 1 January 2015.
Finland	Increases in gross average earnings for regular working hours in sectoral collective agreements. The earnings concept includes one-off payments based on the relevant collective agreements. Compensation for overtime, holiday pay and other such items are not included	Laspeyres index using the same weight structure (year 2005). The effects of negotiated pay increases are estimated in relation to the earnings level at the previous year-end.
France	Minimum wage in pay scales (hourly, monthly or annual)	Annual change in all minimum wages in each CA weighted by the number of employees of each CA.
Germany	Basic wage: collective wages that are to be paid permanently and regularly. This also includes capital-forming benefits paid monthly. Wages with special payments: also include collectively agreed one-off payments, vacation and Christmas bonuses and annual capital-forming benefits. The special payments also include collectively agreed lump-sum payments as well as additional payments that are made due to collective agreements that came into force retrospectively or a delay between the effective date and payment of a collective wage increase	Laspeyres index (fixed employment composition in 2015) of wage increase of collective agreements (at company or sector level) with the highest number of employees are selected by sector (NACE Rev. 2 at 2 digits) breakdown by performance (occupational) group.
Italy	Basic hourly pay, seniority and shift work allowance, all bonuses specified in national agreements and payable to all workers as well as those paid periodically (e.g. the 13th month). Bonuses related to individual performance or individual working conditions, supplementary payment agreed at the company or local level are not included. Wages include tax and social security contributions paid by employees.	For each selected nation-wide collective agreement, the number of employees and their composition by specific wage level (combined with indications for seniority, skill, estimation about shift work) are fixed at a base year (2015) and remain constant until the renewal of base has been done.
Japan	Monthly basic wage	Average wage increase weighted by the number of workers in each workplace

Country	Wage definition	Measurement
Korea	The agreed wage increase rate is not based on the actual wages paid, but based on the wages to be paid when the wage increase rate is determined (excluding wages that are decided ex post such as overtime, night-time, and holiday work allowances), overtime work allowances, etc.	Average wage increase weighted by the number of workers in each workplace
Netherlands	Hourly or monthly CAO wages excluding or including special payments (all binding (compulsory) prescribed special (non-monthly) payments included in the gross income, such as holiday allowance, Christmas bonus, once-only payments and compensation for health insurance costs and the employers' contribution to the life course savings scheme).	The statistical units are formed by a large number of well-defined points in collective labour agreements. These points represent a contractual pay level for a certain function group, often combined with indications for seniority, age or skill. A special establishment survey is conducted to determine the structure in the base year (2010). It determines the collective agreements used and their distribution over the workforce groups. From this information estimates are made for every relevant collective agreement showing the distribution of workers for the salary structure and points of highest density are selected to develop a partial wage index.
Portugal	Basic rates as defined in the wage tables annexed to the collective agreements.	For each IRCT renegotiated at a specific month, the average percentage increases between the current salary scale and the previous one are calculated, weighted with the distribution of workers by professional categories, based on the Personnel Boards (Office of Strategy and Planning – GEP) and information directly provided by companies when it comes to company agreements and collective agreements.
Spain	Basic monthly wage (without bonuses). Nevertheless, many collective agreements refer to increases in total salary	For the calculation of the average agreed pay increase, the agreements that have economic effects in the year analysed and that agree on a known wage variation for the reference period and that have been registered in REGCON are taken into account. It is calculated as an average weighted by the number of workers in each agreement. Information on the agreed and revised wage variation is published (applying the wage guarantee clauses that become effective in the agreements where they are included).
Sweden	Basic salary excluding overtime and other extra payments.	Laspeyres index (fixed employment composition in 2009): Weighted averages on agreed wage increases from representative collective agreements. The negotiated wage increases refer to the average percentage wage increase rate that each collective agreement implies for a given employee within the bargaining area. Information on percentage wage increases in the 70 agreements is assessed by the National Mediation Office and combined in two steps: First, the agreed wage increases for each sector are calculated by combining agreed wage increases and the number of employees affected by each collective agreement. Second, increase rates for industry aggregates, sectors, and the entire economy are calculated using wage sum weights for the different industries. The wage sum weights are calculated using official wage statistics.
Switzerland	Minimum wages/tariffs: Minimum amounts of pay negotiated by the contracting parties and enshrined in the CLA or its amendments. Minimum wages are either single amounts (annual, monthly, or hourly) for different categories of workers or, in the case of wage grids, they correspond to the lower limits of the wage classes.	The percentage of adjustment agreed in each CA is weighted by the number of employees subject to the CA.
United States	Wage with or without lump sums	Employee-weighted averages of first-year wage increases based on union contracts ratified in a particular quarter. Prior to 2016, averages are based on the date of each contact was added to the database. Since 2016, averages are based on each contract's ratification date.

Annex Figure 1.C.2. Negotiated wages in selected OECD countries, in real terms

Year-on-year percentage change in negotiated wages (i.e. resulting from collective agreements), Q1 2018 to Q1 2023





Note: International comparability of data on negotiated wages is affected by differences in definitions and measurement. For further details, see Annex Table 1.C.3. and Annex Table 1.C.4.

Statistics are representative of all employees covered by a collective wage agreement for Austria, Belgium, the Euro Area (19), Finland, France, Germany, Italy, the Netherlands and Sweden. In Canada, statistics refer to collective bargaining settlements of all bargaining units covering 500 or more employees (units of 100 or more employees for the Federal Jurisdiction). For Australia, Canada and the United States, statistics refer only to employees affected by an increase of the negotiated wage at date. Wage increases in Austria, Belgium, the Euro Area (19), Finland, Germany, Italy, the Netherlands and Sweden refers to the average increase in negotiated wages weighted by the employment composition for a reference year (Laspeyres index). The reference year of the employment composition used is 2005 for Finland, 2009 for Sweden, 2010 for Belgium and the Netherlands, January 2015 for the Euro Area, 2015 for Germany and Italy, and 2016 for Austria. For Australia, Canada, France and the United States, wage increase refers to the average increase in negotiated wages weighted by the number of employees affected of the period considered. Private sector in Germany refer to all industries excluding agriculture, public administration, education, health, and other personal services (Sections B to N of the NACE rev. 2.).

Source: OECD calculations based on national data on negotiated wages and OECD (2023), "Prices: Consumer prices", Main Economic Indicators (database), <https://doi.org/10.1787/0f2e8000-en> (accessed on 4 July 2023).

StatLink <https://stat.link/sheamz>

Notes

¹ Results not reported here show that the increase in inactivity in these countries are even larger when assessed against the linear trend extrapolated from 5 or 10 years of quarterly data before the COVID-19 crisis. While informative, however, such an exercise rests on the strong assumption that pre-crisis trends would have continued in the absence of the COVID-19 crisis, which might not have been the case in all countries given the cyclical nature of participation rates. For example, participation in the United States and the United Kingdom was expected to decline in pre-pandemic projections (Hobijn and Şahin, 2022^[56]; Lee, Park and Shin, 2023^[57]).

² Data on vacancies registered at the Japanese public employment service (Hello Work) suggest that labour market tightness did not increase significantly in Japan (https://www.mhlw.go.jp/stf/newpage_33806.html).

³ <https://www.mbie.govt.nz/business-and-employment/employment-and-skills/labour-market-reports-data-and-analysis/monthly-labour-market-fact-sheet/>.

⁴ <https://fred.stlouisfed.org/series/JTSQR>.

⁵ <https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/labourforcesurveyflowsestimatesx02>.

⁶ <https://www.abs.gov.au/statistics/labour/employment-and-unemployment/job-vacancies-australia/latest-release>.

⁷ The analysis of job posting data presented in this section was conducted by Diego Eslava and Fabio Manca.

⁸ This analysis leverages text included in nearly 8 million online job postings collected by Lightcast in Canada, the United Kingdom and the United States. As the analysis is very computationally intensive, it has been restricted to these three countries due to resource constraints.

⁹ It is also possible that the results reported in this section reflect an increase in mere *mentions* of benefits that were already offered rather than an increase in the proportion of jobs offering such benefits. This could also be driven by the tightening of labour markets, making employers more likely to highlight specific aspects of their employment package that might attract applicants. However, the evidence presented in the rest of the section on temporary contracts and involuntary part-time (along with the wage dynamics discussed later in the chapter) do suggest that workers have seen an appreciable improvement in at least some aspects of their working conditions in recent times.

¹⁰ See OECD (2018^[60]) for a discussion of the evidence that temporary contracts are associated on average with worse working conditions.

¹¹ Data on the share of new hires in involuntary part-time are only available from Eurostat from Q1 2021.

¹² This section draws on OECD (2023^[2]).

¹³ The share of items in consumer price baskets that have had annual price rises of more than 5% for at least 12 months has gone from near zero at the beginning of 2021 to around a quarter on average by April 2023, and to a third or more in Germany and the United Kingdom (OECD, 2023^[2]).

¹⁴ For example, in the Euro Area the difference between the effective inflation rate in the lowest and highest income quintiles in September 2022 was at its highest level since 2006 (Charalampakis et al., 2022^[21]). Similarly, in the United Kingdom, the difference between the inflation rate for low- and high-income households stood at 1.4 percentage points in October 2022 – the largest value since March 2009. New Zealand and the United States appear exceptions to this pattern, with evidence suggesting higher effective inflation rates for mid- or high-income households in recent times. See <https://www.bls.gov/spotlight/2022/inflation-experiences-for-lower-and-higher-income-households/home.htm> and <https://www.stats.govt.nz/information-releases/household-living-costs-price-indexes-december-2022-quarter/>. Causa et al. (2022^[20]) estimate compensating variations (CV) for a number of OECD countries and find that inflation weighs relatively more on low than high-income households, but with marked differences across countries irrespective of differences in inflation – see Causa et al. (2022^[20]) for details.

¹⁵ Consistent with this hypothesis, in the United States the inflation differential between low- and high-income households is more positive when accounting for frequent adjustments in consumer's behaviour in response to price changes, See <https://www.bls.gov/spotlight/2022/inflation-experiences-for-lower-and-higher-income-households/home.htm>.

¹⁶ The German Council of Economic Experts (2022^[22]) estimates that households in the bottom income decile lost 8.3% of their net disposable income because of the price increases – while those in the top decile only 3.7%. This difference is much larger than that between the inflation rates faced by the two types of households (10.5% and 9.2% respectively).

¹⁷ Most of the data reported in Figure 1.15 refer to the “wages and salaries” component of the Labour Cost Index which measures the evolution of aggregate wages for a constant industry structure. Therefore, these results are not driven by compositional changes across industries but can be influenced by those occurring within industries. See notes to Figure 1.15 for the details on the countries for which different wage measures have been used.

¹⁸ Real wage growth is calculated in Figure 1.15 by subtracting consumer price index (CPI) inflation (all items) from nominal wage growth. This is a common and intuitive approach which, however, will tend to produce larger estimates of changes in real wages than computing changes in nominal wages deflated by CPI, when the difference between inflation and nominal wage growth is large. Computing changes in nominal wages deflated by CPI gives an average real wage growth across the OECD countries included in Figure 1.15 of -3.4%. The Spearman rank correlation index across the cross-country distributions of real wage growth calculated with the two methods is always greater than 0.99.

¹⁹ The wage measures used in this analysis are the only ones available in a timely manner for a significant number of countries but suffer from some limitations. They are typically obtained by dividing a measure of total compensation paid by employers by the total number of hours worked by employees. The main issue is that the use of job retention schemes typically causes total hours to fall more than total compensation, leading to an artificial increase in the measure of hourly compensation. Clearly, this does not correspond to an actual increase in the earnings of employees which typically fall when they are placed on job retention schemes. This issue causes variations in the growth rate of wage measures that can be persistent over time due to base effects which become less important over time as the use of job retention schemes returns to very low levels. While these effects should be relatively minor for Q1 2023, their presence cannot be

ruled out entirely. For this reason, the chapter complements evidence on year-on-year changes in wage with that on changes relative to a pre-crisis reference point that is not affected by these base effects. For a more detailed discussion, see for example Bodnár and Le Roux (2022^[64]).

²⁰ Cumulative changes refer to the difference between Q4 2019 and Q4 2022 to account for seasonality effects. Q1 2020 is not desirable as a reference point for Q1 2023 because wage measures in early 2020 are already distorted by the widespread use of job retention schemes in response to the COVID-19 crisis.

²¹ The analysis of this section uses official inflation rates based on changes in the CPI for all industries.

²² These descriptive results do not necessarily reflect a causal relationship and are derived from a simple regression of wage changes at the industry level on changes in vacancy rates at the industry level, dummies for groups of industries by pay levels, country dummies, and calendar quarter dummies. Each industry is weighted by the average share of employees across countries in the sample. Standard errors are clustered at the industry-country level. The extension of the exercise allows for an interaction of the change in vacancy rate with the dummies for the groups of industries by pay levels. The estimates of the differential in pay growth across groups of industries are generally unaffected by the inclusion of these additional controls. To account for the possible role of changes in minimum wages, a different specification regresses changes in wages at the industry level on changes in national minimum wages interacted with the dummies for groups of industries by pay levels (and a dummy is included for countries without a statutory minimum wage). The countries included are Austria, Belgium, Canada, Denmark, Hungary, Ireland, Italy, Japan, Luxembourg, Latvia, the Netherlands, Norway, the Slovak Republic, Slovenia, the United Kingdom and the United States. The industries included are: Trade, Accommodation & food service, Administrative & support service, Arts & entertainment for low-pay industries; Manufacturing, Construction, Transportation & storage, Real estate, Other service for middle-pay industries; Information & communication, Finance & insurance, Professional activities, Education, Health & social work for high-pay industries.

²³ <https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/distributionofgrosshourlyearningsofemployeesearn08>.

²⁴ Using the income approach, nominal GDP can be decomposed as $PY = NCE + GOS + TAXN$ where P is the GDP deflator, Y is real GDP, NCE is nominal compensation of employees, GOS is gross operating surplus, and $TAXN$ is nominal taxes less subsidies on production and imports. This illustrates also the interpretation of GOS as profit margin, i.e. the difference between total revenue and total costs (labour costs, which are part of value added, and intermediate inputs, which are not part of total value added). From this, the GDP deflator P can be expressed as the sum of these three components per unit of real output (i.e. unit labour cost, unit profits and unit taxes less subsidies) or $P = ULC + UP + UT$. This implies that changes in the GDP deflator – which capture changes in domestic prices – can be decomposed into the changes of the three components (see Box 1.5).

²⁵ The anti-cyclical behaviour of the labour share of income is well documented in the literature (OECD, 2012^[53]; ILO/OECD, 2015^[65]), but its pronounced decline in the recovery from the COVID-19 crisis appears particularly robust.

²⁶ For a formal description of the equivalence between real unit labour costs and the labour share of income see (Australian Bureau of Statistics, 2021^[58]). Based on the equation reported in note 24, if changes in unit taxes less subsidies are negligible, larger increases in unit profits than in unit labour costs imply that producer prices per unit of output increase more than unit labour costs. In turn, this implies a reduction in

real unit labour cost defined as unit labour cost deflated by the GDP deflator. Real unit labour costs can increase even when unit profits increase more than unit labour cost in the presence of relatively large changes in unit tax less subsidies.

²⁷ The increase in profit margins (i.e. the difference between revenue and all production costs) likely reflects the presence of market power which allows firms to raise prices over and above the increase in the marginal cost of labour and other inputs. However, the increase in profit margins does not necessarily imply an *increase* in the market-power of firms – as captured by the percentage mark-up of prices over the marginal cost (Colonna, Torrini and Viviano, 2023^[62]). In fact, profit margins can increase even if mark-ups are constant or decreasing when input costs increase quickly. Colonna, Torrini and Viviano (2023^[62]) find that mark-ups have indeed increased in several non-tradable sectors in Germany and the United States, whereas in Italy they have returned to pre-crisis levels after a contraction during the initial stage of the COVID-19 crisis. Hansen et al. (2023^[31]) present a range of indicators for the Euro Area that paint a picture of “resilient but perhaps not (sharply) increasing profitability” In general, therefore, the presence of market power has enabled firms to maintain or increase profit margins. More strikingly, in some cases – and notably in several sectors of the two of the largest OECD economies – the increase in profit margins even appears to reflect an increase in market power.

²⁸ This observation points to the importance of enhancing competition in non-tradable sectors. For an in-depth treatment of these issues, see <https://www.oecd.org/economy/reform/indicators-of-product-market-regulation/>.

²⁹ Fringe benefits are in-kind benefits offered to employees, which in Italy also include healthcare assistance, insurance policies, loan provisions, and provided accommodations.

³⁰ In the eight OECD countries without a statutory minimum (Austria, Denmark, Finland, Iceland, Italy, Norway, Sweden and Switzerland), sector- or occupation-levels collective agreements include de facto wage floors for large parts of the workforce. Yet in Switzerland, five cantons (e.g. local administrative areas such as Geneva and Ticino) have also introduced a statutory canton-wide minimum wage.

³¹ The section on minimum wages builds on and expands the policy brief “Minimum wages in times of rising inflation” published in December 2022 (OECD, 2022^[63]).

³² This renewed attention also echoes an increasing consensus among policy makers and academics that, at the level set in most OECD countries, minimum wage increases (even large ones) have had a positive effects on earnings at the bottom of the earning distribution but no or limited negative effects on employment – see Dube (2019^[55]) for a comprehensive review of the recent evidence. Moreover, the increasing body of evidence across OECD countries on monopsony power, i.e. firms’ power to set wages unilaterally leading to inefficiently low levels of employment and wages, has reinforced the arguments for raising the minimum wage where it is too low, or introducing one where it does not exist, in particular when workers are not already covered by effective collective bargaining (OECD, 2022^[54]).

³³ In France the formula also adds half of past increases in real wages among blue collar workers.

³⁴ In Belgium and Luxembourg, the indexation mechanism is the same as the one for general wages.

³⁵ Currently, 13 states and the District of Columbia index state minimum wages to a measure of inflation. In addition, another 6 states are scheduled in a future year to index state minimum wage rates to a measure of inflation (Congressional Research Service, 2023^[66]).

³⁶ However, in Luxembourg, the second increase in 2022 was postponed on the basis of a tripartite agreement.

³⁷ This one-off increase was decided by the parliament before the sudden increase in prices and marked a departure from the uprating mechanism in place since 2015 whereby decisions on adjustments to the level of the minimum wage are made every two years by the Minimum Wage Commission (composed by workers' and employers' representative with academic experts in a consulting role).

³⁸ However, even in a country like France, the increases have not led to a price-wage spiral and are considered by the French central bank as compatible with a gradual decline in inflation in 2023 and a return towards the 2% target by end-2024 to end-2025 (Baudry, Gautier and Tarrieu, 2023^[61]).

³⁹ Clemens and Strain (2022^[59]) find lower non-compliance in US states where the minimum wage is indexed.

⁴⁰ In October 2022, the collective agreement in the German chemical sector was renewed with a 3.25% wage increase for both 2023 and 2024 and the confirmation of the tax-free one-off payments of EUR 1 500.

⁴¹ In Italy, around 40% of private sector employees are currently covered by a collective agreement that has expired by, on average, 31 months.

⁴² According to the ECB, around 18% of private-sector employees in the Euro Area covered by an agreement indexed to inflation (Koester and Wittekopf, 2022^[38]).

⁴³ The forecast of the harmonised consumer price index (HICP) net of imported energy goods for a four-year horizon is published by the national statistical office every year in June.

⁴⁴ The inflation reference rate used in collective agreements tends to be the year-on-year rate at the end of each year, although in some cases average year-on-year rates for the year as a whole are used.

⁴⁵ What matters for inflation is not wage growth per se, but wage growth over and above productivity growth. For instance, a 3% wage growth is compatible with a 2% inflation target if productivity grows by 1%.

2

Artificial intelligence and the labour market: Introduction

Stijn Broecke

Progress in Artificial Intelligence (AI) has been such that, in some areas, its output has become indistinguishable from that of humans. These rapid developments, combined with the falling costs of producing and adopting these new technologies, suggest that OECD economies may be on the cusp of an AI revolution which could fundamentally change the workplace. While there are many potential benefits from AI, there are also significant risks that need to be urgently addressed. Policies and social dialogue can play a key role in mitigating these risks while not stifling the benefits. However, this requires better evidence, and this edition of the *OECD Employment Outlook* contributes to this goal.

We need to talk about the future of work (again...)

In 2019, the OECD's *Employment Outlook* focused on the future of work and explored how various megatrends such as digitalisation, globalisation, and population ageing were reshaping the world of work. The overall message was one of cautious optimism: many of the megatrends appeared to bring new opportunities for improving labour market outcomes and mass technological unemployment seemed unlikely. Indeed, at the end of 2019, prior to the COVID-19 crisis, employment rates in most OECD countries were at record highs, despite the adoption of automating technologies. While some risks regarding job quality and inclusiveness were identified, most notably for low- and medium-skilled workers, the OECD argued that, with the right policies and institutions in place, the risks could be mitigated and the opportunities seized (OECD, 2019^[1]).

Just four years later, the OECD is dedicating yet another volume of the *Employment Outlook* to the future of work and, more specifically, to the impact of artificial intelligence (AI) on the labour market. The OECD defines AI as:¹

“A machine-based system that is capable of influencing the environment by producing an output (predictions, recommendations or decisions) for a given set of objectives. It uses machine and/or human-based data and inputs to: (i) perceive real and/or virtual environments; (ii) abstract these perceptions into models through analysis in an automated manner (e.g. with machine learning), or manually; and (iii) use model inference to formulate options for outcomes. AI systems are designed to operate with varying levels of autonomy.”

The justification for another *Employment Outlook* on the future of work lies in the astonishing progress that AI has made to a point that, in some areas, it has become difficult if not impossible to distinguish its output from that of humans. This raises urgent and important questions about the future of work. As an example, consider the following two paragraphs about the impact of AI on workers, one of which was written by AI, the other by a human:

- i. *AI has the potential to transform our society and the way we work, just as innovations such as the computer and the internet have in recent decades. With its ability to analyse large amounts of data, perceive the world around it and generate text, AI will be a useful tool for some workers while displacing others. Although economists generally do not believe that AI will lead to the end of work, they do raise concerns about the impact of AI on wages and employment, the potential for AI to deepen inequalities, and whether the right kinds of AI are being developed and deployed.*
- ii. *The impact of AI on workers is likely to be both positive and negative. On the positive side, AI can automate repetitive tasks, which can increase efficiency and productivity, and free up workers to focus on more creative and higher-level tasks. This can lead to new job opportunities and higher wages for workers with the necessary skills to take advantage of the new technologies. On the negative side, AI can also lead to job displacement as machines and algorithms take over tasks that were previously performed by humans. This could lead to a decline in wages and employment opportunities for certain types of workers.*

The second of these paragraphs was written by AI and, more specifically, by Chat Generative Pre-Trained Transformer (more commonly known by its acronym: ChatGPT) – a large language model (LLM) trained on vast amounts of data from the internet to produce text that sounds human-like. While it may have been possible to spot the AI-generated output (e.g. because it is more formulaic or impersonal than the human text) there is no question about its capabilities and the implications for a range of real life situations, including at work, are immediately apparent. In fact, since ChatGPT was launched in November 2022, various potential applications of large language models to the work environment have emerged – from co-authoring scientific papers (Stokel-Walker, 2023^[2]) to passing graduate-level exams in law and business (Murphy Kelly, 2023^[3]), assisting in clinical decision-making (Science Media Centre, 2023^[4]) and helping to make court decisions (Jamal, 2023^[5]).

Even before the advent of large language models like ChatGPT, high-profile examples of rapid AI progress had received significant attention. While recent advances in generative AI have been mind-boggling (including also in image,² voice and even video generation), AI has made equally impressive progress in many other domains, including: computer vision (e.g. image classification and labelling), reasoning, solving problems, playing games, as well as reading comprehension and learning. AI can already answer 80% of the literacy questions of the OECD Survey of Adult Skills of the Programme for International Assessment of Adult Competencies (PIAAC), and two-thirds of the numeracy questions (OECD, 2023^[6]). Even more astonishing is the short time span in which this progress has been made. Just six years ago, the biggest AI news story was that it had defeated the world champion at Go, a relatively simple game that follows a clear set of rules (BBC, 2017^[7]). Today, AI is capable of beating humans at Diplomacy, a strategy board game that requires persuasion, co-operation and negotiation (Hsu, 2022^[8]). Experts believe that AI will be able to solve the entire PIAAC literacy and numeracy tests by 2026 (OECD, 2023^[6]).

However, there are still limitations to what AI can do. While the progress in AI has been impressive, there are still many things it cannot do – so-called “bottleneck skills” like complex problem-solving, high-level management and social interaction (Lassébie and Quintini, 2022^[9]). Also, despite the hype, AI still frequently makes headlines for the wrong reasons, such as: driverless car crashes (Laing, 2023^[10]) racist image recognition software (Kayser-Bril, 2020^[11]), biased recruitment tools (Dastin, 2018^[12]) and chatbot blunders (Laing, 2023^[10]). ChatGPT has been accused of bias (Jain, 2023^[13]), hallucinations (Smith, 2023^[14]) and copyright infringements (McKendrick, 2022^[15]), amongst others. These limitations point to some of the risks of using AI tools, particularly without human oversight.

For better or for worse, AI is already making its way into the workplace

Despite the limitations and risks, AI is beginning to make its way into the workplace. In 2022, through new surveys and case studies, the OECD gathered data on the impact of AI on workers and the workplace in the manufacturing and finance sectors of eight OECD countries.³ The research, which pre-dates some of the latest developments in generative AI, collected many interesting examples of AI use in the workplace, including: an image recognition technology that identifies spare auto parts from photos uploaded by customers; a production tracking and monitoring system that uses a computer vision system to locate tools and bring them to the correct place in the factory at the right time; and a natural language processing tool that assists maintenance workers in troubleshooting the root causes of machine breakdowns by querying a database of past service issues and their resolutions.

While the adoption of AI still remains relatively low, rapid progress, falling costs and the increasing availability of workers with AI skills indicate that OECD economies might be on the brink of an AI revolution. The available data suggest that the share of firms that have adopted AI remains in the single digits, although large firms are more likely to have done so (approximately one in three) (Lane, Williams and Broecke, 2023^[16]). Cost was the greatest barrier to AI adoption: it was cited by more than half of the finance and manufacturing firms the OECD surveyed in 2022 about AI use in the workplace (Lane, Williams and Broecke, 2023^[16]).⁴ The second biggest barrier identified was a lack of skills to adopt AI (see also Chapter 5). These findings align closely with those of other surveys – e.g. IBM (2022^[17]). Yet the cost of AI technologies is rapidly declining. For example, since 2018, the cost to train an image classification system has decreased by 63.6% (Zhang et al., 2022^[18]) and, as AI enters the public domain, the rate at which these costs fall may be expected to accelerate. Generative AI applications such as ChatGPT are becoming increasingly available at a low monthly fee or even for free. At the same time, the availability of workers with suitable skills is growing. OECD research suggests that the AI workforce has more than tripled between 2012 and 2019 (Green and Lamby, 2023^[19]). Combined with the fact that AI is a general-purpose technology – i.e. a technology that can affect an entire economy – the indication is that AI may soon permeate workplaces, affecting all sectors and occupations.

A key motivation for employers to adopt AI is to boost productivity, and workers may gain as well. As an automating technology, AI carries the promise of cost savings and productivity gains, helping employers gain a competitive advantage. Indeed, one works council member at a manufacturer of automotive parts told the OECD of the importance of AI adoption in his industry as follows: “If a company does not adopt new technologies, then sooner or later it will no longer be able to continue to exist” (Milanez, 2023^[20]). AI can also help companies improve product or service quality. At the same time, workers may benefit through improvements in job quality, worker well-being and job satisfaction. Indeed, AI has the potential to eliminate dangerous or tedious tasks and create more complex and interesting ones instead. It can boost worker engagement, give workers greater autonomy, and even improve their mental health. Some workers may also benefit from higher wages (Chapter 4).

While there are potential benefits, there are also significant risks, including for employment. Firms do not hide the fact that one of their main motivations to invest in AI is to improve worker performance (i.e. productivity) and reduce staff costs (Lane, Williams and Broecke, 2023^[16]). It is not surprising, therefore, that about 20% of workers in finance and manufacturing (across seven OECD countries) said that they were very or extremely worried about job loss in the next ten years (Lane, Williams and Broecke, 2023^[16]). A key distinction between AI and previous technologies is that AI is capable of automating non-routine tasks. As such, AI has made most progress in areas like information ordering, memorisation, perceptual speed, and deductive reasoning – all of which are related to non-routine, cognitive tasks (see Chapter 3). As a result, high-skilled occupations have been most exposed to recent advances in AI, including: business professionals; managers; science and engineering professionals; and legal, social and cultural professionals. This extends the potential scope of automation considerably beyond what had previously been possible.⁵ While to date there is little evidence of negative employment effects due to AI (Chapter 3), this may be because AI adoption is still relatively low and/or because firms prefer to rely on voluntary quits and retirement to make workforce adjustments. Any negative employment effects of AI may therefore take time to materialise. Moreover, the risks of automation are not equally spread across socio-demographic groups, which could harm inclusiveness. While the impact of the latest wave of generative AI is not entirely clear yet, early estimates of occupational AI exposure that take into account the capabilities of large language models like ChatGPT reach conclusions similar to those of previous estimates of AI exposure: it is primarily high-pay occupations requiring higher than average education or training that are most exposed to AI.

There are also risks to job quality and AI raises a number of ethical questions. Although AI has the potential to improve certain aspects of job quality, there are also reports that AI can heighten work intensity and increase stress (Chapter 4). In addition, the use of AI in the workplace opens up, or amplifies, a whole set of ethical issues (Chapter 6), some of which can also negatively impact on job quality. For example, AI can change the way work is monitored or managed, which can increase perceived fairness, but poses risks to workers’ privacy and autonomy to execute tasks. AI can also introduce or perpetuate bias. In addition, there are concerns around transparency and explainability, as well as around accountability. While many of these issues are not new, AI has the potential to amplify them. For example, even though human beings can be biased when making hiring decisions, the adverse impact of AI could be far greater by virtue of the volume and velocity of the decisions it takes, which could systematise and multiply bias. Once again, these risks tend to be greater for some socio-demographic groups who are often disadvantaged in the labour market already.

The time to act is now

While there is much uncertainty about the impact AI will have on labour markets, there is a need to avoid technological determinism. A key message of the *OECD Employment Outlook 2019* was that “The future of work will largely depend on the policy decisions countries make.” This message is also one

brought by prominent labour economists like David Autor who argue that “As we ponder our uncertain AI future, our goal should not merely be to predict that future, but to create it.” (Autor, 2022^[21]).

There is urgent need for policy action to ensure that AI is developed and used in a trustworthy way. This means that AI must be safe and respectful of fundamental rights such as privacy and fairness, the right of labour to organise, transparency and explainability. It also means that it must be clear who is accountable in case something goes wrong. Proactive and decisive action is not only important to protect workers, but also to promote AI innovation and diffusion because it reduces uncertainty. Principles like those developed by the OECD can help promote the use of AI that is innovative and trustworthy and that respects human rights and democratic values (OECD, 2019^[22]). As an OECD legal instrument, the OECD AI principles represent a common aspiration for its adhering countries and were adopted in May 2019. Since then, other countries, including Argentina, Brazil, Egypt, Malta, Peru, Romania, Singapore and Ukraine have adhered to the principles and, in June 2019, the G20 adopted human-centred AI Principles that draw from the OECD AI Principles. In addition, many firms, sectors and industries have adopted their own AI principles.

Some countries are adapting, strengthening and/or enforcing legislation. While guidelines can be more timely and adaptable in response to a changing landscape, legislation is more enforceable. In most countries, existing non-AI-specific legislation already provides a foundation for addressing several concerns about the use of AI in the workplace, for example legislation on data protection, discrimination, and consumer protection (see Chapter 6). Making sure that such legislation is up to date and reflects the new realities and challenges brought by AI will be important. In addition, many countries are considering AI-specific legislation, such as the AI Act in the European Union and the Algorithmic Accountability Act in the United States. The latest generative AI developments seem to have rekindled action in this area. The success of these measures will depend as much on their formulation as on their implementation. Measures that could facilitate implementation include technical standards and oversight mechanisms such as regulatory bodies or independent auditing. Additionally, guidance for AI developers and employers to understand and comply with the legislation, as well as engagement with stakeholders, can foster a shared understanding of the goals and requirements of the legislation. A multifaceted approach that combines these measures may be necessary to ensure effective implementation.

Collective bargaining and social dialogue have an important role to play in supporting workers and businesses in the AI transition. They can facilitate AI adoption and use in the workplace, as well as shape and implement rights to address AI-related issues in a flexible and pragmatic manner while promoting fairness. Collective bargaining can also complement public policies in enhancing workers’ security and adaptability. In the insurance and telecommunication sector, for instance, European social partners have signed two framework agreements on AI that addressed transparency in data use and protection against bias and discrimination. More recently, social partners have started engaging in “algorithm negotiations”, but only a few AI-related agreements have been signed to this date. Yet, social dialogue and collective bargaining are facing a number of challenges: the number of workers who are members of unions and are covered by collective agreements has declined in many OECD countries. In addition, the specific characteristics of AI and the way it is implemented – such as its rapid speed of diffusion, its ability to learn and the greater power imbalance it can create – add further pressure on labour relations. While AI technologies have the potential to assist social partners to pursue their goals and strategies, the lack of AI-related expertise among social partners is a major challenge (Chapter 7).

Training will be important for workers to successfully navigate the transition. The impact of AI on tasks and jobs will engender changing skills needs. On the one hand, AI will replicate some skills, like manual and fine psychomotor abilities, and cognitive skills such as comprehension, planning and advising. On the other hand, skills needed to develop and maintain AI systems, and those to adopt, use and interact with AI applications, will become more important. The demand for basic digital skills, data science and other cognitive and transversal skills will also increase. While companies using AI say they provide training for AI, a lack of skills remains a major barrier to adoption, suggesting more could be done. Public policies

will therefore have an important role to play, not only to incentivise employer training, but also because a significant proportion of training for the development and adoption of AI takes place in formal education. AI itself may present opportunities to improve the design, targeting and delivery of training, but several risks exist and challenges must be addressed (Chapter 5).

Policy should be evidence-based, yet little is currently known about the impact of AI on workers, the workplace, and the labour market more generally. The current edition of the *OECD Employment Outlook* seeks to address this gap and the chapters that follow provide policy makers with the current state of knowledge about the impact of AI on job quantity (Chapter 3) and quality (Chapter 4), as well as the implications for three key policy areas: skill policy (Chapter 5), the ethical challenges posed by AI (Chapter 6), and the role of social dialogue and collective bargaining in supporting the AI transition (Chapter 7). These chapters draw on the OECD's own work in these areas over the past few years, as well as on other available evidence.⁶

While this *Employment Outlook* is a step towards more evidence-based policy making on AI, there are still many unknowns. The challenge for research is similar to that facing policy makers: the exponential speed of AI development and its growing pervasiveness imply that one is constantly running after the facts. In addition to keeping tabs on the labour market impact of some of the latest AI technologies (e.g. generative AI), some key areas for future research include: the impact of AI on inclusiveness and labour market concentration; its role in the delivery of public services; how it will change management practices; and the governance processes and structures required for the trustworthy adoption of AI in the workplace, amongst others. The OECD will continue to work on these as well as other related topics in years to come. In doing so, it will be important to continue to gather new and better data on AI adoption and its use.

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Notes

¹ <https://oecd.ai/en/ai-principles>.

² In 2022, AI astonished the world with its image creation abilities (e.g. DALL-E 2 and Stable Diffusion) which are now so good that it can fool humans and win art competitions, such as the Colorado State Fair's digital art competition (Gault, 2022^[23]).

³ The United States, Canada, Germany, Austria, the United Kingdom, Ireland, France and Japan (Lane, Williams and Broecke, 2023^[16]; Milanez, 2023^[20]). Note however that the results of these studies do not necessarily generalise to other sectors. Also, as in all cross-sectional studies, caution should be exerted in interpreting the results insofar as they may be partially affected by selectivity bias as only workers who remain in the firm after AI adoption are surveyed.

⁴ Although the survey did not go into further detail about the various types of costs, these might include: the cost of acquiring the technology but also the data processing capabilities required to run the tools.

⁵ Some have raised concern that the latest wave of generative AI may expand the range of occupations at risk of automation even further. Several occupation groups have voiced concern about the most recent wave of generative AI. In February 2023, animators were up in arms when an animation studio used AI

generative software to create background images for a new film, threatening many jobs in the industry (Harris, 2023^[27]). Voice actors (O'Connor, 2022^[24]) and writers (Brodsky, 2022^[25]) are equally worried about what AI might mean for their jobs, and lawyers are another profession where AI is expected to replace a considerable share of human work (Hirani, 2023^[26]).

⁶ The OECD's work on Artificial Intelligence in Work, Innovation, Productivity and Skills (AI-WIPS) has been generously supported by the German Federal Ministry of Labour and Social Affairs (BMAS), with support also from Austria's Federal Ministry of Labour, Social Affairs and Consumer Protection; the department for Employment and Social Development Canada; Ireland's Department of Enterprise, Trade and Employment, the U.S. Department of Labor; the UK Economic and Social Research Council; ESSEC Business School, and the Japan Institute for Labour Policy and Training.

3

Artificial intelligence and jobs: No signs of slowing labour demand (yet)

Andrew Green

Artificial Intelligence (AI) is the latest technology to stoke fears of rapid automation and job loss. This chapter reviews the current empirical literature on the employment effects of AI to date. It begins with a discussion of the progress in AI's capabilities and what that implies for the tasks, occupations and jobs most exposed to these advances. An overview is then given of the findings of recent studies of the effect of AI on employment including econometric studies, as well as surveys and case studies of firms and workers. The chapter concludes by discussing policies that can minimise the possible displacement effects of AI while enhancing economic growth.

In Brief

Key findings

Artificial intelligence (AI) is the current technological innovation sparking hopes of rapid productivity gains and stirring fears of job loss. Using a fast-evolving suite of algorithms and statistical models – in particular, machine learning – increasingly available big data and falling costs of compute capacity, AI has made rapid advances in its ability to supply answers to problems where formal rules are impossible to codify, and where humans have until recently had a comparative advantage in inferring decisions from their training or past experiences.

AI's improving ability to complete these non-routine tasks raises new worries of job displacement for occupations previously thought impervious to automation. Occupations in finance, medicine and legal activities which often require many years of education, and whose core functions rely on accumulated experience to reach decisions, may suddenly find themselves at risk of automation from AI.

This chapter explores whether such fears are grounded in the empirical evidence that has accumulated so far. To do this, it analyses the emerging empirical literature on the effect of AI on labour demand in general, and on the occupations most exposed to advances in AI. Caution is however required in drawing conclusions from these stylised facts since this evidence does not account for the impact of recent advances in large language models and generative AI generally, whose potential impacts are difficult to quantify. The key findings are:

- Theoretically, the net impact of AI on employment is ambiguous. AI will displace some human labour (displacement effect), but it can also raise labour demand because of the greater productivity it brings (productivity effect). AI can also create new tasks, resulting in the creation of new jobs (reinstatement effect) particularly for workers with skills that are complementary to AI.
- Measures of AI exposure, which are used in this chapter to evaluate the degree of overlap between tasks performed in a job and those which AI is theoretically capable of performing, show that AI has made the most progress in its ability to perform non-routine, cognitive tasks, such as information ordering, memorisation and perceptual speed. These are often key abilities demanded in occupations that usually require several years of formal training and/or tertiary education. These measures pre-date the recent advances in generative AI applications (ChatGPT, for example), and one should therefore interpret them with caution: both the occupational range and extent of AI exposure might rapidly become larger as generative AI use is increasingly incorporated into production processes and new, more powerful AI systems are developed.
- High-skilled occupations are those most likely to involve non-routine cognitive tasks, and they have therefore been the most exposed to progress in AI. Examples of such occupations include business professionals, managers, chief executives and science and engineering professionals.
- So far, there is little evidence of significant negative employment effects due to AI. Empirical studies using cross-country variation in AI exposure, or studies using within-country variation by local labour markets, do not find any statistically significant decrease in employment. Similarly, recent surveys of workers and firms, or case studies of firms adopting AI, find few employment changes. However, AI is evolving rapidly, and advances in generative AI may disprove some of the evidence accumulated so far.

- Despite their higher exposure to AI, high-skilled workers have seen employment gains relative to lower-skilled workers over the past ten years. This may be because AI creates new tasks and jobs for workers who have the right skills, and this chapter does provide evidence that this reinstatement effect is prominent at this early stage of AI adoption in production activities.
- Other reasons why the impact of AI on employment may so far have been limited is that adoption rates remain relatively low or that firms are reluctant to lay off workers in the short term and instead rely on natural attrition (e.g. retirement and voluntary quits) to lower employment. Firms may also need time to implement new technologies after adoption. Any negative employment effects of AI may therefore take time to materialise. However, the latest wave of generative AI may further expand the tasks and jobs that can be automated.
- From a policy perspective, the evidence points to the need for education and training to ensure that workers have the skills to take advantage of this new technology (see also Chapter 5), and for social dialogue to effectively manage transitions and achieve a fair distribution of productivity gains (see also Chapter 7). Moreover, to minimise possible negative employment effects, countries could further enhance competition in both the product and the labour market and review their mix of labour and capital taxation to ensure that it does not incentivise labour-replacing technology adoption. Recent developments in large language models and generative AI additionally necessitate policies to prepare for potential economic and labour market disruptions (see Chapter 6).

Introduction

Advances in artificial intelligence (AI) may unsettle the established narrative on the risk of employment loss from automation. The most recent wave of AI started around 2011 when advances in machine learning, a branch of computational statistics used to make predictions from unstructured data, began to find applications in a variety of industries and settings (Agrawal, Gans and Goldfarb, 2019^[1]; OECD, 2019^[2]). Like electricity or the steam engine before it, AI can be considered a general purpose technology due to its ability to be used pervasively across many industries and to foster general productivity gains (Bresnahan and Trajtenberg, 1995^[3]; Lane and Saint-Martin, 2021^[4]). The consensus among economists and policy makers from previous rounds of automation technologies, however, is that labour demand should remain strong. Human labour complements new technologies, which gives rise to new jobs and productivity gains, and raises demand for labour overall (Autor, 2015^[5]; OECD, 2019^[6])

However, AI is different from previous automation technologies. Previous technologies automated primarily routine tasks and did not lead to reductions in labour demand overall (OECD, 2019^[7]). AI is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments (OECD, 2019^[8]). In other words, AI takes data and, (usually) using a statistical model, generates predictions, decisions or recommendations. Importantly, AI can learn from its actions, and improve its predictions and recommendations over time. Noteworthy applications include credit scoring and lending, legal assistance and medical diagnosis. Previously, it was widely believed that humans had a comparative advantage over machines in these sorts of complex tasks. AI, however, may render these tasks more amenable to automation (Agrawal, Gans and Goldfarb, 2019^[9]). Some have gone as far as to theorise that AI will have the potential to “increase [its] productivity and breadth to the extent that human labour and intelligence will become superfluous” – see Nordhaus (2021^[10]).

This chapter assesses the emerging empirical evidence for how AI may affect labour demand. During the past decade, the economics profession has revised its thinking on how technology affects labour demand.

Theories of automation take much more seriously the displacement effects of automation, and the possibility that new technologies may lead to decreased labour demand (Susskind, 2022^[11]). At the same time, advances in applications of machine learning have led to a greater overlap with abilities used in the workplace. Measures of AI exposure can be used to gauge the overlap between tasks performed in a job and tasks which AI is theoretically capable of performing, and therefore to make predictions for the occupations and jobs most affected by AI. The theory of how AI will automate and complement labour, combined with measures of AI exposure, form the basis for the empirical evidence of the employment effect of AI (Section 3.1).

Using these measures of AI exposure, the chapter discusses the emerging estimates on the effect of AI on employment. The automation of routine tasks was previously shown to decrease the share of jobs in middle-skill occupations (Autor, Levy and Murnane, 2003^[12]; OECD, 2017^[13]). AI is now expected to affect a much broader set of occupations. The chapter therefore also assesses how certain groups may be particularly vulnerable to AI exposure. The discussion analyses empirical estimates at various levels including firms, occupations and countries, but also draws on new OECD research including surveys of workers and employers, and firm-level case studies based on interviews with those tasked with implementing or managing AI within firms (Section 3.2).

Policy should be designed to mitigate the harmful effects of displacement from AI. AI will substitute for labour in certain jobs, but it will also create new jobs for which human labour has a comparative advantage. The chapter discusses policies to encourage the ways AI and human labour can complement each other, and in cases where AI must replace labour, to ensure that the policy in place amplifies the productivity effects to the largest extent possible, creating new demand for labour in jobs not substituted by AI (Section 3.3).

3.1. Artificial intelligence expands the set of jobs at risk of automation

In the last decade, AI has made impressive progress in many domains including computer vision, playing games, as well as reading comprehension and learning. These domains can be loosely viewed as grouping many non-routine, cognitive tasks which are key demands in many highly paid occupations, which typically require a post-secondary education. Even more astonishing than the capabilities is the short time span in which this progress has been made. In November 2022, OpenAI launched ChatGPT, a large language model (LLM) trained on vast amounts of data, which has obvious applications in the workplace including the ability to write text, pass exams in law or business and assist in clinical decision making (see Chapter 2). The occupational range impacted by AI might rapidly grow as generative AI use finds applications in a wider set of production processes and new, more powerful AI systems are developed.

From a theoretical perspective, **AI will automate tasks employed in production, but it will also complement labour and create new tasks**. The effect of AI on the quantity of labour demanded is therefore ambiguous. AI will displace human labour (displacement effect), but it can also raise labour demand in jobs not exposed to AI because of the greater productivity it brings (productivity effect), as well as the creation of entirely new jobs (reinstatement effect). Which of these effects dominates, and whether aggregate labour demand therefore increases, or decreases is unclear a priori. However, not all workers are exposed to AI to the same degree, and the employment of certain groups may be more affected than others. **Workers who perform a high share of non-routine cognitive tasks, such as white-collar professionals, have been the most exposed to advances in AI.**

3.1.1. Artificial intelligence will automate certain tasks, but the net impact on employment is ambiguous

The most basic building block for understanding the impact of AI on labour demand is tasks. The production of a final good or service requires the completion of a set of tasks, and groupings of tasks are what defines production in a firm, a job, or an occupation.¹ For example, a worker in a warehouse where incoming orders are received, processed and filled will be required to complete a set of tasks including reading an order, walking to the correct set of shelves and picking items. The firm operating the warehouse will employ different sets of workers and therefore encompass a wider set of tasks for production. Continuing the example, the picker may pass the completed order to a packer who is tasked with preparing a box for shipping, securely packing the items in the box, and then sealing the box with a shipping label.

Sets of tasks currently performed by human labour are at risk of automation by AI.² Workers complete tasks that have not already been automated,³ but firms are cost minimisers, and they will replace human labour with AI if it is technologically feasible and cheaper for AI to complete a task.⁴ For example, if the firm that owns the warehouse can develop or purchase AI to automatically queue and move the shelves rather than have the worker walk to each one, this will replace the task of picking by a worker and could lead to cost savings and productivity improvements.

AI can affect labour demand by automating certain tasks, complementing humans in completing existing tasks, but also creating new tasks. First, just as in the example above, developments in AI can automate tasks previously done by human labour. This results in AI replacing human labour in tasks. Second, AI may create new tasks which will require human labour. In the warehouse example, if the firm is successfully able to use AI to install moving shelves, the new technology will require monitoring, maintenance, and possibly improvements, thereby creating new tasks for workers to perform. Finally, AI may complement workers, which means that AI will uniformly improve a worker's productivity in all tasks to which they are assigned. With this last channel, AI neither replaces workers in the completion of tasks nor creates new tasks; it allows workers to perform the same tasks more efficiently.⁵ The three channels are not mutually exclusive, and all may be present at the same time.

The implications for labour demand depend on which effects dominate. The creation of new tasks should lead to increases in labour demand. In particular, the creation of new tasks results in a *reinstatement effect* that creates new jobs and leads to increasing employment. These jobs can come from anywhere, but real-world examples usually link them to the operation of the new technologies themselves (Acemoglu and Restrepo, 2018^[14]; Autor et al., 2022^[15]). For AI, these new jobs are likely to be workers with the skills to develop or maintain AI systems (see Chapter 5), but they also include new jobs for the larger set of workers who will only interact with AI applications.

The automation channel, or the replacement of tasks previously performed by human labour, is ambiguous with respect to whether it increases or decreases demand for labour. The automation channel results in a *displacement effect*, which decreases labour demand as human labour is replaced by AI. To return to the warehouse example, if workers do not need to walk to each shelf, the warehouse will probably need fewer of these workers resulting in decreased labour demand. Finally, in addition to the displacement effect, the automation channel can give rise to a *productivity effect* which can result in increases in labour demand for tasks or jobs not automated by AI such as packers and forklift operators. The productivity effect neither arises (directly) from the automation of tasks, nor the ability to perform tasks more efficiently. The productivity effect is a product of the induced demand for tasks or jobs generated from the cost savings of automation.

Whether the productivity effect dominates the displacement effect, and therefore whether automation increases or decreases labour demand, is the core question facing the future of labour and AI. The automation resulting from AI can lead to increases in labour demand if the cost savings from AI increase demand for the final good or service produced by a firm, or demand for goods produced in other firms. In

the warehouse example, if the decrease in labour demand for pickers decreases costs enough so the firm can reduce prices sufficiently to raise demand for their services, this may result in the firm hiring more packers and forklift operators. It may also result in the firm increasing demand for other goods and services produced outside the firm thereby contributing to greater labour demand.⁶ This productivity effect needs to be sufficiently large so that increases in employment for workers not exposed to AI more than offset the workers displaced by AI (Acemoglu et al., 2022^[16]). Finally, the productivity effect depends on the share of the cost savings from AI that are passed along to customers in the form of lower prices and the elasticity of demand for the final product.⁷

To summarise, there are two key questions concerning the effect of AI on aggregate employment. Broadly, is AI increasing or decreasing labour demand in the aggregate with all channels (productivity, displacement and reinstatement) included?⁸ More narrowly, when tasks are automated with AI, which effect is dominant: the productivity or displacement effect?⁹ Although the first question is often the first order point of concern, policy makers should pay careful attention to which effect is driving the results. The effects that are dominating point to which groups' employment prospects may be most harmed by AI and suggest specific points where policy makers may wish to intervene to ensure that the cost savings from AI do not result in lower demand for labour (see Section 3.3 for a discussion of policies).

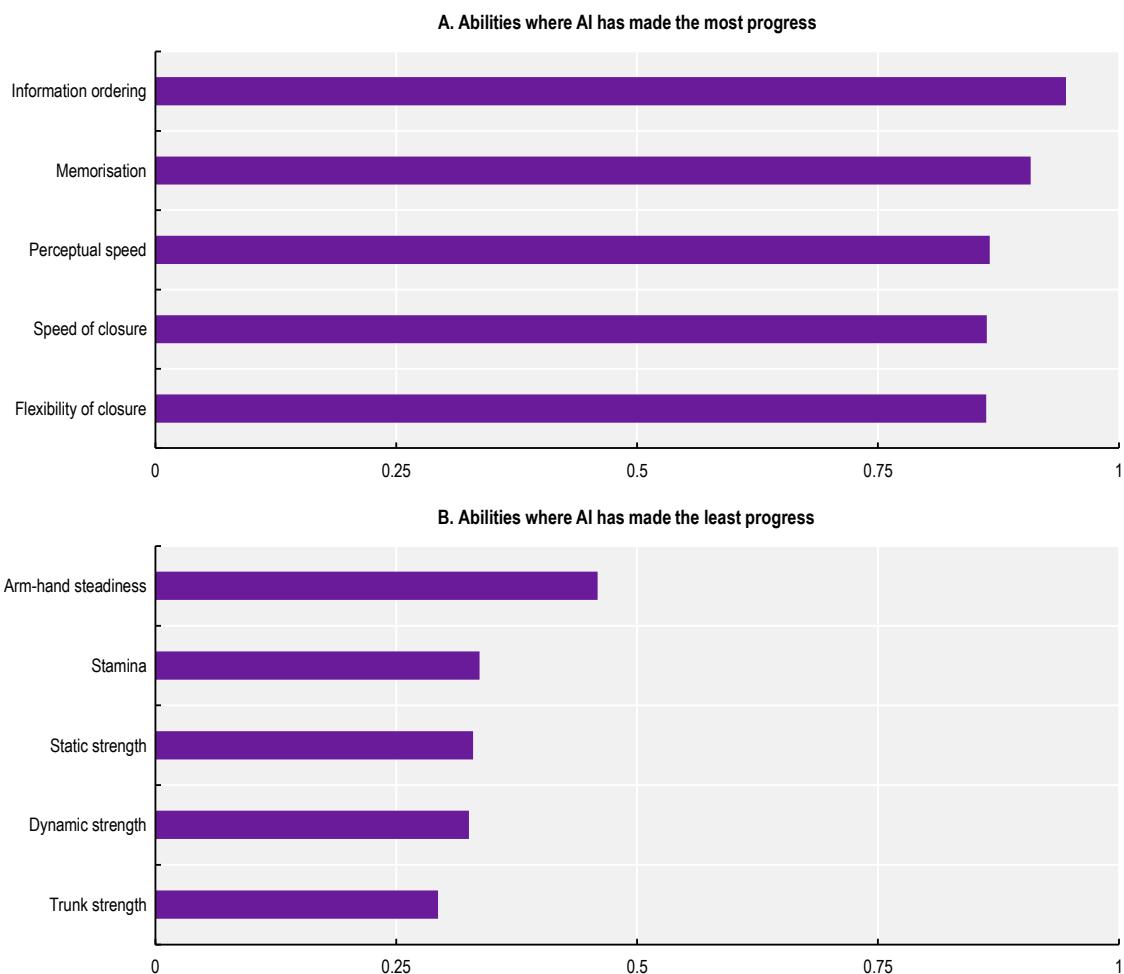
3.1.2. AI has made the most progress performing non-routine, cognitive tasks

AI has made the most progress in automating non-routine, cognitive tasks. Figure 3.1 shows the abilities where AI has made the most progress in replicating human performance as of 2015. The most progress has been made in the abilities “Information ordering”, “Memorisation”, and “Perceptual Speed”. The overlap of these abilities with AI is straightforward. For example, “Speed of Closure” is the ability to quickly make sense of, combine, and organise information into meaningful patterns. Examples include making sense of messy handwriting and recognising a song after the first few notes (O*NET, 2023^[17]). These cognitive abilities are often important for high-skill occupations, such as air traffic controllers, engineers, and managers. In contrast, various abilities related to strength are where AI has made the least progress. These are more indicative of non-cognitive, non-routine occupations such as dancers, athletes, bricklayers and farm workers.¹⁰

This chapter uses advances in the capabilities of AI compared to the tasks performed in jobs as a proxy for AI exposure. This approach draws on matching the assessed capabilities of AI (Brynjolfsson, Mitchell and Rock, 2018^[18]; Webb, 2020^[19]; Tolan et al., 2021^[20]; Felten, Raj and Seamans, 2021^[21]; Lassébie and Quintini, 2022^[22]) to the tasks currently performed by human labour as described in the Occupational Information network (O*NET, see Box 3.1). For example, the measure of AI exposure used in this chapter comes from Felten, Raj and Seamans (2021^[21]) who measure progress in AI applications from the Electronic Frontier Foundation's AI Progress Measurement project and connect it to abilities from O*NET using crowd-sourced assessments of the connection between applications and abilities.¹¹ The measured exposure of each task to AI is then aggregated to the occupation (industry or local labour market, respectively) level to derive measures of exposure. The measure is theoretically ambiguous with respect to whether the overlap between progress in AI and the abilities required in a job means “risk of displacement”, or if AI will be complementary. Finally, these exposure measures can also be viewed as an instrument for actual AI adoption, which may be concomitant with the adoption of other technologies, and where workers are likely to be aware of its deployment.¹² This allows for more credible empirical strategies for measuring employment effects than observational studies of AI adopting firms.¹³

Figure 3.1. AI has made the most progress in abilities that are required to perform non-routine, cognitive tasks

Relative progress made by AI in relation to each ability, 2010-15



Notes: The x-axis measures the relative exposure to AI scaled such that the minimum is zero and the maximum is one. Exposure is defined as the link between O*NET abilities and AI applications (a correlation matrix) taken from Felten, Raj and Seamans (2019^[23]). The matrix was built by an Amazon Mechanical Turk survey of 200 gig workers per AI application, who were asked whether a given AI application – e.g. image recognition – can be used for a certain ability – e.g. near vision. The correlation matrix between applications and abilities is then calculated as the share of respondents who thought that a given AI application could be used for a given ability. To obtain the score of progress made by AI in relation to a given ability, the shares corresponding to that ability are first multiplied by the Electronic Frontier Foundation (EFF) progress scores in the AI applications; these products are then summed over all nine AI applications.

Source: Reproduced from Georgieff and Hyee (2021^[24]), “Artificial intelligence and employment: New cross-country evidence”, <https://doi.org/10.1787/c2c1d276-en>, using data from Felten, Raj and Seamans (2019^[23]), “The Variable Impact of Artificial Intelligence on Labor: The Role of Complementary Skills and Technologies”, <https://doi.org/10.2139/ssrn.3368605>.

StatLink <https://stat.link/5lkmi6>

Box 3.1. The O*NET database

The Occupational Information Network (O*NET) contains information on occupations including the skills and abilities they require. Created in 1998 by the U.S. Department of Labor, and updated on a regular basis, it covers almost 1 000 occupations.¹ Most of this information is collected from job incumbents and experts through surveys (Tsacoumis, Willison and Wasko, 2010^[25]). Skill and ability requirements of occupations are measured in terms of importance and level. The former indicates whether a skill or ability is important to perform the job. The latter indicates the level of mastery or proficiency in that skill or ability needed for the job. Both O*NET Skills and Abilities ratings on Importance and Level are also based on the responses of incumbent workers (or occupational experts) to other items on the O*NET survey questionnaire. More information on the O*NET database, and current and archive versions of the dataset can be found online.²

As O*NET is developed by the Employment and Training Administration in the United States, it is geared towards the content of jobs in the labour market in the United States. Despite this, O*NET has been regularly used for the analysis of countries other than the United States. The assumption that skill measures from one country can be generalised to other countries has been tested and largely holds (Handel, 2012^[26]; Cedefop, 2013^[27]). For example, Handel (2012^[26]) finds that occupational titles refer to very similar activities and skill demands across different countries. Specifically, high correlations are found between O*NET scores and parallel measures from the European Social Survey, EU Labour Force Survey, Canadian skill scores, the International Social Survey Program, and the UK Skill Survey, respectively, with average correlations of 0.80. Most skill scores can thus be generalised to other countries with a reasonable degree of confidence. As a result, the O*NET information on skill and ability requirements has been used extensively in labour market research, including to study issues of automation (Deming, 2017^[28]; Webb, 2020^[19]).

1. See O*NET Taxonomy at: <https://www.onetcenter.org/taxonomy.html#latest>.

2. <https://www.onetcenter.org/database.html#overview>.

Other approaches to measuring AI exposure that have been used in the literature do not capture workers without AI skills or are less suited for cross-country comparative analysis. One popular method for identifying AI exposure uses job postings and their associated skill demands to infer AI adoption by firm, occupation or industry (Alekseeva et al., 2021^[29]; Squicciarini and Nachtigall, 2021^[30]; Calvino et al., 2022^[31]; Manca, 2023^[32]; Green and Lamby, 2023^[33]).¹⁴ However, this method misses firms who adopt AI but do not develop or service it in-house, or workers whose abilities overlap with AI advances but who do not need AI skills.¹⁵ Another approach used in the literature relies on government surveys of AI adoption by firms. These surveys have the advantage of being representative of the labour market, and they are already emerging in some countries, but they are often not uniform across countries,¹⁶ and too recent to track longer term employment changes.

One downside of the AI exposure measure used in this chapter is that it is backward-looking. The exposure measures developed in Felten, Raj and Seamans (2021^[21]) and used as inputs in Figure 3.1 and Figure 3.2 stem from 2010-15. This is necessary because it takes time for scientific advances to be confirmed; developed into commercial applications; and then have firms adopt and implement them before one can reasonably expect to detect employment changes. However, it does raise the question of whether these AI exposure measures are still relevant given recent developments in large language models (LLM) as exemplified by ChatGPT, for example. However, various researchers have produced updated estimates of AI exposure considering the advances in LLM, and the results of early uses of LMM do not seem to suggest qualitative differences in exposure compared to the measures used in this chapter (see Box 3.2).

Box 3.2. The growth of large language models (LLM) and the perils of predicting the effects of rapidly progressing AI

In late November 2022, OpenAI released ChatGPT, which astounded AI researchers, policy makers and the public with its ability to generate human-like responses with knowledge of a multitude of subjects. Essentially a chatbot that responds to users' queries, ChatGPT has a range of potential applications from everyday convenience to automating tasks in the workplace. It can write legal contracts, summarise the literature and accumulated knowledge on a particular subject, write and debug computer code, translate among languages, and even do arithmetic. Microsoft, Google, among other large technology companies, are developing their own versions of AI-trained chatbots. The widespread potential use and the phenomenal speed of improvement of LLM potentially changes what it means to be "exposed" to AI and raises questions about the relevance of existing estimates of the effect of AI on employment.

Recent estimates of how LLM may change AI exposure measures do not find large differences in AI exposure compared to previous estimates. Felten, Raj and Seamans (2023^[34]) update their original AI exposure measures in light of the release of ChatGPT by reweighting their initial estimates to only include language modelling. Their results are largely in line with their previous studies with teaching professions notably becoming the most exposed. Researchers affiliated with OpenAI, the firm that created ChatGPT, released their own measures of exposure by evaluating whether the time to complete tasks on the job can be reduced by at least 50% with the aid of ChatGPT or similar applications (Eloundou et al., 2023^[35]). They find that exposure rises with average earnings (based on data from the United States) as well as education and training requirements. The investment bank Goldman Sachs also released estimates of AI exposure, based on the existing literature and their own assessments of likely use cases of large language models. They find that AI exposure is most heavily concentrated in high-skill professional services industries (Briggs and Kodnani, 2023^[36]).

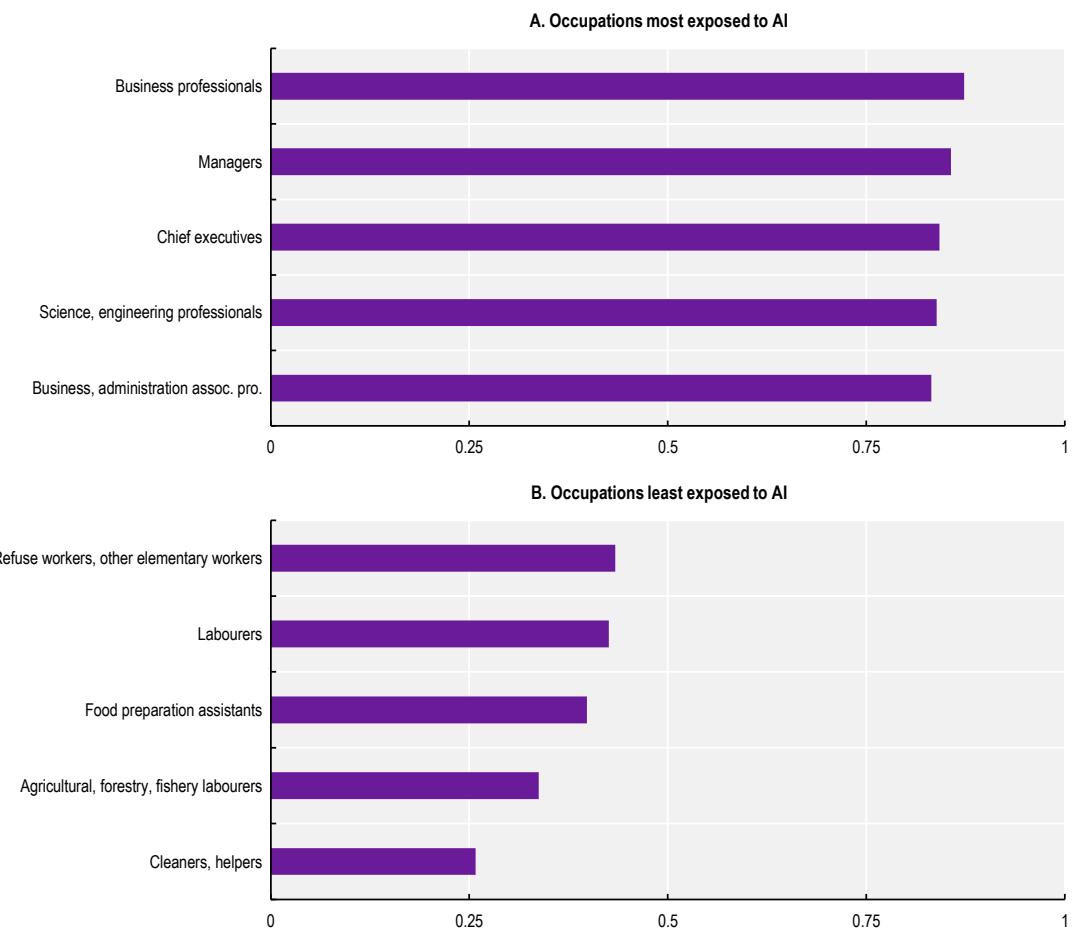
These early estimates of occupational AI exposure that take into account the capabilities of large language models like ChatGPT reach similar conclusions as previous estimates of AI exposure. It is primarily high-pay occupations requiring higher than average education or training that are most exposed to AI. However, these estimates are based on the early assessments of the researchers, and they have not yet been validated on external data. In addition, exposure is not necessarily equivalent to automation, and the effect of AI on employment will require continuous monitoring.

3.1.3. High-skilled, white-collar occupations have been most exposed to recent progress in AI

The occupations most exposed to recent progress in AI are high-skill, white collar occupations. Georgieff and Hyee (2021^[24]) use the Survey of Adult Skills (PIAAC) data to allow the assessed progress of AI to vary by country.¹⁷ They find that, on average across OECD countries in their sample, "Business Professionals", "Managers", "Chief Executives" and "Science and Engineering Professionals" are the most exposed occupations to AI (Figure 3.2). This follows intuitively from the abilities where AI has made the most progress. In contrast, "Food preparation assistants", "Agriculture, forestry and fishery labourers" and "Cleaners, helpers" are the least exposed to AI.

Figure 3.2. Highly educated white-collar occupations are among the occupations with the highest exposure to AI

Average exposure to AI across countries by occupation



Notes: The x-axis measures the relative exposure to AI scaled such that the minimum is zero and the maximum is one. Estimates are derived from cross-country averages taken over the 23 countries included in Georgieff and Hyee, (2021[24]). The analysis uses the Survey of Adult Skills (PIAAC) to derive cross-country variation in occupational exposure to AI from Felten, Raj and Seamans (2019[23]). All estimates are unweighted and do not rely on cross-country differences in the occupation distribution. Occupations are ISCO-08 2-digit.

Source: Georgieff and Hyee, (2021[24]), "Artificial intelligence and employment: New cross-country evidence", <https://doi.org/10.1787/c2c1d276-en>, calculations using data from the Survey of Adult Skills (PIAAC) and Felten, Raj and Seamans (2019[23]), "The Variable Impact of Artificial Intelligence on Labor: The Role of Complementary Skills and Technologies", <https://doi.org/10.2139/ssrn.3368605>.

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3.2. It is too early to detect meaningful employment changes due to artificial intelligence

This section examines the emerging empirical evidence for the effect of AI on employment. It draws a distinction between aggregate studies which cannot disentangle the specific effects of AI on employment (i.e. displacement, productivity and reinstatement), and more fine-grained microeconomic studies which try to isolate the competing displacement and productivity effects. The section then discusses which groups of workers have been found to be most affected by AI and ends with an attempt to reconcile the results from different studies.

3.2.1. In the aggregate, negative employment effects due to artificial intelligence are (so far) hard to find

Studies examining the effect of AI on aggregate employment have so far found little to no effect on employment. Using their AI occupational impact exposure measure (AIOI, see above) and variation in occupational exposure within U.S. states, Felten, Raj and Seamans, (2019^[23]) find no effect of AI exposure on employment growth between 2010 and 2016. Georgieff and Hyee, (2021^[24]) use data from PIAAC to extend AIOI and allow for within-country variation in the AI exposure measures of Felten, Raj and Seamans, (2019^[23]). They find positive but insignificant effects of AI exposure on aggregate employment using variation in occupation exposure to AI within a sample of OECD countries.

Even at lower levels of aggregation, there is currently no detectable effect of AI on aggregate employment. Acemoglu et al. (2022^[16]) examine employment changes from AI using differences in AI exposure by U.S. commuting zones by industry, and separately, variation by detailed occupation. In all specifications they find no statistically significant effect of AI exposure on employment between 2010 and 2017 (industry) and 2018 (occupation). Fossen and Sorgner (2022^[37]) estimate the effect of AI exposure on the probability of leaving employment using short panels of individual workers in the United States between 2011 and 2018. They find that exposure to AI *decreases* the probability of workers to exit employment.

Surveys of firms' AI adoption and ensuing employment changes similarly find no detectable decreases in employment. In a survey of 759 managers of firms in the United Kingdom, Hunt, Sarkar and Warhurst (2022^[38]) find that AI is leading to greater turnover, but when the researchers look at net employment changes, the results are inconclusive as firms are equally likely to report net employment gains and losses compared to firms not adopting AI. Similarly, an OECD survey of firms in manufacturing and finance across seven OECD countries finds that most firms adopting AI say that it did not change employment (Lane, Williams and Broecke, 2023^[39]). Slightly more firms report employment decreases compared to increases, but these differences are not statistically significant. These results accord with national surveys of firms that adopt AI. A random sample of over 300 000 employer businesses in the United States from the U.S. Census Bureau collected information on firms' adoption of advanced technologies from 2016 to 2018. The majority of firms reported no changes in employment levels due to advanced technologies but, of the firms adopting AI, 26% said that this caused them to increase employment compared to less than 10% which saw their employment levels decrease (Acemoglu et al., 2022^[40]).

Although employment may not (yet) have declined because of AI, firms more exposed to artificial intelligence tend to hire less in jobs not requiring AI skills. Acemoglu et al. (2022^[16]) use online job postings and a firm's AI exposure in 2010 (roughly before the proliferation of AI) to show that firms more exposed to AI decreased vacancy posting for jobs not requiring AI skills. This result even holds *within* firms using the variation in AI exposure across local labour markets where the firms operate. Compared to aggregate studies, the empirical design attempts to isolate the competing productivity and displacement effects of AI on employment from the reinstatement effect.¹⁸ The authors interpret their results as evidence that, as of now, AI is not generating a large productivity effect to offset the decrease in hiring from the displacement effect. However, the authors also find a strong effect of AI on the growth of AI-related vacancies, which can be interpreted as evidence of a strong reinstatement effect. This may be why the authors find no evidence of aggregate effects of AI on employment (see above).¹⁹

There is some evidence of employment declines due to AI when examining specific sectors. Grennan and Michaely, (2020^[41]) find that sell-side equity analysts – high-skill workers who predict stock performance for clients – are more likely to exit the profession the more they are asked to cover stocks with a lot of publicly available data, which they use as a proxy for the ease with which AI could perform the same task. In addition, analysts more exposed to equities, which are easier for AI to model, are more likely to leave research altogether suggesting that AI has a powerful displacement effect on this profession. In short, the only two studies that try to isolate the productivity effect from the displacement effect find evidence that the displacement effect dominates. Yet more research is clearly needed on this issue.

3.2.2. High-skilled workers have seen employment gains

Although high-skill workers are more exposed to AI, many studies find that high-skill workers have had better employment prospects after the introduction of AI. The effect of AI exposure on the probability of transitioning into non-employment declines the most for workers with a tertiary education (Fossen and Sorgner, 2022^[37]). Using the median annual income for an occupation, and variation across U.S. states, Felten, Raj and Seamans, (2019^[23]) find a positive relationship between employment growth and AI exposure for high-skill (high income) occupations but not for low- and medium-skill occupations. Using within- and cross-country variation in AI exposure, Georgieff and Hyee (2021^[24]) find AI exposure is associated with higher employment growth only in occupations with the highest degree of computer use, which is a proxy for higher skills. These occupations are highly correlated with measures of skill, including education and median annual income. All these studies appear to be picking up a similar signal, but exactly what that is, and its causal interpretation, remains an open question for future research. Moreover, given the rapid increases in the capabilities of AI, in particular with generative AI models, it is likely that these associations will evolve in the future (see Box 3.2).

There is also evidence that low-skilled workers may face declining employment prospects because of AI. In their survey of AI-producing firms, Bessen et al., (2018^[42]) find that, within customer firms for AI products, higher skilled occupations are the most likely to see employment growth from AI adoption, but that occupation groups including front-line service workers and manual workers are the most likely to see employment declines. OECD case studies of manufacturing and finance firms adopting AI similarly find that low-skill workers were often at the greatest disadvantage because when their tasks (and, by extension, their jobs) would be automated – unlike other workers – they were often the most difficult to retrain or move to another position within the firm (Milanez, 2023^[43]).

3.2.3. Why is the employment effect of AI small (so far...)?

The results in the previous section have shown that, so far, AI has had little effect on aggregate employment. Moreover, although high-skilled workers are disproportionately exposed to recent advances in AI, they do not seem to have been adversely affected (yet). The rest of this section presents reasons for why the employment effects of AI to date are small, including: low overall AI adoption and productivity gains; firms' preference to adjust labour demand through attrition rather than layoffs; the fact that advances in AI and AI exposure do not necessarily imply automation; and the creation of new tasks and jobs.²⁰

Currently, AI adoption is low and the cost savings to firms are modest

Firms' adoption of AI is just beginning, and overall penetration rates are still low. A recent module of the Annual Business Survey (ABS) from the U.S. Census Bureau which sampled 300 000 businesses finds that just 3.2% of firms used AI between 2016 and 2018. This is consistent with data from Eurostat, which finds that, among OECD European Union countries, enterprise-level AI adoption ranges from 23% in Ireland, 12% in Finland and 11% in Denmark to 3% in Hungary and Slovenia and 2% in Latvia (Eurostat, 2021^[44]). Estimates from non-official sources tend to be higher though their qualitative findings are generally in line with official estimates – see Lane, Williams and Broecke, (2023^[39]) for a discussion of the different sources of measurement.²¹

Low adoption rates should lead to marginal employment changes, which may be too small to detect in aggregate studies. The low adoption rates combined with little evidence for substantial productivity gains (see Chapter 4) from AI suggests that neither the displacement nor the productivity effect will be large enough compared to the overall labour market. This is the preferred interpretation of Acemoglu et al., (2022^[16]) who find firm-level evidence of decreases in hiring from AI exposure, but argue that such changes are too small to detect in aggregate studies of the effect of AI on employment.

Firms rely on worker attrition rather than layoffs to adjust labour demand

Displacement from tasks or jobs does not necessarily imply short-term losses in employment. The studies (Section 3.2.1) that do find evidence of a displacement effect rely on data on hiring or narrow occupation groups. While these studies show that firm or establishment hiring may decline, or that narrow occupation groups within a firm may contract, they do not show that *employment* within the firm goes down.

Firms may keep affected workers within the firm and allow natural attrition to decrease employment levels over time. This would dampen or mitigate any short-term impacts of AI on employment. OECD case studies of finance and manufacturing firms adopting AI find that this is overwhelmingly the case. For example, a Canadian manufacturer of auto parts adopted an AI software that performs the cutting of custom metal moulds for auto parts. According to the firm, the ensuing productivity gains were large, and the necessary employment declines were managed gradually through planned retirements rather than immediate layoffs (Milanez, 2023^[43]).

Firms may also be slow to adjust employment after adopting AI as a hedge against uncertainty in the efficacy of the applications themselves. Firms adopting AI may need time to understand the capabilities of AI and how to optimise its deployment to maximum effect (see below). However, there is no guarantee that AI applications will increase productivity to the extent it is hoped at the time of adoption. Retaining workers after AI adoption, and by extension their accumulated firm-specific human capital, provides insurance in the case AI applications underperform their projected benefits (Milanez, 2023^[43]).

This gradual adjustment through attrition rather than immediate redundancies has previously been found to be the dominant way that firms in OECD labour markets adjust employment to accommodate the productivity gains from new technologies (OECD, 2020^[45]).²² If firms are relying on attrition to adjust their labour demand, this does imply employment declines (or much slower growth), but it is preferable to mass layoffs. Workers who lose their jobs due to layoffs or other economic reasons often see long-term earnings losses (Jacobson, LaLonde and Sullivan, 1993^[46]; Farber, 2017^[47]; OECD, 2018^[48]).

AI may be leading to greater efficiencies in labour market matching

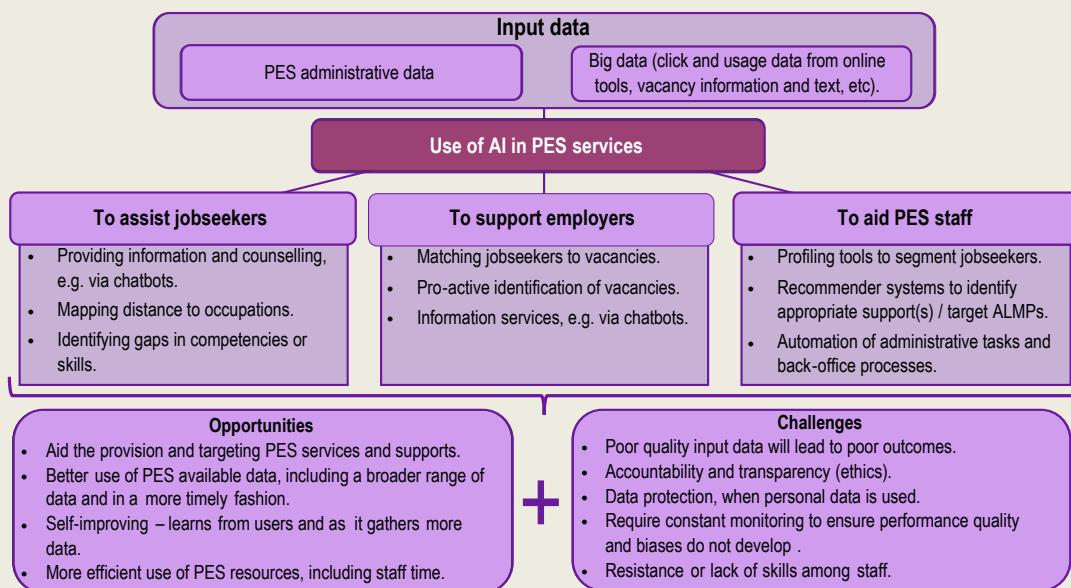
One way the increasing use of AI may lead to higher employment is through improved labour market matching. One aspect of labour market performance is the efficiency and quality of labour market matching – i.e. the process by which workers are matched to jobs. Labour market matching involves a range of steps from writing job descriptions and opening vacancies all the way to making offers and salary negotiations. It covers private recruitment by firms, but it can also refer to the activities of public (see Box 3.3) and private employment services, as well as those of jobs boards and online platforms. It can even include internal matching within a firm.

Improved labour market matching should lead to lower unemployment. Matching jobseekers to vacancies is time-consuming and therefore costly. The longer it takes to match workers to vacancies, the higher equilibrium unemployment will be (Blanchard et al., 1989^[49]; Mortensen and Pissarides, 1999^[50]). AI has vastly expanded the range of time- and resource-saving possibilities when screening and shortlisting candidates. For example, AI, through “semantic expansion”, can parse CVs and take a single word such as “accountant” and expand the information linked to the candidate to include known synonyms, such as “account specialist.” This increases the efficiency of matching and ensures that candidates are not ruled out by narrow phrasing or phrasing that is slightly different from advertised text as is done in many current screening applications (Broecke, 2023^[51]).

Box 3.3. The use of AI in Public Employment Services (PES) is growing in precedence across OECD countries

PES across the OECD have been increasingly engaging in efforts to modernise and digitalise in recent years, with the COVID-19 pandemic undoubtedly acting as an accelerant of this trend. As part of this digitalisation trend, PES are exploring how AI and advanced analytics can be used to enhance their tools, services and processes and, ultimately, help jobseekers find work more quickly, or find better work (OECD, 2022^[52]). Combining PES administrative data, along with broader data, the application of AI can assist the provision of many areas of PES activity (Figure 3.3).

Figure 3.3. AI presents various opportunities and challenges for PES



Note: AI – artificial intelligence, ALMP – active labour market policy, PES – public (and private) employment services.

While many opportunities exist for PES in adopting AI, the territory also comes with challenges. PES must therefore take additional steps to ensure that AI tools perform well and that their intended benefits are realised. First, monitoring and evaluation of AI-powered tools should be imbedded into their design and implementation. This can include experimentation, testing and piloting in the development phase, close monitoring (including user feedback) and ongoing fine-tuning upon rollout and counterfactual impact evaluations (or process evaluations where appropriate) to understand their true impact. PES staff should also be supported through this journey, with ongoing training sessions, the provision of guidelines and informational materials, or dedicated support staff or units. Policy makers must also ensure that the development and use of AI in PES adheres to ethical standards. For example, the French PES has recently implemented a charter for the ethical use of AI. The OECD is undertaking further work in this area in order to better understand levels of AI adoption across PES and the associated development practices and governance approaches.

Source: OECD (2022^[52]), Harnessing digitalisation in Public Employment Services to connect people with jobs, https://www.oecd.org/els/emp/Harnessing_digitalisation_in_Public_Employment_Services_to_connect_people_with_jobs.pdf; Pôle Emploi (2022^[53]), Pôle emploi se dote d'une charte pour une utilisation éthique de l'intelligence artificielle, <https://www.pole-emploi.org/accueil/communiques/pole-emploi-se-dote-dune-charte-pour-une-utilisation-ethique-de-lintelligence-artificielle.html?type=article>.

Advances in artificial intelligence only account for a small part of automation

The indicators of AI exposure discussed in this chapter, and used by many authors to estimate the effect of AI on employment, measure progress in the capabilities of AI as related to the abilities needed in occupations. However, progress in the capabilities of AI is not equivalent to the probability of automation. Recent progress in AI may complement human labour rather than automate it. More importantly, AI is just one of the many advanced technologies (ICT, robotics etc.) which can lead to the automation of tasks previously done by human labour. Aggregate changes in employment will ultimately depend on all sources of automation, and the predicted effect of AI on certain groups may be very different when one does not carefully consider all sources of automation.

To account for the latest progress in automation technologies, a new study by the OECD conducted in 2021 reassesses occupations' exposure to automation exploiting novel data collected through an original survey on the degree of automatability of approximately 100 skills and abilities (Lassébie and Quintini, 2022^[22]). The survey was developed with the help of, and completed by, experts from different AI research fields. The study does not only focus on AI technologies but extends to other automation technologies – e.g. robotics – now enhanced with AI.²³ This allows different technologies to complement each other.

The study finds that high-skill occupations have the lowest risk of automation. Although AI has made several skills required in high-skilled jobs susceptible to automation, many other skills in those jobs remain bottlenecks to automation. The net effect is that high-skill occupations, although more exposed to recent progress in AI, are still some of the least at risk of automation. Low- and middle-skilled jobs are the most at-risk including construction and extraction, farming, fishing, and forestry, and to a lesser extent production and transportation occupations. The least at-risk jobs include management, and community and social service occupations (Figure 3.4).

On average across OECD countries in the sample, the occupations at the highest risk of automation account for 27% of employment (Figure 3.5).²⁴ Luxembourg, the United Kingdom and Sweden have the lowest shares of employment in the occupations at the highest risk of automation while Hungary, the Slovak Republic and the Czech Republic have highest shares

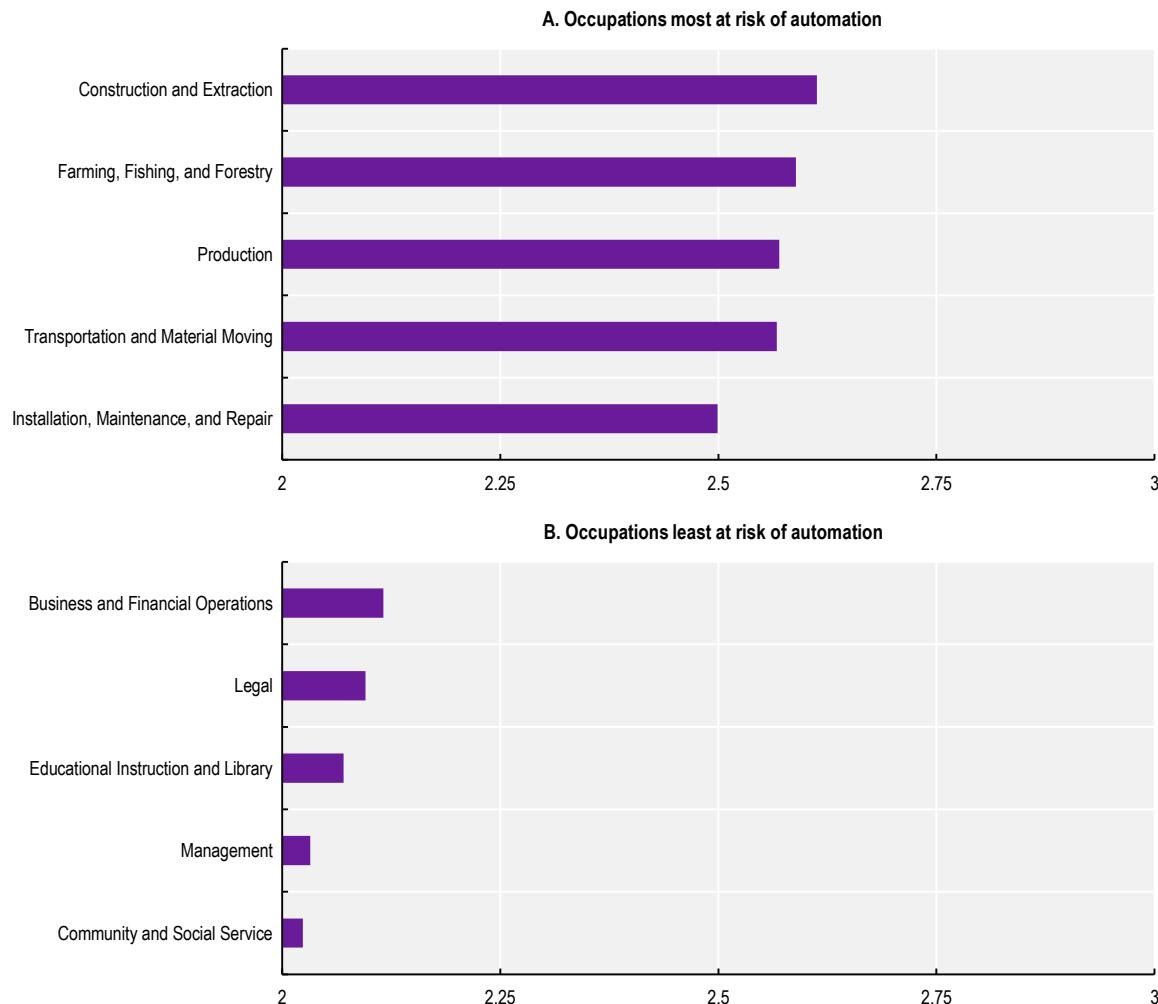
The creation of new tasks and jobs is not well captured by studies focusing only on exposure

Studies that focus on the effect of AI exposure on employment while trying to isolate the displacement and productivity effects will miss the creation of new tasks and jobs. AI exposure measures the overlap between the tasks performed in a job and the tasks which AI is theoretically capable of performing. It is much more difficult to predict what types of new tasks AI will create. New research from Autor et al. (2022^[15]) find that the majority of current employment in the United States is in new job specialties introduced after 1940. The authors link these new job specialities to the introduction of new processes, products and industries.

In the case of AI, many of these new jobs will likely be created for workers with AI skills, or skills to exploit/work with AI. These are generally high-skill workers such as statisticians and software engineers who have the skills to develop, maintain and improve AI systems. Demand for workers with AI skills has grown briskly in the last decade (see Chapter 5). Strong demand for workers with complementary skills to AI, for example, high-skill workers with strong computer skills, have also seen increased demand.²⁵ This channel will be picked up by aggregate studies but can often not be addressed by studies focused on particular industries.

Figure 3.4. The occupations most at risk of automation are quite different from occupations most exposed to artificial intelligence

Occupations most and least at risk of automation including AI and other automation technologies, 2021

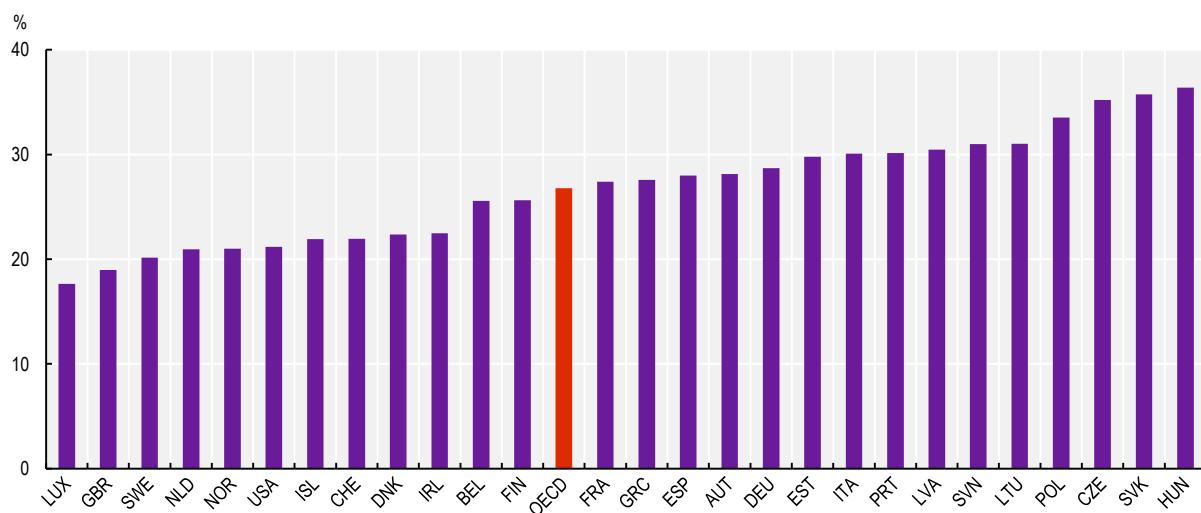


Notes: Occupations are SOC-2 digit (2018). The results are based on a survey of experts who evaluated the degree of automatability for 98 skills and abilities. The risk of automation measure is then computed by occupation as the average rating for each skill or ability used in the occupation across all expert responses weighted by the skills or abilities' importance in the occupation as rated by O*NET. Scale is 0-5 for all occupations. Source: Reproduced from Lassébie and Quintini (2022^[22]), "What skills and abilities can automation technologies replicate and what does it mean for workers? New evidence", <https://doi.org/10.1787/646aad77-en>, based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

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Figure 3.5. Countries with higher shares of manufacturing employment and routine tasks are still more at risk of automation

Share of employment in occupations at the highest risk of automation by country, 2019



Notes: The SOC 3-digit occupations at highest risk of automation (top quartile). The results are based on a survey of experts who evaluated the degree of automatability for 98 skills and abilities. The risk of automation measure is then computed by occupation as the average rating for each skill or ability used in the occupation across all expert responses weighted by the skills or abilities' importance in the occupation as rated by O*NET.

Source: Lassébie and Quintini (2022^[22]), "What skills and abilities can automation technologies replicate and what does it mean for workers? New evidence", <https://doi.org/10.1787/646aad77-en>, based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

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The strong demand for workers with AI skills, but otherwise negligible aggregate employment changes, is characteristic of the dynamics of the introduction of new automation technologies. Writing about general purpose technologies in general, and AI in particular, Brynjolfsson, Rock and Syverson (2019^[54]; 2021^[55]) argue that firms need time to restructure and adapt to new technologies before harnessing their full potential. Specifically, firms will spend heavily in the early adoption period on complementary investments including workers with AI skills, and other workers such as managers and computer engineers. These early intangible investments are unlikely to produce immediate productivity gains (see Chapter 4), and by extension employment changes, as firms continue to try new production processes and discover how best to deploy AI. Over time, however, these intangible investments will begin to take off, leading to a productivity "J-Curve" with initial declines in productivity as firms add complementary capital and labour followed by fast growth once they have pieced together how to use the new technology. The evidence of the employment effects of AI is consistent with this theory.

3.3. Policy can promote AI use that complements human labour and broadly shared productivity gains

There is a suite of policies that could help maximise AI's impact on economic growth, while minimising job displacement. Policy should encourage the productivity and reinstatement effects of AI keeping in mind that the various effects depend on how the technology is used. For example, in many places the methods used by the teaching profession have not fundamentally changed over the past 200 years, so one could conceive of AI systems that could take over the tasks of some teachers. However, another approach would

be to use AI to understand the different ways students learn, and then tailor teaching to their individual needs. If the latter were effective, it would not only raise student achievement, but it could also raise demand for teachers who would then specialise in different types of learning – see also Acemoglu and Restrepo (2019^[56]) and Chapter 5.

Policy makers should review skills policies to ensure that workers can complement emerging AI systems. This chapter has documented a rise in demand for workers with computer, programming and data skills that are complementary to AI. Chapter 5 discusses the general increase in the demand for workers with AI skills as well as the skills that best complement AI, and it explores how adult learning systems should be adapted in response.

The tax system may also work against workers and favour excessive AI adoption. Many economies subsidise capital through the tax code while at the same time taxing labour at much higher rates. At the margin, this pushes firms to automate, but in such cases, automation would not be worthwhile without the implicit tax subsidy, and such marginal investments result only in small cost savings and a low productivity effect, which ultimately lowers labour demand. In short, employment is not reduced by large and truly innovative automation events but by the replacement of a small number of low value-added tasks. Rebalancing capital and labour taxes away from marginal investments may halt excessive automation (Acemoglu, Manera and Restrepo, 2020^[57]).

Tight labour markets can further ensure that automation produces the largest productivity effects. The cost savings from automation are greatest when unemployment is low and wages are high (Acemoglu and Restrepo, 2019^[58]). Low unemployment should also increase the demand for, and speed of development of, new technologies. When unemployment is low and firms must compete for scarce workers, they have additional incentives to adopt new technologies and demand new innovations (Dechezleprêtre et al., 2021^[59]). Policies to reach full employment may have the added benefit of helping automation technologies translate into higher productivity gains and stronger labour demand, although such a policy goal is not without risks (see Chapter 1).

Antitrust regulation can bolster the benefits of AI. One would like to ensure that automation from AI results in large cost savings which can then be passed through to the wider economy in the form of higher demand (Acemoglu and Restrepo, 2019^[56]; Acemoglu, 2021^[60]). Competition authorities can ensure that markets are competitive and cost savings from automation translate into lower prices and higher output (OECD, 2018^[61]). Regulatory policy for AI is not confined to competition policy, however. A well-co-ordinated combination of soft law and legislation is needed to effectively ensure trustworthy AI in the workplace as AI continues to evolve (see Chapter 6).

Finally, some share of the cost reductions from AI will ultimately be retained inside the firm. Policies to empower social partners and strengthen worker bargaining power can ensure that the gains from these savings are shared with incumbent workers rather than just benefiting owners. In addition, social partners can facilitate the retention of workers whose jobs are at risk of automation by ensuring that they are kept on in different roles – see Chapter 7 for a detailed discussion of the role of social partners in the deployment and use of AI.

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Notes

¹ The task-based framework discussed in this section follows Acemoglu and Restrepo (2018_[14]). See Acemoglu and Autor (2011_[62]) for an earlier sketch of the theory of automation and Acemoglu and Restrepo (2019_[58]) for a non-technical overview.

² Following Acemoglu and Restrepo (2018_[14]), the discussion assumes full substitution between AI and labour (the elasticity of substitution in a CES production function is infinity, $\sigma = \infty$), however everything that follows holds if one assumes partial substitution in tasks so long as AI and labour have some degree of substitution ($\sigma > 1$).

³ Workers are assumed to have an absolute and comparative advantage in completing these tasks over automation technologies.

⁴ The explanation in this chapter follows the case of Acemoglu and Restrepo (2018_[14]) where firms are “technologically constrained” such that given prices for labour and capital, firms would like to automate a

set of tasks up to a threshold \tilde{I} , but due to existing technologies they are constrained to only automate $I < \tilde{I}$ tasks.

⁵ This is the case of AI acting as a labour-augmenting productivity increase, and it is usually what one refers to as technology acting as a complement to labour. For a long time, this was the main mechanism for how economists theorised technological change affected labour demand (along with the elasticity of substitution). However, it lacks realism – the task content of labour never changes. Moreover, it implies that in almost all cases labour demand should never decline and wages should always rise with new technological improvements (Acemoglu and Restrepo, 2019^[58]). For these reasons, this channel, while certainly present in some cases, is not the emphasis of this chapter.

⁶ AI is intensive in electricity and data. If the firm operating the warehouse invests heavily in AI, this may lead to higher demand for employment in electrical installation services and data storage which complement AI but are employed outside the warehousing firm.

⁷ Bessen (2019^[63]) further argues that the elasticity of product demand is not constant over time and that initial price decreases due to artificial intelligence may spur a large productivity effect, but subsequent price reductions do little to increase demand and will then bring longer term employment declines.

⁸ The effects of AI on labour demand are much broader than questions of displacement, productivity and reinstatement effects, and encompass also cultural, legal, organisational and ethical considerations. For example, chief executives are one of the occupations most exposed to AI (see Section 3.1.3). However, for legal and ethical reasons it seems likely that firms will always need to have a human as the head of a firm regardless of how many of the tasks of a current CEO AI may be able to automate.

⁹ The reinstatement effect is thought to be small compared to the productivity and displacement effects, hence the emphasis on the latter two effects, but more research is needed (Acemoglu and Restrepo, 2019^[56]).

¹⁰ The difference between routine and non-routine tasks is often not clear in practice. The work of farmworkers and bricklayers can be seen as adding up together a very large number of routine tasks, where their order is non-routine (and somewhat cognitive). AI, in fact, may be able to automate many of these tasks.

¹¹ To give a sense of similar measures, Brynjolfsson, Mitchell and Rock (2018^[18]) apply a rubric for evaluating task potential for machine learning to tasks in O*NET. Webb (2020^[19]) measures AI progress from patents and connects this to O*NET as well.

¹² The concern is that workers, aware of newly deployed AI, may decide to exit the firm whether they are at risk of automation or not. Any estimates of the effect of AI on employment, and especially the types of workers affected, will be contaminated with the effect of workers' beliefs about AI, for example.

¹³ More specifically, the literature has used these exposure measures as "shift-share instruments" (Borusyak, Hull and Jaravel, 2021^[64]) which posit that occupations' or firms' underlying task structures are uncorrelated with recent advances in AI and, therefore, provide more credible estimates of employment effects than simply regressing employment changes on AI adoption.

¹⁴ Calvino et al. (2022^[31]) also combine job postings with other data sources that allow identifying different types of AI adopters, focusing on the United Kingdom. These include AI-related Intellectual Property Rights and information on AI-related activities mentioned on company websites.

¹⁵ See Georgieff and Hyee (2021^[24]) for a thorough discussion of the relative merits of the various approaches to measuring AI exposure including which effects of AI on tasks each approach can recover.

¹⁶ Calvino and Fontanelli (2023^[66]) is a recent exception. They use harmonised code to measure AI adoption on firm-level surveys from a subset of European countries.

¹⁷ The authors link O*NET abilities and PIAAC tasks manually by asking whether a given ability is indispensable for performing a given task. An O*NET ability can therefore be linked to several PIAAC tasks, and conversely, a given PIAAC task can be linked to several O*NET abilities. This link was made by the authors and, in case of diverging answers, agreement was reached through an iterative discussion and consensus method, similar to a Delphi method.

¹⁸ The researchers do this by excluding industries producing AI products (Information, and Professional and Business Services) as well as vacancies in the remaining industries demanding AI skills. Assuming the reinstatement effect can be proxied by workers with AI skills, they therefore plausibly exclude the reinstatement effect and focus only on whether increased AI exposure is dominated by the productivity or displacement effect.

¹⁹ This effect may be sufficiently large to compensate for the net decline in hiring due to the displacement and productivity effects, which would imply positive or no vacancy growth. However, the authors never analyse the effect of AI exposure on all vacancies (regardless of AI skills) so this interpretation cannot be confirmed.

²⁰ AI may also induce general equilibrium effects, which may take the form of increased demand for intermediate goods and services in sectors of the economy little touched by AI. These general equilibrium effects may also increase aggregate labour demand because of strong demand for final goods and services consumption from the higher income AI brings to the economy. However, these general equilibrium effects are hard to isolate, and they are beyond the scope of this chapter.

²¹ One important caveat to these estimates is that the definition of AI varies from survey to survey, and one should be cautious interpreting estimates across countries unless the definitions were explicitly harmonised.

²² Although not specifically about AI, Georgieff and Milanez (2021^[65]) find that occupations most at risk of automation grow more slowly rather than shedding employment compared to occupations less at risk. This is further suggestive of firms allowing employment to adjust gradually rather than through sharp job displacement events.

²³ There are a few reasons for this. First, it is in most cases difficult to distinguish empirically between the different types of automation technologies. Even when it is possible, their impacts on labour markets are much harder, if not impossible, to disentangle from one another since production processes are likely to use a mix of different technologies and because their effects tend to reinforce each other. In addition, according to experts consulted for the study, most recent technological developments concerning automation technologies are now in the field of AI and several less novel technologies, in particular in robotics, are being improved thanks to AI. This is the case for instance of AI-powered robots that can now

pick up objects of variable shapes and sizes in unpredictable orientations and with remarkable accuracy, while previous generations of robots could only move objects of fixed size and could not deviate from their programmed trajectory.

²⁴ Lassébie and Quintini (2022^[22]) report that 28% of employment is in the occupations with the highest risk of automation across OECD countries. The authors use a wider set of countries, including non-OECD countries, than what appears in Figure 3.5, accounting for the slight difference.

²⁵ These jobs need not be done by workers with skills to develop AI, but they are generally tightly linked to the new technology. For example, the development of the internet saw the rise of a new type of journalist. These were workers who had no formal journalism training, and instead aggregated and commented on news stories from other parts of the internet. Whether these aggregations formed a new type of news site, or were commentary on a blog, these journalists did not interview or cultivate sources, but used their knowledge of the internet (and maybe some basic HTML skills at the beginning) to create a new type of journalism with a different set of tasks which would have been impossible without the internet.

4

Artificial intelligence, job quality and inclusiveness

Andrew Green, Angelica Salvi del Pero and Annelore Verhagen

For many workers, the effects of artificial intelligence (AI) will be visible not in terms of lost employment but through changes in the tasks they perform at work and changes in job quality. This chapter reviews the current empirical evidence of the effect of AI on job quality and inclusiveness. For workers with the skills to complement AI, task changes should be accompanied by rising wages, but wages could decline for workers who find themselves squeezed into a diminished share of tasks due to automation. AI may affect job quality through other mechanisms as well. For example, it can reduce tedious or dangerous tasks, but it may also leave workers with a higher-paced work environment. The chapter further shows that using AI to support managers' tasks affects the job quality of their subordinates. Finally, the chapter shows that using AI affects workplace inclusiveness and fairness, with implications for job quality.

In Brief

Key findings

Like other automation technologies before it, artificial intelligence (AI) may make some jobs redundant, forcing some workers to find a new job or update their skills (Chapter 3). However, according to workers' own accounts, so far, the greatest impact of AI has been felt mostly through changes in the tasks they perform in their current roles as well as changes in the working environment. These changes can have a direct impact on the quality of people's jobs and therefore on their well-being. For example, AI can automate dangerous tasks, which should improve job satisfaction and safety in certain hazardous jobs. On the other hand, workers may find themselves squeezed into a shrinking set of simpler tasks, which could put downward pressure on their wages.

AI also presents other challenges and opportunities for job quality and inclusiveness. For example, when used to support or automate managerial tasks – such as monitoring workers, allocating tasks, or deciding who should receive training or promotion (“algorithmic management”) – AI systems can lead to more data-driven and consistent management and assessment of workers. If not designed and implemented well, however, AI systems can reinforce pre-existing biases, harm privacy, increase work intensity and reduce autonomy in executing tasks.

This chapter reviews the current empirical evidence of the effect of AI on job quality and inclusiveness, also drawing on recent OECD AI surveys of employers and workers and case studies of AI use in the workplace. While these studies provide unprecedented detail on firms' current AI implementation and workers' perceptions of AI, it is important to emphasise that the findings are limited to the manufacturing and finance sectors and that they only capture the perceptions of workers who are employed after AI adoption. A number of key findings emerge:

- Workers with AI-specific skills – i.e. workers who develop, train or maintain AI systems – earn high wages and enjoy substantial wage premiums, even compared to observably similar workers with other advanced skills (e.g. software, cognitive, etc.). The highest AI wage premiums are found in management occupations, suggesting substantial demand for workers who know how AI can fit into the broader production process.
- For the larger set of workers exposed to AI – i.e. workers who use or interact with AI but do not necessarily have or require special AI skills – the use of AI has had only a minimal impact on wages so far.
- These minimal impacts on wages are consistent with empirical findings that suggest that, so far, AI has only had a modest impact on productivity. AI is currently more likely to be adopted by larger and more capital-intensive firms (which tend to be more productive), but productivity gains are small after accounting for observable differences between firms. This said, more recent case study evidence examining specific applications of generative AI finds larger effects on productivity.
- The OECD AI surveys find that the majority of workers report higher enjoyment in their jobs and improved mental and physical health due to AI. In case studies of AI use, workers frequently report AI's capability to improve the safe use of machines as one reason for improved physical safety.

- A potential mechanism for AI's impact on job quality is that the task composition of jobs changes. To date, AI appears to be automating more tedious, repetitive tasks than it creates, while also broadening the range of tasks performed by workers and aiding them in their decision making.
- Most workers in the OECD AI surveys said that AI improves autonomy, defined as control over the sequence in which they perform their tasks. This depends, however, on how AI is implemented and used. One in five respondents reported that AI decreased their autonomy, and this share is larger among the relatively small group who report to be subject to algorithmic management.
- The advanced monitoring and feedback made possible by using AI for managerial tasks can be more pervasive than human monitoring and feedback. In the OECD AI surveys, workers report higher work intensity after the adoption of AI and, in some cases, less human-to-human interaction. The surveys also show that, when employers' use of AI involves data collection on workers or how they do their job, the majority of workers are worried about their privacy.
- The impact of AI on job satisfaction and health differs across groups of workers, affecting inclusiveness in the workplace. Workers in managerial roles, those with the skills to develop and maintain AI systems, and workers with tertiary degrees tend to report higher job satisfaction and improved health after AI adoption. Workers who are subject to algorithmic management or those who work with AI report instead the least positive outcomes of using AI on their job quality. If implemented well, AI can also increase accessibility and job satisfaction for workers traditionally disadvantaged in the labour market, such as workers with disabilities.
- Close to half of workers who use AI in the OECD AI surveys believe that AI has improved how fairly they are being treated by their manager. However, AI systems can struggle with bias, both at the data level and at the system level. While bias is widespread in human decisions as well, the use of biased AI systems carries the risk of multiplying and systematising biases.
- AI's capabilities are progressing faster than the studies measuring its effects. New work will be needed in the future to see if the results of this chapter also hold for newer AI applications such as large language models, and across a larger set of sectors.

Introduction

For most workers, the effect of artificial intelligence (AI) is likely to be felt through changes to the tasks they perform in their current jobs and through changes in the working environment, rather than through lost employment. This could happen because AI changes task content – for example, by displacing a manufacturing worker from the visual inspection and quality control of a product, leaving her with a diminished set of elementary tasks. AI may also alter jobs without fundamentally changing their task content. For instance, the job of food delivery has remained fundamentally unchanged over the past few decades. However, where 30 years ago one might have taken direction from a manager, now an algorithm dictates where one must deliver, how to get there, and even determines if the worker keeps their job on the delivery platform based on anonymous customer reviews. How AI changes tasks and more generally shapes the work environment has important implications for the quality of people's jobs and ultimately their well-being.

The OECD job quality framework sets out a comprehensive structure for measuring and assessing job quality, focusing on those aspects of a job that have been shown to be particularly important for workers' well-being (OECD, 2014^[1]). These include things such as the level and distribution of earnings, employment security and the quality of the working environment. The latter includes the cumulative effect of job demands such as work intensity and performing physically demanding tasks. It also includes job resources that help workers cope with difficult demands such as worker autonomy to change the order of tasks or the method of work.

A core question addressed in this chapter is to what extent AI leads to wage changes (Section 4.1). AI has the potential to change the task profile of jobs, automating some tasks, complementing others and introducing new tasks (see Chapter 3). These tasks changes should result in cost savings for firms and higher productivity (Acemoglu and Restrepo, 2018^[2]). However, whether the expected productivity increases from AI lead to wage increases or decreases for workers is theoretically ambiguous.

Beyond earnings changes, this chapter is also concerned with how AI changes the demands and resources for workers, and what that means for job satisfaction (Section 4.2). An AI-powered chatbot, for example, may automate customer service representatives' easy or mundane calls, leaving them with only the more complex and involved customer queries. This could result in higher job quality as the representative takes on a higher share of more complex calls which require greater human interaction leading to more rewarding work. On the other hand, the disappearance of the routine calls may deprive the worker of the respite provided by these calls, leading to more mentally taxing shifts. Whether the sum of the new demands and resources brought by AI improves job satisfaction is the other side of job quality explored in this chapter.

AI also brings a new set of issues to the table when it comes to job quality. For example, AI can support or automate supervisory functions previously performed by humans, including giving direction, monitoring and evaluation ("algorithmic management"). This means that some workers may see little to no changes in the tasks they perform, but their manager is supported or replaced by an algorithm, which could, for instance, lead to reductions in privacy and autonomy, and increases in work intensity and stress (Section 4.3).

This chapter also reviews the potential of AI to improve labour market inclusiveness. Inclusive workplaces not only improve access to higher quality jobs for disadvantaged workers, but other workers also stand to benefit because workers value workplaces they perceive as fair to their co-workers as well as to themselves (Dube, Giuliano and Leonard, 2019^[3]; Heinz et al., 2020^[4]). By promoting more objective performance evaluations, for example, AI can increase fairness for workers who have traditionally suffered from bias in the labour market with the additional benefit of improving the job quality of their peers by improving the perceived fairness of their employer. However, if not designed and implemented well, AI can have negative effects on inclusiveness and fairness in the workplace. Through its reliance on data trained on past human experience, for example, AI risks introducing or reinforcing systematic bias into a range of labour market decisions if not implemented with care (Section 4.4).

This chapter reviews the empirical literature on the effect of AI on job quality and inclusiveness. This is a nascent, but active, area of research and new work will be needed in the future to see if the results of this chapter hold with the adoption of new AI applications such as large language models (ChatGPT, for example). The chapter begins by reviewing the empirical literature on the effect of AI on wages and productivity (Section 4.1). The chapter then elaborates on the effect of AI on job quality more generally including on job demands and resources (Section 4.2). Section 4.3 discusses the impact of algorithmic management on job quality and Section 4.4 explains how AI can increase fairness, but also the potential bias AI may inject into the labour market. The chapter concludes by offering some policy suggestions for promoting a positive impact of AI on job quality (Section 4.5).

4.1. Workers with AI skills earn significant wage premiums, but it is too soon to see AI's effects on labour productivity

The accumulating evidence on wages for workers with AI skills finds that these workers earn substantial wage premiums. However, for the larger set of workers exposed to AI, the technology appears to have had minimal effects on wages so far. AI is currently more likely to be adopted by larger and more capital-intensive firms, but after adjusting for observable differences between firms, the literature currently finds only modest gains to productivity.

4.1.1. Some workers with the right skills have seen wage gains after AI adoption

The changing composition of tasks due to the adoption of AI brings theoretically ambiguous predictions for the direction of wage changes. AI changes tasks through two main channels. First, AI can create entirely new tasks for workers (see Chapter 3). These are often, but not exclusively, new jobs for workers with AI skills (see as well Chapter 5).¹ When AI creates new tasks for workers, it should lead to rising wages for affected workers.

In addition, AI can automate a set of tasks within a firm or occupation, which leads to two competing effects producing ambiguous changes in wages. First, a *productivity effect* arises from the costs savings from AI. If these cost savings are sufficiently large, this productivity effect leads to greater demand for tasks that are not yet automated and pushes up wages for workers who have not seen their tasks automated by AI. However, automation also leads to a *displacement effect* that leads to lower wages. Intuitively, when tasks are automated, affected workers are bunched into a few sets of tasks putting downward pressure on wages.²

Workers with AI skills earn significant wage premiums

Workers with AI skills are a small, but rapidly growing share of the OECD employed population, and they earn relatively high wages. Green and Lamby (2023^[5]) use Lightcast job posting data combined with labour force surveys to measure the size and characteristics of the AI workforce – defined as workers with a combination of skills in statistics, computer science and machine learning.³ They find that the share of the employed population with AI skills is small – at most 0.3% of those employed in OECD countries, on average – but growing rapidly. In EU countries, they show that nearly half the AI workforce has labour earnings in the top two deciles of the labour earnings distribution, which is higher than for the employed population with a tertiary degree in these countries.

The available evidence for workers with AI skills in the United States suggests that they receive a significant wage premium. Alekseeva et al. (2021^[6]) use Lightcast data of online job postings which include offered wages and skills demanded to measure wage premiums of AI skills. After controlling for skills demanded and the local labour market, they find a wage premium of 11% for job postings that require AI skills within the same firm, and 5% within the same firm and job title. The wage premium is higher than the premiums associated with other skills commonly demanded in high-paying occupations (e.g. software, cognitive and management skills). The highest wage premium for AI skills is found in management occupations, suggesting that employers value skillsets that signal understanding of how to deploy AI in the broader production process (see Chapter 3).

Significant wage premiums for AI skills are also found in a wider set of Anglophone countries. Manca (2023^[7]) also uses Lightcast data but from a larger set of countries including the United Kingdom, Canada, Australia, New Zealand in addition to the United States. The analysis finds that job postings demanding skills closely related to AI skills (Machine Learning, for example) pay significantly higher wages on average in the five Anglophone countries. The analysis further shows that occupations with skill bundles most similar to skills associated with AI offer wage premiums that range from 4% in Australia and New Zealand to over 10% in the United States.

Surveys of workers with AI skills find that they are similarly optimistic about the future trajectory of wages. The OECD AI surveys of employers and workers (hereafter: “OECD AI surveys”, see Box 4.1) find that, among workers who actively develop or maintain AI systems, 47% in manufacturing and 50% in finance expected that their wages would increase after the implementation of AI. This contrasts with 18% and 29% in finance and manufacturing, respectively, who expected that wages would decrease (Lane, Williams and Broecke, 2023^[8]).

Box 4.1. The OECD surveys of AI use, and case studies of AI

While there is a growing body of research on the impact of AI on job quality, there has been little analysis to date examining what happens in organisations and to workers when AI is introduced. To fill this void, the OECD conducted surveys and case study interviews of workers and firms that have adopted AI in the workplace. Both the case studies and firm surveys focused on two sectors to better understand the specific, AI-related technologies used in those sectors. The two chosen sectors, finance/insurance and manufacturing, offer a higher prevalence of AI use compared to other sectors, as well as heterogeneity between the two sectors in terms of worker profile.

The OECD AI surveys of employers and workers (OECD AI surveys, henceforth)

Wishing to capture workers' and employers' own perceptions of the current and future impact of AI on their workplaces, the OECD surveyed a total of 5 334 workers and 2 053 firms in the manufacturing and financial sectors in Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States. The surveys examine how and why AI is being implemented in the workplace; its impact on management, working conditions and skill needs; its impact on worker productivity, wages and employment; what measures are being put in place to manage transitions; and concerns and attitudes surrounding AI. The most frequently reported uses of AI include data analytics and fraud detection in the finance sector, and production processes and maintenance tasks in manufacturing.

The OECD commissioned two surveys between mid-January and mid-February 2022. The polling firm conducted a telephone survey of employers by contacting management representatives of companies with 20 or more employees. The sampling frames for the employer survey were predominantly provided by Dun & Bradstreet, which claims to have the largest business databank worldwide. The employer survey was weighted by country and firm size. The worker survey was implemented as an online survey using access panels – databases of individuals who have indicated a willingness to participate in future online surveys for compensation. The worker survey was weighted by age, education, gender and country. One disadvantage of these panels, which may undermine representativeness, is that they exclude those without internet access.

The OECD case studies of AI implementation (OECD AI case studies, henceforth)

The OECD case studies examine the perceived impact of AI technologies on job quantity, skills needs and job quality at the firm level in the same two sectors as the surveys – i.e., finance/insurance and manufacturing – and in eight countries: Austria, Canada, France, Germany, Ireland, Japan, the United Kingdom and the United States. In each country, the OECD engaged a research team to recruit firms that had implemented AI technologies and to carry out semi-structured interviews with different stakeholders able to speak to the impact of the technology on workers.

The research teams sought interviews with a range of different stakeholders to capture a variety of perspectives. The stakeholders interviewed included workers affected by the AI technology, managers, human resource personnel, AI technology developers or suppliers, AI implementation leads, and worker representatives. A total of 90 firms participated in the project. In firm recruitment, the researchers were free to identify potentially suitable firms as they chose, including using existing personal or professional contacts/networks and/or making new contacts. The OECD supported the research teams by advertising the project and using its own network. Across the 90 firms, 325 interviews were held as part of the case studies: 147 in finance, 154 in manufacturing and 24 in the energy and logistics sectors.¹

1. Due to difficulties encountered in firm recruitment, AI case studies researchers were encouraged to recruit a limited set of firms in the energy and logistics sector.

Source: Lane, Williams and Broecke (2023^[8]), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", <https://doi.org/10.1787/ea0a0fe1-en>; Milanez (2023^[9]), "The impact of AI on the workplace: Evidence from OECD case studies of AI implementation", <https://doi.org/10.1787/2247ce58-en>.

Workers exposed to AI have seen stable or increasing wages, but more research is needed

Some researchers find wage gains for the larger set of workers exposed to recent advances in AI, who do not necessarily have AI skills. Felten, Raj and Seamans (2021^[10]) measure exposure to AI as progress in AI applications from the Electronic Frontier Foundation's AI Progress Measurement project and connect it to abilities from the Occupational Information Network (O*NET)⁴ using crowd-sourced assessments of the connection between applications and abilities.⁵ They find that a one standard deviation increase in exposure to AI is associated with a 0.4 percentage point increase in wage growth. This is largely driven by occupations that require a high level of familiarity with software, but the research design does not separate workers with AI skills (Felten, Raj and Seamans, 2019^[11]).⁶

Research using the same AI exposure measure, but different data sets from the United States, similarly finds that workers exposed to AI tend to earn more. Using data from the United States over the period 2011-18, and exploiting short panels following workers over time, Fossen and Sorgner (2019^[12]) find that the more workers are exposed to AI, the higher their wages. In their preferred specification (using the same exposure measure as above), a one standard deviation increase in AI exposure increases wages by over 4%. Similar positive results are obtained using different measures of AI exposure, but the effect is attenuated by workers who change jobs.⁷

In contrast, the OECD case studies of AI implementation (hereafter: "OECD AI case studies", see Box 4.1) find that, so far, AI has led to little wage changes (Milanez, 2023^[9]). Case study interviewees most often reported that the wages of workers most affected by AI technologies remained unchanged (84% of case studies). In fewer instances, interviewees reported wage increases (15% of case studies). Increases tended to be due to greater complexity of tasks or new skill acquisition following training or to increases in performance metrics that impact wages. Most commonly, wage increases were on account of greater complexity of tasks or new skill acquisition following training. Notably, instances of wage increases tended to occur in Austrian case studies, where collective bargaining over such matters can be strong (see Chapter 7 for the role of social partners in AI implementation).

Although AI does not currently appear to be putting downward pressure on wages, surveys of workers who use AI find that they are worried about future changes to wages. The OECD AI surveys found that, when asked what impact they expect of AI on wages in the next 10 years, 42% of workers surveyed in finance expected that AI would decrease wages. A further 23% expected that wages would remain the same and 16% expected wages to increase. In manufacturing, 41% of workers suggested that AI would decrease wages, followed by 25% suggesting that wages would remain the same and 13% reporting that wages would increase (Lane, Williams and Broecke, 2023^[8]). Workers with a university degree and managers were among the most likely to say they expected their wages to increase which is consistent with much of the other empirical findings in this chapter. Additionally, men – particularly in finance – were more likely than women to expect a wage increase and less likely to expect a wage decrease due to AI. These results indicate that AI may put further pressure on currently existing wage inequalities.

4.1.2. Larger, more productive firms tend to adopt AI, but its effects on labour productivity are so far inconclusive

Wage changes induced by AI adoption ultimately stem from the productivity gains enjoyed by firms after AI implementation. The limited effect of AI on wages – particularly for workers exposed to AI – may reflect its limited impact on productivity so far. This section summarises the current empirical evidence for the effect of AI on labour productivity.

Larger, more productive firms are more likely to adopt AI

Larger, more productive firms are more likely to adopt AI. A representative sample of businesses from the United States in 2018 finds that the incidence of AI adoption rises with firm size and the average wage of the firm (Acemoglu et al., 2022^[13]). Similarly, an OECD study on the United Kingdom in 2019 finds that AI adopters tend to be towards the top of their industry's productivity distribution. Using information from websites, patents and job postings to identify AI adopters, the report finds that AI adoption increases with firm size (Calvino et al., 2022^[14]).

Harmonised, cross-country survey evidence also finds that larger firms are more likely to adopt AI. Calvino and Fontanelli, (2023^[15]) analyse official firm-level surveys of AI use across 11 OECD countries using a common statistical methodology and find that AI is more widely adopted by larger firms. The authors speculate that this may be because larger firms have more resources to allow the adoption of complementary assets to fully leverage AI (see also Chapter 3).

The positive relationship between firm size and AI adoption is also confirmed from studies using job vacancies in the United States. Alekseeva et al. (2021^[6]) use Lightcast job vacancy data to measure firm-level hiring of workers with AI skills as a proxy for AI adoption. They find that AI adoption is positively associated with a firm's level of sales, employment and market capitalisation. This finding is confirmed in the United States using a different database of job postings and CVs and again using sales to measure firm size (Babina et al., 2020^[16]).

AI appears to be producing modest productivity increases, but the evidence is far from conclusive

Although larger, more productive firms are more likely to adopt AI, evidence for a positive causal relationship between AI and productivity is so far tenuous. Using the same employer survey from the U.S. Census Bureau, Acemoglu et al. (2022^[13]) find that AI and dedicated equipment are not correlated with labour productivity. Using a regression model to adjust for observable differences in firms that adopt AI from those that do not, they find a modest positive, but not statistically significant, effect of AI adoption on productivity. The authors provide a few reasons for this finding, including that the effects of AI on labour productivity had not fully materialised at the time of the study (the data are from 2018), and/or that the various automation technologies are often adopted together, muddying any clear interpretation of the effect on AI productivity.

Using job postings and a database of CVs with job histories, Babina et al. (2020^[16]) document a strong and consistent pattern of higher growth among U.S. firms that invest more in AI: a one-standard-deviation increase in a resume-based measure of AI investments over an 8-year period corresponds to a 20.3% increase in sales, a 21.7% increase in employment, and a 22.4% increase in market valuation. However, AI investments are not associated with changes in sales per worker (a rough measure of labour productivity), total factor productivity, or process patents (i.e. patents focusing on process innovation). In other words, while sales and employment increase from AI, they increase proportionally, leading to no statistically significant changes in productivity.⁸

Evidence from a larger set of OECD countries similarly finds inconclusive effects of AI on productivity. Calvino and Fontanelli (2023^[15]) find that productivity premia emerge for AI adopters, but only when adopted with complementary assets. Looking only at the United Kingdom, Calvino et al. (2022^[14]) report that when focusing on larger firms (more than 249 employees), productivity premia emerge for AI adopters. However, when including all firms in the sample, the effect is no longer statistically significant. Furthermore, when focusing on the “intensive margin” of AI adoption, using the differential hiring rate of workers with AI skills, productivity premia again are present for firms with at least 250 employees. The authors also find that much of this productivity premium for firms hiring workers with AI skills comes from managers and high-skill professionals, which is consistent with evidence on wages (above) and job satisfaction (see Section 4.2), as well as employment and skills found in other chapters in this volume (Chapters 3 and 5, respectively).

When asked directly, however, employers do report that AI increases productivity. The OECD AI surveys asked what effect AI adoption had on productivity. Fifty-seven percent of employers in finance and 63% of employers in manufacturing said AI had a positive impact on worker productivity, compared to 8% and 5% who said it had a negative impact (Lane, Williams and Broecke, 2023^[8]). The positive reported impact on worker productivity is consistent with emerging studies of adoption of generative AI applications in the workplace, although these applications tend to be quite specific in scope, and it is too soon to see how they generalise to a wider set of firms (see Box 4.2).

Workers who use AI also believe it has a positive impact on their performance. The same OECD AI surveys find that a majority of workers who interact with AI (either themselves, developing AI or managing others who use AI) report that their performance has improved after the introduction of AI. Across both sectors, over 80% of workers who work with AI report higher job performance. Workers with a university degree as well as workers in management and professional occupations report higher performance from AI than those without a university degree and workers in production and non-supervisory roles.⁹

Box 4.2. Emerging evidence shows that generative AI produces productivity gains and equalises performance between workers in the same roles

Emerging research on the effect of generative AI applications in the workplace finds that they increase productivity and often increase the performance of the least experienced or lowest skilled workers. For instance, Brynjolfsson, Li and Raymond (2023^[17]) find that a generative AI application, which makes real-time suggestions for how customer support workers should answer calls, increases productivity by 14% defined as the number of calls resolved in an hour. The application was introduced gradually over time to allow the researchers to compare workers using the application to those who did not yet have access. The researchers find that the gains in productivity mostly accrue to the least experienced workers, suggesting that the generative AI application infers and implicitly conveys the behavioural patterns of the most productive customer support workers to those who are least skilled or experienced.

Generative AI applications may also improve workers' writing skills. In an experiment by Noy and Zhang (2023^[18]), business professionals using ChatGPT performed writing tasks in less time and produced output of higher quality than those working unaided. The researchers assigned all business professionals two writing tasks, and only suggested ChatGPT between the first and second tasks to a randomly selected subset of participants. They find that the poorest performers from the first writing task saw quality improvements and completion time decrease after exposure to ChatGPT. On the other hand, those with the highest quality writing after the first task saw no increase in quality due to the use of ChatGPT, but they did complete the writing assignment faster.

An experiment using an AI tool to help programmers write basic code also finds that generative AI applications improve productivity specifically for the least experienced. Peng et al. (2023^[19]) ran an experiment where programmers were incentivised to complete a coding task as quickly as possible. A randomly selected treated group had access to CoPilot, a generative AI programme that suggests code and functions in real time depending on the context. The study finds that programmers in the treated group completed the task over 50% faster than those in the control group, and that the benefits accrued most to the least experienced programmers. Overall, these results again suggest that generative AI may decrease performance inequality in the workplace (see also Section 4.4).

4.2. Using AI is associated with higher job satisfaction and occupational safety, but there are some risks

This section reviews the nascent literature on the effect of AI on occupational safety and job satisfaction analysed through the framework of changing workplace demands and resources. It draws mostly on the OECD AI surveys and OECD AI case studies, as well as on studies in the wider literature. As with many studies of job quality and technology adoption, the results often apply only to workers who remain in firms after they have adopted AI, which may be a non-representative sample of workers exposed to AI.

4.2.1. So far, AI use appears to be associated with greater job satisfaction

Workers who use AI report higher enjoyment in their jobs. The OECD AI surveys find that more than half (63%) of AI users in finance and manufacturing reported that AI had improved enjoyment either by a little or by a lot (Lane, Williams and Broecke, 2023^[8]). Despite being positive about the impact of AI on their own performance, results varied based on how workers interact with AI. The workers who reported the greatest positive effect on their enjoyment were those who develop or maintain AI, and those who manage workers who are using AI. Workers using AI or who are subject to algorithmic management were the least likely to report greater enjoyment after the introduction of AI, although most workers in each group still said it improved their enjoyment on the job (see also Section 4.3).

Other surveys of workers similarly observe that AI adoption is associated with greater worker satisfaction. Ipsos (2018^[20]) polled over 6 000 workers across six OECD countries (France, Germany, Spain, the United Kingdom, the United States and Canada) in June 2018 on their feelings towards AI and effects of AI on the workplace after adoption. In all countries surveyed, at least 59% of workers interviewed in each country said that AI had positive effects on their well-being at work. Most workers also said that AI had led to positive implications for the appeal of their work.

Survey evidence from Japan similarly finds that AI adoption is correlated with greater job satisfaction. Surveying over 10 000 workers in Japan, Yamamoto (2019^[21]) finds that adoption or planned AI adoption increases job satisfaction. However, the same survey finds that AI adoption is also concomitant with increased stress. Similarly, the authors find conflicting results on both job demands and resources. With the adoption of AI, workers report less routine work, but also more complex non-routine tasks.

AI is more likely to automate tedious, repetitive tasks

One reason AI may be leading to greater enjoyment on the job is that AI is more likely to automate than create repetitive tasks. The OECD AI surveys asked both workers and firms what types of tasks AI is creating or automating (see also Chapter 3). In both sectors, roughly twice as many employers said that AI had automated repetitive (greater than 50%) tasks than created them, and these differences were statistically significant (Lane, Williams and Broecke, 2023^[8]).

The OECD AI case studies similarly find that AI adoption often results in fewer tedious and repetitive tasks. In finance, this was often through a reduction in simple administrative tasks. For example, a UK financial firm implemented an AI system to assist with a range of activities including mortgage underwriting, interest rate adjustments, commercial banking and brokerage. Workers view these changes as improvements to their job quality because their work has become less administrative and they saw greater value in more time spent supporting customers and colleagues across the firm (Milanez, 2023^[9]). Workers also stressed the reduction of time spent on tedious tasks, giving them greater opportunities to do more research, planning and project management.

AI broadens and deepens the task content of jobs and gives workers greater autonomy in their work

AI's ability to process and model large amounts of data can help decision making and deepen workers engagement with their work. In the OECD AI surveys, 70% and 56% of AI users in finance and manufacturing, respectively, reported that AI assisted them with decision making with overwhelmingly positive effects (Lane, Williams and Broecke, 2023^[8]). The results were similarly positive when the same workers were asked whether AI helped them make better decisions and whether AI helped them make faster decisions. The same survey finds that managers – i.e. positions which rely heavily on decision making – are generally the most positive about the impact of using AI on their job quality than other workers. One potential explanation for this is that partial automation of management tasks can increase efficiency in supervision and administrative tasks or the quality of managers' decisions, allowing them to focus on the more complex and interpersonal tasks, with potentially positive impacts on their productivity and job satisfaction.

The OECD AI surveys also find that AI adoption is associated with greater autonomy over workers' tasks. Autonomy, in turn, appears to be positively associated with performance and working conditions. Most workers in finance (58%) and manufacturing (59%) said AI had increased the control they have over the sequence in which they perform their tasks compared to 20% and 21% of AI users who said that AI had decreased control.

In the OECD case studies, workers reported performing a greater range of tasks after the introduction of AI (Milanez, 2023^[9]). A financial services provider in the United Kingdom implemented a chatbot used for customer service. The chatbot assists customers to serve themselves by directing them to the answers to frequently asked questions. Customer service representatives now handle a reduced volume of basic customer queries, which has helped diversify the range of topics they cover with customers. One representative interviewed as part of the case study summarised the shift in tasks: "The work is more interesting, definitely. It adds variety because customers don't ask the same things every time." She also described how the technology allows workers to form more personal relationships, making the work more rewarding.

AI can change the social environment of the workplace

Increased use of AI in the workplace may decrease human contact to the detriment of job quality. This may be, for example, because AI-powered chatbots answer workers' questions they would otherwise ask a human co-worker or HR advisor, or because an algorithm rather than a human manager "tells" workers when their next shifts will be. Increasing use of AI in the workplace can, therefore, have negative effects on people's well-being and productivity at work, because reducing the social dimension of work can generate an isolation feeling among workers (Nguyen and Mateescu, 2019^[22]). Some experiments also show that human-machine interactions via AI-powered chatbots can increase people's selfish behaviour (Christakis, 2019^[23]), which could negatively affect the well-being of co-workers.

However, other experiments show opposite results and suggest that human-machine interactions can improve human-human interactions. For instance, Traeger et al. (2020^[24]) find that people who interacted with an AI-powered social robot or chatbot while performing a task were more relaxed and conversational, laughed more and were better able to collaborate, although the effect depended on the type of social skills the robot portrayed. For instance, robots that provided neutral fact-based statements were not as successful in improving human-human interactions as those that admitted mistakes or told jokes. See Chapter 6 for a discussion of the policy responses to a lack of human determination and human interaction due to AI use in the workplace.

4.2.2. AI is associated with improved mental health and physical safety but also greater work intensity

AI generally leads to improved mental health and physical safety

AI systems may be able to help with occupational safety and health. Monitoring systems can help alert workers who are at risk of stepping too close to dangerous equipment, for example, or who may not be following safety procedures (Wiggers, 2021^[25]). AI systems are also being developed to detect non-verbal cues, including body language, facial expressions and tone of voice: these systems can be used in the workplace to detect workers who are overworked and those whose mental well-being is at risk (Condie and Dayton, 2020^[26]).¹⁰ For example, train drivers on the Beijing-Shanghai high-speed rail line were wearing “brain monitoring devices” inserted into their caps. The firm manufacturing these devices claims these devices measure different types of brain activities, including fatigue and attention loss, with an accuracy of more than 90%. If the driver falls asleep, the cap triggers an alarm (Chen, 2018^[27]). These monitoring systems, however, often entail extensive data collection and the accompanying risks to data protection.

The OECD AI surveys find that mental health and physical health improved after the introduction of AI, although the benefits are not enjoyed evenly. In manufacturing, 55% of workers using AI said that AI had improved their mental health and 54% in finance. In manufacturing, over 60% of workers using AI reported greater physical health as well.¹¹ Men and workers with a tertiary education report much higher rates of mental and physical health improvements compared to women and those who do not have a tertiary degree, with under 40% of the latter groups reporting improved mental and physical health in the finance sector (Lane, Williams and Broecke, 2023^[8]).

The OECD AI case studies confirm AI’s role in improving physical safety. In many of the worker responses, AI implementation was reported as improving physical safety by improving the capabilities of dangerous machines, which then allowed workers to be physically separated from them. For example, an Austrian manufacturer implemented an AI software that controls a straightening machine used to correct the concentricity of steel rods. Before the introduction of AI, workers controlled the straightening which could lead to accidents, but now workers simply need to monitor the machine from behind a barrier (Milanez, 2023^[9]). To give a further example, the rise of AI and notably computer vision, has allowed sophisticated trash-sorting robots to be deployed to recycling plants – at present, recycling workers face some of the highest risk of workplace incident (Nelson, 2018^[28]).¹² The previous examples show how the use of robots with embedded AI can “[remove] workers from hazardous situations” (EU-OSHA, 2021^[29]).

AI may also lead to a higher pace and intensity of work

The introduction of AI may also result in a faster pace of work. The OECD AI surveys find that 75% of surveyed workers in finance, and 77% in manufacturing who use AI reported that AI had increased the pace at which they performed their tasks. These workers were more than five times more likely to report that AI had increased pace than decreased it (Lane, Williams and Broecke, 2023^[8]). However, the authors caution that the increase in work pace may not necessarily lead to greater stress because it is often concomitant with greater worker control over the sequence used to complete tasks (see above).¹³

The OECD AI case studies provide further evidence that AI may lead to increasing intensity of work. AI applications may automate the “easy” set of a worker’s tasks leaving them with the same amount of work, but without the “break” afforded by the easy problems. For example, an AI developer interviewed as part of the case studies from a Canadian manufacturing firm reported that they purposefully did not automate all of the easy tasks so that workers could benefit from the mental health break when they are completing fewer demanding tasks (Milanez, 2023^[9]). This example showed a keen awareness of the stress to workers from completing more tasks of greater intensity at a higher pace. It is not obvious, however, that all firms are adopting AI in the same way.

4.3. AI-led reorganisation or automation of managers' tasks has downstream effects on their subordinates

AI can help managers in their jobs, for instance, by providing training recommendations tailored to individual workers, or by optimising work schedules according to team members' preferences and availability. AI can also fully automate some or all managerial tasks, for instance by automatically assigning shifts to workers without the need for any human intervention. These various forms of "algorithmic management" (see Box 4.3) can affect the job quality of subordinates regardless of whether they interact with AI to do their jobs. The impact of algorithmic management on subordinates' job quality may depend on the degree of AI involvement in managerial decision making, although evidence differentiating between supported and automated management decisions is still lacking. For example, a human manager can take their knowledge of a workers' team spirit into account – data that may not be recorded and therefore cannot factor in AI systems' decision making.

Box 4.3. Algorithmic management

Algorithmic management consists of using AI to either support or automate management decisions – such as deciding who should receive a bonus, training or promotion – or other managerial tasks such as monitoring workers.¹ For instance, AI can select CVs that have the best fit with a job description while respecting diversity criteria, it can optimise the assignment of tasks or training to workers based on their characteristics and preferences, and it can monitor large numbers of workers at any time and location.

Although some AI systems may be capable of performing each of these tasks independently without the need for any human intervention (i.e., full automation in algorithmic management), the most likely scenario is that managers receive AI-powered recommendations which they can (but do not have to) implement in their own decision making. For instance, managers are usually able to review and overrule algorithmic evaluations of workers or automatic shift assignments (Wood, 2021^[30]). It will be important to ensure that managers are able to critically evaluate and overrule AI-powered recommendations.

Regulating algorithmic management

One of the reasons why full automation in algorithmic management is rare, is that it is limited by regulation in several countries. For instance, the European General Data Protection Regulation (GDPR) effectively prohibits algorithmic management that entails fully automatic decision making, and many non-European countries have GDPR-like legislation as well – see Chapter 6.

While algorithmic management is increasingly used in warehouses, retail and hospitality, and manufacturing (Briône, 2020^[31]; Wood, 2021^[30]; Jarrahi et al., 2021^[32]), it remains most common in platform work (e.g. to assign shifts to riders). The European Union's Platform Work Directive is a landmark legislative proposal, designed to address the challenges posed by algorithmic management in platform work. With a focus on ensuring fair working conditions, the directive aims to regulate the use of algorithms by platforms to manage and monitor workers. It places a strong emphasis on transparency and accountability, requiring platforms to provide clear information about the functioning and impact of algorithms on workers' rights and performance evaluations. The directive also promotes the right to collective representation, enabling workers to negotiate and challenge algorithmic management practices. By tackling algorithmic bias, enhancing transparency, and empowering workers, the EU Platform Work Directive seeks to establish a more balanced and human-centric approach to platform work within the European Union (European Commission, 2021^[33]).

1. A common, related, term is people analytics which describes the use of statistical tools, including AI systems, to measure, report and understand the workforce's performance in various dimensions (Briône, 2020^[31]).

The OECD AI surveys find that around 7% of workers in manufacturing and 6% of those in finance report that they are managed by AI. This could either mean that they are aware that their manager receives AI-powered recommendations, or that certain or all managerial tasks are automated. In both sectors, men are more likely to report being subject to algorithmic management than women (8% compared to 5%, respectively). Being subject to algorithmic management is also more common among respondents with a university degree (8%, compared to 5% among those without a university degree) and among those who are born in another country than where they work (9% compared to 6% among natives).

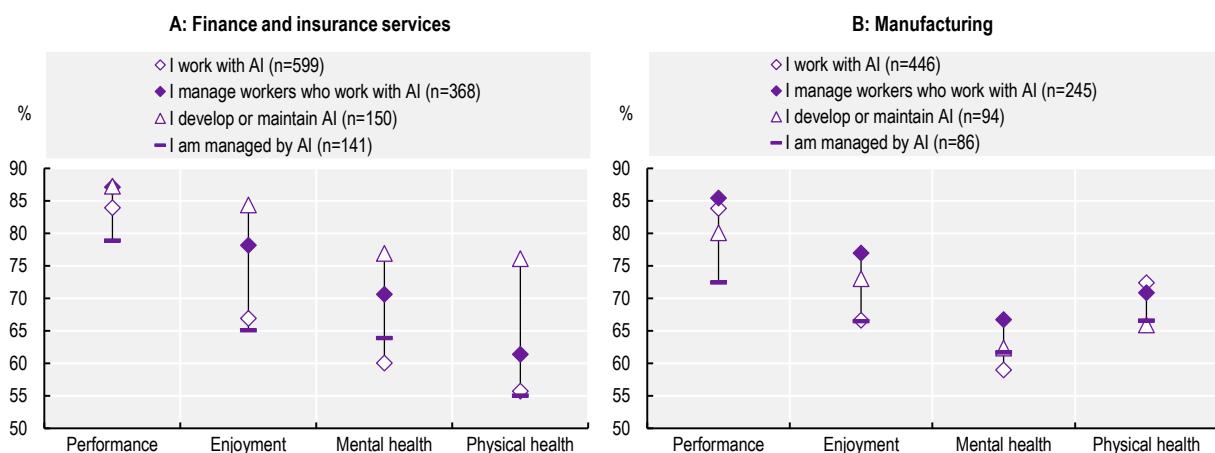
Despite being overall positive about the impact of AI on their own performance and working conditions, respondents who are subject to algorithmic management are less positive than respondents who interact with AI in another way (see Figure 4.1). Compared to other interactions with AI, being subject to algorithmic management appears to be particularly less beneficial for workers' own job performance.

These results might, however, be affected by the fact that the survey question on algorithmic management can only identify workers who are aware that they are subject to it. While workers who are subject to fully automated managerial tasks are probably aware of it, they may not be aware that their manager is "merely" supported by AI in their decision making. Although this means that the results in this section may be driven by workers who are subject to full automation of some managerial tasks, it is uncertain if and how the impact on their job quality would differ from that of workers whose manager is supported by AI.

Possible reasons why workers who are subject to algorithmic management are less positive about AI's impact on their jobs include: the risk of increased work intensity, loss of worker autonomy, and privacy infringements. This section discusses these three risks in further detail. The use of algorithmic management also raises a more fundamental question about whether fully automated decision making should be allowed in the workplace for decisions that affect people's opportunities and well-being – an issue addressed in Chapter 6.

Figure 4.1. Workers who are subject to algorithmic management benefit less from AI

Percentage of AI users reporting improvement in performance, job enjoyment and health



Note: Workers in companies that have adopted AI were asked: "Which of these statements best describes your interaction with AI at work: I work with AI; I manage workers who work with AI; I develop/maintain AI; I am managed by AI; I interact with AI in another way; I have no interaction with AI at work" (Exclusive response option. Otherwise, respondents could select multiple answers). Those who interact with AI were then asked: "How do you think AI has changed your own job performance (performance)/how much you enjoy your job (enjoyment)?/your physical health and safety in the workplace (physical health)?/your mental health and well-being in the workplace (mental health)?" The figure shows the proportion of AI users who said that each of these outcomes were improved (a lot or a little) by AI.

Source: Lane, Williams and Broecke (2023^[8]), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", <https://doi.org/10.1787/ea0a0fe1-en>.

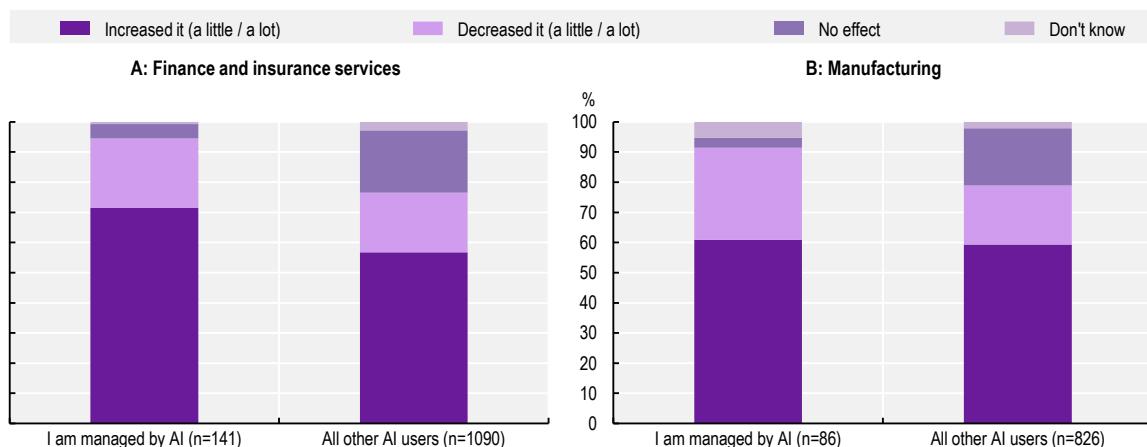
4.3.1. Algorithmic management raises risks for increased work intensity

Algorithmic management can increase work intensity. The constant and pervasive monitoring and data-driven performance evaluations made possible by AI can create a high-stress environment with negative impacts on mental health, as employees may feel constantly scrutinised and under pressure to perform. Additionally, workers who are subject to excessive monitoring may feel compelled to sacrifice their personal time and work-life balance. For example, AI-led telematics systems used to monitor and manage delivery drivers are often introduced with the declared intention to increase drivers' safety, but they put such pressure on drivers to "beat their time" that the resulting work intensification decreases workplace safety. In some warehouses, wearable AI-powered devices to monitor and manage workers score employees and communicate picking targets continuously. Combined with the threat of layoff, this can generate increased work intensity, leading to heightened stress and physical burnout, and create potentially physically dangerous situations at work (Moore, 2018^[34]). In some countries, workers' legal right to disconnect should offer protection against this (e.g. Belgium, France, Italy and Spain (Eurofound, 2021^[35]).

The results from the OECD AI surveys confirm that there is a risk that algorithmic management increases work intensity, although this appears to depend on the context in which it is implemented. Among workers in finance, 85% of those who report being subject to algorithmic management experienced an increase in their pace of work due to AI, compared to 74% among those who interact with AI in another way (Figure 4.2). However, in manufacturing, the share of workers who experienced an increase in their pace of work due to AI is similar for those who are subject to algorithmic management and those who interact with AI in another way (76% and 78%, respectively).

Figure 4.2. The pace of work of subordinates increases with algorithmic management

Percentage of AI users, by interaction with AI and change in the pace of work



Note: AI users were asked: "How has AI changed how you work, in terms of the pace at which you perform your tasks?"

Source: Lane, Williams and Broecke (2023^[36]), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", <https://doi.org/10.1787/ea0a0fe1-en>.

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4.3.2. Algorithmic management affects subordinates' space for autonomy

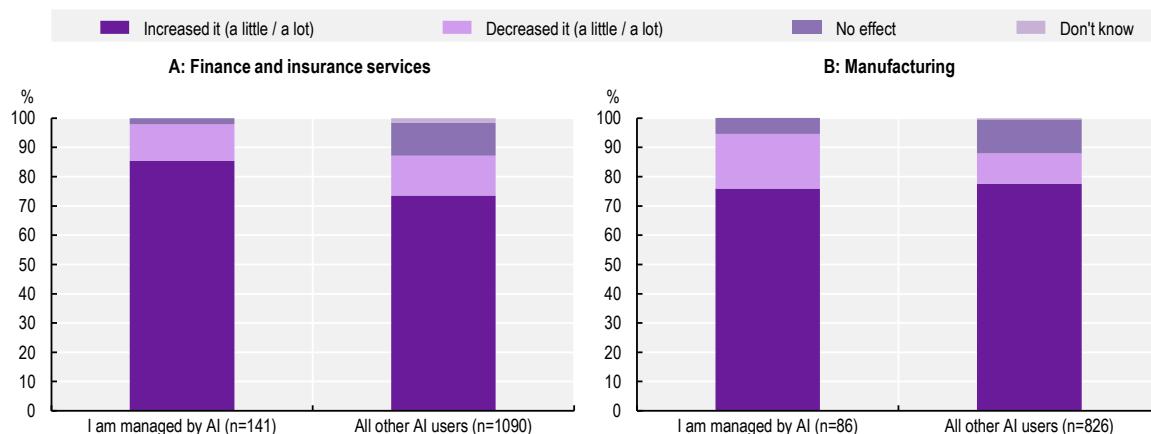
There is a risk that systematic management and monitoring through AI systems reduces space for workers' autonomy and sense of control over how to execute their tasks, especially if taken to the extreme and involving the full automation of managerial tasks. For instance, evidence on warehouse workers subject to full automation in algorithmic management shows that these workers are often denied the ability to make marginal decisions about how to execute their work, or even how to move their own limbs (Briône, 2020^[31]). Devices used in some call centres give feedback to employees on the strength of their emotions to alert them of the need to calm down (Briône, 2020^[31]). Other industries – including consultancy, banking, hotels and platform work – are also adopting software that enables continuous real-time performance reviews either by managers or by clients (Wood, 2021^[30]). These extreme levels of monitoring and performance feedback made possible by algorithmic management can make workers feel commoditised, and it can create a sense of alienation (Fernández-Macias et al., 2018^[36]; Bucher, Fieseler and Lutz, 2019^[37]; Frischmann and Selinger, 2018^[38]; Maltseva, 2020^[39]; Jarrahi et al., 2021^[32]). It may also decrease employees' engagement with work, since for many, work is an integral part of finding meaning and purpose in life (Saint-Martin, Inanc and Prinz, 2018^[40]; Hegel, 1807^[41]; OECD, 2014^[42]; Bowie, 1998^[43]).

A lack of transparency and explainability of decisions based on AI systems would also reduce workers' autonomy. For example, not providing explanations for decisions affecting them does not enable workers to adapt their behaviour in ways to improve their performance (Loi, 2020^[44]). Additionally, a lack of transparency and explainability of AI systems can create a sense of arbitrariness in algorithmic decision making, thereby decreasing trust in these systems and hindering the possibility to contest or redress wrong outcomes – see Chapter 6.

While the OECD AI surveys find that, on average, AI adoption is associated with greater autonomy over workers' tasks (see Section 4.2.1), respondents who report that they are subject to algorithmic management have more polarised views on their sense of control than the overall sample. A larger proportion of those managed by AI report that AI increased their autonomy in finance, while the opposite is true in manufacturing – see Figure 4.3. These findings suggest that the impact of algorithmic management on workers' sense of autonomy depends on the way and the context in which it is implemented.

Figure 4.3. Algorithmic management impacts subordinates' sense of control over their tasks

Percentage of AI users, by interaction with AI and change in own work autonomy



Note: AI users were asked: "How has AI changed how you work, in terms of the control you have over the sequence in which you perform your tasks?"

Source: Lane, Williams and Broecke (2023^[8]), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", <https://doi.org/10.1787/ea0a0fe1-en>.

4.3.3. Algorithmic management raises risks for workers' privacy

Even if the extensive worker surveillance made possible by AI systems may not be legal in many OECD countries (see Chapter 6), some AI-powered monitoring and surveillance software include features leaving very little privacy to workers. While managers monitoring their workers is not a new phenomenon, the type of data that can be processed by using AI is much more elaborate than data processed by humans or other technologies (Ajunwa, Crawford and Schultz, 2017^[45]; Sánchez-Monedero and Dencik Sanchez-Monederoj, 2019^[46]). This can lead to infringements of workers' privacy, which not only violates their fundamental rights (see Chapter 6), but privacy infringements and cybersecurity breaches (or fears thereof) can also have psychosocial impacts and affect people's well-being at work more generally.

The use of remote surveillance software has exponentially increased as workers shifted to mass teleworking during the COVID-19 crisis. For example, *ActivTrak*, an AI-powered tool that continuously monitors how employees are using their time on computers, went from 50 client companies to 800 in March 2020 alone. *Teramind*, which uses AI to provide automatic real-time insights in employee behaviour on their computers, such as unauthorised access to sensitive files, reported a triple-digit percentage increase in new leads since the pandemic began (Morrison, 2020^[47]).

Wearable devices that capture sensitive physiological data on workers' health conditions, habits, and possibly the nature of their social interaction with other people are another example. While this information can be collected and used to improve employees' health and safety, it can also be used by employers to inform consequential judgments (Maltseva, 2020^[39]). Chapter 7 discusses the risk that employers use AI-powered worker surveillance to detect workers' intention to organise as a trade union.

The OECD AI surveys show that, among workers who report that their employers' use of AI involves the collection of data on workers or how they do their work,¹⁴ more than half expressed worries regarding their privacy (Lane, Williams and Broecke, 2023^[8]). Additionally, 58% and 54% in finance and manufacturing, respectively, said that they worry that too many of their data are being collected.

4.4. The impact of AI on inclusiveness and bias in the labour market

The adoption of AI is likely to improve job quality for some groups of workers, but it could worsen it for others, affecting labour market inclusiveness. At the same time, AI systems can help reduce bias in the workplace and strengthen fairness, but only if bias is addressed in AI's development and implementation.

Labour market inclusiveness and fairness are relevant for job quality (Barak and Levin, 2002^[48]; Brimhall et al., 2022^[49]). Disadvantaged workers (e.g. workers with disabilities, ethnic minorities, or non-native speakers) tend to have better access to jobs of good quality in inclusive labour markets with benefits for their job satisfaction, stress levels and sense of fairness. Moreover, there can be positive spill-over effects on the job quality of other workers who value fairness in the workplace.

4.4.1. AI can improve inclusiveness for some disadvantaged groups but not for others

By improving accessibility of the workplace for workers that are typically at a disadvantage in the labour market, AI can improve inclusiveness in the workplace. AI-powered assistive devices to aid workers with visual, speech or hearing impairments, or prosthetic limbs, are becoming more widespread, improving the access to, and the quality of work for people with disabilities (Smith and Smith, 2021^[50]; Touzet, forthcoming^[51]). For example, speech recognition solutions for people with dysarthric voices, or live captioning systems for deaf and hard of hearing people can facilitate communication with colleagues and access to jobs where inter-personal communication is necessary.

AI can also enhance the capabilities of low-skilled workers, with potentially positive effects on their wages and career prospects. For example, AI's capacity to translate written and spoken word in real-time can

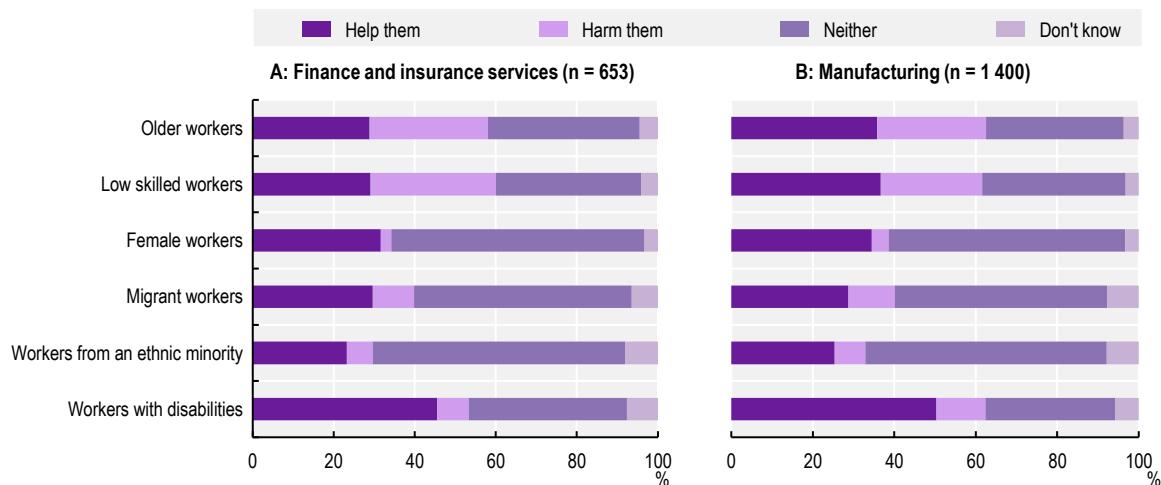
improve the performance of non-native speakers in the workplace. Moreover, recent developments in AI-powered text generators, such as ChatGPT, can instantly improve the performance of lower-skilled individuals in domains such as writing, coding or customer service (see Box 4.2).

At the same time, some AI systems that are used in the workplace are harder if not impossible to use for individuals with low levels of digital skills such as the low-skilled more generally, older workers or women, with negative impacts on inclusiveness. Although using AI may only require moderate digital skills, in the OECD on average, more than a third of adults lack even the most basic digital skills (Verhagen, 2021^[52]). Additionally, the availability and quality of translations and other AI-generated text depends on the number of users that speak a certain language, leading to inequalities in who can benefit from the technology (Blasi, Anastasopoulos and Neubig, 2022^[53]).

Employers and workers often have conflicting views of AI's potential to improve the inclusiveness for disadvantaged groups. Almost half of the employers in finance and manufacturing surveyed in the OECD AI surveys believe that AI would help workers with disabilities, but for low-skilled and older workers, employers are more likely to say that AI would harm rather than benefit them (Figure 4.4). Although employers think that women are more likely to be helped than harmed by AI, female AI users are, themselves, less positive about AI's impact on their job quality than men, and part of this difference remains when controlling for the fact that male and female AI users tend to have different occupations (Lane, Williams and Broecke, 2023^[8]). The findings thus raise questions about whether the current uses of AI could risk leaving certain workers behind as AI diffuses more widely. Chapter 5 discusses in detail the impact of AI on skills and the implications for inclusiveness.

Figure 4.4. Employers think that workers with disabilities are likely to be helped by AI, while older and low-skilled workers could face some harm

Percentage of all employers



Note: All employers (regardless of whether they adopted AI) were asked: "I'm going to name a few different groups of workers. For each of them, please tell me whether you think artificial intelligence is more likely to help them or harm them or neither help nor harm them in their work."

Source: Lane, Williams and Broecke (2023^[8]), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", <https://doi.org/10.1787/ea0a0fe1-en>.

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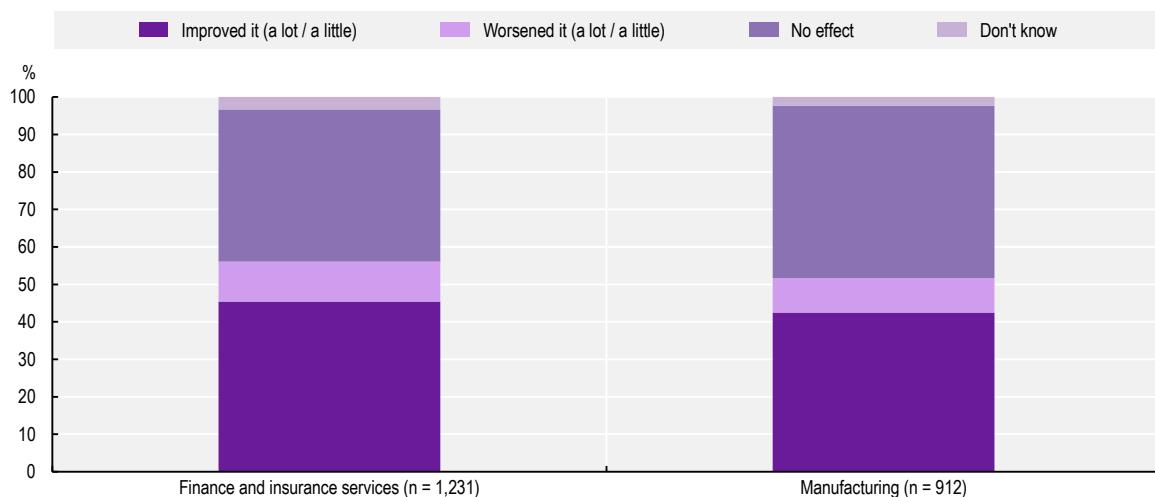
4.4.2. If not designed and implemented well, AI may systematise existing human biases

AI systems used in the workplace are still not always designed and implemented in ways that are unbiased and can therefore have different effects on job quality across groups. For example, since AI can promote more objective performance evaluations (Broecke, 2023^[54]), it could bring better opportunities for recognition and promotions for workers who have traditionally suffered from bias in the labour market, such as women or older workers. However, if AI replicates existing biases the effect will be the opposite, leading to more systematic discrimination. The potential for AI to increase fairness in the workplace resulting in greater job quality and inclusiveness hinges on how well AI overcomes and mitigates inherent biases.

The OECD AI surveys find that 45% and 43% of workers who use AI in finance and manufacturing, respectively, think that AI has improved how fairly their manager or supervisor treats them (Figure 4.5). These positive results notwithstanding, around one in ten AI users think that AI has worsened fairness in management. This suggests that AI's impact on fairness depends on the way the system is designed and used by managers.

Figure 4.5. AI has the potential to improve fairness in management, but not for all workers

Percentage of AI users by change in perceived management fairness



Note: AI users were asked: "How do you think AI has changed how fairly your manager or supervisor treats you (fairness in management)?"
Source: Lane, Williams and Broecke (2023^[58]), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", <https://doi.org/10.1787/ea0a0fe1-en>.

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Bias in AI systems can emerge both at the data or input level and at the system level (Accessnow, 2018^[55]; Executive Office of the President of the United States, 2016^[56]). At the system level, the choice of parameters and the choice of data on which to train the system are decisions made by humans based on their own judgements. The lack of diversity in the tech industry poses risks in this respect (West, Whittaker and Crawford, 2019^[57]). Bias can also be introduced at the data level, as data can be incomplete, incorrect or outdated, and reflect historical biases.

Bias can occur at all points of use of AI systems in the workplace. In hiring – while offering great promise for improving matching between labour demand and supply – there is evidence of bias in who can see job postings, and in the selection and ranking of candidates when AI systems are used (see Chapter 3) (Broecke, 2023^[54]). Bias can also emerge when AI systems are used to evaluate performance in the

workplace. If the data on which the systems are trained are biased, then seemingly neutral automated predictions about performance will be biased themselves. In addition, when assessing performance, AI systems would not be able to take into account context information, such as personal circumstances, typically not coded in the data used by the algorithm.

The use of AI-powered facial recognition systems to authenticate workers when accessing the workplace or workplace tools also presents challenges linked to bias. Facial recognition systems have been found to perform worse for people of colour (Harwell, 2021^[58]), and several researchers question AI's ability to accurately detect emotions and non-verbal cues across different cultures (Condie and Dayton, 2020^[26]).

However, bias is widespread in human decisions as well. A meta-analysis of 30 years of experiments in the United States found that white job applicants were 36% more likely to receive a call-back than equally qualified African Americans, and 24% more likely than Latinos – with little significant evolution between 1989 and 2015 (Quillian et al., 2017^[59]). However, compared with biased human-led decision making, a systematic use of biased AI systems carries the risk of multiplying and systematising bias (Institut Montaigne, 2020^[60]), reinforcing historical patterns of disadvantage (Kim, 2017^[61]; Sánchez-Monedero and Dencik Sanchez-Monederoj, 2019^[46]). Furthermore, discrimination in AI systems is more unintuitive and difficult to detect, which challenges the legal protection offered by non-discrimination law (Wachter, Mittelstadt and Russell, 2021^[62]). The challenge for policy is to encourage AI and humans as complements to ensure they collectively reduce bias.

Recent research on the use of AI systems in the workplace highlights both the potential of AI to surmount bias, improve workplace productivity and improve inclusiveness, but also how AI may perpetuate existing inequalities if not implemented properly. Li, Raymond and Berman (2020^[63]) designed machine learning algorithms to screen resumes and decide whether to grant first round interviews for high-skill positions in a Fortune 500 company. They show that an algorithm that only uses past firm data to decide who to interview improves quality (as measured by hiring yield) compared to human reviewers, but at the expense of decreased representation for minority candidates. They additionally show that when the algorithm is adapted to not only exploit past data, but to explore candidates who were under-represented in historical data, the algorithm both improves quality *and* inclusiveness. Crucially, the algorithm is not incentivised to incorporate inclusiveness; it does so by occasionally exploring under-represented profiles because they have higher variance in the data. The results show that AI applications can improve productivity and inclusiveness, but only if they are thoughtfully designed.

4.5. Concluding remarks

This chapter reviews the current literature on the effect of AI on job quality and inclusiveness. There is evidence that workers with AI skills earn a substantial wage premium, even over similar workers with in-demand skills (for example, software skills). However, for the wider set of workers who are exposed to AI but do not necessarily have AI skills, the effect on wages is inconclusive so far. Taking a broader view of job quality which includes the sum of demands on workers and resources available, AI adoption appears to be associated with greater job satisfaction. This is likely because AI automates more tedious tasks than it creates, and it may also help to improve mental health and the physical safety of workers. The latter is often achieved by improving existing machines to the point where workers no longer need to work with them in close proximity. The evidence points to managers, workers with AI skills, and workers with tertiary degrees enjoying improved job quality.

The discussion of job quality is not limited to wages or job demands and resources, but how AI shapes the broader working environment. AI can change how managers execute their tasks and, in some instances, may even become the manager. While the overall impact of AI on job performance and working conditions tends to be positive, in the OECD AI surveys, respondents who are subject to algorithmic management are often less positive than those who interact with AI in other ways. Some are also more likely to say that

AI has reduced their autonomy and increased their work intensity. Additionally, most workers are worried about their privacy when their employers' use of AI includes data collection on workers and, specifically, how they do their job.

The impact of AI on job satisfaction and workers' health differs across groups of workers, with risks for workplace inclusiveness. Workers in managerial roles, those with the skills to develop and maintain AI systems, and workers with tertiary degrees tend to report higher job satisfaction and improved health after AI adoption. AI systems may also struggle with bias, both at the data and at the system levels. While bias is widespread in human decisions as well, the use of biased AI systems carries the risk of multiplying and systematising biases, leading to decreased inclusiveness of the workplace, with negative impacts on the job satisfaction of disadvantaged groups as well as their colleagues.

Policy can promote AI implementation in the workplace that enhances job quality. Some OECD countries, for example, enable workers to opt-out of full automation in algorithmic management by providing individuals with a right to meaningful human input for important decisions that affect them. Chapter 6 provides a detailed discussion of countries' policy efforts regarding privacy, full automation in algorithmic management, and measures to prevent and address bias linked to the use of AI systems in the workplace, amongst others. Chapter 7 provides a discussion of the current challenges and opportunities for social partners brought about by AI adoption. Skills policies and agile workplace training systems can also help workers benefit from AI. Chapter 5 provides policy lessons for skills and training with particular attention focused on the broader proliferation of AI in the workplace.

Finally, while this chapter reviews the current literature on the impact of AI on job quality and inclusiveness, it should be viewed as a springboard for further research rather than the final word. The literature on the effect of AI on wages – one of the most vital questions facing AI and the labour market – has focused mostly on the tiny set of workers who have AI skills. There are comparatively fewer empirical studies on the much larger set of workers who will use AI but have no specialised training in computer science or machine learning. For the broader picture of job quality considering all job demands and resources, this chapter has relied extensively on the OECD AI surveys and case studies. These studies have already moved the literature forward greatly, but they rely on just two industries, and they cannot account for unobserved worker selection after AI adoption. Further research is needed on these topics, not only to confirm the findings in this chapter, but because AI is a fast-moving field, and the studies in this chapter are fundamentally backward looking. As AI's capabilities evolve, what is true today may not hold in the near future.

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Notes

¹ These new tasks and jobs are not limited to workers with AI skills and include the wider set of workers who are able to exploit the new technology, but who do not necessarily have AI skills.

² See Chapter 3 for a more detailed summary, and Acemoglu and Restrepo (2018^[2]) for the full discussion.

³ See Green and Lamby (2023^[5]) for a discussion of the various approaches for identifying AI skills. Most studies use skill demands in job postings and classify postings as requiring AI skills if a posting demands skills in subfields of AI such as machine learning or natural language processing, or software packages frequently used by AI practitioners.

⁴ See Box 3.1 in Chapter 3 for more information.

⁵ Other examples of AI progress and exposure include Brynjolfsson, Mitchell and Rock, (2018^[64]) who construct a suitability of machine learning index and Webb (2020^[65]) who measures AI progress from patents.

⁶ This suggests that workers with AI skills may be driving the results, which clouds the interpretation for workers exposed to AI but lacking AI skills – see also Chapter 5.

⁷ Alekseeva et al., (2021^[6]) similarly find that workers without AI skills but who work in firms with a higher share of workers with AI skills – a proxy for AI adoption – earn higher wages compared to similar workers.

⁸ Using a database of German firms with information on AI adoption in 2018, Czarnitzki, Fernández and Rammer (2022^[67]) find evidence that AI increases sales, which they then interpret as productivity. They do not examine the impact on sales per employee as is typical in the literature. It is therefore difficult to interpret their results. However, they find a positive association between employment and sales which would suggest an attenuation of their measured productivity effect consistent with Babina et al. (2020^[16]).

⁹ As with all studies of this kind, the results only account for workers who remain with the firm. If workers who find their performance decreases due to AI exit the firm, these responses would not be considered.

¹⁰ Several researchers, however, are questioning AI's ability to accurately detect emotions and non-verbal cues across different cultures (Condie and Dayton, 2020^[26]).

¹¹ AI appears to have improved physical safety much less in finance, but this is not surprising as finance is not usually a physically demanding industry, nor is it known to be physically hazardous to one's health. It may also be the case that workers whose health deteriorated due to AI were more likely to exit the firm.

¹² In 2020, the Waste Management and Remediation Services industry had a fatal injury rate of 15 per 100 000 full-time-equivalent workers, or about 5 times the average rate in the United States (BLS, 2021^[66]).

¹³ One should interpret these results with caution, however, as workers who feel particularly stressed by a higher pace of work may have separated from the firm after the introduction of AI.

¹⁴ Forty-nine percent of workers in finance and 39% in manufacturing said that their company's application of AI collected data on them as individuals or how they do their work.

5

Skill needs and policies in the age of artificial intelligence

Julie Lassébie

The development and adoption of artificial intelligence (AI) will likely have a profound impact on labour markets, not only in terms of employment levels and job quality, but also on how work is organised, the type of tasks workers perform, and therefore on the skills that will be needed. This chapter discusses changes in skill requirements due to AI development and adoption and how adult learning systems should be adapted in response. The chapter reviews the available evidence on firm-provided training for AI. It makes the case for public intervention and presents examples of policies to promote training for AI. It also shows how AI technologies could be used to improve adult learning systems and concludes by discussing avenues for future research.

In Brief

Key findings

The development and adoption of artificial intelligence (AI) will have an important impact on skill needs, as they will modify the task and skill composition of jobs and the distribution of occupations in the economy. Adult learning systems will need to quickly adapt to these rapid transformations.

This chapter addresses two related questions: What is the specific impact of AI on skill needs? And how can adult learning systems be better designed and implemented to meet these needs? The main findings of the chapter are:

- As a result of AI development and adoption, some skills can be increasingly replicated by technologies. This is the case for manual and fine psychomotor abilities, as well as cognitive skills such as expression and comprehension, planning, and advising. ChatGPT, an AI model that made headlines recently for its performance in language tasks, is a striking example of how AI development and adoption are accelerating, which suggests that the impact of AI, including on skill needs, might be larger in the near future.
- At the same time, skills needed to develop and maintain AI systems, and to adopt, use and interact with AI applications, will become more important. In some cases, specialised AI skills will be required, but the shift in skill needs is much broader, and there will be growing demand for basic digital and data science skills, as well as for complementary cognitive and transversal skills. As AI becomes widespread, it will be increasingly important for workers in various occupations to possess a broad range of skills to effectively develop and interact with AI systems.
- Training for specialised AI skills requires a combination of formal higher education and on-the-job learning. Basic AI knowledge or “AI literacy” should be taught at different levels of formal education, including in schools.
- Training for AI should be provided not only to vulnerable groups (low-skilled and older workers in particular) to help them adapt to the changes AI will bring to the workplace, but also to higher-skilled workers and managers, to foster AI development and adoption.
- Following adoption, companies tend to provide training for AI. Yet, the lack of appropriate skills remains a major barrier to AI adoption. Firms may under-invest in training for AI for several reasons including the existence of an important informational gap around AI and the fact that the benefits of training for AI may be wider than the firm.
- Public policies have an important role to play to promote greater training provision by employers, to ensure an integrated approach to skills development for AI at all stages of the lifecycle, from initial education to lifelong learning, and to encourage diversity in the AI workforce.
- Although most policies and strategies for AI recognise the importance of skills, few propose sufficient measures to develop them.
- Greater use of AI could be made to improve the design, targeting and delivery of training. Several examples of its use already exist, but they are currently limited. Yet, using AI in training also poses non-negligible risks. These risks need to be considered carefully and properly addressed before the use of AI in training becomes more widespread.

Introduction

Even if the available evidence does not point to large employment effects so far (Chapter 3), artificial intelligence (AI) is likely to have a more sizeable impact on labour markets going forward, and in particular on skill needs. Emerging and growing occupations will require different skillsets to those needed in shrinking occupations. Further, much of the impact of AI on jobs is likely to be experienced through the reorganisation of tasks within occupations (Chapter 4), and changes in tasks carried out by workers will modify the skills required at work. This chapter examines how AI will impact skill needs, assessing both skills that may become redundant and those that will become more important.

The potential for firms and workers to adapt to the introduction of AI will depend largely on ensuring workers are equipped with the necessary skills. This chapter highlights the main challenges involved in designing adult learning systems for an AI-ready workforce and points to policy priorities. It provides details on the type of training that will be needed, and the groups of workers that should be targeted. It presents evidence suggesting that while some enterprises already offer AI training to their employees, in general most firms may not be doing enough. Public intervention is warranted but existing policies promoting training for AI are not sufficient.

AI poses challenges for adult learning systems but may also represent an opportunity to improve training design, targeting and provision. AI technologies could be used to better plan and deliver training, and to increase training participation and inclusiveness, and the chapter looks at some examples of where this is already happening. Yet, the use of AI in training also poses some risks and challenges: the costs related to AI adoption may exacerbate inequalities between small and large actors; the fact that interacting with AI requires a basic level of digital skills may limit participation by low skilled individuals; and the tendency of some algorithms to scale up human biases may decrease inclusiveness. An additional challenge is that the use of AI in training will likely bring about important changes in skill needs among teachers and trainers. These issues need to be considered carefully.

The chapter starts by reviewing existing evidence on changes in skill needs brought about by AI development and adoption (Section 5.1). Section 5.2 then discusses how training should be delivered in order to respond to these changes, focusing on the type of training and on groups of workers that should receive particular attention. Section 5.3 reviews available evidence on firm-provided training for AI. Section 5.4 makes the case for government intervention and reviews existing policies to promote training for AI. The chapter then shows how AI can be used to improve adult learning systems (Section 5.5) and concludes by discussing avenues for future research (Section 5.6).

5.1. The development and adoption of AI will have an impact on skill needs

There are two reasons why AI will modify skill needs. On the one hand, AI can replicate more and more skills, in particular cognitive and manual skills. On the other hand, AI raises the demand for skills needed to develop AI and for skills necessary to use AI. This section describes in details changes in skill needs due to AI, and is based mainly on several recent OECD studies (Green and Lamby, 2023^[1]; Lane, Williams and Broecke, 2023^[2]; Lassébie and Quintini, 2022^[3]; Milanez, 2023^[4]).¹

5.1.1. AI has made important progress replicating cognitive and manual skills

Recent technological advances in AI and automation technologies mean that several skills and abilities previously considered hard to replicate by technologies are now more susceptible to automation. This is the case of fine arts, several psychomotor abilities, and cognitive skills such as expression and comprehension, scheduling, and advising, as detailed below (Lassébie and Quintini, 2022^[3]).

AI can, in some cases, compose, produce, and perform works of music and visual arts, according to experts interviewed for the study by Lassébie and Quintini (2022^[3]). Zhang et al. (2022^[5]) make a similar point in the AI Index 2022 report, as they claim that for some constrained applications, text, audio, and images generated by AI systems are as good as if they had been composed by humans. However, one challenge developers face when developing the systems further is that there is no consensus on what can be labelled true or false, or good or bad. Hence, it is not straightforward to find or construct reliable training sets with which algorithms can be trained.

Important progress has also been made in the past few years in replicating psychomotor abilities, and in particular manual and finger dexterity, and the ability to work in cramped workspace, albeit to different degrees. Robots that have manual dexterity have existed for several decades and are present in many manufacturing plants. This can be considered a mature technology. Finger dexterity is more challenging for robots, but significant progress has been made. Thanks to deep learning-based vision systems, robots can manipulate objects, pick them up and place them at speeds that are practical for real-world applications (Littman et al., 2021^[6]). However, the gesture of pushing while applying the right force and all gestures that rely on feeling the texture of an object are much more challenging. Dealing with very small objects is also complex; one important difficulty is that tolerance for error must be very low because any mistake might lead the robot to harm persons, damage objects or disrupt systems (Nolan, 2021^[7]). Similarly, working in cramped workspaces that requires getting into awkward positions is difficult but not impossible for robots. Specialised robots can be built for specific applications: for instance, there are robots that can manoeuvre inside airplane wings to verify their condition, and there exist drones to inspect industrial buildings. In these environments, one difficulty for robots lies in the darkness and absence of vision. While humans can rely on other senses to form a mental image of the space, robots cannot, as it would be computationally too demanding. Hence, many of the solutions that now exist are remotely controlled and still rely on human intervention.

AI technologies are increasingly capable of oral and written expression and comprehension, thanks to important progress made in recent years. In 2017, an OECD report investigating computer capabilities with respect to certain human skills (Elliott, 2017^[8]) showed that computers were not performing as well as humans on answering literacy questions, even for those that were the easiest for adults, although the difference between computers and humans for these questions was small. However, a new study by the OECD (2023^[9]) finds that today, experts believe AI can answer around 80% of literacy questions asked to adults in the Survey of Adult Skills (PIAAC). These questions involve, at basic levels, locating information in short texts and identifying basic vocabulary, and, at higher levels, navigating across larger chunks of text to formulate responses. Experts suggest that AI technologies can answer most questions at basic levels and some more complicated ones and predict that AI will be able to successfully answer the entire literacy test by 2026. The difference between human and AI performance on the most complex linguistic tasks has been narrowing, due to the development of network architectures with enhanced capability to learn from complex and context-sensitive data and relying on increasing data resources and computing power (Littman et al., 2021^[6]).

One class of Natural Language Processing models that has drawn much attention recently are Large Language Models, in particular ChatGPT.² ChatGPT is a striking example of an AI model that can perform as well as humans on several language and more generally cognitive tasks, and much faster. Emerging experience with the use of ChatGPT shows that it can write jokes, computer code and essays, formulate medical diagnoses, create games, and explain complex scientific concepts to a wider audience. Its output is, in many cases, very convincing. When evaluated against answers given by experts on different questions, its performance has been assessed as good as a team of experts (Guo et al., 2023^[10]). It exhibits human-level performance on various professional and academic benchmarks, including passing a simulated bar exam with a score around the top 10% of test takers (OpenAI, 2023^[11]). Its adoption appears to happen at fast pace, for instance it has been added to Microsoft's industrial grade search engine Bing a few months after its release. However, ChatGPT produces in some cases superficial content, and

can even generate false information. In all cases, it needs to be prompted correctly and its output must be reviewed. Human intervention thus remains crucial.

Systems that provide recommendations to humans are also becoming more and more widespread. There exist AI-powered task planning and dynamic scheduling tools that perform better than humans in many cases. They also necessitate human intervention: time constraints have to be recorded in the system, and humans can accept or reject recommendations made by AI. For instance, in online marketing, “recommender systems”, that automatically prioritise products seen online by users, have become essential and have an important influence on individuals’ consumption of products, services, and content (news, music, videos...). In the case of preventive maintenance, AI systems can provide advice on what to replace or check on a machine. In the field of education, tasks that are complementary to pure instruction (targeting learning activities to students, determining which modules they should follow, or what instruction method to use) can also be performed by AI systems (these applications are discussed in more details in Section 5.5).

Looking at firms that have adopted AI reveals that there is already evidence of some skills becoming redundant. In the OECD AI surveys of workers and employers on the impact of AI on the labour market in the sectors of finance and manufacturing in seven OECD countries (Lane, Williams and Broecke, 2023^[2]), approximately half of AI users declare that AI has made some of their skills less valuable (51% of AI users in the finance sector and 45% in manufacturing), and these proportions were even higher among workers who reported that some of their tasks had been automated (56% in finance and 51% in manufacturing). In case studies of employers having implemented AI carried out by the OECD, Milanez (2023^[4]) finds that skills that are made redundant by AI adoption are mainly manual skills, and examples of skill redundancies were concentrated in the manufacturing sector. For instance, in a Canadian manufacturing firm, an AI-powered robot is used to measure and cut glass for tiles, a task previously performed manually by workers. After the introduction of the AI tool, workers only have to interact with the machine, loading input materials and monitoring the machine’s output.

5.1.2. AI increases the demand for both skills required to develop AI systems and skills to use AI applications

Higher skills demand will come, on the one hand, from the need to develop and maintain AI systems and, on the other hand, from using and interacting with AI applications. Jobs to develop and maintain AI systems are usually technical in nature and some of these jobs are new, in the sense that workers will perform tasks specific to AI that are not present in today’s occupations. In firms adopting AI, workers in several occupations will have to use and interact with AI. Most of these occupations are not new but, in some cases, the tasks involved, and the skills required to perform them, will change. This subsection discusses the skills required in these two types of jobs, and analyses commonalities and divergences.

Skills to develop and maintain AI systems

AI development requires specialised AI knowledge and skills, at the intersection between computer programming, database management and statistics. Skills mentioned together with the keyword “artificial intelligence” in online job postings include, for instance, programming languages such as Python, the ability to work with and manage big data, and skills for data analysis and visualisation. More specific knowledge of AI models (e.g. “decision trees”, “deep learning”, “neural network”, “random forest”, etc), AI tools (e.g. “tensorflow”, “pytorch”, etc) and AI software (e.g. “java”, “gradle”, “galaxy cluster”, etc) is also required (Alekseeva et al., 2021^[12]; Manca, 2023^[13]; OECD.AI, 2023^[14]; Squicciarini and Nachtigall, 2021^[15]). Findings from the OECD surveys of firms having adopted AI in Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States, confirm that a majority of workers who develop and maintain AI possess such specialised AI skills (79% of workers in finance and 75% in manufacturing) (Lane, Williams and Broecke, 2023^[2]). Yet, these findings also show that not all workers that develop and maintain AI

possess such skills: 10% of them explicitly state that they do not have specialised AI skills. This suggests that some of these jobs, for instance to provide input to Machine Learning models or to correct outputs of AI systems, do not require specialised AI knowledge (see below for a discussion of different types of jobs that might be created as a result of AI and the skills they involve).

The demand for specialised AI skills in online job postings has been rising over the past few years. It grew fourfold between 2010 and 2019 in the United States, accelerating in the last three years, across a wide range of occupations. In comparison, over the same period, the share of job postings mentioning computer skills was stable and demand for software skills seems to have declined slightly (Alekseeva et al., 2021^[12]; Acemoglu et al., 2022^[16]). Similar trends have been observed in job postings in Canada, Singapore and the United Kingdom (Squicciarini and Nachtigall, 2021^[15]).

Job postings that require specialised AI skills also necessitate high-level cognitive skills, including creative problem solving, and transversal skills such as social skills (communication, teamwork, collaboration, negotiation, presentation) and management skills (project management, staff supervision and management, mentoring, leadership), suggesting that these skills are complementary (Alekseeva et al., 2021^[12]; Manca, 2023^[13]).

AI development thus requires a specific bundle of skills that few individuals may possess, although it is not straightforward to determine whether supply is keeping up with demand. Analysis of wage data by the OECD provides indirect evidence: while the wages of workers with specialised AI skills are high (see Box 5.1 that presents some socio-demographic and wage characteristics of the AI workforce), their wage growth does not exceed that of other occupations on average across OECD countries, suggesting that, so far, supply may be sufficient to satisfy the level of demand. However the OECD average masks important differences across countries. In particular, Austria, Belgium, Denmark and Finland, saw the largest gaps between hourly wage growth for those with AI skills and the economy overall. Furthermore, employers may use non-wage adjustments to adapt to imbalances. For example, they may use other types of financial compensation, such as lump-sum bonuses or shares of the company for which they work. This explanation is particularly relevant for the AI workforce. This may lead earnings growth to be understated (Green and Lamby, 2023^[1]). Other non-wage benefits may include pension schemes and retirement benefits, health insurance, student loan support, and workplace amenities. The issue of a potential shortage of workers with the right bundle of skills to develop and maintain AI systems thus deserves more research.

In terms of the new types of jobs to build, train, update, and maintain AI technologies, Wilson, Daugherty and Morini-Bianzino (2017^[17]) foresaw already in 2017 that three new types of jobs might be created. The first category would be composed of “trainers” of Machine Learning models to teach AI systems how they should perform. These roles usually involve technical and data science skills, but not only, and not all. For instance, chatbots need to be trained to communicate with humans using compassionate and sympathetic language and to understand humour and language subtleties. This requires behavioural training of the algorithm, and hence interpersonal skills for the “trainer”. The second category of new jobs could include “explainers” of AI systems that will clarify the functioning of algorithms and the different types of outcomes that are being generated, notably to managers and non-technical professionals in firms implementing or seeking to implement AI applications, but also to consumers and the general public. These jobs could become less necessary if or when AI systems become more transparent and self-explanatory, but remain crucial for the time being as governments start taking actions to ensure transparency (see Chapter 6). These jobs will necessitate a good knowledge of AI, but also communication skills and the ability to convey technical information to a non-technical audience, among others. Finally, “sustainers” will check that AI systems are working as intended, detecting biases, fakes and mistakes, and will ensure that unintended consequences are addressed as they should and in a timely manner. They will monitor algorithms’ outcomes, and ensure they continue to work as intended over time, as the technology, data and environment change.

Box 5.1. Characteristics of the AI workforce

According to OECD research, the AI workforce, i.e. workers with specialised AI skills, is concentrated in a few high-skilled occupations: mathematicians, actuaries and statisticians, software and application developers, ICT managers, database and network professionals, and electrotechnology engineers (Green and Lamby, 2023^[1]). The AI workforce is disproportionately highly-educated and male. Over 60% of the AI workforce has at least a tertiary degree, on average across OECD countries, and less than 40% of the AI workforce are women compared to more than 50% of the employed population with a tertiary degree across OECD countries. In contrast, the AI workforce is just as likely to be young or foreign-born compared to the employed population with a tertiary degree.

Regarding wages, Green and Lamby (2023^[1]) show that across European OECD countries in their sample, almost 50% of the AI workforce earns above the 80th percentile in the earnings distribution. Manca (2023^[13]) shows that job postings where skills related to AI are highly relevant offer higher wages than the average even after accounting for average years of schooling, skill complexity of the job and geographical factors related to the job offer. Similarly, Alekseeva et al. (2021^[12]) find a wage premium of 11% for job postings that require skills related to AI within the same firm, and 5% within the same firm and job title. This wage premium is the highest for management occupations, and higher than the premium associated to other skills (software, cognitive, or management skills).

Source: Alekseeva et al. (2021^[12]), "The demand for AI skills in the labor market", <https://www.doi.org/10.1016/j.labeco.2021.102002>; Green and Lamby (2023^[1]), "The supply, demand and characteristics of the AI workforce across OECD countries", <https://www.doi.org/10.1787/bb17314a-en>; Manca (2023^[13]), "Six questions about the demand for artificial intelligence skills in labour markets", <https://www.doi.org/10.1787/ac1bebf0-en>.

These new roles are already emerging in firms implementing AI. Based on the OECD AI case studies, Milanez (2023^[4]) finds that a significant share of firms adopting AI experience job creation related to the further development and maintenance of AI. The new job profiles are not clearly defined yet, but usually involve providing suitable operating environments for machine learning models, developing, maintaining, and training the models, and tracking their efficiency and accuracy over time. For instance, a French banking and insurance firm mentions the role of employees that make sure that AI models remain accurate over time and that their predictive power is satisfactory as new data are used. They indicate when the AI model has to be modified, and how to prepare the data to this end.

Skills to use and interact with AI applications

In some cases, the implementation of AI technologies does not lead to changes in skills required in adopting firms. In the OECD study by Lane, Williams and Broecke (2023^[2]), 57% and 48% of employers that have adopted AI in finance and manufacturing report no change in skill needs to date. Similarly, in the OECD AI case studies of firms having implemented AI, 60% of firms say that AI adoption has not modified skill requirements (Milanez, 2023^[4]). To explain this, the study points to several possible explanations. First, in several instances, AI implementation has had, so far, a small impact on the tasks carried out by workers and hence a small impact on the skills required to carry out those tasks. In other cases, AI adoption affects the order and relative importance of pre-existing tasks rather than change or add new tasks, raising few additional skill needs. AI implementation sometimes necessitates digital skills that were not required previously, but at such a basic level that firms do not think it is worth mentioning as a change. Other reasons include the fact that, in manufacturing, the preservation of workers' existing skills, at least for a small group, is sometimes seen as a safeguard if the AI system fails. In finance, several firms having adopted AI declare that it led to greater reliance on workers' existing skills, as opposed to the need for different skills. This was the case when AI adoption leads to automation of simple versions of a task, while

complex versions were still performed by workers. Finally, it is important to note that AI adopters are a selected sample of employers that are able to implement AI precisely because their workforce possess the necessary skills. This could very well explain why many AI adopters report no change in skill needs.

But in a significant share of firms, AI implementation is associated with a need for higher and broader skills, and the demand for digital, analytical, and soft skills increases (Lane, Williams and Broecke, 2023^[2]; Milanez, 2023^[4]). General digital skills and elementary knowledge of AI are needed, most often at a basic level (ability to use a computer or smartphone), for workers to be able to use the AI application, even if some firms think such a marginal change is not worth mentioning. Analytical and soft skills are becoming more important for several reasons. First, the automation of simple versions of tasks often gives workers greater shares of complex tasks, requiring higher analytical skills such as specialised knowledge, comprehension and application of new ideas. Second, task automation often leads workers to take on greater shares of tasks requiring soft skills and interpersonal skills. New needs also arise for workers who are redeployed to other departments within the same firm (Milanez, 2023^[4]). Similar findings are reported in Lane, Williams and Broecke (2023^[2]): AI primarily increases the importance of skills such as creativity and communication within the company (42%/41% of employers that have adopted AI in finance/manufacturing), as well as the need for highly educated workers (55% of employers in both sectors).

Only in few cases does the use of AI applications require specialised AI knowledge or digital or data science skills. For instance, Bessen et al. (2018^[18]) found that only 10% of firms surveyed for their work require users to have expert coding or data skills, while 59% require general familiarity with computers, and the remainder require no special skills at all. In the OECD case studies of firms having adopted AI, Milanez (2023^[4]) reports that several developers explain that AI applications are designed to be user-friendly and intuitive and that their use requires the same level of digital skills than the utilisation of a smartphone. This low importance of specialised AI skills is also reported by Lane, Williams and Broecke (2023^[2]).

To sum up, Table 5.1 presents the different types of skills that are becoming more prevalent because of AI. Sophisticated AI and digital skills are necessary to develop and maintain AI systems, while elementary AI knowledge and basic data science skills are necessary, in some cases, to work and interact with AI applications. But beyond technical expertise, a broader range of skills are needed. Indeed, both sophisticated and general AI skills are increasingly required in conjunction with other cognitive skills such as analytical skills and problem-solving, and with transversal skills (social skills, management, communication, teamwork, multitasking). At the moment, these skills are harder to replicate by automation technologies (Lassébie and Quintini, 2022^[3]).

As AI becomes widespread, it will be increasingly important for workers in various occupations to possess this broad range of skills to effectively develop and interact with AI systems. The rest of this chapter discusses how adult learning systems can be adapted to respond to these new skill needs. In particular, Section 5.4.2 presents several country initiatives to foster the development of skills for AI.

Table 5.1. Skill needs in the age of AI

	Type of skill	Examples
Skills to develop and maintain AI systems	Specialised AI skills	General knowledge of AI (such as Machine Learning) Specific knowledge of AI models (“decision trees”, “deep learning”, “neural network”, “random forest”, etc), AI tools (“tensorflow”, “pytorch”, etc) and AI software (“java”, “gradle”, “galaxy cluster”, etc).
	Data science skills	Data analysis Software Programming languages, in particular Python Big data Data visualisation Cloud computing
	Other cognitive skills	Creative problem solving
	Transversal skills	Social skills Management skills
Skills to adopt, use and interact with AI applications	Elementary AI knowledge	Principles of machine learning
	Digital skills	Ability to use a computer or a smartphone
	Other cognitive skills	Analytical skills Problem-solving Critical thinking Judgement
	Transversal skills	Creativity Communication Teamwork Multitasking

Source: Authors' elaborations on Alekseeva et al. (2021^[12]), “The demand for AI skills in the labor market”, <https://www.doi.org/10.1016/j.labeco.2021.102002>, Lane, Williams and Broecke (2023^[2]), “The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers”, <https://www.doi.org/10.1787/ea0a0fe1-en>; Manca (2023^[13]), “Six questions about the demand for artificial intelligence skills in labour markets”, <https://www.doi.org/10.1787/ac1beb0-en>; Milanez (2023^[4]), “The impact of AI on the workplace: Evidence from OECD case studies of AI implementation”, <https://www.doi.org/10.1787/2247ce58-en>; OECD.AI (2023^[14]), *Visualisations powered by JSI using data from www.adzuna.co.uk*, <https://oecd.ai/>; Squicciarini and Nachtigall (2021^[15]), “Demand for AI skills in jobs: Evidence from online job postings”, <https://www.doi.org/10.1787/3ed32d94-en>.

5.2. Changes in skill needs call for new training opportunities

5.2.1. AI development and adoption call for specialised education pathways as well as specific AI literacy courses

Training to develop and maintain AI systems

Skills to develop and maintain AI systems include specialised AI skills, data science, and cognitive and transversal skills (Table 5.1). The acquisition of specialised AI skills requires both advanced academic training and substantial hands-on experience. Initial education is key and a substantial part of the AI workforce possesses a tertiary degree (Green and Lamby, 2023^[1]). Learning-by-doing is also important (Daugherty, Wilson and Michelman, 2019^[19]), and may take the form of apprenticeships or informal learning (e.g. being part of a research team or the AI development process within their firms).³

Training to use and interact with AI applications

AI adoption and use in the workplace requires elementary AI knowledge, basic digital skills, as well as cognitive skills and transversal skills (Table 5.1). In firms adopting AI, although a minority of AI users said that they had AI skills, nearly three-quarters said that they were enthusiastic to learn more (73% of workers in finance and 72% in manufacturing) (Lane, Williams and Broecke, 2023^[2]). The question of how to promote elementary knowledge of AI is thus one that deserves particular attention.

Elementary knowledge of AI is often referred to as “AI literacy”, a concept that has recently gained attention in the literature focusing on adult learning. Long and Magerko (2020^[20]) define it as “a set of competences that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace”. Ng et al. (2021^[21]) insist that AI literacy does not necessarily refer to skills needed to develop AI models but rather to understand, use, monitor, and critically reflect on AI applications. Based on a review of existing literature, the authors distinguish four levels of AI literacy. At the most basic level, AI literacy entails the knowledge of basic functions of AI and how to use AI applications in everyday life. The second level of AI literacy involves the ability to apply AI knowledge, concepts and applications in different contexts. AI literacy at higher levels includes skills to implement and evaluate AI. It thus requires the ability to manage data needed for the development of AI algorithms and skills to critically reflect on their outputs. All levels necessitate basic analytical skills and knowledge of mathematics and statistics and include some elements of AI ethics. However, research in this area is still in its infancy and needs refinement in terms of how to define AI literacy in adult education and how to measure AI literacy of adults (Laupichler et al., 2022^[22]).

Another important but under-researched topic concerns the structure and content of AI literacy courses for non-experts. In a scoping literature review, Laupichler et al. (2022^[22]) show that most courses have one or several initial units aiming at providing a first understanding of what AI is, where it came from, and what it can and cannot do. Most courses review machine learning and deep learning, as they form the basis for most AI applications today. Finally, some courses also discuss ethical issues in AI, addressing algorithmic bias or the black box nature of AI. Another characteristic of AI courses designed for non-experts is that they are commonly presented in short modules that are easier to follow and integrate. They mostly rely on decentralised, digitally available instructional courses or learning materials.

5.2.2. Specific groups of workers deserve special attention

Training programmes should be developed for several groups of workers, for different reasons. On the one hand, equity arguments motivate the focus on vulnerable groups, in particular older workers and the low-skilled, so that they can adapt to changes brought about AI adoption in the workplace. The motivation for training the low-skilled stems from the disadvantage that they still have in general in terms of automation risk (see Chapter 3) and is not specific to AI only. This specific group is thus discussed in more details in Box 5.2.

The motivation for targeting older workers stems from the fact that they are particularly vulnerable to the implementation of AI in the workplace, because they are less likely to possess the new skills required (especially digital skills) and are also less likely to engage in training. The fact that older workers lag behind when it comes to digital skills has been extensively documented in the literature. For instance, results from the Survey of Adult Skills (PIAAC) show low levels of proficiency in problem solving in technology-rich environments among older adults (OECD, 2019^[23]). Furthermore, in every single country participating in the PIAAC survey, older adults are less likely to take part in adult learning. The average gap in participation rates between older (54+) and prime-age (25-53) individuals was about 22 percentage points in 2015 (OECD, 2019^[24]). While these issues are not new, they are likely aggravated by the introduction of digital and AI technologies in workplaces. Indeed, older workers are perceived by their colleagues as particularly sceptical and worried about AI technologies, and this may limit their desire and capability to adapt (Milanez, 2023^[4]). Yet, it is important to note that the study does not report examples of older workers themselves voicing their scepticism regarding AI or lack of willingness to work with it. The evidence is thus based on

other workers' beliefs and it is possible that these beliefs are contaminated by biases against older workers that do not reflect their actual abilities and attitudes. In any case, given their lower levels of digital literacy, training for AI for older workers should be carefully designed and adapted.

On the other hand, efficiency reasons may justify the targeting of higher-skilled workers, managers and business leaders. As shown in Chapter 3, workers in high-skilled occupations have been the most exposed to recent progress in AI, since these occupations are the most likely to involve non-routine cognitive tasks that AI is increasingly capable of performing. Examples of such occupations include business professionals, managers, chief executives and science and engineering professionals. At this early stage of AI adoption, higher exposure to AI for high-skilled workers appears to lead to the creation of new tasks and jobs rather than the destruction of jobs. Yet, for high-skilled workers to be able to adapt to changes in the task composition of their jobs and work with AI technologies, they need basic digital skills, elementary knowledge of AI, cognitive skills such as problem-solving and critical thinking, and transversal skills such as communication, teamwork, or multitasking (see Section 5.1.2). While it is likely, but not certain, that most high-skilled workers already possess many of these skills, it is important to make sure all high-skilled workers are equipped with the right skill bundle.

The skills and knowledge of managers and business leaders also matter for AI adoption. Indeed, in most cases, AI adoption would entail important changes in business processes and corporate culture and require managers and business leaders to reconfigure tasks and organisational structures accordingly. For this, managers need not only skills related to change management practices, but also some knowledge of AI and its potential risks and benefits. A German firm interviewed for the OECD case studies of AI implementation in firms reported that even managers planning AI projects are expected to have a minimum knowledge of how the technology works (Milanez, 2023^[4]). Understanding what AI systems can and cannot do is key to assess where and how the innovation could be used in a company, what the benefits and risks of AI are, and how to best integrate AI systems in existing processes (Lassébie and Quintini, 2022^[3]; Mc Kinsey, 2018^[25]). Managers would also have to decide which activities are to be performed by humans and which are to be carried out by the AI systems. To do so, they must understand the strengths and weaknesses of each actor. Furthermore, the relationship between AI systems and workers needs to be managed (Peifer, Jeske and Hille, 2022^[26]), and algorithms need to be managed too, as clear objectives have to be specified and compromises must be made (Luca, Kleinberg and Mullainathan, 2018^[27]). Robust systems and mechanisms need to be developed and maintained to ensure human oversight of algorithmic decision-making and management. However, managers and business leaders are likely to lack AI knowledge necessary to do so. Indeed misconceptions about AI seem widespread (Roffel and Evans, 2018^[28]) and there is no reason to believe that business leaders and managers differ in that respect.

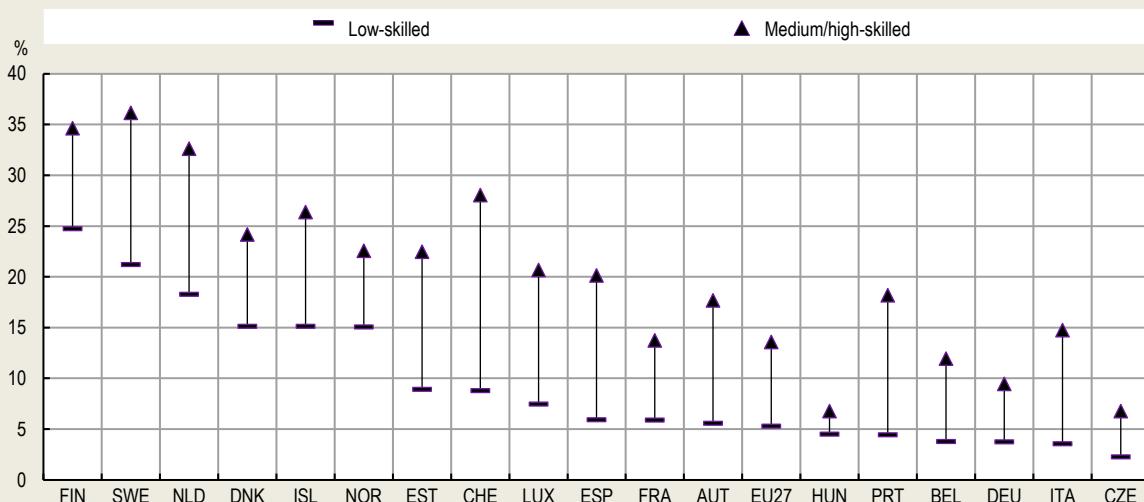
Finally, specific training actions should also be targeted at social partners to make sure they are equipped with the right tools to support workers facing and adapting to the challenges that AI development and adoption will bring about. Social partners report that changing skill demand is one of their main concerns related to AI (see Chapter 7). Yet, they could help identify changes in skill needs and promote and ensure fair access to training for AI to help workers face these changes. Trade unions and worker representatives also have a key role to play to give workers the trust to participate in training activities, especially low-skilled workers who are often reluctant to reveal their training needs to employers. Social dialogue is also particularly important to mitigate the impact of job restructuring resulting from technological change as social partners may agree on requalification schemes for existing staff that allow internal flexibility instead of mass lay-offs. More generally, they may negotiate collective bargaining agreements for the implementation of AI in the workplace. In practice, however, social partners are currently engaging mainly in outreach and information activities highlighting the need for new competences that will be required to work with digital tools, robotics and data, and the need to become "AI literate" (BusinessEurope, 2019^[31]; ETUC, 2020^[32]; ETUI, 2021^[33]; ILO/IOE, 2019^[34]; UNI Europa ICTS, 2019^[35]) but very few have engaged in negotiating agreements. This might be due to a lack of AI-related knowledge, as well as a lack of capacities and resources to attain it (see Chapter 7 for more details).

Box 5.2. Low-skilled workers should remain a policy priority for training

Even if AI enables the automation of some high-level skills, low-skilled workers continue to be disproportionately employed in occupations most at risk of automation, because older automation technologies remain and are in many cases improved by AI, and because these occupations usually do not require skills and abilities that cannot be replicated by automation technologies (see Chapter 3). However, and despite efforts made by governments over the past decade, in several countries the low-skilled still have participation rates in education and training activities that are lower than medium and high-skilled individuals (Figure 5.1). The participation gap ranges between 2 percentage points (Hungary) and 19 percentage points (Switzerland) and is equal to 8 percentage points on average in the European Union.

Figure 5.1. The low-skilled are still participating less in education and training activities

Percentage of individuals participating in education and training activities in 2021 over a four-weeks period, by education level



Note: The figure reports share of individuals that participated in formal and non-formal education or training activities during the four weeks preceding the survey, by education level. Sample is restricted to employed individuals aged 25–54. High-skilled individuals are those with tertiary education, medium-skilled individuals have achieved upper secondary or post-secondary non-tertiary education, and low-skilled have attained less than primary, primary, or lower secondary education. EU27 is the weighted average of countries in the European Union. Several countries are excluded from the graph because of low data reliability.

Source: EU-LFS.

StatLink <https://stat.link/0knspv>

Broadening participation in training is necessary to help workers employed in occupations at high risk of automation to transition to jobs that are less at risk. OECD (2019^[29]) shows that low participation in training and education activities by the low-skilled is due to a myriad of factors, including lack of time, financial constraints, lack of prerequisites, lower willingness to train, and lower propensity of employers to train these workers. Addressing these challenges remains a priority. Policy options include raising awareness, notably through personalised guidance, creating relevant and flexible learning opportunities, including thanks to modular programs, and providing financial support to cover the different costs of training (OECD, 2019^[30]).

5.3. Firms implementing AI say they provide training to their employees, but more training may be necessary

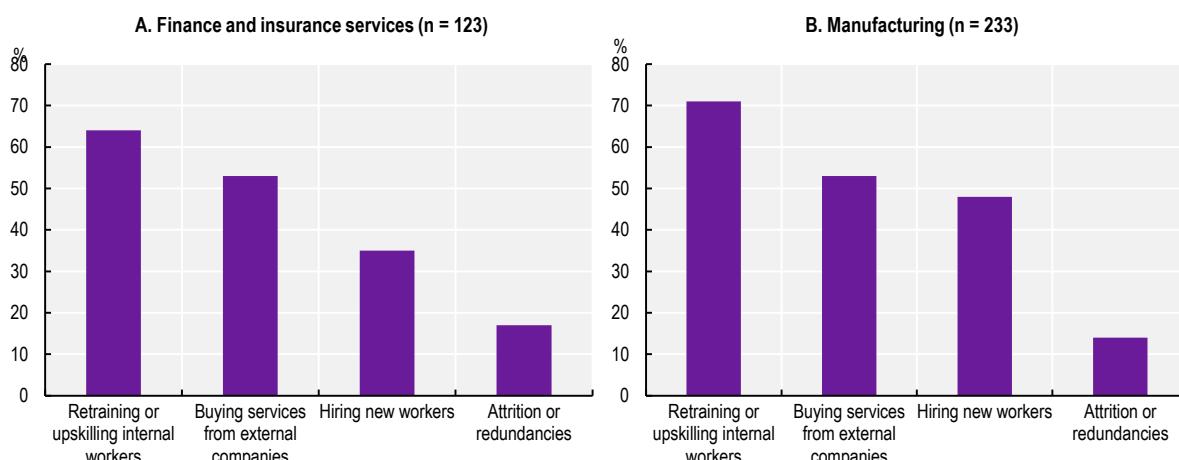
5.3.1. Firms provide training following AI adoption

A large share of firms adopting AI respond to changing skill needs brought about by AI adoption by retraining or upskilling workers. According to the OECD AI surveys, this is the case of 64% of firms in the finance sector and 71% in manufacturing that have adopted AI (Figure 5.2) (Lane, Williams and Broecke, 2023[2]). Training is the most common response to changing skills needs due to AI by firms in the seven countries included in the survey (Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States). An alternative strategy to deal with changes in skill needs is to buy services from external companies, which is chosen by 53% of firms interviewed.⁴

Workers also report firm-provided training following the adoption of AI. In the OECD AI surveys by Lane, Williams and Broecke (2023[2]), more than half of workers who use AI said that their company had provided or funded training so that they could work with AI, even though the study does not investigate the type of training nor its content. Most workers trust their employers to make the right decisions regarding training for AI, at least to some degree: slightly more than a quarter of workers had complete trust in their companies to provide training for workers to work with AI and just under half trusted their companies somewhat in this area. Workers who participated in training were significantly more likely to report positive outcomes of AI on their working conditions and wages but were also more likely to report AI-related worries regarding job stability. It might be that workers participating in training learn about AI's potential to automate work and become concerned about the stability of their job, but it might also be the case that workers who worry about losing their jobs because of AI are more likely to take part in training. The study does not allow to distinguish between these two explanations.

Figure 5.2. Employers are most likely to address skill needs by retraining and upskilling existing workers

Percentage of employers that reported that AI has changed skill needs in their company



Note: Employers that reported that artificial intelligence had changed skill needs in their company were asked: "Has your company addressed these changing skill needs in any of the following ways? By retraining or upskilling internal workers?/By hiring new workers?/By buying services from external companies?/By attrition or redundancies?".

Source: OECD employer survey on the impact of AI on the workplace (2022).

StatLink <https://stat.link/8v95c3>

When the AI technology is simple to use, training is brief and takes the form of webinars, presentations, workshops, etc. to introduce employees to the AI technologies adopted and to provide an overview of their basic functionalities. Only in a limited number of cases do large firms report more ambitious training programmes to help employees transition to other occupations. Finally, some large companies also try to support AI talent in-house to have employees with specialised AI skills able to develop and maintain AI systems internally, as opposed to seeking those employees on the external labour market or outsourcing these activities. However, several firms call for more government funding for AI education and training and recognise that these specialised AI skills should also be developed in initial education (Milanez, 2023^[4]).

5.3.2. Yet, more training would help address existing barriers to AI adoption

A lack of skills is a major barrier to AI adoption

AI cost and a lack of skills are the two most common barriers to adoption of AI reported by firms in surveys. More specifically, in the recent OECD AI surveys of employers and workers, around 40% of employers in finance and manufacturing declare that the lack of relevant skills is a barrier. This is particularly the case in the United States, Germany and Austria, as almost half of employers in the manufacturing and finance sectors of these countries report the lack of relevant skills as an obstacle (Lane, Williams and Broecke, 2023^[2]). These two obstacles were also reported by firms of all sizes and sectors in a Europe-wide survey of enterprises on the use of technologies based on AI led by the European Commission. The skills barrier comes from a lack of relevant skills amongst existing staff, as well as from difficulties hiring new staff with the necessary skills (European Commission, 2020^[36]).

A recent review of the goals and practices of institutions supporting AI diffusion in firms⁵ by the OECD (Barreneche, forthcoming^[37]) confirms these results. Interviewed institutions say the lack of AI skills is an important constraint, not only among employees but also among managers. The authors note that implementing AI in a firm necessitates staff with extensive experience in several AI fields (see Section 5.2.2 for a discussion of the reasons why managers' and leaders' skills matter too), but that AI talent is highly concentrated in some localised hubs. Interviewed institutions also report that uncertainties about the return on investment and poor understanding by managers of how AI could be used to address workplace challenges constitute significant barriers to adoption. Managers also tend to underestimate the changes in business culture and practices needed to effectively implement AI solutions.

Data and cultural acceptance constitute other important adoption barriers that can be addressed through training

Obstacles to AI adoption related to data, such as a lack of internal data or data complexity, are also reported by firms, although less frequently than other barriers (European Commission, 2020^[36]; IBM, 2022^[38]). In most cases, the challenge to having good quality data is closely related to the skills issue. Businesses often possess rich data but that they lack the capacity to process, clean, analyse, and ensure the quality of the vast amount of information included therein. In particular, small and medium-sized firms appear to be lagging behind in that respect (OECD, 2021^[39]).

While acknowledged by only a relatively small share of firms in surveys, challenges related to data availability and management are reported by several institutions supporting AI diffusion. These institutions underscore that most businesses could in theory gather very rich datasets, but they generally lack well-functioning data collection mechanisms including data quality assurance processes, standardised and efficient data collection methods, privacy, data security and ethical considerations, and on-going monitoring and evaluation protocols. When good data collection mechanisms are there, businesses sometimes face data management challenges, as several sources of information of different type, periodicity and format need to be integrated. and challenges related to the need to ensure that AI respects

and promotes workers' right to privacy and complies with legislation and regulatory standards, including data protection requirements (Barreneche, forthcoming^[37]).

Training can help ensure firms possess necessary skills to build, consolidate, and manage high-quality datasets, and know how to deal with issues of data security and privacy. Training is important not only to foster AI adoption but also for an ethical use of AI (see Chapter 6 for a discussion of policies to ensure trustworthy AI in the workplace). Furthermore, issues related to cultural acceptance of the new technologies by existing employees are also often mentioned by companies (Lassébie and Quintini, 2022^[3]) and existing evidence shows that training can help improve employees' attitudes towards AI (Lane, Williams and Broecke, 2023^[2]). Yet, the challenges related to data quality and cultural acceptance are broader than just a skills issue and cannot be solved entirely thanks to training.

5.4. Existing public policies supporting training for AI are not sufficient

5.4.1. Public policies could encourage the provision of more training for AI

The role of governments for the development of skills related to AI is primarily justified by the fact that an important share of training activities for the development and adoption of AI should take place in initial education. Basic AI literacy should be taught and promoted in secondary education, while specialised AI skills necessitate vocational and higher education. Other cognitive skills needed to both develop and work with AI should also be developed during initial education.

Regarding continuous education, the justification of public intervention and public funding of training programmes is less clear. The case for public funding of training programmes targeting low-skilled workers who face a high risk of automation (Box 5.2) is justified on the grounds of equity reasons, but the need for policy intervention is, *prima facie*, less clear for high-skilled employees. However, as discussed in Section 5.2.2, the fact that skills remain a major barrier to AI adoption suggests that the amount of training that is provided in general is not sufficient.

Public intervention would be warranted if market failures or barriers to training provision and participation prevent firms from providing the optimal amount of training. Whether this is the case still needs to be proved. However, what is clear is that among the barriers to training that have been described in general (OECD, 2021^[40]), one type in particular, informational barriers, is likely to be particularly important in the case of training for AI. In the OECD AI surveys of employers and workers (Lane, Williams and Broecke, 2023^[2]), the vast majority of workers surveyed had heard of AI (95% in finance and 93% in manufacturing), but most said that it was difficult to explain what the term "artificial intelligence" means (52% in finance and 60% in manufacturing). Workers whose firms had adopted AI were more likely to be able to explain what it is. Information on relevant AI-related training programmes is also limited. Yet, individuals seem interested in learning more about AI (Lane, Williams and Broecke, 2023^[2]). This suggests that there may exist an important informational gap around training for AI. Addressing this type of barriers to training provision would not call for public funding of training programmes but would rather take the form of awareness campaigns.

Another reason why the amount of AI training provided by firms might not be sufficient, and hence public intervention may be justified, is that the benefits of training for AI may accrue not only to the firm but also to the society more generally. When firms do not reap all the benefits of the training that they may provide, there is a clear risk of under-provision. This could be the case for training programs designed for managers and business leaders so that they understand the implications of increased AI adoption in their industry and are able to ensure that AI technologies are implemented in a trustworthy way.

Finally, public policy could promote diversity in the AI workforce. In particular, career guidance for AI could encourage more individuals to develop skills for AI, including specialised AI skills, AI literacy, and other

skills needed to use AI. Actually, the aim would be twofold: addressing the lack of diversity in the AI workforce, and more particularly the under-representation of women (see Box 5.1 above for figures on the share of women in the AI workforce), and tackling the issue of skills shortages that prevent AI adoption.

5.4.2. Few policies propose sufficient actions to develop skills for AI

The vast majority of OECD countries have issued national AI strategies, even though they are at different stages of implementation (Galindo, Perset and Sheeka, 2021^[41]).⁶ Most national AI strategies recognise the importance of skills, but not all propose concrete actions to develop them. Yet, interesting examples exist and are discussed in this section.

First, the increased use of AI in professional environments requires the anticipation of future skill needs and several national strategies explicitly mention skills anticipation and assessment for AI. For instance, in the United Kingdom, the national AI strategy mentions research activities to understand skills that are needed to enable employees use AI in a business setting and to identify how national skills provision can meet those needs.

Many national strategies acknowledge that advances in AI will make several skills redundant and emphasise retraining for those likely displaced by AI. For example, in Lithuania, the national AI strategy (Lithuanian Artificial Intelligence Strategy: A Vision of the Future)⁷ mentions the creation of vocational training programs in AI and other emerging technologies, specifically targeted to workers in occupations at higher risk of automation. The aim of the programs will be to teach individuals how to work with AI in their current job, rather than re-training for a different occupation.

In several cases, national AI strategies discuss training policies to develop specific skills. This is often addressed within the wider framework of the digital agenda and thus focuses on digital skills, overlooking basic and specialised AI skills, and cognitive and transversal skills that are needed to develop AI systems or use AI applications (see Section 5.1). Spain is an interesting exception: within the framework of the third investment of Component 19 of the Recovery, Transformation and Resilience Plan of Spain, the State Public Employment Service finances, through a public call for grants, state-wide training for the acquisition and improvement of professional skills related to technological change and digital transformation. Basic, medium and advanced training programmes have been developed. Medium and advanced training courses include extensive modules on AI, such as “Introduction to artificial intelligence and algorithms”, “Artificial intelligence applied to the company”, and “Machine Learning and artificial intelligence”.

The issue of basic AI skills is gaining more and more attention and several initiatives aiming at developing them are emerging. For example, in Finland, the University of Helsinki together with MinnaLearn developed a programme called “Elements of AI”, offering free online courses to strengthen AI literacy for non-experts, to increase social acceptance of AI and individuals’ motivation to learn about it. The initial objective of training 1% of the Finnish population has been largely exceeded and the programme has subsequently expanded to other European countries. For instance, the national AI strategy in Germany (Artificial Intelligence Strategy of the German Federal Government – 2020 update)⁸ acknowledges that every individual should be well informed about the importance of AI and the opportunities and challenges it presents and explicitly refers to the course “Elements of AI”.

Employers are important stakeholders to foster the development of workplace-focused AI upskilling and reskilling strategies and for the development of relevant training programmes to foster AI adoption. Yet not all national strategies mention the role of employers in providing training for AI. Norway is an exception, as it relies on further education programmes in AI and data analysis launched by several large enterprises. One initiative discussed in the Norwegian strategy (Norway National Strategy for Artificial Intelligence)⁹ is a training course in data science proposed by a bank to its employees. The Norwegian Government also co-operates with employee and employer organisations to develop and provide industry-specific training programmes for the municipal care and industry and construction sectors. Another example of employers’

involvement is the Italian Tax Credit on Training 4.0. This programme implemented in 2021 and 2022 aimed to support employees' training for the consolidation or acquisition of skills in technologies relating to the technological and digital transformation of businesses.¹⁰ More specifically, eligible training topics included, for instance, big data and data analysis, virtual reality (VR) and augmented reality (AR), advanced and collaborative robotics, human-machine interfaces, and Internet of things and machines. The tax credit was available to all enterprises, regardless of their sector or size, although the amount of subsidy depended on company size.¹¹ The tax credit rate was higher for disadvantaged employees.¹² Eligible expenses comprised costs of employees participating in training (employees' salary), consulting costs relating to the training project, if any, training fee when provided by external training providers, and operating costs for the training programme (travel costs, materials, and equipment).

Institutions supporting AI diffusion in firms¹³ also develop on-the-job training programmes to facilitate AI adoption (Barreneche, forthcoming^[37]). For instance, the Vector Institute, one of the three national Artificial Intelligence Institutes based in Canada, offers training courses to raise management and technical staff skills and improve awareness of AI applications. Individuals are invited to analyse real-world AI use cases and identify opportunities and challenges underpinning successful adoption. It is part of the broader national strategy to support AI adoption in Canada.¹⁴ In the United States, the Digital Manufacturing and Cybersecurity Institute (MxD) offers another interesting example as it has developed an online platform where workers can access free and paid courses on frontier technologies developed by leading companies, and where companies can find information to support their AI skills management, including curricula and career pathways information.

An integrated approach to the development of skills for AI, including all levels of education, the various stakeholders and the different types of skills needed to develop and work with AI, is crucial. On-the-job training programmes and informal learning are necessary for employees to contextualise coursework with the specific challenges and requirements of work and for firms to address current skill shortages in a timely manner, but they are not a substitute for initial education. Several institutions interviewed in Barreneche (forthcoming^[37]) insisted on the fact that specialised AI education must be addressed in priority in tertiary education and that countries need to step up efforts in embedding AI across tertiary education programmes.

In general, while several existing programmes focus on digital or AI skills, few recognise the importance of complementary skills such as transversal competences, and a minority develop an integrated approach to AI skills development. The Irish national AI strategy (AI – Here for Good: A National Artificial Intelligence Strategy for Ireland)¹⁵ is one exception, as it mentions the provision of digital, technical, and complementary skills. The strategic actions listed in the strategy consider all relevant levels and types of education, including Higher Education Institutions and employers. Digital skills and technologies are developed in school, as outlined in the "Digital Strategy for Schools 2015-20 Enhancing Teaching, Learning and Assessment". The "STEM Education Policy Statement 2017-26" also aims to improve STEM education for all learners at primary and post-primary levels. Key complementary skills such as communication, creativity and working with others are also embedded throughout primary and post primary curricula. The AI Strategic Vision for Luxembourg (Artificial Intelligence: a strategic vision for Luxembourg)¹⁶ also aims to address several dimensions of AI education and training. Key actions include the development of digital training modules for the general public to providing them with an introduction to AI, its opportunities and risks, the integration of AI courses into other disciplines, such as law, business, human sciences, environment and health, and into the curricula of secondary and postsecondary education, including vocational training.

Most national strategies also highlight the importance of AI skills in government, not only to exploit technological advances in AI to improve the quality and efficiency of public administrations, but also to be able to understand whether and what type of public intervention is needed (see also Chapter 6). In Canada, the School for Public Service's Digital Academy provides support to public servants to improve their digital skills, including in AI and Machine Learning. The Government of Singapore offers AI workshops to public

officers to increase their digital literacy and provide them foundational knowledge about the potential of AI for public organisations (Berryhill et al., 2019^[42]). More recently, in France, the Council of State issued an official statement advocating for the use of AI for better public services. The statement acknowledges the importance of human and technical resources to implement AI in the public sector and declares the training of public managers a priority, alongside the recruitment of data experts (Conseil d'État, 2022^[43]). In the United States, the AI Training Act¹⁷ is a legislation that aims to create an artificial intelligence training programme for the federal workforce to better understand the technology, know the potential benefits and risks of its use for the government, and be able to ensure that it is used in the federal administration in an ethical way.

Finally, training for AI for teachers and educators is another area in which governments should invest. An example of such initiative can be found in Spain, where the School of Computational Thinking and Artificial Intelligence (EPCIA) has been set up by the Spanish Ministry of Education and Vocational Training in collaboration with the regional educational administrations. The objective of the project is to explore the possibility to introduce artificial intelligence for learning in the classroom. The school offers open educational resources, teacher training programmes, and a monitoring tool tracking the creation of didactic proposals and their implementation in schools. The school, together with a university, also conducts research focused on student learning and teaching practice for AI.

5.5. AI has the potential to improve adult learning systems but risks exist

While AI is generating new training needs, it may also provide an opportunity to improve adult learning systems in general. It can be used to better plan and deliver training, and to increase training participation and inclusiveness. While not widespread, several examples exist, and some are presented below. However, for AI to improve adult learning systems more generally, several risks exist and a number of challenges need to be addressed.¹⁸

5.5.1. AI could be used to help plan training

AI can help assess skill needs, build individuals' skill profiles, identify appropriate training courses, find viable job transitions and select appropriate training to facilitate these transitions. Regarding skill needs assessments, AI and machine learning algorithms can be used to process and analyse the text of online job ads to understand skills demanded by employers. This information is more granular and more timely than traditional sources of information such as annual surveys or expert consultations, but might be less representative, less stable over time, and less accurate, notably regarding skills required to perform a job. These two types of data can thus complement each other. In particular, the higher level of detail and timeliness are necessary to develop a training offer that is well-aligned with labour market needs. For instance, the European Centre for the Development of Vocational Training (Cedefop) processes and analyses information gathered from more than 100 million online job advertisements collected in 28 European countries to build the Skills Online Vacancy Analysis Tool for Europe (Skills OVATE). The skill information is extracted from job advertisements using ESCO, the European classification of skills, competences, qualification and occupations, and machine learning techniques.

AI may also be used to build individual skill profiles – i.e. the characterisation of a person's skills based on his/her level and field of formal education, previous work experience and direct and indirect skill assessments – to be compared to the skills required in available jobs. AI can help automatically categorise vast amounts of textual data, such as the descriptions of education programmes and occupations, into pre-defined skill categories. This can facilitate the translation of an individual's information on education and professional background into a profile of knowledge, skills and abilities. It can also help categorise manually imputed text describing tasks carried out in everyday life or in one's job and feed the information into the individual's skills profile. An interesting example of the use of AI for individual skill profiling is

provided by VDAB, the Flemish public employment service, that has developed a tool called Competence-Seeker. The tool helps jobseekers enrich the CV they upload online with additional skills they are likely to possess given their professional experience but forgot to mention, by automatically screening jobseekers' CVs. It uses the VDAB taxonomy of occupations and skills (Competent) to find skills required in occupations in which the individual has worked but that are missing in their online CV (Broecke, 2023^[44]). However, building these profiles requires stocking and sharing information on individuals, in a way that might not always be compatible with existing data protection and privacy regulations (on these issues, see Chapter 6).

AI can help identify appropriate training courses for individuals willing to undertake training. To do so, one pre-requisite is to understand what skills are developed in each training programme. While formal education follows structured and standardised curricula, this is not the case of non-formal training. The start-up Boostrs applies natural language processing algorithms to automatically transform the descriptions of education and training programmes into pre-defined skill categories, thereby creating a mapping between training and skills that can be used by individuals who want to acquire specific skills to identify relevant training.

Furthermore, AI can be used to identify viable job transitions as well as training needs to permit these transitions. Frank et al. (2019^[45]) discuss how non-traditional sources of data such as online resumes and job postings could be used to have a better sense of labour market dynamics and to improve the understanding of the relationship between individuals' education and skills and possible careers. They talk about "viable job transitions" when workers of one job can meet the skill requirements of another job. This supposes some sort of skill similarity between jobs. Since this publication in 2019, real-world examples have been developed and tested in the field. For instance, the public employment service in Flanders, the VDAB, uses the application Jobbereik to help jobseekers consider transitions to occupations that require similar skill profiles. VDAB is also developing a new functionality that will enable Jobbereik to suggest a list of possible education and training programmes for each proposed career move (Broecke, 2023^[44]).

More generally, AI can be used in career guidance activities. Using focus groups, scenario work and practical trials, Westman et al. (2021^[46]) discuss requirements and possibilities for using artificial intelligence in career guidance from the viewpoints of students, guidance staff and institutions. They show that students were quite positive about AI-powered career guidance services, especially about the possibility of receiving personalised advice and their online accessibility, while career guidance staff expressed several concerns, notably related to individuals' agency and autonomy, data privacy, as well as ethical issues. Staff mentioned in particular the tendency of AI to scale up human biases as concerning. This particular issue is discussed in more details in Section 5.5.3 and in Chapter 6.

5.5.2. AI could be used to deliver and personalise training

AI can also be used by teachers and trainers to develop materials for their classes. For example, tools such as ChatGPT can help to create courses outlines and curricula, develop lesson plans with a list of objectives, activities, and assessments, create exercises, quizzes, discussion questions, and multiple choice exams, and write detailed answers to problems. It can also be used as a virtual tutor, especially for language training, as the chatbot can engage in conversations with learners, allow them to practice, provide feedback and offer suggestions for improvement. It is a useful tool for adapting teaching style (i.e. transforming a traditional course into a problem-based class or a flipped classroom) or to simplify topics for learners of any level. However, it is important to note that models such as ChatGPT are only probabilistic models with no explicit educational goals, have not been optimised for student learning, and do not provide the social experience necessary for efficient learning.

Several AI-powered technologies such as Augmented Reality (AR), Virtual Reality (VR), and technologies for speech recognition, could play a role in the provision of vocational training online or virtually. Augmented and Virtual Reality technologies expand the availability of practice-oriented training, allowing students to

complete exercises at distance, more often or more safely. For instance, virtual reality surgery training allows students and healthcare professionals to gain exposure to a surgical environment and procedures through life-like simulations. Users gain unlimited access to simulations anywhere, anytime, all while diminishing risks for patients. Yet, potential downsides and risks related to the use of AR, VR and other AI-powered technologies in the delivery of training exist, including the loss of the social aspect of learning, which is important from an information retention perspective.

AI can also be used to personalise training content to individuals' needs, selecting relevant modules and hence shortening training actions when possible. Traditional training usually requires all students to go through the same learning materials, irrespective of their abilities, preferences or learning styles. When training content is driven by AI, it can be adapted to the individual starting level and progress achieved during the course. By linking content to assessments or reading time, for instance, AI can suggest skipping certain content, and may provide additional learning materials when the student appears to be struggling.¹⁹ Training personalisation is done, for instance, by Duolingo, a language-learning platform.

The use of AI in training will lead teachers and trainers use and interact with AI technologies on a regular basis, and hence will bring about changes in the skills that are needed in teaching professions. In particular, as detailed in Section 5.1.2, using and interacting with AI will require that employees possess digital skills, at least at a basic level. Some elementary knowledge of AI would also be necessary to enable teachers and trainers to understand well the benefits and risks of using AI in training. Furthermore, and as discussed in Chapter 4, the use of AI in training could also decrease teachers' autonomy and agency and increase work intensity, ultimately affecting overall job quality. These represent non-negligible risks.

Another risk is that the use of AI-powered educational tools may modify the skills that learners acquire. In his essay on the potential harms of AI, Acemoglu (2021^[47]) argues that if students stopped learning arithmetic because calculators are better at it, their ability to engage in other type of mathematical and abstract reasoning may suffer. A similar argument may be made for Large Language models such as ChatGPT: if students use it to write essays and complete exams, this may lead to a decrease in their written expression skills and knowledge. Actually, this appears to be a concern for several schools and universities, and they are taking actions to make sure that students do not use this tool in exams. Some institutions are reconsidering the exam process, moving back to in-person written exams that allow a close monitoring of the use of technologies. Others are introducing tools to assess whether written tests have been answered by an algorithm. Other institutions, on the contrary, think about how to integrate the tool in the learning system, including in exams, in the view that students need to learn how to work with the technology.

5.5.3. AI may impact training participation and inclusiveness

AI technologies may increase training participation by: (i) decreasing the length of training (thanks to training modularity); (ii) alleviating time constraints (thanks to distance training and shorter courses); and (iii) increasing motivation (thanks to a better matching between individuals and training courses and with the use of interactive tools, such as Augmented or Virtual Reality). AI's potential to reduce training time may be particularly powerful as time constraints have been shown to constitute a major obstacle to training participation (OECD, 2021^[40]). AI could also assist policy makers or companies in identifying individuals most in need of training or those who would benefit most. For instance, an AI-based application is used by the VDAB, the Flemish public employment service, to target the most vulnerable jobseekers, i.e. those who are less likely to find a new job (Broecke, 2023^[44]). The use of AI in training may also facilitate training participation of disabled individuals. Text-to-speech and speech-to-text technologies may help hearing or visually impaired individuals access training. Technologies already exist to support the educational needs of blind and visually impaired students in initial education, for instance to facilitate notetaking (OECD, 2021^[48]), and there are no reasons to think that those technologies could not be implemented in training courses for adults. Non-native speakers could also benefit from AI-assisted translation technologies.

However, there are also several reasons why the use of AI in training may decrease, rather than increase, training participation and inclusiveness. First, using AI in training is costly, in particular to develop the necessary data and infrastructure and may increase overall training costs. The fixed costs related to AI adoption may exacerbate inequalities between small and large actors, e.g. between small and large firms for training provision, or between individuals who can afford training and those who cannot. Furthermore, the participation in training that is powered by AI technologies requires some degree of digital skills, which may limit participation by low skilled individuals. If used to inform participants' selection, AI may decrease the inclusiveness of learning systems rather than increase it as it may scale up human biases when appropriate safeguards are not put into place (a similar issue regarding labour market inclusiveness and how biased AI systems may decrease it is discussed in Chapter 4, Section 4.4, and Chapter 6 discusses legislation to address bias of AI systems). In this context, close monitoring of how widespread the use of AI for training is, and of its impact on inclusiveness, is necessary and will be key in deciding whether and what type of public intervention is warranted.

5.6. Despite a growing body of research on AI and its impact on skills and learning systems, important knowledge gaps persist

This chapter shows that the impact of AI on skill needs is not trivial. AI can now replicate more and more skills that have long been unique to humans, in particular cognitive skills. It is also increasing demand for other skills such as AI knowledge and digital skills (at a basic level to simply use AI applications and at a more sophisticated level to develop AI systems), as well as complementary skills such as social and management skills. The chapter discusses the new training opportunities that should be developed to address these changes in skill needs. It argues that training actions should be targeted at vulnerable groups (the low skilled and older workers) who risk being left behind if they do not have the necessary skills to adapt to changes in the workplace brought about by AI implementation, but also at higher-skilled workers, managers and leaders to facilitate the development and adoption of trustworthy AI and to allow them to work effectively with the technologies. While the evidence base on these issues is solid, other questions discussed in this chapter deserve more research.

First, more data on AI and training are needed. Cross-country data on the extent of training for AI is lacking. Firms implementing AI say they provide training to their employees, yet a shortage of appropriate skills remains a major barrier to AI adoption. This suggests that the current amount of training for AI is not sufficient, but there are not enough data to assess the veracity of this claim. There are still unanswered questions about the type of training for AI that exists, the amount of training that is provided (both in terms of the number of individuals participating and the length of the training), the groups of individuals that are covered, and the content, form and level of training that is offered. Further data and research on available training programs will be key to provide actionable policy recommendations.

There is also very little evidence on the effectiveness of policies for AI skills development. This chapter argues that governments have an important role to play in encouraging employers to provide more training for AI, embedding AI courses in all levels of education, and addressing the lack of diversity in the AI workforce. However, AI policies and strategies do not always include comprehensive and concrete actions to develop skills for AI. This is an area where more should be done, but information on successful policies does not yet exist, as the impact of most AI strategies has not been properly evaluated. Monitoring and evaluating initiatives will be key to better understand the benefits and costs of different policy interventions and permit an optimal allocation of public resources.

It is also important to collect data on the use of AI for training. This chapter presents examples of how AI can be used to improve training systems, but these technologies are still in their infancy and their use in training appears to be low, although there is a lack of robust quantitative evidence on this. Going forward, it would be interesting to monitor more consistently the use of AI in training, as it will be key in understanding the risks and benefits.

Finally, several related issues deserve more attention. The role of social partners in assessing and addressing changes in skill needs due to AI is touched upon in Section 5.2.2 but this topic is covered more extensively in Chapter 7 that presents examples of initiatives aimed at upskilling and reskilling workers so that they can benefit from AI adoption at their workplace. Another topic of interest is the adaptation of active labour market policies to make sure job-seekers possess the right skills to develop AI and work with it. Ultimately, the aim is to ensure that all workers are equipped with the necessary skills to thrive in an AI-powered economy.

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Notes

¹ Box 4.1 in Chapter 4 presents the methodology used in the OECD AI surveys (Lane, Williams and Broecke, 2023^[2]) and in the OECD AI case studies (Milanez, 2023^[4]) and discusses their representativeness.

² ChatGPT is a chatbot developed by OpenAI and launched in November 2022.

³ However, it is important to note that even if informal learning represents a significant share of learning activities (Fialho, Quintini and Vandeweyer, 2019^[49]), ensuring that all workers have access to informal learning opportunities is difficult. Indeed, the provision of informal learning opportunities in enterprises seems to be particularly dependent on work practices and the work environment. As fostering a learning culture at work is difficult, encouraging informal learning is more difficult than developing formal and non-formal training activities (OECD, 2021^[40]).

⁴ Attrition or redundancies are used by a minority of enterprises to deal with changes in skill needs brought about by AI (17% of firms in finance and 14% in manufacturing).

⁵ Institutions for technology diffusion are public or quasi-public bodies that facilitate the spread and use of knowledge and methods that assist firms in adopting particular technologies (OECD, 2017^[50]).

⁶ Some countries, such as Canada, Finland, Japan, France, Germany and the United Kingdom developed their national AI strategies in 2017-18. Other countries, such as Brazil, Poland and Spain, launched a national AI strategy more recently – see also Chapter 6.

⁷ Available at https://wp.oecd.ai/app/uploads/2021/12/Lithuania_Artificial_Intelligence_Strategy_2019.pdf.

⁸ Available at https://www.ki-strategie-deutschland.de/files/downloads/Fortschreibung_KI-Strategie_engl.pdf.

⁹ Available at

https://wp.oecd.ai/app/uploads/2021/12/Norway_National_Strategy_for_Artificial_Intelligence_2020.pdf.

¹⁰ This programme has been terminated in 2022.

¹¹ More specifically, the tax credit was available to: small enterprises, for an amount equal to 50% of eligible expenses, up to a maximum of EUR 300 000; and medium-sized enterprises and large enterprises, for an amount respectively equal to 40% and 30% of eligible expenses, up to a maximum of EUR 250 000.

¹² The tax credit rate increased to 60% for all businesses when training participants fell within the category of “disadvantaged employees”, as defined by the decree issued by the Italian Minister of Labour and Social Policies dated 17 October 2017.

¹³ These institutions are public or quasi-public bodies that assist companies in adopting new technologies. They use a bundle of mechanisms to support AI diffusion, such as technology extension services, grants for business R&D, business advisory services, industrial extension programmes, technology-oriented business services, grants for applied public research, networking and collaborative platforms, on-the-job-training, and information services and open-source code. Barreneche (forthcoming^[37]) reviewed practices of several institutions supporting AI diffusion in firms in Canada, France, Germany, Italy, Japan, Singapore, the United Kingdom, and the United States and identified the different mechanisms that they use to assist firms in overcoming adoption challenges. In addition to on-the-job training programmes discussed in this paragraph, three other mechanisms used by institutions supporting AI diffusion in firms can indirectly provide support for the development of skills. First, technology extension services, whose aim are to convey results stemming from scientific and technological research to the private sector, often involve employees from the beneficiary firm, who learn informally by working closely with diffusion institutions. The purpose of this mechanism is precisely to raise firm capabilities to implement and use AI, including workers’ skills. Second, business advisory services offer non-technical guidance and informal learning opportunities to managers and executives to support AI adoption. Third, information services may take the form of publication of case studies and open-source code for AI solutions, material that can be used for self-learning.

¹⁴ See the Pan-Canadian Artificial Intelligence Strategy available at <https://ised-isde.canada.ca/site/ai-strategy/en>.

¹⁵ Available at <https://enterprise.gov.ie/en/publications/publication-files/national-ai-strategy.pdf>.

¹⁶ Available at

https://wp.oecd.ai/app/uploads/2021/12/Luxembourg_Artificial_Intelligence_Strategic_Vision_for_Luxembourg.pdf.

¹⁷ Public Law No: 117-207 (17 October 2022) Artificial Intelligence Training for the Acquisition Workforce Act, also referred to as the AI Training Act.

¹⁸ This whole section is based on Verhagen (2021^[51]) and more examples can be found in the paper.

¹⁹ This is modular training as recommended by the European Commission (Council Recommendation on a European approach to micro-credentials for lifelong learning and employability) taken one step further.

6

Ensuring trustworthy artificial intelligence in the workplace: Countries' policy action

Angelica Salvi del Pero and Annelore Verhagen

This chapter provides an overview of countries' policy action affecting the development and use of artificial intelligence (AI) in the workplace. It looks at public policies to protect workers' fundamental rights, ensure transparency and explainability of AI systems, and clarify accountability across the AI value chain. It explores how existing non-AI-specific laws – such as those pertaining anti-discrimination and data protection – can serve as a foundation for the governance of AI used in workplace settings. While in some countries, courts have successfully applied these laws to AI-related cases in the workplace, there may be a need for AI- and workplace-specific policies. To date, most countries primarily rely on soft law for AI-specific matters, but a number of countries are developing new AI-specific legislative proposals applicable to AI in the workplace.

In Brief

Key findings

While artificial intelligence (AI) systems have the potential to improve the workplace – for example by enhancing workplace safety – if not designed or implemented well, they also pose risks to workers' fundamental rights and well-being over and above any impact on the number of jobs. For instance, AI systems could systematise human biases in workplace decisions. Moreover, it is not always clear whether workers are interacting with an AI system or with a real person, decisions made through AI systems can be difficult to understand, and it is often unclear who is responsible if anything goes wrong when AI systems are used in the workplace.

These risks, combined with the rapid pace of AI development and deployment, underscores the urgent need for policy makers to move swiftly and develop policies to ensure that AI used in the workplace is trustworthy. Following the OECD AI Principles, “trustworthy AI” means that the development and use of AI is safe and respectful of fundamental rights such as privacy, fairness, and labour rights, and that the way it reaches employment-related decisions is transparent and understandable by humans. It also means that employers, workers, and job seekers are made aware of and are transparent about their use of AI, and that it is clear who is accountable if something goes wrong.

This chapter provides an overview of countries' policy efforts to ensure trustworthy AI in the workplace (see Chapter 7 for social partners' efforts in this respect). By providing a range of examples, the chapter aims to help employers, workers, and their representatives, as well as AI developers navigate the existing public policy landscape for AI, and to inspire policy makers looking to regulate workplace AI in their country. The key findings are:

- When it comes to using AI in the workplace to make decisions that affect workers' opportunities and rights, there are some avenues that policy makers are already considering: adapting workplace legislation to the use of AI; encouraging the use of robust auditing and certification tools; using a human-in-the-loop approach; developing mechanisms to explain in understandable ways the logic behind AI-powered decisions.
- Currently, most OECD countries' AI-specific measures to promote trustworthy AI in the workplace are primarily non-binding and rely on organisations' capacity to self-regulate (i.e. soft law). The number of countries with an AI strategy has grown significantly in the past five years, particularly in Europe, North America and East Asia. Many countries are also developing ethical principles, frameworks and guidelines, technical standards, and codes of conduct for trustworthy AI.
- One of the key advantages of using soft law for the governance of AI is that it can be relatively easy to implement and adjust when needed, which ensures the necessary flexibility for such a fast-changing technology. However, given that soft law often lacks enforceability, a well-co-ordinated combination of soft law and enforceable legislation (or “hard law”) may be needed to effectively prevent or remedy AI-related harm in the workplace as the technology continues to evolve.
- Existing (non-AI specific) legislation – for instance on discrimination, workers' rights to organise, or product liability – is an important foundation for regulating workplace AI. For instance, all OECD member countries have in place laws that aim to protect data and privacy. In some countries, such as Italy, existing anti-discrimination legislation has been successfully applied in court cases related to AI use in the workplace.

- However, existing legislation is often not designed to be applied to the use of AI in the workplace, and relevant case law is still limited. Case law will therefore need to be monitored to determine whether and how much existing legislation will have to be adapted to address the deployment of AI in the workplace effectively.
- Some countries have taken proactive steps to prevent potential legal gaps by developing new AI-specific legislation, and these proposals often have important implications for the use of AI in the workplace. While some of these AI-specific legislative proposals may still go through significant changes before coming into effect, many represent promising progress towards ensuring the trustworthy development and use of AI in the workplace.
- A notable example is the proposed EU AI Act, which seeks to regulate many aspects of AI systems in its member states. The Act takes a differentiated approach for regulating AI, which includes specific provisions for certain high-risk applications in the workplace. A risk-based approach helps to avoid regulating uses of AI that pose little risk and it allows for some flexibility.
- Countries have also been developing AI-specific legislation that is narrower in its approach. For example, measures have been proposed that would require regular risk assessments and audits throughout the AI system's lifecycle to identify and mitigate potential adverse outcomes. There are also AI-specific legislative proposals requiring that people are notified when they interact with an AI system. Additionally, there are explainability measures, such as in the Canadian Artificial Intelligence and Data Act (AIDA), that require "plain language explanations" of how AI systems reach their outcomes. Finally, new legislative efforts seek to increase the accountability of AI-based decisions by requiring human oversight.
- Ensuring trustworthy AI in the workplace requires a coherent framework of soft law and legislation that addresses all dimensions of trustworthiness. Since the dimensions are interrelated, there is a potential for public policies to serve multiple purposes, which helps to minimise the regulatory burden. Transparency is essential for accountability, for example, and explainability regulations can help mitigate bias in AI systems.
- At the same time, the policy framework for AI needs to be flexible and consistent within and across jurisdictions, in order not to obstruct enforcement, stifle innovation or create unnecessary barriers to trustworthy AI adoption in the workplace. Differentiated approaches to regulating AI minimise the regulatory burden and regular reviews of the definitions/frameworks used in legislation help it remain up to date with advances in AI technology. Using regulatory sandboxes to develop and test AI systems helps foster innovation and it provides regulators with practical evidence about where adjustments to the regulatory framework may be necessary. Additionally, collaboration between countries and regions is needed when developing public policies. It is also important that AI developers and users are given guidance to help them understand and comply with existing and changing hard and soft law.
- To continue to improve AI policy decisions and facilitate their enforcement, it is crucial that policy makers, regulators, workers, employers and social partners understand the benefits and risks of using AI in the workplace. It is therefore important to provide access to training on the issues to all stakeholders (see also Chapter 5). Finally, evaluations and assessments will be key to determining what works and where legal gaps remain. This is particularly important, considering that countries' policies will need to keep up with the fast pace at which AI evolves. The latest developments in generative AI and its increasingly pervasive use across various jobs and activities highlight the need to move swiftly and develop coordinated actionable and enforceable plans to ensure that the use and development of AI in the workplace is trustworthy.

Introduction

To fulfil their potential to improve workplaces, AI systems need to be developed and used in a trustworthy way (hereafter: “trustworthy AI”). Following the OECD AI Principles, trustworthy AI can be defined as (see Box 6.1):

- proactive engagement by AI stakeholders in responsible stewardship of AI in pursuit of beneficial outcomes for people and the planet;
- respect for the rule of law, human rights and democratic values by all AI actors throughout the AI system lifecycle;
- commitment by AI actors to transparency and responsible disclosure of AI systems;
- robustness, security and safety of AI systems throughout their entire lifecycle;
- accountability of all AI actors for the proper functioning of AI systems and for the respect of the other dimensions of trustworthiness.

Ensuring trustworthy AI in the workplace can be challenging because the technology entails risks, notably for human rights (e.g. on privacy, discrimination and labour rights), job quality, transparency, explainability, and accountability (Salvi Del Pero, Wyckoff and Vourc'h, 2022^[1]).¹ Moreover, it is important to identify possible risks that currently do not manifest themselves, but which may appear in the near future when new AI systems are being developed or applied in new contexts.

The risks of using AI in the workplace, coupled with the rapid pace of AI development and deployment (including the latest generative AI models), underscores the need for decisive and proactive action from policy makers to develop policies that promote trustworthy development and use of AI in the workplace. Delaying such action could result in negative impacts on society, employers and workers. In the short term, workplace AI policies will help towards ensuring the safe and responsible development and use of AI in the workplace. In the long term, they will also help to avoid unnecessary obstacles to AI adoption. Legal clarity may enhance trust amongst potential users that AI’s risks are already being mitigated. It may also alleviate ungrounded fears for litigation amongst employers and developers, which can stimulate research, development and innovation, leading to improvements in AI systems in the future.

At the same time, there are concerns that ill-designed or inconsistent policies and multiplications of standards may have the opposite effect and increase uncertainty and compliance costs, obstruct enforcement, and unnecessarily delay the adoption of beneficial and trustworthy AI. Policy makers are therefore facing the challenge of creating a clear, flexible and consistent policy framework that ensures trustworthy AI in the workplace without stifling innovation or creating unnecessary barriers to AI adoption. Recognising this difficulty, OECD and other adhering countries have recently adopted a set of detailed policy principles – AI Principles – that set standards for AI that are practical and flexible enough to stand the test of time (OECD.AI, 2023^[2]), while ensuring that AI is trustworthy and respects human-centred and democratic values (see Box 6.1).

Box 6.1. OECD Principles for responsible stewardship of trustworthy AI

The OECD Principles on Artificial Intelligence were adopted in May 2019 by the OECD member countries. Since then, other adhering countries include Argentina, Brazil, Egypt, Malta, Peru, Romania, Singapore and Ukraine. The OECD AI Principles also form the basis for the G20 AI Principles, <https://www.mofa.go.jp/files/000486596.pdf>.

Principle 1.1. Inclusive growth, sustainable development and well-being

Stakeholders should proactively engage in responsible stewardship of trustworthy AI in pursuit of beneficial outcomes for people and the planet, such as augmenting human capabilities and enhancing creativity, advancing inclusion of underrepresented populations, reducing economic, social, gender and other inequalities, and protecting natural environments, thus invigorating inclusive growth, sustainable development and well-being.

Principle 1.2. Human-centred values and fairness

AI actors should respect the rule of law, human rights and democratic values, throughout the AI system lifecycle. These include freedom, dignity and autonomy, privacy and data protection, non-discrimination and equality, diversity, fairness, social justice, and internationally recognised labour rights. To this end, AI actors should implement mechanisms and safeguards, such as capacity for human determination, that are appropriate to the context and consistent with the state of art.

Principle 1.3. Transparency and explainability

AI actors should commit to transparency and responsible disclosure regarding AI systems. To this end, they should provide meaningful information, appropriate to the context, and consistent with the state of art i) to foster a general understanding of AI systems, ii) to make stakeholders aware of their interactions with AI systems, including in the workplace, iii) to enable those affected by an AI system to understand the outcome, and, iv) to enable those adversely affected by an AI system to challenge its outcome based on plain and easy-to-understand information on the factors, and the logic that served as the basis for the prediction, recommendation or decision.

Principle 1.4. Robustness, security and safety

AI systems should be robust, secure and safe throughout their entire lifecycle so that, in conditions of normal use, foreseeable use or misuse, or other adverse conditions, they function appropriately and do not pose unreasonable safety risk. To this end, AI actors should ensure traceability, including in relation to datasets, processes and decisions made during the AI system lifecycle, to enable analysis of the AI system's outcomes and responses to inquiry, appropriate to the context and consistent with the state of art. Moreover, AI actors should, based on their roles, the context, and their ability to act, apply a systematic risk management approach to each phase of the AI system lifecycle on a continuous basis to address risks related to AI systems, including privacy, digital security, safety and bias.

Principle 1.5. Accountability

AI actors should be accountable for the proper functioning of AI systems and for the respect of the above principles, based on their roles, the context, and consistent with the state of art.

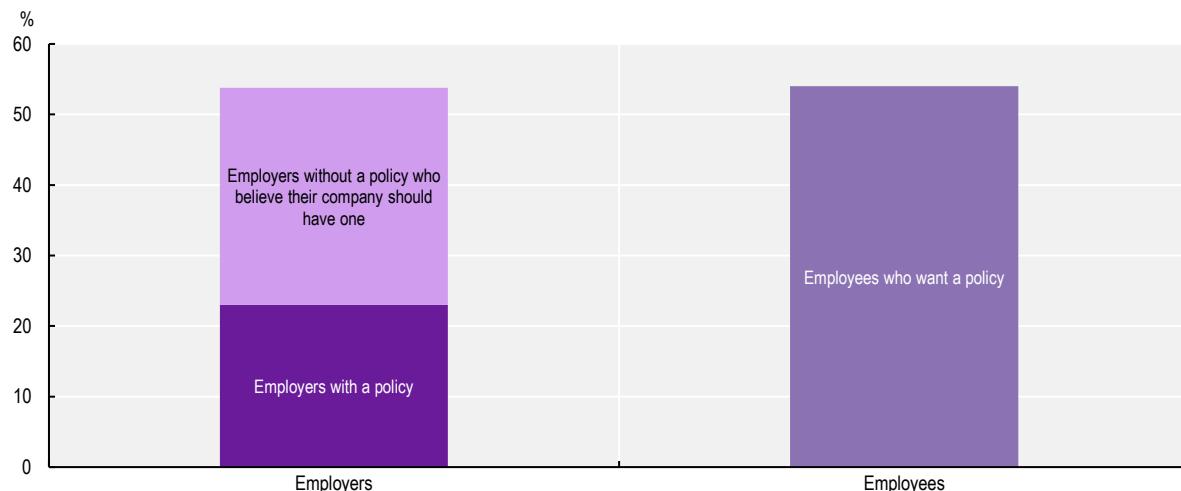
Source: OECD (2019^[3]), *Recommendation of the Council on Artificial Intelligence*, <https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449>.

All dimensions of AI's trustworthiness are equally important and need to be addressed in a coherent policy framework. Since the dimensions are very closely related and inter-dependent, there is a potential for policies to address multiple dimensions at once, which can help to avoid unnecessary regulatory burdens. For instance, when workers or their representatives can access algorithms and understand how an AI system reached an employment-related decision (transparency and explainability: Principle 1.3), it will be easier to identify the cause of a wrongful decision and who is responsible for it (accountability: Principle 1.5), which may encourage developers to fix the problem and prevent future harm (Principles 1.1, 1.2 and 1.4).

Policies to promote trustworthy AI in the workplace are important to workers, employers and social partners alike. The 2019 Genesys Workplace Survey (Genesys, 2019^[4]) found that 54% of workers believe their company should have a written policy on the ethical use of AI or bots (Figure 6.1). Only 23% of surveyed employers had such a policy, while 40% of those without it (31% of all surveyed employers) think their company should have one.

Figure 6.1. Most workers and employers see the value of written policies on the ethical use of AI

Percentage of respondents in favour of a written policy on the ethical use of AI/bots



Note: Based on an opinion survey into the broad attitudes of 1 103 employers and 4 207 employees regarding the current and future effects of AI on their workplaces. The 5 310 participants were drawn from the United States, Germany, the United Kingdom, Japan, Australia and New Zealand.

Source: Elaborations based on Genesys (2019^[4]), *Genesys Workplace Survey*, <https://www.genesys.com/en-gb/company/newsroom/announcements/new-workplace-survey-finds-nearly-80-of-employers-arent-worried-about-unethical-use-of-ai-but-maybe-they-should-be>.

StatLink <https://stat.link/awhe84>

This chapter provides an overview of public policy initiatives for the trustworthy development and use of AI in the workplace. This includes general measures that are not AI- or workplace-specific (but which have implications for AI used in the workplace), as well as measures specific to AI and/or the workplace. It covers non-binding approaches such as AI strategies, guidelines and standards ("soft law") as well as legally binding legislative frameworks ("hard law"). Social partners also have an important role to play in managing AI uses in the workplace, through collective bargaining and social dialogue – see Chapter 7.

Section 6.1 addresses how soft law may encourage trustworthy development and use of AI in the workplace. Section 6.2 discusses how legally binding legislative frameworks can prevent AI from causing harm to job seekers and workers and protect their fundamental rights, increase the transparency and explainability of workplace AI,² and the extent to which accountability of AI actors can be identified in existing and draft legislation. Section 6.3 concludes.

Although this chapter discusses soft law and hard law approaches separately, in practice they are often combined. This is in part because both approaches have benefits as well as drawbacks (as discussed in Sections 6.1 and 6.2). A well-co-ordinated framework of soft law and legislation may ensure that policies are enforceable and easy to comply with, while staying up to date with the latest developments in AI. It should also be noted that, since all dimensions of trustworthiness are inter-related, the examples of policies discussed in a particular sub section can be relevant to other dimensions of trustworthiness, too.

6.1. Soft law for trustworthy AI in the workplace

So far, OECD countries' AI-specific measures to promote trustworthy AI in the workplace have been predominately focusing on soft law, i.e. non-binding approaches that rely on organisations' capacity to self-regulate. They include, for instance, the development of ethical frameworks and guidelines, technical standards, and codes of conduct for trustworthy AI.³ In many OECD member countries, soft law is consistent with the OECD AI Principles (see Box 6.1). Trade Unions, employer organisations, as well as individual employers have also developed their own AI guidelines and principles, as well as tools strengthening trustworthy AI – see Chapter 7.

One of the key advantages of using soft law for the governance of AI is that it is easier to implement and adjust than legislation (or "hard law") (Abbott and Snidal, 2000^[5]), which helps close some of the gaps that exist or appear in AI legislation. Most AI-specific legislation is currently in development and will likely still take several years to come into effect. In the meantime, soft law for AI is a valuable governance tool to provide incentives and guidelines for trustworthy AI in the workplace. Moreover, since AI is such a rapidly evolving technology, soft law may ensure the necessary flexibility: legislation may not always be able to effectively cover the risks created by the most recent developments (Gutierrez and Marchant, 2021^[6]). Soft law can also be used to facilitate legal compliance when legislation is too broad or complex for AI actors to understand or translate into practice. Finally, since soft law tends to be easier to implement, it is also being used to establish international co-ordination and collaboration on AI policies. International co-ordination and collaboration are important to help minimise inconsistent policies and potentially consolidate them across countries, which could decrease uncertainty and compliance costs for businesses, especially smaller ones.

While several OECD member countries are developing AI-specific legislation (see Section 6.2), some countries are managing AI predominantly through soft law, in addition to applying existing legislation to workplace AI. The UK Government is one such example, where regulators are asked to use soft law and existing processes as far as possible for the governance of AI development and use (see Box 6.2). Another example is Japan, where "legally-binding horizontal requirements for AI systems are deemed unnecessary at the moment" (METI, 2021^[7]). Instead, the Japanese Government focuses on guidance to support companies' voluntary efforts for AI governance based on multistakeholder dialogue (Habuka, 2023^[8]).

Box 6.2. The United Kingdom's AI Regulation Framework

On 29 March 2023, the UK Government published the AI Regulation White Paper, outlining their latest proposals for regulating AI in the United Kingdom. The proposals are based on five core principles, setting out the UK Government's expectations for good, responsible AI systems:

- Safety, security, robustness
- Appropriate transparency and explainability
- Fairness
- Accountability and governance
- Contestability and redress

The United Kingdom's independent regulators¹ would be supported by the government to interpret what these principles mean for AI development and use in their specific contexts and sectors, and to decide if, when and how to implement measures that suit the way AI is being used in their sectors. This could involve issuing guidance or creating template impact or risk assessment models. The White Paper also confirms the UK Governments' commitment to establish a regulatory sandbox for AI to help developers navigate regulation and get their products to market. The sandbox would also help the government understand how regulation interacts with new technologies and refine this interaction where necessary.

Due to the protections available in the existing rule of law across domains and sectors, the UK Government currently does not see the need for additional or AI-specific legislation. Additionally, the White Paper emphasises that the soft law approach "will mean the UK's rules can adapt as this fast-moving technology develops, ensuring protections for the public without holding businesses back from using AI technology" (UK Government, 2023^[9]). The context-specific approach recognises that risks may differ within and across sectors and over time. To avoid incoherent and contradictory regulations, the government encourages regulatory co-ordination, for example through the Digital Regulation Co-operation Forum.

The regulatory framework proposed in the White Paper relies on a set of new, central functions, initially housed within central government. The new central functions include central risk assessment and will oversee and monitor the framework to ensure that it is having the required impact on risk, while ensuring that the framework is not having an unacceptable impact on innovation.

The UK Government is expected to publish a response to stakeholders following a consultation period that will engage individuals and organisations from across the AI ecosystem, wider industry, civil society, and academia (deadline mid-June 2023).

1. These are often sectoral regulatory bodies, such as the Health and Safety Executive, as well as the Equality and Human Rights Commission or the Competition and Markets Authority.

Source: UK Government (2023^[9]), *A pro-innovation approach to AI regulation*, <https://www.gov.uk/government/publications/ai-regulation-a-pro-innovation-approach/white-paper#part-3-an-innovative-and-iterative-approach>.

Countries are also developing guidance on using trustworthy AI in the workplace. For example, the Centre for Data Ethics and Innovation (CDEI)⁴ in the United Kingdom developed a practical guide in collaboration with the Recruitment and Employment Confederation (REC) to help recruiters effectively and responsibly deploy data-driven recruitment tools, ensure that appropriate steps have been taken to mitigate risks, and maximise opportunities (REC/CDEI, 2021^[10]). In Singapore, the Info-Communications Media Development Authority (IMDA) and Personal Data Protection Commission (PDPC) are developing a toolkit – called A.I. Verify – that would enable companies to demonstrate what their AI systems can do and what measures have been taken to mitigate the risks of their systems. The toolkit would allow to verify the

performance of any AI system (including workplace AI) against the developer's claims and with respect to internationally accepted AI ethics principles (IMDA, 2023^[11]).

Countries also often wrap measures to promote trustworthy AI in the workplace into AI strategies. Rogerson et al. (2022^[12]) show a steep increase in the share of countries with a published national AI strategy in the past five years, particularly in Europe, North America and East Asia. For instance, Germany's Artificial Intelligence Strategy states that AI applications must augment and support human performance. It also includes an explicit commitment to a responsible development and use of AI that serves the good of society and to a broad societal dialogue on its use (Hartl et al., 2021^[13]). Spain's National AI Strategy includes an ethics pillar, including an impetus for developing a trustworthy AI certification for AI practitioners (La Moncloa, 2020^[14]). The Spanish Agency for the Oversight of Artificial Intelligence – Europe's first AI oversight agency – will be responsible for promoting trustworthy AI and supervising AI systems that may pose significant risks to health, security and fundamental rights (España Digital, 2023^[15]).⁵

Several countries have published strategies for the use of trustworthy AI in the public sector specifically: an initial mapping by Berryhill et al. (2019^[16]) identified 36 countries with such strategies. For example, Australia's Digital Transformation Agency developed a guide to AI adoption in the public sector, stipulating, amongst others, that human decision-makers remain responsible for decisions assisted by machines, and that they must therefore understand the inputs and outputs of the technologies (Australian Government, 2023^[17]).

Countries and stakeholders are also supporting the implementation of trustworthy AI in the workplace by developing standards.⁶ In some cases, like the United States, the development of standards is mandated by legislation (U.S. Congress, 2021^[18]). The United States National Institute of Standards and Technology (NIST) is establishing benchmarks to evaluate AI technologies, as well as leading and participating in the development of technical AI standards (NIST, 2022^[19]).⁷ AI standards to support trustworthiness have also been the focus of international co-operation, as set out in the EU-US Trade and Technology Council Inaugural Joint Statement (European Commission, 2021^[20]), or an initiative by the United Kingdom via the Alan Turing Institute to establish global AI standards (Alan Turing Institute, 2022^[21]).

Overall, this section shows that soft law is an important governance tool to encourage trustworthy development and use of AI in the workplace. However, because of its non-enforceable nature, soft law may not be sufficient to prevent or remedy AI-related harm in the workplace. For its critics, soft law for AI can even be a form of "ethics washing", because voluntary AI ethics efforts have limited internal accountability or effectiveness in changing behaviour (Whittaker et al., 2018^[22]; McNamara, Smith and Murphy-Hill, 2018^[23]). Given the speed of technological change, a combination of soft and hard law may therefore be needed to continue to ensure trustworthy AI in the workplace.

6.2. Legislation for trustworthy AI in the workplace

The subsequent sections will discuss developments of hard law to ensure trustworthy AI in the workplace. Legislation not only has strong powers of enforceability, it is also often more detailed and precise than soft law and can have a delegate authority (e.g. judges) for interpreting and implementing the law (Abbott and Snidal, 2000^[5]). Moreover, legislation necessarily goes through democratic processes such as discussions and votes in parliament, whereas this is not necessarily the case for soft law. These processes, however, make legislation less flexible than soft law, which may create legal gaps when regulating a fast-changing technology such as AI.

One approach to ensuring that legislation remains up to date with advances in AI technology is to incorporate requirements for a regular review of the legal framework. These reviews could involve input from experts in the field, as well as social partners and stakeholders such as industry groups and consumer

organisations. For instance, the proposed EU AI Act and Canada's Artificial Intelligence and Data Act (AIDA) proposal adopt a “differentiated” or “risk-based” approach, meaning that only specific (high-risk) AI applications are subject to certain regulation or are banned altogether (see Box 6.3 and Box 6.4). Regular updates of the definition of “high-risk” and “unacceptable risk” systems can improve the flexibility of the legislative framework. This differentiated approach also makes legislation more targeted and proportionate, focusing oversight on AI applications with the potential to cause most harm while minimising the burden of compliance for benign and beneficial applications (Lane and Williams, 2023^[24]).

Another approach to making legislation more flexible is to develop regulatory “sandboxes”, which allow for the controlled testing of new AI technologies in a safe and regulated environment. Sandboxes provide an opportunity to explore new applications of AI without exposing users or society to undue risk, and allow for the adjustment of existing legal frameworks or the development of new ones in response to these new technologies or applications (Appaya, Gradstein and Haji Kanz, 2020^[25]; Madiega and Van De Pol, 2022^[26]; Attrey, Lesher and Lomax, 2020^[27]).

6.2.1. Legislation to protect workers' fundamental rights

This section investigates the role of AI- and/or workplace-specific legislation as well as more general legislation that is applicable to AI (in the workplace), including legislation that is already in effect and other still in development. Public policies for workers whose jobs are at risk of automation from AI are discussed in Chapter 3, and collective bargaining and social dialogue for AI are discussed in Chapter 7. The section does not discuss legislation to address adverse outcomes for organisations (such as economic loss, or damage to property) as a result of using AI in the workplace.

Capacity for human determination and human interaction

AI has the capacity to fully automate employment-related decisions, including which job seekers see a vacancy, shortlisting candidates based on their CVs, assigning tasks at work, and for bonus, promotion, or training decisions. While this capacity potentially frees up time for managers to focus more on the interpersonal aspects of their jobs (see Chapter 4), it raises the question whether decisions that have a significant impact on people's opportunities and well-being at work should be made without any human involvement, or at least the possibility for a human to intervene. The OECD AI Principles therefore call on AI actors to implement mechanisms and safeguards that ensure capacity for human intervention and oversight, to promote human-centred values and fairness in AI systems (OECD, 2019^[3]).

To date, full automation in workplace management and evaluation of staff remains rare (see Chapter 4). In addition to the technical difficulties inherent to modelling all the tasks and uncertainties that human managers have to take into account in their work (Wood, 2021^[28]), factors potentially limiting adoption include costs, lack of skills to work with AI (see Chapter 5) and in some cases regulation. For example, some countries – notably in the EU through the General Data Protection Regulation (GDPR) (see Box 6.3) – provide individuals with a right to meaningful human input on important decisions that affect them, which enables them to opt-out of fully automated decision-making in the workplace (Official Journal of the European Union, 2016^[29]; UK Parliament, 2022^[30]; Wood, 2021^[28]).⁸ Additionally, there are new legislative efforts that would prevent the adoption of fully automated decision-making tools in high-risk settings such as the workplace, by requiring human oversight (i.e. a “human in the loop”). Section 6.2.3 discusses this concept more in-depth.

Box 6.3. Examples of European legislation applicable to the use of AI in the workplace

EU GDPR

The EU General Data Protection Regulation (GDPR) enshrines data rights for persons located in the EU and obligations on entities processing personal data (Official Journal of the European Union, 2016^[29]). These rights apply to general data gathering and processing technologies and have specific implications for AI. This is particularly the case for rights to transparent information and communication, as well as rights of access (Art. 12, 13, 15), rectification, erasure and restriction of processing (Art. 16-17). Among other things, these rights aim to protect individuals' personal data and increase transparency how data are processed. Article 88 of the GDPR is specifically targeted at data protection in the employment context, giving member states the ability to enact more specific rules to protect employees' personal data.

Additionally, and importantly, GDPR Article 22 gives individuals the right "not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her [...]" . Since it can be extremely difficult to obtain this type of legal consent in employment relationships, Article 22 effectively prohibits algorithmic management that entails fully automatic decision-making (Parviainen, 2022^[31]; Wood, 2021^[28]). The EU Directive on Working Conditions and Platform Work provides additional protection as regards the use of algorithmic management for people working through digital labour platforms (see Chapter 4).

EU AI Act

The 2021 proposal for the European Union's AI Act seeks to regulate AI systems made available or used in the EU 27 member states to address risks to safety, health and fundamental rights, including specific provisions for use of certain high-risk AI applications in the workplace. It lays down a uniform legal framework to ensure that the development, marketing, and use of AI does not cause significant harmful impact on the health, safety and fundamental rights of persons in the Union (European Commission, 2021^[32]).

The proposed act follows a risk-based regulatory approach that differentiates between uses of AI that generate: i) minimal risk; ii) low risk; iii) high risk; and iv) unacceptable risk. It classifies certain AI systems used for recruitment, decisions about promotion, firing and task assignment, and monitoring of persons in work-related contractual relationships as "high risk". Due to this classification, these AI systems would be subject to legal requirements relating to risk management, data quality and data governance, documentation and recording keeping, transparency and provision of information to users, human oversight, robustness, accuracy, and security.

The risk-based approach has drawn praise (Ebers et al., 2021^[33]; DOT Europe, 2021^[34]; Veale and Borgesius, 2021^[35]), although there is debate about what should fall under each category (Johnson, 2021^[36]). The proposal, which is expected to take effect in 2025, may therefore still face significant changes before coming into effect. For instance, the Council suggests that the Commission assesses the need to amend the list of high-risk systems every 24 months (Council of the European Union, 2022^[37]), and the parliament proposes additional transparency measures for generative foundation models like GPT (European Parliament, 2023^[38]).

To address the main issues that raise legal uncertainty for providers and to contribute to evidence-based regulatory learning, the act encourages EU member states to establish "AI regulatory sandboxes", where AI systems can be developed and tested in a controlled environment in the pre-marketing phase. For instance, the Spanish pilot for an AI regulatory sandbox aims to operationalise the requirements of the future EU AI regulation (European Commission, 2022^[39]).

Even without fully automated decision-making, AI use in the workplace can reduce workers' autonomy and agency, decrease human contact, and increase human-machine interaction. This could lead to social isolation, decreased well-being at work and – taken to the extreme – deprive workers of dignity in their work (Briône, 2020^[40]; Nguyen and Mateescu, 2019^[41]). Policies and regulations to address the risk of decreased human contact due to the use of AI in the workplace remain limited. Occupational safety and health regulation might cover mental health issues, but there is some uncertainty about whether psychosocial risks posed by AI systems are appropriately covered by these regulations (Nurski, 2021^[42]). One exception is Germany: a report produced by the German AI Inquiry Committee highlighted the need to “ensur[e] that, as social beings, humans have the opportunity to interact socially with other humans at their place of work, receive human feedback and see themselves as part of a workforce” (Deutscher Bundestag Enquete-Kommission, 2020^[43]).

Breaches of privacy

Collecting and processing personal data – whether for AI systems or other purposes – poses a risk of privacy breaches if the data governance is inadequate, such as data that are misused, used without the needed consent, or inadequately protected (GPAI, 2020^[44]; OECD, 2023^[45]). Privacy breaches are a violation of fundamental rights enshrined in the United Nations' Universal Declaration of Human Rights (United Nations, 1948^[46]) as well as several other national and regional human rights treaties. Although the risk of a privacy breach for digital technologies is not limited to using AI, the personal data processed by AI systems are often more extensive than data collected by humans or through other technologies,⁹ thereby increasing the potential harm if something goes wrong (see Chapter 4). Moreover, AI systems can infer sensitive information of individuals (e.g. religion, sexual orientation, or political affiliations) based on non-sensitive data (Wachter and Mittelstadt, 2019^[47]). At the same time, AI may also be part of the solution regarding privacy protection and data governance, by helping organisations automatically anonymise data and classify sensitive data in real-time, thereby ensuring compliance to existing privacy rules and regulations.

Due to AI's reliance on data, general data protection regulations usually apply to the use of AI in the workplace. All OECD member countries, and 71% of countries around the world, have laws in place to protect (sensitive) data and privacy (UNCTAD, 2023^[48]). The 2018 EU General Data Protection Regulation (GDPR) is perhaps the best known for such protection principles (see Box 6.3). Under the GDPR, organisations are required to protect personal data appropriately, such as through two-factor authentication. This applies to applications in any context, including the workplace. Article 35 of the GDPR also requires data protection impact assessments, in particular for new technologies and when the data processing is likely to result in a high risk to the rights and freedoms of natural persons. Additionally, the GDPR requires transparency about which personal data are processed by AI systems and limits the ability to process sensitive personal data such as data revealing ethnic origin, political opinions or religious beliefs, which people may not wish to share even with the best data protection measures in place (GDPR.EU, 2022^[49]).¹⁰ For instance, during April 2023, Italy's data protection agency temporarily banned ChatGPT from processing personal data of Italian data subjects due to several alleged violations of the GDPR (Altomani, 2023^[50]). Several other European countries have started investigating ChatGPT's compliance to privacy legislation, and the European Parliament is working on stricter rules for generative foundation models like ChatGPT in the EU AI Act, distinguishing them from general purpose AI (Madiega, 2023^[51]; Bertuzzi, 2023^[52]; European Parliament, 2023^[53]).

Several OECD member countries have EU GDPR-like legislation. For instance, the UK GDPR and Brazil's *Lei Geral de Proteção de Dados* (LGPD) are modelled directly after GDPR, and South Korea's 2011 Personal Information Protection Act includes many GDPR-like provisions, including requirements for gaining consent (Simmons, 2022^[54]; GDPR.EU, 2023^[55]). However, the level of protection in countries' data and privacy legislation varies, and in some countries it is relatively low. For example, there is no federal data privacy law that applies to all industries in the United States, and state-level legislation is limited (IAPP, 2023^[56]).

The employment context can pose distinct challenges that existing data and privacy protection legislation does not effectively address, such as the collective rights and interests of employees and the informational and power asymmetry inherent in the employment relationship (Abraha, Silberman and Adams-Prassl, 2022^[57]). For instance, while privacy and data protection laws such as the GDPR often require that data subjects give explicit consent for the use of their personal data, it is uncertain whether meaningful consent can be obtained in situations of power asymmetry and dependency, such as job interviews and employment relationships. Job applicants and workers may worry that refusing to give consent may negatively impact their employment or career opportunities (Intersoft Consulting, 2022^[58]). Additionally, some experts question whether workers with limited knowledge and understanding of AI systems can truly give informed consent. Indeed, the view of the European Data Protection Board is that it is “problematic for employers to process personal data of current or future employees on the basis of consent as it is unlikely to be freely given” (EDPB, 2020^[59]).¹¹ In 2019, a court in Australia upheld an appeal from a sawmill employee, concluding that he was unfairly dismissed for refusing to use fingerprint scanners to sign in and out of work (Chavez, Bahr and Vartanian, 2022^[60]).

Germany is one of the few European countries that used GDPR Article 88 to develop data protection rules specifically applicable in the workplace (Abraha, Silberman and Adams-Prassl, 2022^[57]). However, the independent interdisciplinary council on employee data protection recently concluded that, even with the additional regulation, the German legislative framework still does not effectively ensure legal certainty for employee data protection. For instance, the legal framework would need to include standard examples of the (in)admissibility of consent, and the council strongly recommends that the use of AI in the context of employment be regulated by law (Independent interdisciplinary council on employee data protection, 2022^[61]).

Bias and discrimination

Even without AI, bias and discrimination in the workplace are unfortunately not uncommon (Cahuc, Carcillo and Zylberberg, 2014^[62]; Quillian et al., 2017^[63]; Becker, 2010^[64]; Bertrand and Mullainathan, 2004^[65]) which is in violation of workers’ fundamental rights (United Nations, 1948^[46]). The use of trustworthy AI in recruiting can provide data-driven, objective and consistent recommendations that can help increase diversity in the workplace and lead to selecting better performing candidates overall (Fleck, Rounding and Özgül, 2022^[66]).¹² Yet, many AI systems struggle with bias, because AI’s potential to decrease bias and discrimination can be hindered by bias in the specific design of the AI system and by use of biased data (Accessnow, 2018^[67]; Executive Office of the President, 2016^[68]; Fleck, Rounding and Özgül, 2022^[66]; GPAI, 2020^[44]). As a result, using AI in the workplace can cause bias regarding who can see job postings, the selection of candidates to be interviewed, and workers’ performance evaluations, amongst others – see Chapter 4.

A range of existing laws in OECD member countries against discrimination in the workplace can be applied to the use of AI in the workplace. For instance, in 2021, an Italian court applied existing anti-discrimination laws to throw out an algorithm used by the digital platform Deliveroo to assign shifts to riders. The court found that Deliveroo gave priority access to work slots to workers using an algorithm which “scored” workers based on reliability and engagement.¹³ The tribunal ruled that the algorithm used an unclear data processing method and no possible contextualisation for rankings and therefore indirectly discriminated against workers who had booked a shift but could not work, including if due to personal emergencies, sickness or participation in a strike (Geiger, 2021^[69]; Allen QC and Masters, 2021^[70]; Tribunale Ordinario di Bologna, 2020^[71]).¹⁴ Bornstein (2018^[72]) argues that employers in the United States may be litigable if they have intentionally chosen to feed biased data into the model that reflects past discrimination, and, as a result, AI reproduces such discrimination.

However, existing anti-discrimination legislation is usually not designed to be applied to AI use in the workplace, and relevant case law is still limited. In practice, it may therefore be difficult to contest AI-based

employment-related decisions using only existing anti-discrimination laws. For instance, plaintiffs may face difficulties accessing the algorithm due to privacy and intellectual property regulations, and even if they do get access, the algorithm may be so complex that not even the programmers and administrators know or understand how the output was reached (Rudin, 2019^[73]; O'Keefe et al., 2019^[74]; Bornstein, 2018^[72]). In addition, many applicants and workers may not even know that AI is being used to assess them, or may have neither the resources, nor the skills and tools necessary to evaluate whether the AI system is discriminating against them, which poses challenges in countries that rely heavily on individual action for seeking redress (more on this in Section 6.2.2). Case law applying anti-discrimination legislation to AI will need to be monitored, to determine whether and how much this legislation will need to be adapted to address the use of AI in the workplace.

Some institutions are also calling for strong regulation or even society-wide bans of (AI-powered) facial processing technologies,¹⁵ due to concerns about privacy and the limited accuracy of these technologies for certain groups, such as for women and ethnic minorities (Buolamwini and Gebru, 2018^[75]). Additionally, some experts do not consider that facial recognition technology can reliably interpret someone's personality or emotions (Whittaker et al., 2018^[22]). In May 2020, the State of Maryland in the United States passed a law banning the use of facial recognition in employment interviews, unless the interviewee signs a waiver (Fisher et al., 2020^[76]). However, it is unclear how much real choice job applicants and workers might have in signing a waiver and the law has faced criticism for leaving broad gaps in terms of what will be recognised as "facial recognition services" and "facial templates" created by the facial recognition service, and may therefore require additional interpretation (Glasser, Forman and Lech, 2020^[77]). Additionally, a 2021 report by the United Nations Human Rights Office called for a temporary ban on the use of facial recognition (UN Human Rights Council, 2021^[78]), and in its 2021 guidelines on how European countries should regulate the processing of biometric data, the Council of Europe called on European countries to impose a strict ban on facial analysis tools that purport to "detect personality traits, inner feelings, mental health or workers' engagement from face images" (Council of Europe, 2021^[79]).

Freedom of association and the right to collective bargaining

The right of workers to form and join organisations of their choice (freedom of association) is a fundamental human right stated in the Universal Declaration of Human Rights (United Nations, 1948^[46]) and the ILO Declaration of Fundamental Principles and Rights at Work (ILO, 1998^[80]). This right is closely tied to the right to collective bargaining (ILO, 1998^[80]). As discussed in Chapter 7, AI technologies can aid social dialogue and collective bargaining by providing information, insights, and data-driven arguments to social partners. However, using AI can also diminish workers' bargaining power due to power imbalances and information asymmetries between workers, employers, and representatives, and AI-based monitoring can hinder collective organising and union activities (see Chapter 7).

Workers' right to organise and participate in collective bargaining are typically translated into national labour laws, but the level of protection and enforcement of these laws varies across countries, amongst others due to varying shares of union membership (OECD, 2019^[81]). Spain passed legislation in August of 2021, making it mandatory for digital platforms to provide workers' representatives with information about the mathematical or algorithmic formulae used to determine working conditions or employment status (Pérez del Prado, 2021^[82]; Aranguiz, 2021^[83]). The Spanish law thereby provides for a continued role for social dialogue and collective bargaining, and further rounds of dialogue between the platforms and unions are likely, with the possibility of further policy changes.¹⁶

Occupational safety and health

AI has the potential to contribute to increased physical safety for workers, for instance by taking over hazardous tasks (Lane, Williams and Broecke, 2023^[84]; Milanez, 2023^[85]; EU-OSHA, 2021^[86]), or alerting workers who may be at risk of stepping too close to dangerous equipment (Wiggers, 2021^[87]) – see

Chapter 4. However, if not designed or implemented well, AI systems can also threaten the physical safety and the well-being of workers, for instance through dangerous machine malfunctioning, or by increasing work intensity brought on by higher performance targets. The need to learn how to work with new technologies and worries over greater monitoring through AI may also increase stress (Milanez, 2023^[85]).

Labour law and Occupational Safety and Health (OSH) regulations often apply directly to AI use in the workplace,¹⁷ for instance by requiring employers to pre-emptively ensure that tools used in the workplace will not harm workers (ILO, 2011^[88]), which would also apply to AI-powered tools. Accountability for AI-related harm in the workplace could therefore potentially fall fully on the employer, with court cases already arising as regards AI-based decisions about hiring (Maurer, 2021^[89]; Engler, 2021^[90]; Butler and White, 2021^[91]) and performance management (Wisenberg Brin, 2021^[92]).¹⁸ Moreover, algorithmic management may put strain on bargaining and informational dynamics at the workplace level – see Chapter 7.

As AI systems become more integrated in the workplace, OSH regulation will likely need to adapt and possibly be extended to effectively address concerns raised by the use of AI (Jarota, 2021^[93]; Kim and Bodie, 2021^[94]). However, to date, much remains uncertain about if and how these changes would take effect, and how they would interact with new legislative proposals, such as the EU AI Act, that also cover risks to occupational safety and health.

6.2.2. Legislation to increase transparency and explainability of workplace AI

Even with the most elaborate legislative framework in place to mitigate or prevent AI-related risk, individuals and employers need to be able to verify if and how the system affects employment-related decisions. Providing this type of information (“transparency”) in an understandable way (“explainability”) not only enables individuals to take action if they suspect they are adversely affected by AI systems: it also allows workers and employers to make informed decisions about buying or using an AI system for the workplace, and it may increase acceptance and trust in AI, all of which is crucial for promoting the diffusion of trustworthy AI in the workplace.

However, implementing transparency and explainability of AI can be complicated. For example, transparency requirements may put the privacy of data subjects at risk. Requiring explainability may negatively affect the accuracy and performance of the system, as it may involve reducing the solution variables to a set small enough that humans can understand. This could be suboptimal in complex, high-dimensional problems (OECD.AI, 2022^[95]). Transparency and explainability might also be hard to achieve because developers need to be able to protect their intellectual property,¹⁹ and because some AI systems – such as generative AI or deep neural networks – are so complex that even their developers will not be able to fully understand or have full insight into how it reached certain outcomes. Transparency and explainability may also increase complexity and costs of AI systems, potentially putting small businesses at a disproportionate disadvantage (OECD.AI, 2022^[95]).

Nevertheless, transparency and explainability do not necessarily require an overview of the full decision-making process, but can be achieved with either human-interpretable information about the main or determinant factors in an outcome, or information about what would happen in a counterfactual (Doshi-Velez et al., 2017^[96]). For example, if an employee is refused a promotion based on an AI system’s recommendation, information can be given on what factors affected the decision, whether they affect it positively or negatively and what their respective weights are. Alternatively, counterfactual models could provide a list of the most important features that the employee would need to possess in order to obtain the desired outcome, e.g. “you would have obtained the position if you had had a better level of English and at least three additional years of experience in your present role” (Loi, 2020^[97]). Yet, these counterfactuals would need to be checked for fairness as well. This section discusses what countries are doing to ensure that AI used in the workplace is transparent and explainable.

Transparency

People are not always aware that they are being hired, monitored, promoted, or managed via AI. A global survey²⁰ found that 34% of respondents think they interacted with AI in the recent past, while their reported use of specific services and devices suggests that 84% have interacted with AI (Pega, 2019^[98]). For instance, job seekers might not be aware that the vacancies they see are a selection made by AI, or that their CV or video interview are analysed through AI, and hence that a job offer, or rejection, is (in part) based on AI. Additionally, employers may not see the need to inform workers or job applicants about the fact that they are using AI. By contrast, transparency implies providing insight into the way in which employment-related decisions are made by or with the help of AI. For instance, there is a pending decision by the Dutch data protection authority about complaints by French Uber drivers concerning their deregistration from the platform without satisfactory explanation and denial of access to information, amongst others. (Hießl, 2023^[99]).

Employers, in turn, may not be aware that their employees or job candidates are using AI to help them do their jobs. For instance, AI-powered text generators such as ChatGPT can write CVs, application letters, essays and reports (as well as pieces of code), in a writing style that is convincingly human, and which often remains undetected by current plagiarism software. So-called “deepfakes” – whereby AI systems convincingly alter and manipulate image, audio or video content to misrepresent someone as doing or saying something – are also a risk for employers (and potentially also workers). The Federal Bureau of Investigation (FBI) in the United States has warned for an increase in the use of deepfakes and stolen identities to apply for remote work positions (FBI, 2022^[100]). Informing actors that they are interacting with (the output of) an AI system is a fundamental element of ensuring transparency in AI system use.

In the EU and the United Kingdom, the GDPR requires employers to ask job applicants and workers for their explicit consent when they want to use their personal data,²¹ and for automated decisions that involve no meaningful human involvement.²² For instance, the Dutch court²³ recently ruled that the account deactivation of five Uber drivers was in violation of GDPR Article 22 because it was based on automated data processing (Hießl, 2023^[99]). While the GDPR will continue to be applicable to AI systems that are built on or process data subjects' personal data, the proposed EU AI Act would also ensure that providers of AI systems notify people of their interactions with an AI system, including those that are not based on personal data (European Commission, 2021^[32]).²⁴ The latest proposed amendments to the AI Act by the European Parliament include additional transparency measures for generative foundation models (such as ChatGPT) like disclosing that the content was generated by AI and publishing summaries of copyrighted data used for training (European Parliament, 2023^[38]; European Parliament, 2023^[53]). The proposed EU Directive on Working Conditions and Platform Work (Platform Work Directive for short) also includes the right to transparency regarding the use and functioning of automated monitoring and decision-making systems (European Commission, 2021^[101]; European Commission, 2021^[102]).

In the United States, too, some jurisdictions require that job applicants and workers are notified about their interactions with AI, but also that they need to give their consent before that interaction can take place. The Artificial Intelligence Video Interview Act of Illinois requires employers to inform candidates of their use of AI in the video interview before it starts, explain how it works, and obtain written consent from the individual (ILCS, 2019^[103]).²⁵ However, as Wisenberg Brin (2021^[92]) highlights, the law is not clear on what kind of explanations need to be given to candidates, as well as the required level of algorithmic detail. The law also does not clarify what happens to the application of a candidate who refuses to be analysed in this way. In addition, this law could conflict with other federal and state laws that require the preservation of evidence.

Some countries have passed legislation to regulate transparency of AI systems in the workplace specifically. For instance, emerging “rider laws”, such as the one enacted by Spain (see the subsection on Freedom of association and the right to collective bargaining in Section 6.2.1), are expected to increase awareness and help mitigate risks associated with the transparency and explainability of AI systems for

workers (De Stefano and Taes, 2021^[104]). Another example of legislation for workplace AI transparency is the EU's draft Platform Work Directive (European Commission, 2021^[105]), which would specify in what form and at which point in time digital labour platforms should provide information about their use and key features of automated monitoring and decision-making systems to platform workers and their representatives, as well as to labour authorities (Broecke, 2023^[106]).

Explainability

Thanks to AI's reliance on data, sufficiently transparent and explainable AI systems in the workplace may lead to better insights into how employment-related decisions are made, when AI-powered, as compared to when those decisions are made only by humans. After all, human decision-making can be opaque and hard to explain, too. AI would also open the possibility to provide feedback for AI-informed decisions to job seekers and workers systematically and at lower costs.

However, AI systems are often more complex and their outcomes more difficult to explain than other technologies and automated decision-making tools. To make AI in the workplace trustworthy, and ensure the possibility to rectify its outcomes when necessary, workers, employers and their representatives should have understandable explanations as to why and how important decisions are being made, such as decisions that affect well-being, the working environment/conditions, or one's ability to make a living. Without being able to determine the logic of employment-related decisions made or informed by AI systems, it can be extremely difficult to rectify the outcomes of such decisions, which would violate people's right to due process (see Section 6.2.3). Additionally, AI-based decisions that are not explainable are unlikely to be accepted by employees (Cappelli, Tambe and Yakubovich, 2019^[107]).

In New Zealand, the Employment Relations Act of 2000 was used in 2013 to invalidate a decision to dismiss an employee, in part because the decision was informed by the results of an AI-powered psychometric test which the employer could not explain, or even seemingly understand. Since the algorithm information (including whether it was AI per se or a less complex algorithm) was not available to the employee, they were denied the right to "an opportunity to comment" before the decision is made (Colgan, 2013^[108]; New Zealand Parliamentary Counsel Office, 2000^[109]). This example highlights the need for transparency and explainability, not only for the person subject to the AI-powered decision, but also for the organisation using or deploying the AI system.

Some countries are regulating transparency and explainability of AI systems through AI-specific legislation. For instance, the proposed Canadian Artificial Intelligence and Data Act (AIDA) and Consumer Privacy Protection Act (CPPA) would oblige developers and users of automated decision-making systems and high-impact AI systems to provide "plain-language" explanations about how the systems reach a certain outcome (House of Commons of Canada, 2022^[110]) – see Box 6.4.

Box 6.4. The Canadian Digital Charter Implementation Act, 2022

On 16 June 2022, the Canadian Government introduced Bill C-27, also known as the *Digital Charter Implementation Act, 2022*. If passed, the Charter will introduce three proposed acts: the *Consumer Privacy Protection Act (CPPA)*, the *Personal Information and Data Protection Tribunal Act (PIDTA)*, and the *Artificial Intelligence and Data Act (AIDA)* (House of Commons of Canada, 2022^[110]).

The CPPA would reform existing personal data protection legislation, which the new Tribunal (PIDTA) should help to enforce. The CPPA would apply to all actors using personal information for commercial activities, thereby explicitly including automated decision systems based on, for instance, machine learning, deep learning, or neural networks.

The AIDA aims to strengthen Canadians' trust in the development and deployment of AI systems in the private sector (Government of Canada, 2022^[111]): government institutions are explicitly exempt from the AIDA. The AIDA would establish common requirements for the design, development, and use of AI systems, including measures to mitigate risks of physical or psychological harm and biased output, particularly of "high-impact AI systems". The AIDA would also prohibit certain AI systems that may result in serious harm to individuals or their interests. However, most of the substance and details – including the definition of "high-impact" AI systems and what constitutes "biased output" (Witzel, 2022^[112]) – are left to be elaborated in future regulations (Ferguson et al., 2022^[113]).

Another challenge to explainability is that many managers, workers and their representatives, as well as policy makers and regulators may only have limited experience with AI and may not have the skills to understand what the AI applications are doing or how they are doing it – see Chapter 5. A 2017 survey found that more than two in five respondents in the United Kingdom and the United States admitted that "they have no idea what AI is about" (Sharma, 2017^[114]).²⁶ Although understanding AI may only require moderate digital skills, in the OECD on average, more than a third of adults lack even the most basic digital skills (Verhagen, 2021^[115]).

Equipping people with better knowledge and skills about AI would help facilitate explainability (OECD, 2019^[116]), which may help build trust in AI systems. In practice, countries where people report higher levels of understanding of AI tend to have more trust in companies that use AI (Ipsos, 2022^[117]). This is not only an issue of transparency of AI use, but also of understanding how the technology works. Increasing understanding of AI among workers and their representatives can help better understand the benefits and risks of AI systems used in the workplace and empower them to engage in consultation and take action as needed. For instance, job seekers may not be aware that they did not even see a specific vacancy because an algorithm determined that they were not suitable for the job. Finally, it is important that policy makers, legal professionals and other regulators understand how AI systems work. Increasing people's understanding of AI requires strengthening adult learning systems – see Verhagen (2021^[115]); OECD (2019^[118]); and Chapter 5. Collective bargaining on AI can also play an educational role, fostering greater understanding for both workers and employers on the risks and benefits of AI in a practical forum – see Chapter 7.

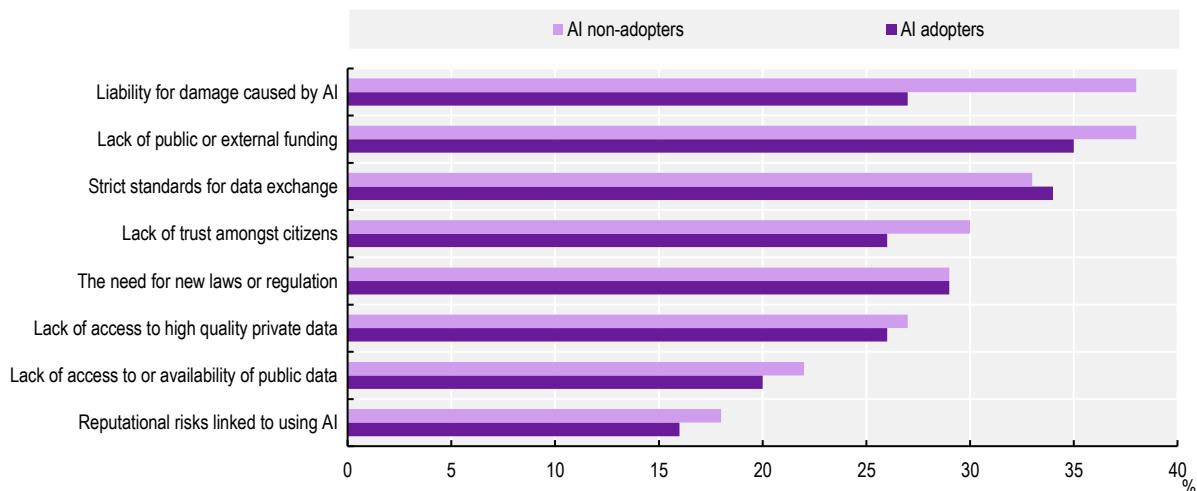
6.2.3. Legislation to ensure accountability for AI used in the workplace

Accountability relies on being able to tie a specific individual or organisation to the proper functioning of an AI system, including harm prevention (see Section 6.2.1), ensuring transparency and explainability of the system (see Section 6.2.2), and alignment with the other OECD AI principles (OECD, 2019^[3]). Besides assigning these responsibilities to different AI actors, clear accountability also enables workers or employers that have been adversely impacted by AI to contest and rectify the outcome.

A lack of clear accountability limits the potential for the diffusion of trustworthy AI in the workplace. For instance, among European enterprises who do not currently use AI, “liability for damage caused by artificial intelligence” is the most cited barrier for AI adoption, together with a lack of funding (see Figure 6.2). Liability risks are also in the top-3 most cited barriers or challenges experienced by AI adopters and are mentioned more frequently in large enterprises and in the healthcare sector and transport sector (European Commission, 2019^[119]).

Figure 6.2. Liability for damage caused by AI is one of the key barriers to AI adoption by EU businesses

Percentage of enterprises who responded that a specific barrier is applicable to their business



Note: Responses to the question “I will name potential external obstacles to the use of artificial intelligence. Please indicate all that your company has experienced as a challenge or a barrier.” Based on responses from 8 661 enterprises in the EU27 member states.

Source: European Commission (2019^[119]), *European enterprise survey on the use of technologies based on artificial intelligence*, <https://digital-strategy.ec.europa.eu/en/library/european-enterprise-survey-use-technologies-based-artificial-intelligence>.

StatLink <https://stat.link/k1d790>

Indeed, AI systems pose challenges for accountability, because it is not always clear which actor linked to the AI system is responsible if something goes wrong. This is related to the fact that, unlike traditional goods and services, some AI systems can change as they are used, by learning from new data. Research shows that there is no guarantee that algorithms will achieve their intended goal when applied to new cases, in a new context, or with new data (Neff, McGrath and Prakash, 2020^[120]; Heavens, 2020^[121]). AI's risks for accountability are further exacerbated by recent developments in generative AI, amongst others because it is uncertain who is responsible for the content created by generative AI systems. Additionally, developers, providers and users of AI systems are not necessarily located in the same jurisdiction, and approaches to accountability may vary across them. This may put SMEs, who may not have legal expertise in-house, in a particularly difficult position.

Overall, accountability is important as a foundation for the use of trustworthy AI in the workplace. Clear accountability not only helps for holding actors accountable and potentially claim damages after harm has occurred; it can also help to pre-emptively ensure that these risks are addressed (i.e. that AI used in the workplace is trustworthy). Without clear accountability, it would not be possible to identify which AI actor is responsible for upholding anti-discrimination principles, for example, or for ensuring that AI systems operate safely. Clear accountability is important for ensuring other dimensions of trustworthiness as well. If no one is responsible when AI systems do not work as they are reasonably expected to, transparency about the problems in the AI system will not necessarily translate into process improvements (Loi, 2020^[97]).²⁷

The importance and challenges of accountability for AI used in the workplace have been well exemplified by some platform-work cases. Drivers for Amazon Flex, for example, encountered difficulties holding AI actors accountable for adverse outcomes such as refusals to accept seemingly genuine reasons for late deliveries or removals from the platform without clear explanations, because official systems for recourse were difficult to navigate (Soper, 2021^[122]). Similar complaints have also been made against Uber Eats in the United Kingdom, concerning an AI-based facial identification software, for which it was difficult to hold actors accountable because it did not allow for the possibility that the technology itself had made a mistake (Kersley, 2021^[123]).²⁸ The fact that platform workers may be self-employed or even in bogus self-employment, and have low trade union density makes it even more difficult for them to have employment decisions contested or rectified (OECD, 2019^[124]).

Legislation for accountability in the context of automated decision-making processes often lies with having a human “in the loop” (e.g. they may have to approve a decision) or “on the loop” (e.g. they are able to view and check the decisions being made), in a deliberate attempt to ensure human accountability (Enarsson, Enqvist and Naarttijärvi, 2021^[125]).²⁹ However, in practice, many uncertainties remain about the legal role and accountability facing the human in or on the loop, in part because, as of yet, the terms “human in the loop” or “human on the loop” have no fixed legal meaning or effect (Enarsson, Enqvist and Naarttijärvi, 2021^[125]). For instance, while the EU AI Act specifies responsibilities and obligations for AI providers, AI users, and human oversight,³⁰ it will be left to future standard-setting to determine the exact role the human in the loop will have in ensuring trustworthy AI.

Additionally, in September 2022 the European Commission proposed a targeted harmonisation of national liability rules for AI through two proposals: a review of the Directive on liability for defective products – Product Liability Directive for short – and a proposal for a Directive on adapting non contractual civil liability rules to artificial intelligence – AI Liability Directive for short – (European Commission, 2022^[126]). Current product liability rules in the EU are based on the strict liability of manufacturers, meaning that when a defective product causes harm, the product’s manufacturer must pay damages without the need for the claimant to establish the manufacturer’s fault or negligence. The revised Product Liability Directive modernises and reinforces existing product liability rules to provide legal clarity to businesses regarding fair compensation to victims of defective products that involve AI, but will maintain the strict liability regime.

In contrast to strict liability, fault-based liability regimes put the burden of proof on the claimant, who must demonstrate that the party being accused of wrongdoing (such as the manufacturer) failed to meet the standard of care expected in a given situation (Goldberg and Zipursky, 2016^[127]). However, the opacity and complexity of AI systems can make it difficult and expensive for victims to build cases and explain in detail how harm was caused. To address these difficulties, the AI Liability Directive – a fault-based liability regime – proposes to alleviate the burden of proof for AI victims through a so-called rebuttable “presumption of causality” (European Commission, 2022^[126]).³¹ The Directive also expands the definition of “harm”, from health and safety issues to infringements on fundamental rights as well (including discrimination and breaches of privacy). Furthermore, together with the revised Product Liability Directive, it aims to facilitate easier access to information about the algorithms for European courts and individuals (Goujard, 2022^[128]).³²

Additionally, according to the EU and UK GDPR, data controllers of automated decision systems using personal data are accountable for implementing “suitable measures to safeguard the data subject’s rights and freedoms and legitimate interests”, including the right to obtain human intervention by the controller, to express their point of view, and to contest the decision (Official Journal of the European Union, 2016^[29]; GDPR.EU, 2023^[55]).³³

In some countries, such as Canada, the algorithmic function of an AI system does not qualify as a “product” under product liability regimes (Sanathkumar, 2022^[129]), which could imply that employers would be liable for AI-related harm due to a defective algorithm. The Canadian AIDA possibly shifts some of this liability to developers of AI systems, for instance by making the assessment and mitigation of risks of harm or biased output that could result from the use of the system a shared responsibility between designers, developers and those who make the AI system available for use or manages its operation (plausibly the employer, in case of workplace AI) (House of Commons of Canada, 2022^[110]).

Box 6.5. Algorithmic accountability in the United States

In October 2022, following a year of public engagement, the Office of Science and Technology Policy of the White House published The Blueprint for an AI Bill of Rights: a set of five non-binding principles to promote trustworthy development and use of automated decision systems (The White House, 2022^[130]), to help shape future policies related to AI. Additionally, the proposed Digital Platform Commission Act of 2022 would establish an expert Federal agency to develop and enforce legislation for digital platforms, with specific mandates to ensure that the algorithmic processes are trustworthy (US Congress, 2022^[131]).

Algorithmic Accountability Act

In April 2022, several members of Congress proposed the Algorithmic Accountability Act of 2022 (US Congress, 2022^[132]), an updated version of the Algorithmic Accountability Act of 2019 (US Congress, 2019^[133]). The bill proposes that organisations that use automated decision systems perform impact assessments both before and after the deployment of the system in order to identify and mitigate potential harms for consumers (Mökander and Floridi, 2022^[134]). The same rules would apply to “augmented critical decision processes”, i.e. activities that employ an automated decision system to make a decision or judgment that can have a significant effect on a consumer’s life, including (amongst others) “employment, workers management, or self-employment” (US Congress, 2022^[132]).

The focus on preventing and mitigating potential harm for consumers implies that the Federal Trade Commission (FTC) is responsible for verifying whether the impact assessment requirements are met. It is left open for the FTC to determine what documentation and information must be submitted after completing such an assessment (Mökander and Floridi, 2022^[134]).

SMEs and government agencies would be exempt from the Algorithmic Accountability Act, because the bill would only apply to companies that fall under the FTC’s jurisdiction¹ and have an annual turnover of more than USD 50 million, have more than USD 250 million in equity value, or process the information of more than 1 million users (US Congress, 2022^[132]).

A number of states have proposed similar regulation, including California’s Automated Decision Systems Accountability Act (California Legislature, 2020^[135]), New Jersey’s Algorithmic Accountability Act (State of New Jersey Legislature, 2019^[136]), Washington D.C.’s Stop Discrimination by Algorithms Act (Racine, 2021^[137]) and Washington’s SB 5 527 (Hasegawa et al., 2019^[138]).

AI accountability policy

The National Telecommunications and Information Administration (NTIA) released a request for comments on AI system accountability measures and policies in April 2023. The deadline for submitting comments was set for mid-June 2023. The request seeks insights on self-regulatory, regulatory, and other measures and policies that are designed to provide assurance to external stakeholders that AI systems are legal, effective, ethical, safe, and otherwise trustworthy. The NTIA will use these submissions, as well as other public interactions on the subject, to publish a report on the development of AI accountability policies. The report will place significant emphasis on the AI assurance ecosystem (NTIA, 2023^[139]).

1. The FTC enforces antitrust and consumer protection laws, targeting unfair competition and deceptive practices. It covers virtually every area of commerce, with some exceptions concerning banks, insurance companies, non-profits, transportation and communications common carriers, air carriers, and some other entities (Federal Trade Commission, 2023^[140]).

An increasingly popular tool to assess AI systems and ensure they follow the law and/or principles of trustworthiness, is “AI auditing” or “algorithmic auditing”. Generally speaking, in an algorithmic audit, a third-party assesses to what extent and why an algorithm, AI system and/or the context of their use aligns with ethical principles or regulation. For instance, in November 2021, the New York City Council banned the use of “automated employment decision tools” without annual bias audits (Cumbo, 2021^[141]). However, there are concerns that vendor-sponsored audits would “rubber-stamp” their own technology, especially since there are few specifics in terms of what an audit should look like, who should conduct the audit, and what disclosure to the auditor and public should look like (Turner Lee and Lai, 2021^[142]). How algorithmic audits should be conducted to ensure they contribute to trustworthy AI is still an area of active research (Ada Lovelace Institute, 2020^[143]; Brown, Davidovic and Hasan, 2021^[144]).

6.3. Concluding remarks

Artificial intelligence (AI) systems have the potential to improve the labour market and workplaces, but they also entail risks. As stated in the OECD AI Principles, AI needs to be developed and used in a trustworthy way. Trustworthy AI means that it is safe and respectful of fundamental rights such as privacy and fairness, and the way it reaches employment-related decisions is transparent and understandable by humans. It also means that employers, workers and job seekers are transparent about their use of AI, and that it is clear who is accountable in case something goes wrong. That entails addressing the risks that emerge when AI systems are used in the workplace, from recruitment and hiring, to worker or manager assistance, to the provision of human services.

The future of AI in the workplace is in societies’ hands and will in part depend on the policy decisions countries make. Policy makers need to act to develop policies to reap the benefits that AI systems can bring to the workplace while addressing the risks they raise for workers’ fundamental rights and well-being. The rapid pace of AI development and deployment underscores the need for policy makers to take quick, proactive steps to ensure trustworthy development and use of AI in the workplace.

This chapter reviews policies that countries have put in place to ensure the use of trustworthy AI in the workplace, as well as public measures that are currently under development. Some measures are workplace-specific, but the chapter also discusses more general AI policies that are directly relevant to the workplace. By providing various examples, this chapter aims to help policy makers, AI developers, employers, workers and their representatives navigate the emerging AI policy landscape.

When it comes to using AI in the workplace to make decisions that affect workers’ opportunities and rights, there are some avenues that policy makers are already considering: adapting workplace legislation to the use of AI; encouraging the use of robust auditing and certification tools; using a human-in-the-loop approach; developing mechanisms to explain in understandable ways the logic behind AI-powered decisions.

Existing non-AI-specific legislation already offers an important foundation for the governance of AI systems in the workplace, for instance through anti-discrimination, data protection and product liability legislation. Given this foundation, some countries, such as the United Kingdom and Japan, have chosen to manage AI development and use through soft law (such as principles, guidelines, and standards) rather than additional legislation. Soft law is advantageous in AI governance as it can be implemented and adjusted more easily than legislation, particularly while AI-specific legislation is still in development. It also aids legal compliance in complex situations and facilitates international collaboration on AI policies. However, because of its non-binding nature, soft law may not be enough to prevent or remedy AI-related harm in the workplace. Experts agree that existing anti-discrimination, data and privacy protection legislation and occupational safety and health regulations will likely need to adapt for the effective governance of the use of AI in the workplace. Relevant case law is still limited, and it will need to be monitored to determine how

effective existing legislation is in regulating the use of AI in the workplace and how much it would need to be adapted.

Novel AI-specific legislative proposals are being developed, for example in Canada, the European Union and in the United States, also in light of the latest developments in generative AI.³⁴ These proposals have important implications for workplace AI, for instance by requiring human oversight for employment-related decisions based on AI. To minimise the regulatory burden and mitigate the risk that AI legislation cannot keep up with such a fast-changing technology, legislative proposals use measures differentiated typically by risk category – with regular reviews of such categories – and regulatory sandboxes.

All dimensions of trustworthiness are interconnected and equally important. Transparency is essential for accountability, for example, and regulation to ensure explainability can help reduce bias in AI systems. Therefore, ensuring trustworthy AI in the workplace will require a framework of policies that prevent AI from causing harm to job seekers and workers, increase transparency and explainability of AI use in the workplace, as well as clarify accountability across the AI value chain. Additionally, since soft and hard law both have benefits and drawbacks, a well-co-ordinated combination of both may be necessary to effectively ensure that AI policies are enforceable and easy to comply with, while staying up to date with the latest developments in AI.

While using different measures at the same time can help address gaps in AI policies, this approach poses challenges in terms of possible regulatory burdens or inconsistent policies. This can have repercussions on enforcement, and unnecessarily delay the adoption of beneficial and trustworthy AI. Additionally, multiplication of standards and policy initiatives within and across countries may increase uncertainty and compliance costs for businesses, especially smaller ones. This calls for collaboration and co-ordination across countries and regions when developing policies for the development and use of workplace AI, to minimise inconsistency. The EU AI Act is unique and ambitious in this respect, by trying to regulate almost all AI development and use in its member states in one piece of legislation. Expert regulatory bodies on AI, such as the one proposed in the United States, may help to co-ordinate regulation across states as well.

Ensuring trustworthy AI in the workplace not only requires a well-designed policy framework, but also the capacity and resources among policy makers and regulators to review and develop policies and to effectively enforce them. To this end, it is important that developers and users are given guidance to help them understand and comply with the existing and changing policies. In addition, policy makers and regulators will need to have a comprehensive understanding of the benefits and risks of using AI in the workplace, and of the effectiveness of existing legislation. Knowledge and understanding of AI systems and their impact on the workplace is also crucial for workers, employers and social partners. More than a third of adults lack even the most basic digital skills. While the expansion of training programmes for digital skills is already high on the policy agenda in most countries, the increasing use of AI in the workplace raises the need to add AI-specific training content to digital skills programmes – see Chapter 5. Policy should also support the role of social partners in fostering the adoption of trustworthy AI in the workplace – see Chapter 7.

Finally, as countries increasingly take policy action, timely, rigorous, evidence-based, and comparative assessments will be key to determining what works, and where legal gaps remain. This is particularly important, considering that policies will need to keep up with a fast-evolving technology such as AI.

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Notes

¹ Unnecessary delays in the adoption of trustworthy AI also involve an implicit risk of losing out on the benefits it brings, such as improvements to health and safety in the workplace or increased productivity.

² “Transparency” refers to disclosing when AI is being used. “Explainability” means enabling people affected by the outcome of an AI system to understand how it was arrived at (OECD.AI, 2023^[2]).

³ The OECD-NIST Catalogue of AI Tools & Metrics collects and classifies procedural, educational and technical tools and metrics for trustworthy AI (OECD.AI, 2023^[153]). For instance, it includes interactive collections of technical tools to remove bias, metrics to measure privacy, documentation tools to increase transparency, and educational tools to acquire AI skills. This should help AI actors be accountable and build and deploy AI systems and applications that respect human rights and are fair, transparent, explainable, robust, secure and safe.

⁴ The CDEI is an expert government body enabling the trustworthy use of data and AI (GOV.UK, 2023^[152]).

⁵ Additionally, the Observatory on the Social and Ethical Impact of Algorithms (OBISAL) will study the ethical and regulatory impact of AI systems and carry out evaluations to generate recommendations and best practices (España Digital, 2023^[15]).

⁶ Several AI standards are under development or are being published, including those developed by organisations such as the International Organization for Standardization (ISO, 2022^[156]) and the Institute of Electrical and Electronics Engineers (IEEE, 2022^[155]). Standard authorities in countries such as Australia (Standards Australia, 2020^[145]), Germany (DKE, 2020^[146]), the United Kingdom (CDDO, 2022^[147]), and the United States (Phillips et al., 2020^[159]) are also working towards such standards. To operationalise the implementation of the EU AI Act, European standardisation organisations will be asked to develop standards as well, including standards for “human oversight” measures that can include “human in the loop” (see Section 0).

⁷ The NIST also issued a publication focused on AI and bias, building on a 2021 proposal for identifying bias across the AI lifecycle (Schwartz et al., 2021^[158]), but also noting the importance of addressing human and systemic biases (Schwartz et al., 2022^[160]).

⁸ The power asymmetry and dependency of employment relationships may effectively render consent to fully automated employment decisions wrongfully obtained because it is unlikely to have been freely given – see Box 6.3 and the subsection on Breaches of privacy.

⁹ For instance, some remote surveillance software reportedly captured frequent live photos of workers through their company laptop webcam, displaying them on a digital shared space; others recorded workers’

unsent emails or activated webcams and microphones on workers' devices (Gray, 2021^[150]; Milne, 2021^[157]). Another example is that wearable devices can capture sensitive physiological data on workers' health conditions, habits, and possibly the nature of their social interaction with other people. While this information can be collected and used to improve employees' health and safety, it can also be used by employers – even involuntarily – to inform consequential judgments (Maltseva, 2020^[162]). Note that many of these breaches of privacy may not be legal in OECD member countries.

¹⁰ The proposed EU AI Act permits, under strict conditions, the processing of sensitive personal data when these data are used to monitor, detect and correct biases of high-risk AI systems, thus providing a legal basis for its lawful processing under the exceptions envisaged in Article 9(2) of the GDPR (European Commission, 2021^[32]).

¹¹ The GDPR prohibits any element of inappropriate pressure or influence which could affect whether data subjects give their consent, as well as linking consent to the performance of a contract (GDPR.EU, 2022^[49]).

¹² For instance, a field experiment in which a hiring algorithm randomly overrides a human recruiters' decision to invite a candidate for a job interview shows that the algorithm increases hiring of more productive candidates as well as non-traditional candidates such as women, racial minorities, and candidates without a job referral, from non-elite colleges, or without prior work experience (Cowgill, 2020^[151]).

¹³ Reliability decreased if a worker did not log in to the application within 15 minutes of the start of an assigned shift; engagement increased if a worker served many periods during peak hours.

¹⁴ The Tribunal highlighted the transparency problems with the algorithm, and that the algorithm needed to take into account context for the data used in its rankings. Deliveroo discontinued the algorithm in November 2020 but noted that the assessment of the algorithm was based on hypothetical cases and not on concrete examples (Tribunale Ordinario di Bologna, 2020^[71]).

¹⁵ Raji et al. (2020^[154]) define facial processing technology as a term encompassing tasks ranging from face detection, which involves locating a face within an image, to facial analysis, which determines an individual's facial characteristics, to face identification, which is the task of differentiating a single face from others.

¹⁶ The law followed a Supreme Court ruling in September 2020 that qualified digital delivery "riders" as employees, and is the formalisation of an agreement reached between unions and business associations in March 2021.

¹⁷ Labour law typically regulates conditions about work time or employee firing notification, for example, while OSH regulations can provide employees with a legal right requiring employers to protect their employees by avoiding risks to safety and health (Nurski, 2021^[42]).

¹⁸ To ensure that workers receive compensation in case of a work-related injury or illness, employers in many countries are required by law to have an employer liability insurance. Nevertheless, employers are usually not liable if it can be proven that the harm was caused by machine malfunctioning, in which case liability would fall on the manufacturer.

¹⁹ Yet, intellectual property rights are not the only way to incentivise the discovery and development of innovation, and they may not be appropriate in the case of strong negative externalities such as for certain AI systems (Boldrin and Levine, 2002^[149]; 2013^[148]).

²⁰Pegasystems, a customer engagement software company, conducted a global study to measure consumer attitudes toward AI and, more specifically, what they think of AI used in customer experience. In total, 6 000 adults were surveyed in North America, EMEA, and APAC (Pega, 2019^[98]).

²¹ There are a few cases in which it is possible to lawfully process personal data without the data subject's consent: (i) when processing is necessary for the performance of a contract to which the data subject is party or in order to take steps at the request of the data subject prior to entering into a contract; (ii) when processing is necessary for compliance with a legal obligation to which the controller is subject; (iii) when processing is necessary in order to protect the vital interests of the data subject or of another natural person; (iv) when processing is necessary for the performance of a task carried out in the public interest or in the exercise of official authority vested in the controller; (v) when processing is necessary for the purposes of the legitimate interests pursued by the controller or by a third party, except where such interests are overridden by the interests or fundamental rights and freedoms of the data subject which require protection of personal data, in particular where the data subject is a child (Official Journal of the European Union, 2016^[29]).

²² However, one can argue that it is extremely difficult to obtain meaningful consent in situations of power asymmetry and dependency, such as job interviews and employment relationships (see also Section 0.552.1).

²³ Although the facts of these cases occurred in the United Kingdom, the Dutch courts rule on the case, as the platforms have their headquarters in Amsterdam (Hießl, 2023^[99]).

²⁴ Providers would not need to notify people about their interactions with AI if this is "obvious from the point of view of a natural person who is reasonably well-informed, observant and circumspect taking into account the circumstances and the context of use" (Council of the European Union, 2022^[37]).

²⁵ In August 2019, the State of Illinois was the first US state to address the deployment of AI systems for recruitment purposes, with the Artificial Intelligence Video Interview Act (ILCS, 2019^[103]). The bill officially went into effect in January 2020 and applies to all employers that use an AI system to analyse video interviews of applicants for jobs based in Illinois, partly with the intention of providing regulatory clarity for companies interested in using such tools (Wisenberg Brin, 2019^[161]). Following an applicant's request, employers will also need to limit the sharing of video interviews and destroy videos and copies of videos within 30 days.

²⁶ The OECD AI surveys (see Chapter 4) find that most respondent reports "I roughly know what AI means, but it is difficult to explain" (52% in finance, 60% in manufacturing), and another 3% reports not knowing what AI means (Lane, Williams and Broecke, 2023^[84]).

²⁷ While particularly true for accountability, all needs for regulation presented in this chapter are in fact interwoven, interdependent and inter-reinforcing.

²⁸ Uber Eats workers in the United Kingdom are required to have their faces scanned and identified at the start of their shifts – yet many BAME (Black, Asian and Minority Ethnic) couriers have claimed that the face-scanning technology failed for them, leading to a dismissal from the application in less than 24 hours.

²⁹ In fact, the GDPR already de facto prohibits fully automated decision-making because, in employment relationships, it is extremely difficult to obtain legal consent to subject individuals to decisions based solely on automated processing.

³⁰ The human in the loop should disregard, override, or reverse the output of the high-risk AI system when needed, or decide not to use it altogether in a specific situation (Council of the European Union, 2022^[37]).

³¹ Yet, it remains to be seen whether in practice it will be sufficiently easy for workers to establish a presumption of causality.

³² This goes hand in hand with the EU AI Act stipulating that high-risk systems need to be transparent and are subject to document-keeping obligations (Council of the European Union, 2022^[37]).

³³ The United Kingdom Data Protection and Digital Information Bill proposes to add that controllers should also provide the data subject with information about decisions taken in relation to them, and to enable the data subject to make representations about such decisions (UK Parliament, 2022^[30]).

³⁴ Note that the policy landscape relevant to the use of AI in the workplace is evolving very quickly and it is possible that the proposals discussed in this chapter go through significant changes.

7

Social dialogue and collective bargaining in the age of artificial intelligence

Sandrine Cazes

Rapid advances in the development and adoption of artificial intelligence (AI) provide new opportunities but also raise fears about disruptive labour market and workplace transitions. This chapter examines the interlinked relationship between social dialogue and AI adoption in the labour market and workplaces. It highlights how social partners can facilitate the AI transition, for both workers and employers, while presenting new descriptive evidence and recent social partners' initiatives related to AI diffusion. The chapter also discusses how AI adoption may affect social dialogue itself: while AI technologies could be used as an enabler for social partners' goals and strategies, they may also pose new challenges to social dialogue, such as insufficient AI-related expertise and resources to respond to the AI transition. Based on these insights, the chapter presents key policy recommendations.

In Brief

Key findings

Artificial intelligence (AI) is likely to bring both benefits and risks for workers and employers. Its overall impact in the workplace and the labour market depends on how it is implemented, how it is regulated and the extent to which all stakeholders are involved. In this context, collective bargaining and social dialogue can play a key role in supporting workers and businesses in the AI transition, and in fostering fair and dynamic labour markets. This chapter explores the relationship between social dialogue, collective bargaining and the adoption of AI in the labour market and workplaces. The main findings are:

- Social partners can facilitate the use of AI by helping to decide which AI technologies are adopted, facilitating their introduction, and defining training needs. They can also help firms in providing flexible and pragmatic – yet fair – responses to technological changes in the workplace and contribute to enhance the quality of the working environment. Social partners can also shape the design and definition of new rights, such as the right to not be subject to automated decision-making without human oversight, and improve existing ones, such as the right to training. Finally, collective bargaining can also complement public policies in enhancing workers' security and adaptability.
- However, the number of workers who are members of unions and are covered by collective agreements has declined in many OECD countries, and the development of new forms of work and new business models, enabled by AI transition, risks exacerbating the under-representation challenge faced by traditional social partners.
- The specific characteristics of AI – such as the speed at which it is spreading, its ability to learn and the greater power imbalances it can create – for instance through information asymmetries or due to complexity of AI – put further pressure on labour relations. New waves of AI technologies, such as generative AI, are likely to significantly exacerbate this risk. At the same time, social partners may be able to make use of AI tools in the pursuit of their own goals and strategies.
- Surveys of social partners' views on AI adoption suggest that their main concerns include a trustworthy use of AI, changing skill demands and the quality of the working environment. While unions identify ethical issues as the biggest threat, employers' organisations are most concerned about new skills requirements.
- Despite these challenges, social dialogue and collective bargaining can play a useful role in promoting fairer AI transitions for workers and a level playing field for firms. New descriptive evidence based on cross-sectional European data shows for instance that the adoption of technologies with AI components in companies which have some forms of workers' representation, is significantly associated with better working conditions than adoption in employers without such workers' voice structures. These employers are also significantly more likely to provide social support to workers. In addition, a new cross-sectional survey carried-out in the manufacturing and financial sectors in Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States points to the beneficial role of consulting workers or workers' representatives for performances and working conditions.

- Both unions and employers' organisations have already undertaken several initiatives on AI at international and national levels. For example:
 - They are engaging in outreach and awareness campaigns highlighting the need for new skills and the associated training requirements, as well as warning about a number of issues of concern, such as the trustworthy use of AI, workers' data privacy and data protection.
 - They have also started to provide guidance through framework agreements and by engaging in "algorithm negotiations" (bargaining on the use of AI, big data and electronic performance monitoring), although only a few AI-related collective agreements have so far been signed in OECD countries.
- However, most ongoing activities stem from a few very active unions and employers' organisations. In this respect, the lack of AI-related expertise among social partners is one of the major challenges to support their members in the AI transition. Moreover, the rapid evolution of the technology, including the recent deployment of the latest wave of generative AI, risks making this skill shortage more salient and problematic.

While each country's situation and labour relations differ, policy makers could consider taking steps to encourage consultations and discussions on the AI transition with social partners and other stakeholders. They could also support social partners' efforts to expand their membership to forms of work and employers where they are not currently represented, such as those involved in the platform economy. And they could introduce measures to promote the development of AI-related expertise, and digital education more generally, in the workplace for management, workers and their representatives.

Introduction

Artificial intelligence (AI) technologies are likely to have an important impact on labour markets, workers and workplaces. As with any technological changes, AI adoption is likely to bring both potential benefits and risks. AI technologies bring real opportunities to create new tasks and jobs, as well as new business models, for instance. Since AI has the potential to complement and augment human capabilities, it can lead to higher productivity and greater demand for human labour. Yet AI technologies also bring a series of significant risks that need to be urgently addressed (Chapter 2).

Against this background, the way AI adoption and diffusion is regulated (e.g. through national and international legislation and collective bargaining), and the extent to which stakeholders are involved in the design of regulations and implementation in the workplace, are key elements to explore. Previous OECD work has highlighted the instrumental role that social dialogue and collective bargaining can play in technological and organisational changes, by easing transitions and spreading best practices for the introduction of new business methods, training and safeguarding quality, as well as by complementing public policy. It has also shown how collective bargaining, provided it has high coverage and leaves some margins of flexibility, can foster inclusive and dynamic labour markets when systems are co-ordinated (OECD, 2018^[1]; 2019^[2]).

This chapter concentrates on the relationship between AI adoption and social dialogue. It examines how social dialogue and collective bargaining can shape the AI transition in beneficial ways for both workers and employers, while also looking at how AI is affecting social dialogue itself. On the one hand, AI technologies and their adoption might generate power imbalances between workers and their employers – due for instance to insufficient AI-related expertise or asymmetric information in the context of datafication of work – and challenge further the representativeness of traditional actors of social dialogue (as measured by quantitative indicators such as the number of members or the share of workers covered

by collective agreements). On the other hand, AI technologies might offer new tools that could enable social partners to increase representation and improve the way they manage their relationships with members.

This chapter starts by discussing to what extent the AI transition may differ from previous technological changes in terms of its impact on social dialogue, drawing notably on OECD questionnaires circulated to social partners through the Trade Union Advisory Committee (TUAC) and Business@OECD (BIAC) networks¹ (Section 7.1). Based on a combination of literature review, OECD AI surveys of employers and workers in the manufacturing and finance sectors, and new descriptive analysis using European cross-sectional data from establishments surveys (ESENER-3 data) on the role of workers' representative voice in the workplace, Section 7.2 then presents new empirical insights on the relationship between workers' voice and risks associated with AI adoption. Section 7.3 describes some concrete examples of social partners' recent initiatives in providing information, raising awareness or signing collective agreements related to AI adoption. Section 7.4 concludes with some policy recommendations.

7.1. AI transition: What is different for social dialogue?

AI adoption may raise idiosyncratic issues such as the development of new AI management models that could change the nature of the relationship between firms and workers, as well as raise more fundamental ethical concerns that call for specific attention from social partners. Another key distinction between AI and previous technologies is that AI can automate non-routine tasks which extends considerably the potential scope of automation (Chapter 3). Along these lines, many experts hint that AI's impact on the labour markets are likely to be magnified by the speed and large potential for application across multiple sectors and occupations (Brynjolfsson, Rock and Syverson, 2017^[3]). The complexity and opacity of AI technologies and the generation of information asymmetries resulting from AI-based surveillance of workers may also trigger greater power imbalance (De Stefano, 2019^[4]). At the same time, AI technologies may bring opportunities to social partners, for instance in helping to strengthen workers' organisation or voice.

7.1.1. Social partners' views on risks and benefits of AI

To better understand social partners' priorities concerning the AI transition, an OECD questionnaire was addressed to trade unions and employers' organisations through the TUAC and Business@OECD networks across OECD countries (see Box 7.1). This questionnaire complements previous social partners' surveys on digital technologies more generally – see for example Voss and Riede (2018^[5]) and country-specific social partners surveys on AI, such as those by ver.di (2019^[6]) and by INPUT Consulting in co-operation with the humAln work lab (2021^[7]) in Germany.

Overall, answers to the OECD questionnaire suggest that social partners' main concerns relate to a trustworthy use of AI,² changing skill demands and physical and mental health risks in the workplace. While unions identify ethical issues as their biggest threat, employers' organisations are most concerned about new skills requirements (Figure 7.1). This does not however prevent heterogeneity within unions' (or employers') responses, a trustworthy use of AI, for instance, not being systematically identified by all unions as their main concerns. Compared to previous surveys of social partners' views on digitalisation or AI adoption,³ social partners' concerns appear to shift from job displacement risks to more societal ones linked to potential discrimination, excessive surveillance and violations of human rights. This apparent focus shift is also echoed by a survey of German works councils through the network of ver.di, IG Metall and DGB, which ranked changing work content and skill demand as their biggest concern of AI adoption – before job destruction (INPUT Consulting/humAln work lab, 2021^[7]). As for the potential benefits of AI adoption, responses to the OECD questionnaire slightly differ between unions and employers: while the former identify improved job quality and the creation of new tasks⁴ as potential biggest opportunities of AI adoption, employers primarily see its potential for productivity gains and higher job safety.

This priority shift is in line with recent waves of evidence on both automation (Georgieff and Milanez, 2021^[8]; Dauth et al., 2021^[9]) and AI specifically (Georgieff and Hyee, 2021^[10]), suggesting that AI adoption so far has not led to job destruction and employment downsizing. The evidence presented in Chapter 3 shows that the clearest effect of AI is the creation of new tasks and jobs, while evidence on the productivity and displacement effects is more mixed. Yet, the fast-moving development of AI latest technologies (such as Chat-GPT) may bring new risks and possibly challenge these results (Chapters 2 and 3).

Box 7.1. The OECD questionnaire on artificial intelligence and social dialogue

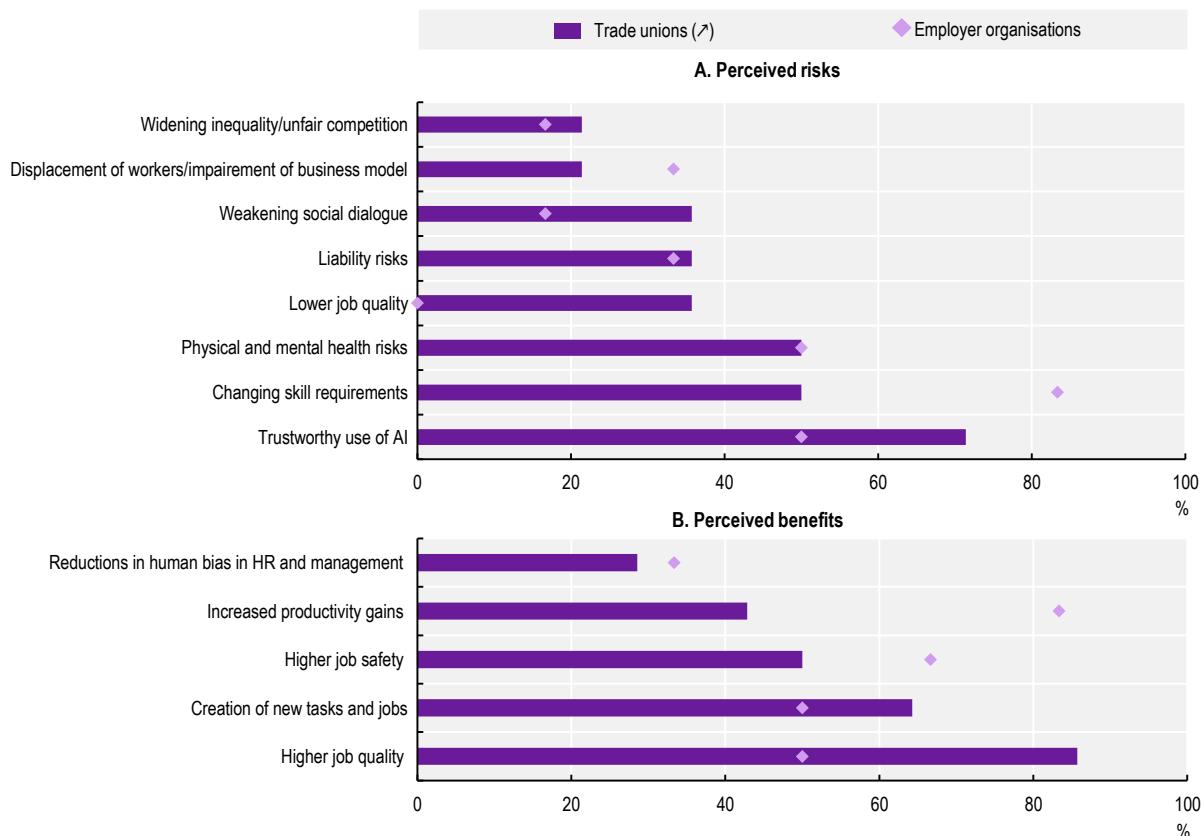
While the AI-related literature has focused primarily on the expected risks and benefits of AI adoption in the workplace, less attention has been devoted to social partners' views and priorities. Filling this gap, the OECD questionnaire sent to social partners focused on: i) understanding social partners' awareness of what AI entails; ii) reviewing social partners' assessments of the risks and benefits relating to AI adoption at labour market and workplace levels; iii) collect information on how social partners are responding to support workers and employers in the AI transition; iv) reviewing social partners' assessment of how AI adoption may affect social dialogue itself, including new challenges for integrating workers or businesses as members, but also new opportunities and tools to facilitate their work (see details in Annex Table 7.A.1).

The questionnaire was circulated to social partners in 2022 through the TUAC and Business@OECD networks across OECD countries. It reached confederations at the national level representing a variety of local unions or employers' organisations. While providing qualitative and non-representative answers, the results collected by the questionnaire were subsequently discussed in two OECD expert meetings including social partners, researchers, employers and AI developers and complemented with existing social partners' views and academic literature.

While responses collected through the OECD questionnaire provide interesting insights that complement and update previous social partners' surveys (Voss and Riede (2018^[5]), ver.di (2019^[6]) and INPUT Consulting in co-operation with the humAlIn work lab (2021^[7])), they remain qualitative and are not representative. Notably, responses may be biased insofar as stemming mostly from social partners already active in the area of AI – which may in turn affect the responses.

Figure 7.1. Social partners focus on AI's impact at workplace levels

Percentage of surveyed trade union and employer confederations



Note: Responses stem from 14 large trade union confederations representing various local unions and six confederations of employers' organisations responded to the questionnaire. Responses are based on pre-defined answer options (see Annex 7.A. OECD Questionnaire on AI impact and social dialogue) and may thus not be exhaustive.

Source: OECD questionnaire on artificial intelligence and social dialogue (Box 7.1).

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7.1.2. What new challenges does AI pose to social dialogue?

In the past decades, social dialogue and collective bargaining have been under increasing pressures. Across OECD countries, trade union density has declined in general from 33% on average in 1985 to 16% in 2019 and the share of employees covered by a collective agreement shrank from 46% in 1985 to 32% on average in 2019. The development of flexible forms of work including platform and gig work, have exacerbated this decline, as workers with such flexible forms of work are 50% less likely to be unionised than standard workers (OECD, 2018^[11]; 2019^[2]). This underrepresentation by unions is particularly relevant in the context of AI adoption as firms in the platform economy tend to be early AI adopters – (Adams-Prassl, 2019^[11]; Liu et al., 2021^[12]; Malik, Budhwar and Srikanth, 2020^[13])

On the employers' side, the share of workers employed in a firm that is represented by an employers' organisation has stayed relatively stable at around 59% across OECD countries – but small firms and those with new business models enabled by organisational and technological changes are also much less likely to be represented (OECD, 2019^[2]). This suggests that employers' organisations also need to improve their representativeness by reaching out to underrepresented or new actors.

Beyond representativeness challenges, AI technologies may also affect social partners' capacity to support their members through dialogue and bargaining, even if the risk of weakening social dialogue through AI adoption was not identified among the main concerns by social partners (Figure 7.1). AI technologies are expected to diffuse rapidly and for some of them to continuously develop through their potential to self-improve, which will require continuing adjustments from workers and employers (Lane and Saint-Martin, 2021^[14]). For social dialogue, this will likely require a shift away from monitoring and agreeing to constant rules towards more regular consultations between social partners and other operating parties as well as new forms of centralised and de-centralised conflict-resolution mechanisms (Albrecht and Kellermann, 2020^[15]). While social partners may therefore need to adapt the frequency and way of co-ordinating with each other, collective bargaining may remain the most effective instrument to address AI-related issues as it has the capacity of shaping new rights and implementing existing ones in a flexible and pragmatic – but yet fair manner (OECD, 2019^[2]; Aloisi, 2021^[16]).

At the same time, AI technologies may also complicate social partners' capacity to co-ordinate and bargain. For example, the British Trade Union Congress (TUC) fears that the use of AI changes the employment relationship in a way that blurs accountabilities of decisions (TUC, 2021^[17]), which may ultimately affect social partners' capacity to represent workers' and employers' interests. Integrating AI into co-determination structures can for example be a challenge, when employers cannot provide the necessary information about AI-influenced decisions to workers or their representatives, because they are themselves detached from AI developers who may not disclose such information (Albrecht and Kellermann, 2020^[15]). Accountabilities may also be unclear if knowledge gaps exist about AI between developers, vendors, and contracting authorities, as well as between those negotiating the procurement (Colclough, 2022^[18]).

In this respect and beyond blurring accountabilities, AI may also affect social dialogue by changing the power balance between workers, employers and their representatives, for instance when AI-based surveillance of workers generates information asymmetries (Rani and Singh, 2019^[19]; De Stefano, 2018^[20]). Such asymmetries are likely to reduce workers' bargaining position (Adler-Bell and Miller, 2018^[21]), especially when workers are not aware that they are interacting with AI, or not sufficiently informed about the outcomes of this interaction – for example when AI is introduced through updates of technologies already in place and thus not considered as new technology on which workers' representations should be consulted (EESC/CFDT Cadres, 2022^[22]). Besides, even in the case where AI is considered as new technology, a prior agreement with workers' representatives before monitoring workers through new technologies is, currently, not necessarily required in all OECD countries (Aloisi, 2021^[16]; Salvi del Pero, Wyckoff and Vourc'h, 2022^[23]) – see also Chapter 6. Finally, power imbalances in the employment relations may question the notion of workers' consent to interact with AI or allow the use of their personal data (whether in recruitment, management or other processes), since they can make it difficult for workers to actually deny consent, even in countries where employers are supposed to obtain their consent. (Data Protection Working Party, 2017^[24]; Moore, 2020^[25]).

Finally, fears exist that the use of AI may limit or prevent social dialogue to some extent. AI-based monitoring of workers can potentially be used to monitor union activity and prevent collective organising, as observed for ride-hailing or delivery platforms (De Stefano, 2016^[26]; EESC/CFDT Cadres, 2022^[22]). In this respect, AI might be used to analyse information such as the location of union offices, the activity of union officials, the use of union-related vocabulary in emails, and even union activity on social media (TUC, 2021^[17]). This risk appears to be higher in non-standard forms of work and in countries where laws do not anchor or support institutionalised forms of social dialogue and collective bargaining, particularly beyond the firm level. The new wave of generative AI is also likely to exacerbate this type of risk.

7.2. Shaping the AI transition: The role of social dialogue

7.2.1. Getting some insights from the empirical literature on social dialogue and automation

As no econometric literature exists on social dialogue and AI adoption (investigating either the role of workers' representation in enhancing AI adoption or in mitigating its effect), some insights can be obtained from studies on social dialogue and automation even though, as shown in Chapter 3, theoretical and empirical effects from automation and AI adoption are not the same. In that context, this section presents a short literature review on automation in the form of robots and social dialogue.

Regarding the relation between workers' representation and robot adoption, the literature finds mixed and only descriptive results that might suffer from reverse causality, i.e. robot adoption may instead impact workers' representation. Keeping these caveats in mind, Onorato (2018^[27]) finds that, at national level, union density is negatively associated with robot adoption in OECD countries, using a constructed panel dataset based on data from the International Federation of Robotics and OECD statistics. Similarly but at the firm level, Genz, Bellmann and Matthes (2018^[28]) find that, in Germany, the existence of works councils is associated with a statistically significant lower adoption of automation – and digital technologies in general. However, the authors find evidence suggesting that works councils foster adoption of these technologies in establishments that employ a high share of workers who are conducting physically demanding tasks. In contrast, Belloc, Burdin and Landini (2022^[29]) find a positive association between workers' representation and the adoption of robots and data analytics in management practices in Europe, using cross-sectional data from the European Company Survey 2019. The authors investigate various potential mechanisms driving these associations and find suggestive evidence that workers' representation influences workplace practices, notably in terms of training intensity and process innovation, in ways that may enhance the complementarity between labour and new technologies.

As for the second issue, namely the link between workers' representation and the effects of automation, the empirical evidence suggests a positive effect on wages and employment. Parolin (2019^[30]) finds for instance that shrinking collective bargaining coverage at the national level is associated with declining relative wage growth for occupations at higher risk of automation. This strand of the literature is further motivated by the paper of Dauth et al. (2021^[9]), which finds that early robot adoption in the German manufacturing sector was not associated with increased unemployment but instead with increased reskilling of workers – contrary to findings from the United States (Acemoglu and Restrepo, 2018^[31]). The authors' conjecture that this finding could be due to stronger labour market institutions in Germany like collective bargaining, but do not provide direct evidence on this. Following this pursuit and using a random effects regression analysis with constructed panel data from the European Labour Force Survey and the U.S. Current Population Survey, Haapanala, Marx and Parolin (2022^[32]) find that union density moderates employment increase in automation-exposed industries for younger workers but enhances employment increase for high-educated workers.

7.2.2. New OECD evidence on workers' voice, AI adoption and its effect

The absence of empirical evidence on the link between social dialogue, AI adoption and its effects is largely due to data limitations. Most existing individual- and firm-level panel data do not simultaneously include indicators on these three aspects and require matching information from different sources or limiting the analysis to cross-sectional or constructed panel data. As reviewed above, the literature focuses on automation, rather than AI adoption, and workers' representation mitigating effects on employment and wages.

Against this background, this section attempts to bring some insights on AI's impact and the role of workers' voice in the workplace, considering different workers' voice arrangements.⁵ It examines first how representative workers' voice might mitigate AI's impact on several risks relating to working conditions in

Europe (for a detailed overview, see Box 7.2). This evidence is based on the 3rd European Survey of Enterprises on New and Emerging Risks (ESENER-3) data that allows for distinguishing proxies for different types of AI components used in the establishment as part of technologies adopted, as well as different types of representative workers' voices.⁶ As for working conditions, only data on non-monetary aspects, such as hard physical work, work intensity or social support (i.e. help and support from colleagues) at work are available in the dataset.

Box 7.2. How does representative workers' voice mitigate the impact of AI on risks relating to working conditions?

The empirical strategy follows the model in Haapanala, Marx and Parolin (2022^[32]) by estimating the moderating (e.g. interaction) effect of representative workers' voice on AI's impact on labour market outcomes. However, instead of looking at employment and wage effects like Haapanala, Marx and Parolin, the analysis is conducted at the workplace level and considers AI's impact on several aspects of the quality of the working environment, such as heavy loads or long working hours. A probit regression is adopted instead of fixed effects regression due to the cross-sectional nature of the data.

The Third European Survey of Enterprises on New and Emerging Risks (ESENER-3) (EU-OSHA, 2019^[33]) asked 45 420 establishments from 33 countries and different sectors how health and safety risks were managed at the workplace level, with a particular focus on digitalisation and psychosocial risks. The survey covers all EU Member States, Iceland, North Macedonia, Norway, Serbia, Switzerland and the United Kingdom. The ESENER-3 survey includes detailed information on various forms of representative workers' voice that co-exist in the workplace, different types of technologies used and some aspects of non-monetary working conditions. AI adoption is defined as firms adopting at least one of the following technologies: i) robots that interact with workers; ii) wearable devices, such as smart watches, data glasses or other (embedded) sensor; iii) machines, systems or computer determining the content or pace of work; iv) machines, systems or computers monitoring workers' performances.

The probit regression model is specified as follows:

$$Y_{ijc} = \beta_0 + \beta_1 AI_{ijc} + \beta_2 WR_{ijc} + \beta_3 WR_{ijc} \times AI_{ijc} + \beta_4 X_{ijc} + \varepsilon_{ijc}$$

where subscript i denotes the establishment; Y_i is the dependent variable (e.g. different working conditions outcomes as dummy variables); AI_i is a dummy variable equal to 1 if the establishment i in industry j and located in country c uses either robots, smart devices or software to monitor workers or determine the content and pace of their work; WR_i is a dummy variable for the presence of worker representation at the establishment level (tested separately for three types of representation, e.g. the presence of a trade union representative, a works council or a health and safety committee/representative elected by workers); X_i is the vector of controls at the establishment level (e.g. country, industry, size, age, economic situation, share of old workers, if the person interviewed is the owner/manager, and if teleworking is possible) similarly to Belloc, Burdin and Landini (2022^[29]), who use a similar European-level dataset; and ε_i are the residuals.

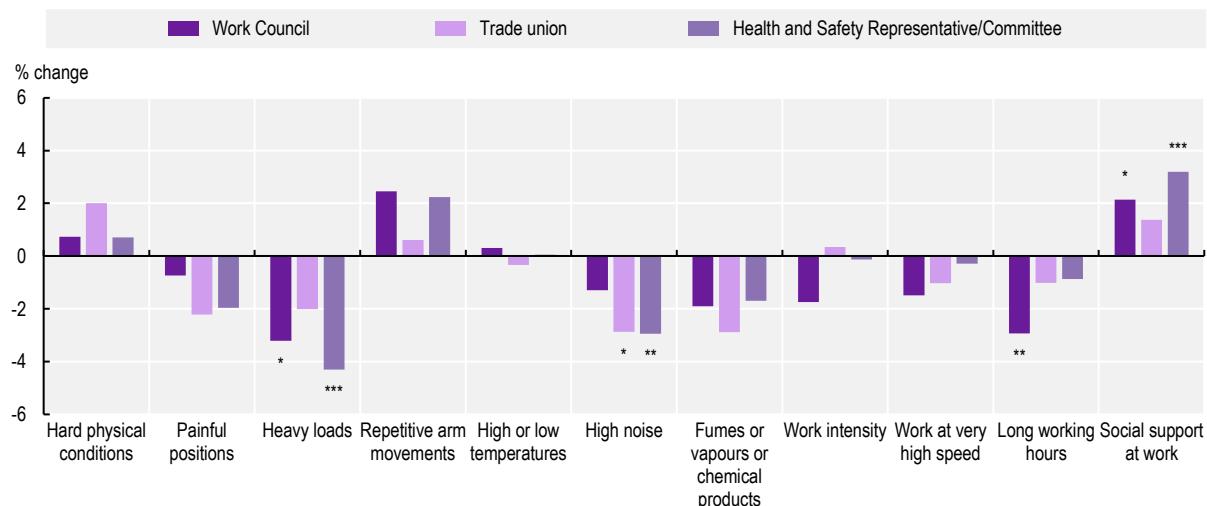
The variable of interest here is the coefficient β_3 that captures the AI and worker representation interaction. If β_3 is negative, the effect of AI on the selected outcome will be mitigated in establishments with worker representation compared to establishments with no worker representation. The (unmitigated effect) of AI is denoted by β_1 and the actual mitigated effect of AI is obtained by adding $\beta_1 + \beta_3$ (see Annex 7.B).

Source: EU-OSHA (2019), *The Third European Survey of Enterprises on New and Emerging Risks*, <https://visualisation.osha.europa.eu/esener/en/survey/overview/2019>; Haapanala, H., I. Marx and Z. Parolin (2022), "Robots and Unions: The Moderating Effect of Organised Labour on Technological Unemployment", *IZA Discussion Paper Series No. 15 080*, <https://www.iza.org/publications/dp/15080>.

Results from probit regressions suggest that workers' representation may mitigate the impact of technology with AI component on some risks relating to working conditions. Figure 7.2 reports marginal effects (interaction effect of AI adoption and representative voice):⁷ it shows for instance that in establishments using AI and having a works council, or a health and safety representative/committee, AI adoption is associated with a significantly larger reduction in worker exposure to heavy loads (by 3 percentage points and 4 percentage points respectively for works council and health and safety representation) than establishments using AI but without representative workers voice.⁸ Moreover, in AI-using establishments that have a trade union representative or health and safety representative/committee, AI adoption is associated with a significantly larger reduction in exposure to high noise than establishments using AI but do not have representative workers' voice. Finally, the presence of a works council appears to reduce risks to be exposed to long working hours, while the presence of health and safety representative/committee tend to increase social support at work.

Figure 7.2. Representative workers' voice is associated with mitigating AI's impacts on risks relating to working conditions, but causality remains unclear

Marginal effects, i.e. percentage change in the probability of outcome variable following a discrete change in the relevant explanatory variable



Note: Results are based on probit regressions including establishment-level controls (country, industry, size, age, economic situation, share of old workers, if the person interviewed is the owner/manager and if teleworking is possible). The figure reports marginal effects on the interaction coefficient of AI adoption and the different types of workers representation i.e. the percentage point difference between AI adopters and non-adopters of the change in the probability of the outcome variable following a discrete change in the relevant explanatory variable. For example, the reduction in heavy lifting associated with AI adoption is 3 percentage points (resp. 4 percentage points) larger for firms with the presence of works councils (resp. health and safety representative/committee) than for those without. *, **, *** denote the statistically significance at the 10%, 5%, and 1% level, respectively. For further details on regression results and the definition of job quality outcomes, see Annex 7.B.

Source: OECD estimates based on the Third European Survey of Enterprises on New and Emerging Risks (2019) (ESENER-3).

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These results are robust to different sets of controls and checks. They confirm both the supporting and mitigating effects of representative workers' voice when testing for the different types of AI components adopted by the establishments, although impacts may differ between AI-related software (e.g. workers more likely to be provided help and social support, less likely to be exposed to painful positions, heavy loads, repetitive arm movements, high noise, fumes or vapours or chemical products and long working hours) and AI-related hardware (e.g. workers less likely to be exposed to painful positions, repetitive arm movements and work at very high speed); moreover, in the case of AI-related software used for monitoring

performance, the estimated mitigation effect for repetitive arm movements is positive, suggesting the possibility of reverse causality.

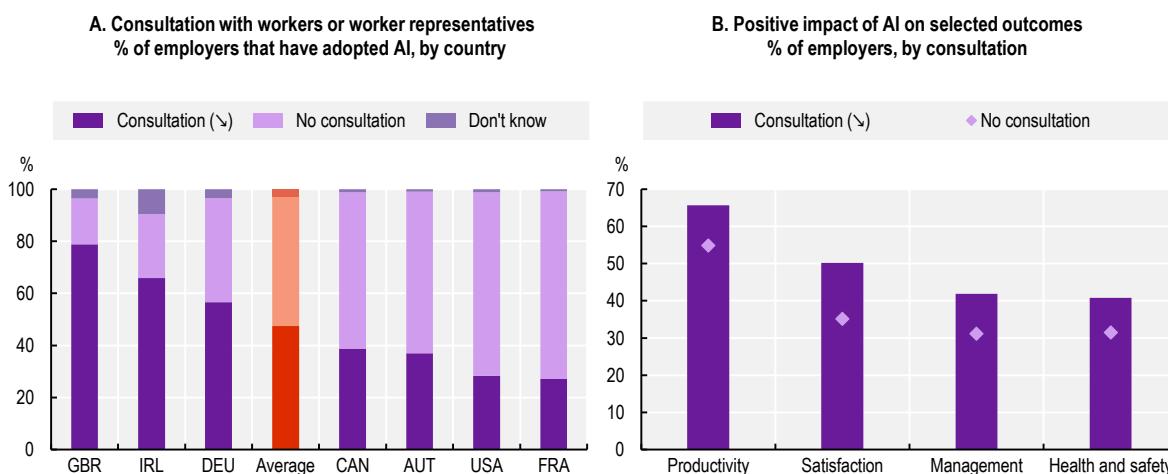
In terms of potential mechanisms driving the mitigating effect of representative workers' voice on several risks related to working conditions, a recent paper suggests that representation indirectly affects the type of AI systems employers invest in by shaping job designs (Belloc et al., 2022^[34]). Specifically, the authors find that in establishments with representative workers' voice, job designs are richer, i.e. more complex and with tasks less routinised – and thus more difficult to monitor, potentially helping to orient AI-related investments towards those AI systems that improve working conditions.

Although the analysis controls for an extensive set of variables, it remains descriptive and mostly serves as a motivation to investigate further any causal relation between workers' voice and the AI transition. Moreover, as illustrated by some estimates of the mitigation effect, results might also suffer from reverse causality. Finally, one cannot exclude the fact that the effects of AI use are properly identified and not driven by the general degree of technological advancement of the establishment. Unfortunately, data do not permit to control for this effect. Future research should further investigate the role of different measures of social dialogue and collective bargaining indicators, as well as workers' voice arrangements.

On this latter aspect, the OECD carried out a cross-sectional survey with 5 334 workers and 2053 firms in the manufacturing and financial sectors in Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States (Lane, Williams and Broecke, 2023^[35]) considering different types of outcomes and of workers voice (representative and direct voices). As shown in Panel A of Figure 7.3, the survey revealed significant heterogeneity across OECD countries in the incidence of consultations as regards AI adoption, being typically twice as large in Germany or the United Kingdom than in the United States. Furthermore, averaging countries and sectors, results indicate that workers using AI are more likely to report that AI improved their performance and working conditions if their companies consulted workers or worker representatives regarding the adoption of new technologies in the workplace (Panel B of Figure 7.3). For example, workers in companies that consulted workers or worker representatives are 9 percentage points more likely to say that AI had improved their health and safety, compared to workers in companies that did not consult workers or workers representatives.

This is consistent with previous OECD research that found that direct voice between workers and managers (either alone or mixed forms, i.e. combined with representative workers' voice) was associated with a higher quality working environment (OECD, 2019^[2]). However, since the analysis cannot establish causality, it is not possible to say definitively that consultation encourages employers to deploy AI in a more productive, fulfilling and safe manner. It could also be that the act of being consulted generates positive perceptions of the AI, even if little has changed.

Figure 7.3. Employers that consult workers or worker representatives are more likely to report positive impacts of AI on worker productivity and working conditions



Note: In Panel A, employers were asked: "Does your company consult workers or worker representatives regarding the use of new technologies in the workplace?". In Panel B, employers that have adopted AI were asked "Has artificial intelligence had a positive effect, negative effect or had no effect on worker productivity/worker satisfaction/managers' ability to measure worker performance/health and safety in your company?". Figures in Panel B show the proportions that reported a positive effect across the seven countries shown in Panel A. Average is the unweighted average of countries shown in Panel A.

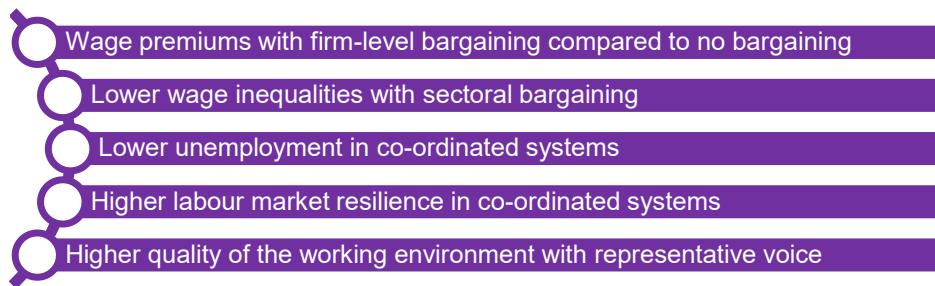
Source: Lane, Williams and Broecke (2023^[35]), "The Impact of AI on the labour market: Main findings from the OECD AI surveys of employers and workers", <https://doi.org/10.1787/ea0a0fe1-en>.

StatLink <https://stat.link/34bepy>

7.2.3. Fostering inclusive labour markets and easing technological transitions

Previous OECD research (OECD, 2019^[2]) has highlighted the granularities of collective bargaining systems and workers' voice arrangements, and the importance of understanding their actual organisation and functioning to properly assess how social dialogue may shape labour market outcomes and job quality.⁹ The main findings are reported in Figure 7.4. They show that collective bargaining, provided it has high coverage while leaving some margins of flexibility, can foster inclusive and dynamic labour markets when bargaining systems are co-ordinated¹⁰ and the quality of labour relations between the social partners is high. Social partners can also contribute to determine what technologies, including AI, are adopted, facilitate their introduction, and anticipate skills needs: through their representation in skills council and training provisions in collective agreements, as well as their involvement in the process of developing, funding and managing adult educational and training programmes, social partners has also been found to be beneficial both in terms of the quality of training and accessibility for all workers. Finally, through workers' voice, they can ease AI introduction in defining pragmatic responses to technological and organisational changes in the workplace and contribute to enhance the quality of the working environment¹¹ (OECD, 2018^[1]; 2019^[2]).

Figure 7.4. Workers' voice and collective bargaining can improve labour market performance and the quality of the working environment



Note: Results when studying the link between collective bargaining systems, types of worker voice and a series of labour market performance outcomes and indicators of the quality of the working environment, using micro- and sector-level data available.

Source: OECD (2019^[2]), *Negotiating Our Way Up: Collective Bargaining in a Changing World of Work*, <https://www.doi.org/10.1787/1fd2da34-en>.

In addition, collective bargaining systems and workers' voice arrangements also matter for job quality. The quality of the working environment is higher on average in countries with well-organised social partners and a large coverage of collective agreements. At the firm level, both direct and mixed forms of voice (where workers' representatives coexist with direct dialogue between workers and managers) are also associated with a higher quality of the working environment compared to the absence of voice. By contrast, the presence of representative workers' voice in firms where there are no parallel means of direct exchange between workers and managers is not associated with a better quality of the working environment. However, the presence of solely representative arrangements of voice could be characteristic of poor social dialogue contexts, where employers are unwilling to engage in direct exchanges with workers, so that workers react by mobilising formal worker representation bodies, thus blurring the empirical relationship between worker representation and quality jobs. While these results are not evidence of causal relationships, they highlight the importance of good labour relations and social dialogue context at the firm level (OECD, 2019^[2]).

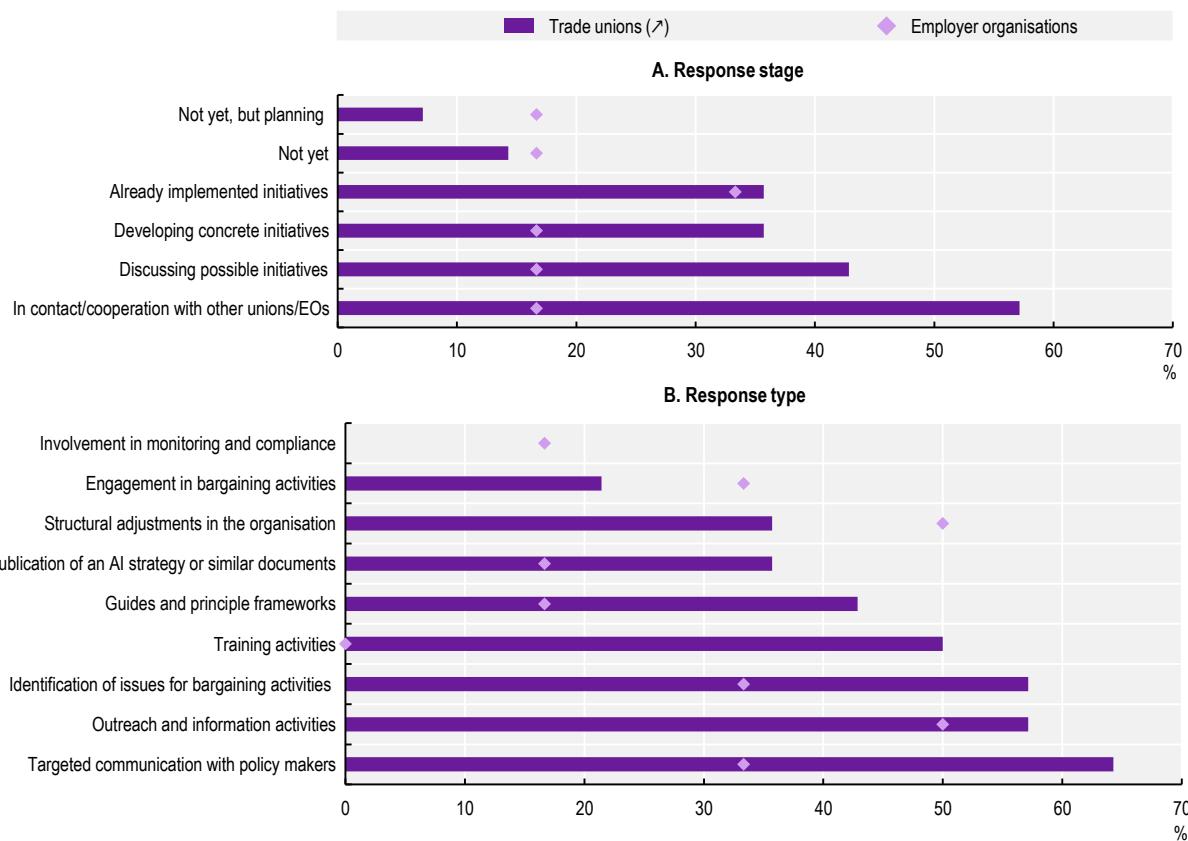
7.3. Social partners are engaging in outreach, awareness raising and advocacy

Depending on the national and regulatory settings as well as practices and traditions across OECD countries, social partners can engage in various initiatives and at different levels (e.g. workplace, firm, sectoral and national). They can raise voice and inform, advise policy makers, participate in decision-making for example when it comes to determining what technology is adopted, manage and fund programmes like training, negotiate agreements and monitor compliance of terms set out in agreements. Beyond these main activities, social partners are also increasing their efforts to broaden their outreach through the use of digital technologies – for example to attract, recruit and inform members through social platforms (Houghton and Hodder, 2021^[36]) and to gain insights that strengthen their position in negotiations (Voss and Riede, 2018^[5]). In this respect, AI technologies may also provide innovative solutions and new opportunities for social partners (for some examples, see Section 7.3.4).

Social partners have already taken several initiatives to shape the AI transition. Overall, the detailed review conducted for this chapter through the OECD questionnaires sent to social partners (Figure 7.5) suggests that social partners are mainly engaging in outreach and information activities, but very few have engaged in negotiating agreements.

Figure 7.5. Unions' responses to the AI transition mainly concentrate on raising voice and advising policy

Percentage of surveyed trade union and employer confederations



Note: Responses stem from 14 large trade union confederations representing various local unions and six confederations of employers' organisations responded to the questionnaire. Responses are based on pre-defined answer options (see Annex 7.A) and may thus not be exhaustive. EO: Employer organisation.

Source: OECD questionnaire on artificial intelligence and social dialogue (Box 7.1).

StatLink <https://stat.link/2rwtc1>

7.3.1. Raising voice and informing

Both unions and employers' organisations across the OECD have engaged, at international and national levels, in outreach and awareness campaigns highlighting the need for new competences that will be required to work with digital tools, robotics and data and the need to become "AI literate". (ETUI, 2021^[37]) (ILO/IOE, 2019^[38]; BusinessEurope, 2019^[39]; UNI Europa ICTS, 2019^[40]; ETUC, 2020^[41]). Social partners have also expressed concerns about a number of issues, such as the trustworthy use of AI, ethical concerns, workers' data privacy and protection, as well as training needs, mainly through position papers, guidelines about the application of AI and advice directed towards workers,¹² employers but also policy makers (Cazes, 2021^[42]).

Unions, for instance, are calling for greater involvement of workers and their representatives in AI-related decisions making. According to a survey from the German ver.di union, almost two-thirds of co-determination bodies at workplace and firm levels are not involved in the planning and implementation of AI projects, and one-third is not even aware of whether AI is being used (ver.di, 2019^[6]). Against this backdrop, the European Trade Union Institute (ETUI) emphasises the need for a preventive engagement

of workers and trade unions in the way algorithms are designed and deployed, calling for collective bargaining to ensure the interest of workers and fundamental rights are protected (ETUI, 2021^[37]). This is echoed by national unions such as the Teamsters Union in the United States and the German Trade Union Confederation (DGB), which call for social dialogue and collective bargaining specifically over the parameters of AI-induced or exacerbated workplace surveillance (Teamster, 2018^[43]; DGB, 2020^[44]). The German union DGB also proposes a guiding framework for the introduction of AI and its deployment in a participative way (DGB, 2020^[44]; Stowasser and Suchy, 2020^[45]).

In addition, unions are calling for greater participation of workers and their representatives in the governance of AI adoption. For example, European social partners have proposed the adoption of data governance models for data stewardship in the form of data trusts, data collectives and co-operatives (Allen and Masters, 2021^[46]; ETUC, 2020^[41]; Colclough, 2020^[47]; Ada Lovelace Institute and UK AI Council, 2021^[48]; British Academy for the Humanities and Social Sciences/The Royal Society, 2017^[49]). When used in the workplace, these governance mechanisms could provide workers with access and rights over the collection, analysis and storage of data that concerns them (Colclough, 2020^[47]) – ultimately to promote a trustworthy and beneficial use of data that is collected or used by AI applications in the workplace (Salvi del Pero, Wyckoff and Vourc'h, 2022^[23]).

Finally, unions have been very active in promoting a trustworthy use of AI and outlining training needs. For instance, the Association of Nordic Engineers proposes principles to strengthen transparency and develop technical standards and certifications to increase accountability (ANE/IT University of Copenhagen, 2018^[50]; ANE et al., 2021^[51]). Similarly, UNI Global Union proposes a list of principles relating to workers' surveillance privacy and human dignity, which unions can use as guidance in negotiating agreements (UNI Global Union, 2019^[52]; 2019^[53]), while ETUI offers a capacity-building questionnaire for unions to go through when assessing the risks of algorithmic management in particular and forming initiatives in response (ETUI, 2021^[37]). As for unions' efforts to inform about the provision of training for workers affected by AI adoption, UNI Europa ICTS (2019^[40]) has produced a position paper on AI adoption recommending social partners' co-operation to identify training needs, design new education pathways, and find funding opportunities. This is also echoed by ETUC (2020^[41]), which proposes AI and digital literacy schemes for workers to understand and be part of AI adoption at their workplace.

Employers and their representatives have also published a number of AI-related information and strategy papers, focusing on issues such as ensuring competitive advantage and growth (Ilsøe, 2017^[54]; BusinessEurope, 2018^[55]). These papers notably look at challenges for AI adoption, training needs, data sharing practices and cybersecurity, as well as funding issues. In its AI strategy, BusinessEurope (2020^[56]) for instance proposes the creation of common European data spaces for business-to-business data access and sharing. In another paper, BusinessEurope (2019^[39]) highlights the need to help workers establish a data culture and awareness of AI through re-skilling in job programmes, proposing to organise them through a cost-sharing approach – sponsored by the EU and co-ordinated by the European social partners. Along similar lines, the Confederation of British Industry (CBI) proposes the enhancement of social dialogue through the creation of joint commissions, comprising employers, academics, worker representatives and government officials in order to examine the impact of AI on jobs and jointly propose courses of actions (CBI, 2017^[57]).

At the same time, a few employers' organisations have started voicing concerns relating to a trustworthy use of AI (Salvi del Pero, Wyckoff and Vourc'h, 2022^[23]). In its *AI Utilisation Strategy*, the Japan Business Federation Keidanren, for example, emphasises the need for ethical standards such as fairness, accountability and transparency, as well as rules that ensure a balance between the use and protection of personal data and guarantees for the safety and dependability of AI systems as a whole (Japan Business Federation-Keidanren, 2019^[58]). Similarly, the World Employment Confederation (WEC) adopted a Code of Ethical Principles in the use of Artificial Intelligence (<https://wecglobal.org/uploads/2023/04/AI-principles-WEC-AI-Code-of-Conduct-March-2023.pdf>), while the US Chamber of Commerce's Technology Engagement Center published a report with Deloitte, recommending the development of standards for AI

trustworthiness, the rapid implementation of an AI risk management framework, and the development of international partnerships and standards including by the OECD (Deloitte/U.S. Chamber of Commerce Technology Engagement Center, 2021^[59]).

7.3.2. Advising policy

Raising voice, informing and alerting can be ways to inform workers and employers, but also to shape policy debates. Additionally, some social partners have started explicitly calling for policy responses, which revolve around reviewing and further developing existing regulations in areas related to AI adoption, as well as closing regulatory gaps of AI-induced or exacerbated risks with new legislation.

Regarding the first aspect, social partners' discussion has focuses to a large extent on data protection – and in Europe, the GDPR¹³ is the most advanced legal instrument in Europe in this respect – but also on occupational health and safety issues, labour law and co-determination rights.¹⁴ Social partners have also started developing proposals for closing regulatory gaps. At the European level, ETUI for instance calls for European regulation that will ensure that AI algorithms will be required to have transparent purposes in the workplace¹⁵ (Ponce del Castillo, 2020^[60]). In its resolution, ETUC calls for the reinforcement of workers' protections from undue surveillance, as well as from biased discrimination in the workplace (ETUC, 2020^[41]). On the employers' side, BusinessEurope (2020^[56]) published a position paper on AI, which calls for legal certainty, specific responsibilities for all actors involved and a clear framework for firm compliance so that AI-based products are covered by a single set of clearly assigned product safety rules.

Finally, national unions across OECD countries are making proposals for new legislation in their countries. The British TUC, for example, proposes the introduction of a universal right to human review of high-risk decisions and the right of human contact when important decisions are made about people at work in addition to the right to data reciprocity giving workers the right to collect and combine workplace data (TUC, 2021^[61]). The Association of Nordic Engineers also provides AI-related policy recommendations, including the need for defining responsibility (notably beyond the engineering profession) and the need for frameworks about explainability of AI-influenced decisions (ANE/IT University of Copenhagen, 2018^[50]; ANE et al., 2021^[51]). In the United States, the union AFL-CIO (2019^[62]) highlights that, in the absence of data protection regulation similar to the European GDPR, platforms are already using algorithms and AI tools to make decisions about hiring and firing, promotions and work organisation that are often implemented without the consent of workers.

7.3.3. Negotiating new framework and collective agreements

Social partners have also started to provide guidance through framework agreements and, to a lesser extent, negotiate collective agreements. This modest engagement in bargaining activities reflects the scarcity of collective agreements on digital technologies more generally, especially with respect to non-monetary aspects of work (Kreinin, Artale and Kossow, 2022^[63]). Moreover, the language of collective agreements that relates to new technologies may need to be updated to stay relevant, as highlighted for example in the AI OECD surveys in the United States and Canada (Milanez, 2023^[64]).

In Europe, the European Social Partners Framework Agreement on Digitalisation (2020^[65]) provides guidance on issues related to data, consent, privacy protection and surveillance, and the need to systematically link the collection and storage of data to ensure transparency – using the EU GDPR as a reference.¹⁶ The framework also calls for a fair deployment of AI systems, i.e. ensuring that workers and groups are free from unfair bias and discrimination. At sectoral level in the insurance and telecommunication sector, European social partners have also signed two framework agreements on AI that addressed similar elements (UNI Europa Finance; Insurance Europe; Amice; Bipar, 2021^[66]; UNI Europa ICTS and ETNO, 2021^[67]).

More recently, social partners have started engaging in “algorithm negotiations”, i.e. they are including as a subject of bargaining the use of artificial intelligence, big data and electronic performance monitoring (“people analytics”) in the workplace, as well as their implications for occupational health and safety, privacy, evaluation of work performance and hiring and firing decisions (De Stefano, 2018^[20]).

To this date, a few AI-related collective agreements have already been signed in OECD countries. Although these agreements are rarely exclusively on AI, they include aspects of AI use and resulting implications for occupational health and safety, privacy, evaluation of work performance and hiring and firing decisions in other bargaining processes – see Box 7.3 and De Stefano (2018^[20]). Moreover, several collective agreements have started regulating the use of AI not only in monitoring workers but also in directing their work (Moore, Upchurch and Whittaker, 2017^[68]; OECD, 2019^[2]).

At the same time, a lack of collective agreements specifically pertaining to AI-related issues in some countries may also reflect the strength of existing regulations and social dialogue structures. For example in Sweden, a report by the largest trade union in the private sector finds that the combination of existing collective agreements, ensured co-determination through the Workplace Act and other regulations including the Work Environment Act and the GDPR already provides a good basis for dealing with AI challenges relating to digital surveillance at the firm level – while legislation protecting personal integrity for instance could be strengthened (Unionen, 2022^[69]).

Box 7.3. Algorithm negotiation and collective agreements

A few AI-related collective agreements have recently been signed in OECD countries and at various levels. In Spain, social partners in the banking sector signed an agreement in 2021 guaranteeing workers the right to not be subject to decisions taken solely by algorithmic systems, nor discriminated against based on algorithmic decisions. In addition, the agreement requires banks to inform workers' representatives about the data and algorithmic systems used by “digital models with no human intervention” (Boletín Oficial del Estado, 2022^[70]). Similarly, a tripartite national agreement for platform workers in Spain, has been signed that guarantees platform workers' rights to algorithmic transparency. It required a modification of workers right to information, making it mandatory for platforms to inform workers' legal representatives about the mathematical or algorithmic formula determining their working conditions (Aranguiz, 2021^[71]).

At the local level, the General Staff Council of Stuttgart in Germany and the city as a public employer recently agreed on transparent design processes for new technologies, which in the case of AI must take place before its adoption (Forum Soziale Technikgestaltung, 2022^[72]).

In Switzerland, the trade unions Syndicom and Transfair agreed at the firm level with Swisscom about a “Smart Data” policy in 2018, which includes principles when processing workers' data (Syndicom/Swisscom/Transfair, 2018^[73]). Similarly in the United States, the Teamsters union agreed with UPS in 2018 to establish a national and joint technological change committee to review any planned technological changes and to ensure affected workers are retrained instead of dismissed (Teamster/UPS, 2018^[74]).

7.3.4. Making use of digital and AI tools

A few social partners have started reviewing how digital and AI technologies can facilitate their work and help address AI-specific concerns, such as reducing data asymmetries between workers, employers and their representatives. While they face difficulties in incorporating many of the technological features brought by digitalisation (Rotila, 2019^[75]), social partners tend to agree that they need to make better use of digital tools to help them organise (Voss and Riede, 2018^[5]).

The use of digital technologies for example provides an opportunity to social partners to increase their representation, self-organise and improve communication with their members (Adler-Bell and Miller, 2018^[21]). In this respect, AI technologies may further support unions through increased outreach, especially to younger members and facilitate the renewal and management of memberships (Vandaele, 2018^[76]). Along these lines, Flanagan and Walker (2020^[77]) provide an illustration of an AI-enabled chatbot originally created by IBM, which was adapted for use by the alt-labour network Organization the United for Respect (OUR) to inform workers about their rights and then reconfigured for use by a more traditional union, the United Workers Union (UNU) in Australia. Similarly, the National Domestic Workers Alliance (NDWA) in the United States, which is not formally a union with legal bargaining rights but a non-profit organisation that campaigns for domestic workers' rights, also developed a chatbot for Spanish speaking domestic workers. To increase the visibility of these workers' experience during the COVID-19 pandemic, NDWA then adapted the chatbot into a survey tool and published related insights in a report (NDWA Labs, 2020^[78]). The NDWA initiative highlights that beyond outreach, digital and AI tools could also inform social partners in their work¹⁷ (Vandaele, 2018^[76]) – a proposal that has recently been echoed by the British TUC, suggesting that unions could investigate ways to collect and make use of worker data, for example through engaging data scientists and developing AI-powered tools (TUC, 2021^[61]).

One prominent tool along these lines is WeClock,¹⁸ an open-source self-tracking app for workers to gather key data about the time spent at work, commutes or mistreatments among many other aspects. Workers can then use this information for wage-related or similar negotiations with their own manager, but also hand it over to their unions ultimately to inform broader advocacy campaigns or bargaining processes (UNI Global Union, 2019^[79]).

7.4. Promoting social partners' expertise to shape the AI transition

Despite their involvement in developing initiatives to accompany AI adoption, social partners activities may be limited by their lack of AI-related knowledge (as reported in the OECD questionnaire in Box 7.1), as well as the lack of capacities and resources to attain it. Along these lines, it would be important not only to offer social partners training opportunities or secure expertise on AI at the workplace or firm levels – see Krämer and Cazes (2022^[80]) for various examples across OECD countries, but also to consider allowing them access to some possibly sensitive information and data. In Spain, for instance, the 2021 Labour Law Reform, incorporated the right of the Workers Committee to be informed by the company of the parameters, rules and instructions on which algorithms or AI systems that may affect decisions relating to working conditions, profiling, etc.

One proposal to secure the necessary knowledge on AI at the workplace and firm levels beyond the training of social partners themselves is the recruitment or consultation of technical experts. This could not only ensure more technological understanding within unions and employers' organisations, but also that worker interests are recognised in the workplaces where technology is being developed – which could in turn also contribute towards more trustworthy technology (TUC, 2021^[17]).

Yet, while consulting technical experts could be promising ways to foster knowledge of AI in the workplace, social partners need government support to ensure that a broad access to such expertise can be provided. One recent example in this respect is the German Works Council Modernization Act passed in 2021, which grants works councils the right of consulting an external expert if the introduction or application of AI is in discussion¹⁹ – for a discussion, see for example Maily (2021^[81]) or Polkowski and Deja (2021^[82]).

7.5. Concluding remarks

Social dialogue can play an important role in addressing some of the key challenges created by AI technologies. Previous OECD evidence has shown that when social partners work co-operatively, social dialogue can support and usefully complement public policies in easing technological transitions, for instance by identifying pragmatic solutions to labour market challenges at the firm level and anticipating skill needs (OECD, 2018^[1]; 2019^[2]). Moreover, collective bargaining systems, when co-ordinated, can reduce inequalities and foster inclusive labour markets. However, social partners are facing the challenges presented by AI technologies at a time when they are already dealing with ongoing pressures due, among other things, to declining representation.

This chapter presents new evidence on the role of social dialogue in shaping the AI transition and initiatives by social partners in this area. In doing so, it contributes to the implementation of the OECD AI Principles' recommendation on "Building human capacity and preparing for labour market transformation" which states that governments should take steps, including through social dialogue, to ensure a fair transition for workers as AI is adopted. Governments should also work closely with stakeholders to promote the responsible use of AI at work, enhance the safety of workers and the quality of jobs, foster entrepreneurship and productivity, and ensure that the benefits AI are broadly shared.

In line with the existing empirical literature on the role of workers' voice in mitigating the impact of automation on wages and employment, new findings concerning AI adoption suggest that the presence of workers' representative bodies mitigates AI's negative impact on working conditions, although these relationships are not necessarily causal. Mapping social partners' ongoing responses to AI adoption, the chapter provides examples of social partners' information campaigns, advocacy and the first AI-related agreements. However, many social partners are still at the very beginning of this process and face considerable challenges. In particular, they often lack AI-related expertise and do not have the capacity and resources to acquire this expertise.

Nevertheless, social partners could gain some AI-related expertise by joining forces and co-operating in the use of existing resources, such as capacity-building questionnaires, guidelines and similar information published by other social partners and governments. It is also important that social partners continue adapting to the changing world of work, particularly by reaching out to under-represented workers and businesses in AI-exposed sectors and occupations. Moreover, social partners can themselves seek to use AI and digital tools more broadly as these offer opportunities for outreach, organisation and bargaining activities, as well as for tackling issues caused or exacerbated by AI, such as information asymmetries. However, they have made little use of AI technologies for such purposes thus far.

Finally, some avenues exist for public policies to accompany social partners' efforts to shape the AI transition. While each country's situation and labour relations systems differ, policy makers could promote national consultations and discussions on the AI transition with social partners and other stakeholders, to discuss challenges such as training, data use, implementation in the workplace, as well as share practices on new initiatives through common knowledge platforms. They could also support the development of AI-related expertise in the workplace for management, workers and their representatives (through educational programmes, for example) and make it easier to bring external experts into the workplace.

Ultimately, the impact of AI on labour markets and workplaces will depend on how it is implemented – which includes both the role of regulation in AI adoption and the extent to which workers and employers are involved through social dialogue at workplace, firm, sectoral, national and international levels. In this respect, regulations and social dialogue can complement each other, for example when AI-related regulations set minimum standards and specify terms that require further dialogue and bargaining. To better understand the relationship between social dialogue, regulations and a beneficial AI transition for both workers and employers in the future, more data and analysis at the individual and firm levels will be necessary. In particular, this will require firm-level surveys that bring together information on AI adoption, social dialogue and labour market outcomes.

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Annex 7.A. OECD Questionnaire on AI impact and social dialogue

Annex Table 7.A.1. List of social partners contributing to the OECD questionnaire

Name of the organisation	Type of organisation	Country	Domain	Representativeness
Association of Nordic Engineers (ANE)	Trade union association	Denmark, Finland, Iceland, Norway, and Sweden	Association of engineer's trade unions co-ordinating positions across Nordic countries.	More than 500 000 engineers across Nordic countries.
Australian Chamber of Commerce and Industry (ACCI)	Employer association	Australia	Private sector companies of all sizes.	9 000 companies
Canadian Chamber of Commerce (CCC)	Employer association	Canada	Private sector companies of all sizes.	200 000 businesses.
Central Organisation of Finnish Trade Unions (SAK)	Trade union confederation	Finland	All workers in manufacturing, public sector, transport, private services, and culture.	861 371 employees in 2021 (around 45% of total union membership).
Confederation of Danish Employers (DA)	Employer organisation	Denmark	Private sector companies of all sizes.	25 000 companies representing 1/3 of all employees in Denmark
Confederation of German Employers' Associations (BDA)	Employer organisation	Germany	Private sector employers in manufacturing industry, commerce, banking, insurance, small-scale crafts and trades, agriculture, transport and the newspaper industry	48 sectoral employer organisations and 14 regional employer organisations
Confederation of Professional Associations in Denmark (Akademikerne)	Trade union confederation	Denmark	Professional and managerial staff graduated from universities and other higher educational institutions	302 626 employees in 2021 (16% of total union membership).
Confederation of Swedish Enterprise (SN)	Employer organisation	Sweden	Private sector companies of all sizes.	60 000 firms and 50 business and employer organisations
Financial Services Union (FSU)	Trade union	Ireland	Financial Services, Fintech and Tech sectors. Trade union affiliated to the Irish Congress of Trade Unions (ICTU).	9 800 employees (around 2% of total union membership)
French Confederation of Professional and Managerial Staff – General Confederation of Professional and Managerial Staff (CFE-CGC)	Trade union confederation	France	White collars in private and public sectors.	152 000 union members in 2019 (6.5% of total union membership).
General Confederation of Liberal Trade Unions of Belgium (CGSLB/ACLVB)	Trade union confederation	Belgium	Blue and white collars in private and public sectors.	Around 300 000 union members in 2019 (9% of total union membership in Belgium).

Name of the organisation	Type of organisation	Country	Domain	Representativeness
General Labour Federation of Belgium (FGTB/ABVV)	Trade union confederation	Belgium	Blue and white collars in private and public sectors.	Around 1 500 000 union members in 2019 (45% of total union membership in Belgium)
German Trade Union Confederation (DGB)	Trade union confederation	Germany	Blue and white collars in private and public sectors.	5 934 000 union members in 2019 (75% of total union membership).
Hellenic Federation of Enterprises (SEV)	Employer organisation	Greece	Private sector companies of all sizes.	Over 600 direct member companies
New Zealand Educational Institute (NZEI)	Trade union	New Zealand	Education (public sector). Trade union affiliated to the New Zealand Council of Trade Unions (NZCTU).	Around 50 000 employees in 2019 (13.5% of total union membership).
Prospect	Trade union	United Kingdom	Scientists, engineers, and tech experts of the private sector. Trade union affiliated to the Trades Union Congress (TUC)	Around 150 000 employees (2.7% of total union membership).
Public Service Association (PSA)	Trade union	New Zealand	Central government, state-owned enterprises, local councils, health boards and community groups. Trade union affiliated to the New Zealand Council of Trade Unions (NZCTU).	Around 80 000 employees in 2022 (31.5% of total union membership).
Trades Union Congress (TUC)	Trade union confederation	United Kingdom	Blue and white collars in private and public sectors.	5 522 739 employees in 2019.
Union of Italian Workers (UIL)	Trade union confederation	Italy	Blue and white collars in private and public sectors.	1 376 000 employees in 2021 (around 23% of total union membership).
Unionen	Trade union	Sweden	White-collar workers in the private sector. Trade union affiliated to the Swedish Confederation of Professional Employees (TCO).	592 400 union members in 2021 (19% of total union membership).

Note: An employer confederation is specialised in representing only interests related to the labour market and industrial relations; an employer association represents only the product market interests of their members.

Extracts of the OECD questionnaire on AI impact and social dialogue

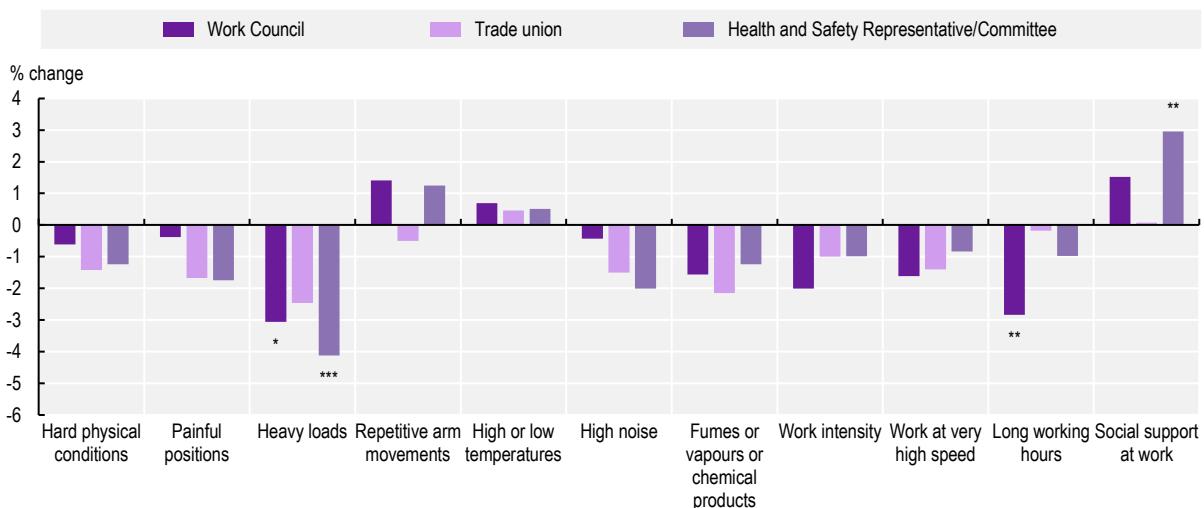
Trade union questionnaire	Employer organisation questionnaire
<p>Question 2.1. When thinking of AI technologies and their impact on workers, what are according to you the three most important opportunities/benefits?</p> <ul style="list-style-type: none"> <input type="checkbox"/> Increased productivity gains through more efficient work processes and greater economic competitiveness, with potentially positive effects on wages <input type="checkbox"/> Creation of new tasks and jobs (including data analysts, computer engineers, scientists, network experts...) <input type="checkbox"/> Higher job quality through effective collaboration between workers and AI, for instance resulting in a reduction of working time, a possible focus on more interesting tasks and increased work autonomy <input type="checkbox"/> Higher job safety, for example because existing machines will be safer or certain dangerous, physically demanding tasks are supported or performed by AI <input type="checkbox"/> Reductions in human bias in HR and management processes among others, increasing fairness for discriminated groups and minorities <input type="checkbox"/> Other 	<p>Question 2.1. When thinking of AI technologies and their impact on businesses, what are according to you the three most important opportunities/benefits?</p> <ul style="list-style-type: none"> <input type="checkbox"/> Increased productivity gains through more efficient work processes and greater economic competitiveness <input type="checkbox"/> Creation of new tasks and jobs (including data analysts, computer engineers, scientists, network experts...) <input type="checkbox"/> Higher job quality through effective collaboration between workers and AI, for instance resulting in a reduction of working time, a possible focus on more interesting tasks and increased work autonomy <input type="checkbox"/> Higher job safety, for example because existing machines will be safer or certain dangerous, physically demanding tasks are supported or performed by AI <input type="checkbox"/> Reductions in human bias in HR and management processes among others, increasing fairness for discriminated groups and minorities <input type="checkbox"/> Other
<p>Question 2.2. When thinking of AI technologies and their impact on workers, what are according to you the three most important challenges/risks?</p> <ul style="list-style-type: none"> <input type="checkbox"/> Destruction of jobs and displacement of workers <input type="checkbox"/> Widening inequalities between workers, as occupations and sectors may experience different wage growth or decline as a result of AI applications <input type="checkbox"/> Rapidly changing/increasing skill requirements, associated with high re- and upskilling costs for both businesses and workers <input type="checkbox"/> Lower job quality, for example through work intensification or less personal work relationships <input type="checkbox"/> Health and psychological risks at the workplace, for example through excessive AI-based surveillance <input type="checkbox"/> Concerns regarding data privacy, data leakages, possible violations of worker's human rights and dignity, and discriminations through automated decisions based on biased data <input type="checkbox"/> Liability risks for decisions and outcomes caused by AI applications <input type="checkbox"/> Weakening collective action and social dialogue, for example through increasing information asymmetries and physical distance between workers and businesses <input type="checkbox"/> Other 	<p>Question 2.2. When thinking of AI technologies and their impact on businesses, what are according to you the three most important challenges/risks?</p> <ul style="list-style-type: none"> <input type="checkbox"/> Impairment or displacement of business models <input type="checkbox"/> Unfair competition between businesses possessing different amounts and kinds of data, with effects on revenues, consumer prices and wage <input type="checkbox"/> Rapidly changing/increasing skill requirements, associated with increased re- and upskilling costs for both businesses and workers <input type="checkbox"/> Lower job quality, for example through work intensification or less personal work relationships <input type="checkbox"/> Health and psychological risks at the workplace, for example through excessive AI-based surveillance <input type="checkbox"/> Concerns regarding data privacy, data leakages, possible violations of workers' human rights and dignity, and discriminations through automated decisions based on biased data <input type="checkbox"/> Liability risks for decisions and outcomes caused by AI applications <input type="checkbox"/> Weakening collective action and social dialogue, for example through an increasing physical distance between workers and businesses <input type="checkbox"/> Other

Trade union questionnaire	Employer organisation questionnaire
<p>Question 3.1. What role does AI adoption in the workplace currently play in your union's agenda and strategy? Please select all options that apply.</p> <ul style="list-style-type: none"> <input type="checkbox"/> We have not considered AI in our agenda yet <input type="checkbox"/> We have not considered AI in our agenda yet, but are planning to do so <input type="checkbox"/> We are discussing possible strategies and initiatives <input type="checkbox"/> We are developing concrete strategies and initiatives <input type="checkbox"/> We have already implemented concrete strategies and initiatives <input type="checkbox"/> We are in contact/co-operation with other national or international partners on the role of AI in our agenda <input type="checkbox"/> Other 	<p>Question 3.1. What role does AI adoption in the workplace currently play in your employer organisation's agenda and strategy? Please select all options that apply.</p> <ul style="list-style-type: none"> <input type="checkbox"/> We have not considered AI in our agenda yet <input type="checkbox"/> We have not considered AI in our agenda yet, but are planning to do so <input type="checkbox"/> We are discussing possible strategies and initiatives <input type="checkbox"/> We are developing concrete strategies and initiatives <input type="checkbox"/> We have already implemented concrete strategies and initiatives <input type="checkbox"/> We are in contact/co-operation with other national or international partners on the role of AI in our agenda <input type="checkbox"/> Other
<p>Question 3.3. Which of the following initiatives has your union already carried out to support workers in the transition to AI adoption? Please select all applicable options.</p> <ul style="list-style-type: none"> <input type="checkbox"/> Outreach and information activities, such as information sessions and awareness campaigns <input type="checkbox"/> Guides and principle frameworks to facilitate the understanding and use of AI applications <input type="checkbox"/> Publication of an AI strategy or similar documents <input type="checkbox"/> Training activities, such as workshops, online courses or partnerships with educational institutions <input type="checkbox"/> Structural adjustments in the union, such as new working groups, consultation meetings, contact points for AI-related questions or the engagement of new personnel <input type="checkbox"/> Identification of issues for bargaining activities and collective agreements <input type="checkbox"/> Engagement in bargaining activities and collective agreements <input type="checkbox"/> Involvement in monitoring and compliance procedures relating to AI applications <input type="checkbox"/> Targeted communication and contact with policy makers to initiate and shape AI regulations or support measures <input type="checkbox"/> Other 	<p>Question 3.3. Which of the following initiatives has your employer organisation already carried out to support businesses in the transition to AI adoption? Please select all applicable options.</p> <ul style="list-style-type: none"> <input type="checkbox"/> Outreach and information activities, such as information sessions and awareness campaigns <input type="checkbox"/> Guides and principle frameworks to facilitate the understanding and use of AI applications <input type="checkbox"/> Publication of an AI strategy or similar documents <input type="checkbox"/> Training activities, such as workshops, online courses or partnerships with educational institutions <input type="checkbox"/> Structural adjustments in the employer organisation, such as new working groups, consultation meetings, contact points for AI-related questions or the engagement of new personnel <input type="checkbox"/> Identification of issues for bargaining activities and collective agreements <input type="checkbox"/> Engagement in bargaining activities and collective agreements <input type="checkbox"/> Involvement in monitoring and compliance procedures relating to AI applications <input type="checkbox"/> Targeted communication and contact with policy makers to initiate and shape AI regulations or support measures <input type="checkbox"/> Other

Annex 7.B. Supplementary materials

Annex Figure 7.B.1. Representative workers' voice is associated with mitigating AI's impacts on risks relating to working conditions, but causality remains unclear – OLS estimates

OLS regression coefficients expressed in percentage change



Note: Results are based on OLS regressions including establishment-level controls (country, industry, size, age, economic situation, share of old workers, if the person interviewed is the owner/manager and if teleworking is possible). *, **, *** denote the statistically significance at the 10%, 5%, and 1% level, respectively.

Source: OECD estimates based on the Third European Survey of Enterprises on New and Emerging Risks (2019) (ESENER-3).

StatLink <https://stat.link/389ezp>

Annex Table 7.B.1. Representative workers' voice and AI's impacts on risks relating to working conditions

Marginal effects, i.e. percentage change in the probability of outcome variable following a discrete change in the relevant explanatory variable

	Hard physical conditions	Painful positions	Heavy loads	Repetitive arm movements	High / low temperature	High noise	Fumes, Vapours or Chemical products	Work intensity	Work at very high speed	Long working hours	Social support at work
Work Council (WC)											
AI adoption (β_1)	5.56*** (0.007)	7.58*** (0.008)	8.92*** (0.010)	9.21*** (0.009)	7.06*** (0.009)	8.67*** (0.008)	9.41*** (0.009)	11.00*** (0.010)	10.5*** (0.010)	6.29*** (0.007)	-5.23*** (0.007)
	1.66** (0.007)	3.95*** (0.009)	4.09*** (0.011)	3.03*** (0.010)	3.38*** (0.010)	3.44*** (0.009)	2.55** (0.010)	3.81*** (0.011)	4.16*** (0.011)	1.84** (0.008)	-3.48*** (0.007)
Representation by WC (β_2)	0.73 (0.014)	-0.74 (0.016)	-3.21* (0.019)	2.46 (0.018)	0.31 (0.017)	-1.29 (0.015)	-1.90 (0.017)	-1.75 (0.017)	-1.49 (0.019)	-2.93** (0.018)	2.14* (0.014)
	Trade union (TU)	5.94*** (0.007)	8.11*** (0.008)	8.73*** (0.010)	9.49*** (0.009)	7.44*** (0.009)	8.56*** (0.008)	9.07*** (0.009)	10.8*** (0.010)	10.10*** (0.010)	6.14*** (0.007)
AI adoption and WC (β_3)	3.25*** (0.008)	5.68*** (0.011)	7.26*** (0.013)	3.47*** (0.011)	5.63*** (0.012)	7.03*** (0.010)	6.33*** (0.011)	6.43*** (0.011)	7.05*** (0.012)	3.78*** (0.012)	-4.04*** (0.008)
	AI adoption and TU (β_3)	2.01 (0.016)	-2.22 (0.017)	-2.01 (0.020)	0.61 (0.019)	-0.33 (0.018)	-2.87* (0.016)	-2.88 (0.016)	0.35 (0.018)	-1.03 (0.021)	-1.01 (0.020)
Health and Safety Representative (HSR)											
AI adoption (β_1)	5.80*** (0.007)	8.27*** (0.010)	9.94*** (0.011)	8.79*** (0.010)	7.24*** (0.010)	9.35*** (0.010)	9.41*** (0.011)	11.20*** (0.011)	10.70*** (0.011)	6.17*** (0.009)	-5.93*** (0.008)
	Representation by HSR (β_2)	2.62*** (0.006)	2.51*** (0.008)	5.40*** (0.010)	3.02*** (0.009)	2.83*** (0.009)	3.48*** (0.008)	3.99*** (0.009)	2.07** (0.009)	2.85*** (0.009)	0.64 (0.007)
AI adoption and HSR (β_3)	0.70 (0.012)	-1.96 (0.014)	-4.30*** (0.017)	2.24 (0.016)	0.05 (0.015)	-2.94** (0.014)	-1.70 (0.015)	-0.13 (0.015)	-0.29 (0.016)	-0.88 (0.016)	3.19*** (0.012)

Note: Results are based on probit regressions including establishment-level controls (country, industry, size, age, economic situation, share of old workers, if the person interviewed is the owner/manager and if teleworking is possible). *, **, *** denote the statistically significance at the 10%, 5%, and 1% level, respectively. Robust standard errors in parentheses.

Source: OECD estimates based on the Third European Survey of Enterprises on New and Emerging Risks (2019) (ESENER-3).

StatLink  <https://stat.link/mpg8fz>

Annex Table 7.B.2. Definitions of the job quality outcomes

Job quality outcome	ESENER questions	ESENER variable	ESENER coding	Final coding
Painful positions (d1)	Is this risk factor present or not in your establishment? regardless of whether it is currently under control and regardless of the number of employees it affects: Tiring or painful positions	Q200_4	Yes/No	1 if Q200_4=Yes; 0 otherwise
Heavy loads (d2)	Is this risk factor present or not in your establishment? regardless of whether it is currently under control and regardless of the number of employees it affects: Lifting or moving people or heavy loads	Q200_1	Yes/No	1 if Q200_1=Yes; 0 otherwise
Repetitive arm movements (d3)	Is this risk factor present or not in your establishment? regardless of whether it is currently under control and regardless of the number of employees it affects: Repetitive hand or arm movements	Q200_2	Yes/No	1 if Q200_2=Yes; 0 otherwise
High temperatures or low temperatures (d4)	Is this risk factor present or not in your establishment? regardless of whether it is currently under control and regardless of the number of employees it affects: Heat, cold or draught	Q200_6	Yes/No	1 if Q200_6=Yes; 0 otherwise
High noise (d5)	Is this risk factor present or not in your establishment? regardless of whether it is currently under control and regardless of the number of employees it affects: Loud noise	Q200_5	Yes/No	1 if Q200_5=Yes; 0 otherwise
Hard physical conditions = 1 if $(d1 + d2 + d3 + d4 + d5) \geq 1$; 0 otherwise				
Work at very high speed (d17)	Is this risk factor present or not in your establishment? Time pressure	Q201_1	Yes/No	1 if Q201_1=Yes; 0 otherwise
Long working hours (d19)	Is this risk factor present or not in your establishment? Long or irregular working hours	Q201_5	Yes/No	1 if Q201_5=Yes; 0 otherwise
Work intensity = 1 if $(d17 + d19) \geq 1$; 0 otherwise				
Help and support from colleagues (r1)	Is this risk factor present or not in your establishment? Poor communication or co-operation within the organisation	Q201_2	Yes/No	1 if Q201_2=No; 0 otherwise
Social support at work = 1 if r1 = 1; 0 otherwise				

Notes

¹ The chapter also makes use of insights of two OECD expert meetings on AI adoption and consultations with researchers, social partners, employers and AI developers during the course of the OECD project on AI in Work, Innovation, Productivity and Skills (AI-WIPS).

² In the OECD questionnaire, questions revolving around trustworthy issues relate to data privacy, data leakages, possible violation of workers' rights and dignity, as well as discriminations based on biased data (see Annex 7.A).

³ In a survey on risks and benefits due to digitalisation carried out with unions representatives in Europe, job destruction (respectively job creation) due to automation were ranked as the most important risk (benefit) of AI in the future of work (with 52% and 45% respectively) (Voss and Riede, 2018^[5]). Similarly, two-thirds of works councils, HR councils and supervisory boards surveyed by the ver.di union in Germany a year later feared AI-induced decreases in available jobs while only half of them expected increasing work intensity (ver.di, 2019^[6]).

⁴ Possible mechanisms include that the use of AI may reduce stress, fatigue and safety risks through a better work organisation and task optimisation. For example, AI can support or substitute repetitive or physically and mentally strenuous tasks, thereby allowing workers to focus on more interesting and safe tasks. Moreover, AI can also offer opportunities to reduce discrimination in the workplace, or better monitor the well-being and security of workers (Cazes, 2021^[42]).

⁵ Workers' voice is made of the various institutionalised forms of communication between workers and managers that offer an alternative to exit (i.e. dissatisfied employees quitting) in addressing collective problems. Voice is often mediated through representative institutions – “representative workers” voice – such as local trade union representatives, work councils or workers representatives; in addition, voice also materialise in the workplace through the organisation of direct exchanges between workers and managers, via regular townhall meetings or direct consultations – “direct voice”. Finally, in “mixed voice” systems, both direct and representative arrangements of workers' voice co-exist (see more details in (OECD, 2019^[2]).

⁶ In the ESENER-3 survey, 26% of establishments report using AI, of which AI-related management software is more common than AI-related hardware devices. While only 5% establishments report using robots or wearable devices, 12% and 15% of establishments report using software to monitor workers or to determine the content and pace of their work respectively. Moreover, 63% of establishments report having at least one form of worker representation. Worker elected health and safety representatives and committees are the most common form of representative workers' voice in surveyed establishments with almost 50%, while only 30% of establishments report having a trade union representative or a works council (forms of representations may co-exist in one establishment).

⁷ The ultimate effect of AI mitigated by workers' voice can be derived from the cumulation of the AI adoption effect and the mitigation effect.

⁸ The dummy variable equals 1 if a worker elected health and safety committee/representative exists in an establishment and it equals 0 if there is no health and safety committee/representative or if it is appointed by the business.

⁹ The OECD Framework for Measuring and Assessing Job Quality takes a multidimensional approach and defines job quality in terms of earnings quality, labour market security and the quality of the working environment (Cazes, Hijzen and Saint-Martin, 2015^[83]).

¹⁰ The presence and degree of co-ordination within and between social partners is important not only to produce independent negotiations, but to ensure inclusiveness across firms and sectors. Co-ordination mechanisms can exist between different levels, for example when sectoral or firm level agreements follow the guidelines fixed by peak-level organisations or by a social pact, or at the same level, for example when sectors or firms follow the standard set in another.

¹¹ For instance, workers' voice can help avoiding the distrust that may be generated by the introduction of new technologies that workers have to work with, through consultation and/or involving them. They can also provide management with better workplace related information including how workers perceive the introduction of new technology and the difficulties they identify.

¹² The material and position papers developed by unions largely focus on promoting a trustworthy use of AI and training – see for instance the principles of Nordic Engineers to develop technical standards and certifications to increase accountability (ANE/IT University of Copenhagen, 2018^[50]; ANE et al., 2021^[51]) or UNI.

¹³ On 25 May 2018, the European Union replaced the Data Protection Directive (European Union, 1995), by the General Data Protection Regulation (GDPR) framework (European Union, 2016). The GDPR introduced new rules governing the collection, process, and free flow of personal data regarding data subjects in the European Union. When data originating in EU member states are transferred abroad, the GDPR ensures that personal data protections travel with them. – see Chapter 6 for more details.

¹⁴ As pointed out by the Hans Böckler Foundation in Germany, the GDPR contains important principles, such as privacy by default and other aspects, which also apply to AI technologies. Article 88 also opens up scope for more specific regulations on data protection by national legislators (Albrecht and Kellermann, 2020^[15]) as well as more specific measures by collective agreements in the Member States – especially for those, which ensure the protection of workers' rights (Klengel and Wenckebach, 2021^[84]). Along these lines, the British TUC proposes in its AI Manifesto to enhance the existing British GDPR with a statutory guidance for employers on matters of automatic or AI-influence decision-making (TUC, 2021^[61]).

¹⁵ In this respect, much of the discussion evolves around the proposed AI Act of the European Commission that aims to govern the development and use of AI systems in the EU on a risk-based categorisation approach, with specific safeguards for high-risk uses (see Chapter 6). The proposed EU AI Act, similarly to the GDPR, has raised concerns of some European unions about its articulation with existing collective bargaining regulation and its capacity to adequately address workplace issues in targeting more at consumers rights (TCO, 2021^[85]) (Klengel and Wenckebach, 2021^[84]).

¹⁶ Notably to the Article 88 of the EU GDPR which refers to the possibility to lay down in collective agreements more specific rules to ensure the protection of the rights and freedom with regards to the processing of employees' personal data in the context of employment relationships.

¹⁷ According to social partners attending the OECD expert workshops, avenues for such investigation could for example include analysing large amounts of wage statements to ensure workers' correct remuneration

or to evidence safety concerns with data on occupational health and safety aspects across workplaces and sectors.

¹⁸ More information on this tool can be accessed through the website <https://www.weclock.it>.

¹⁹ Similarly, the recent agreement between the General Staff Council of the city Stuttgart and the city as a public employer stipulates that the works council may use external consulting services at the city's expense (Forum Soziale Technikgestaltung, 2022^[72]).

Annex A. Statistical annex

Sources and definitions

The tables of the statistical annex show data for all 38 OECD countries where available. Data for Argentina, Brazil, China, India, Indonesia and South Africa are compiled and included in a number of tables and in the Employment database (<http://www.oecd.org/employment/database>).

From this year onwards, the standard tabulations (Tables A to Q) are replaced by web links pointing to data and indicators reported in the OECD central data repository OECD.Stat (<http://stats.oecd.org>) which contains longer time series. Accordingly, web links pointing to data series are also included. Some additional web links entitled Tables R to U complete this year's annex referring respectively to data and indicators on statutory minimum wages, trade union density, collective bargaining coverage and synthetic indicators of employment protection. A richer set of labour market data and indicators is accessible from the web page dedicated to employment statistics (www.oecd.org/employment/database). The metadata section of the online datasets reports definitions, notes and sources retained in national data sources.

In general, Tables A to K and Table M report annual averages of monthly and quarterly estimates based on labour force surveys. Those shown for European countries in Tables B, C, D, H, I, J, K and Table M are mainly data from the European Labour Force Survey (EU-LFS), which are more comparable and sometime more consistent over time than national LFS results. Data for the remaining Tables L, N, O, P and the new Tables R to T are from a combination of survey and administrative sources or national reporting and desk research for Table U.

Regarding the OECD Employment database, it contains both raw data and indicators for longer time series and more detailed individual characteristics and type of main job such as data by age group, gender and employee job tenure, part time employment, involuntary part time employment, temporary employment, duration of unemployment. The database includes more data series than those shown in the web links of the statistical annex, such as, the distribution of employment by weekly usual hours worked intervals, potential labour force, so-called people marginally attached to the labour force, etc. The online database contains additional series on working time, earnings and features of institutional and regulatory environments of labour markets.

Major breaks in series

Table A: Data series have been break-corrected in most countries to ensure that unemployment rates are consistent over time.

Tables B to K and Table M: Most of the breaks in series in the tables occurred for any of the following reasons: changes in survey design, survey questionnaire, survey frequency and administration, revisions of data series based on updated population census results. These changes have affected the comparability over time of employment and/or unemployment levels and to a certain extent the ratios reported in the aforementioned tables:

- **Change in the measurement of the labour force status and methodology in the European Labour Force Survey since 2021:** Data between 2020 and 2021 are affected by a break in series in Tables B, C, D, H, I, J, K and M. The size and direction of the breaks vary by country and statistics as reported in the national documentations on Eurostat website. See: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_Labour_Force_Survey_-_new_methodology_from_2021_onwards.
- **Introduction of a continuous survey producing quarterly results:** Austria (2003/04), Brazil (2011/12), France (2002/03), Germany (2004/05), Hungary (2005/06, monthly results), Iceland (2002/03), Italy (2003/04), Luxembourg (2002/03, quarterly results as of 2007) and Türkiye (2013/14).
- **Redesign of labour force survey:** Introduction of a new survey in Chile since April 2010 (see below), Germany (2010/11), Hungary (2002/03), Poland (2004/05), Portugal (2010/11) and Türkiye (2004/05 from quarterly to monthly results). Change from quarterly to monthly survey results and a change from “civilian” to “total” labour force (including those who are in compulsory or permanent military service) in Israel (2011/12). New Zealand (2015/16): the survey includes non-civilian personnel. Annual results for Colombia in 2020 are averaged over three-quarters (Q1, Q3 and Q4) because of the COVID-19 pandemic outburst and suspension of the survey in the 2nd quarter. Since July 2020, a new edition of the continuous quarterly survey was re-introduced in Mexico (Encuesta Nacional de Ocupación y Empleo, New edition ENOE^N) after its suspension in April 2020 following the COVID-19 pandemic outburst and lockdown measures. It was replaced in Q2 by a telephone interview survey (ETOE) with partial results. The annual results are averages of three-quarters (Q1, Q3 and Q4). For the United Kingdom (2003/2004), data for Tables B to D are annual averages of quarterly estimates from the Annual Population Survey (APS); prior to 2004, they refer to the spring quarter (April-June) Labour Force Survey (LFS). Data for Tables H, I, J, K and M are annual averages of quarterly estimates from APS from 2016 onwards.
- **Change in the operational definition of employment:**
 - Neat application of the criterion of “at least one hour worked in a gainful job” in the Chilean Nueva Encuesta Nacional de Empleo (NENE), a quarterly continuous survey, from April 2010 onward.
- **Change in the operational definition of usual working time:**
 - In Israel, the Labour Force Survey questionnaire was expanded and changed since January 2018. Workers absent from work are asked “how many hours they usually work”. This affects the number of workers reporting usual weekly hours worked in their main job prior and after 2018, notably Table H on the incidence and composition of part-time employment according to a common 30-hour threshold-based definition.

- **Change in the operational definition of unemployment regarding:**
 - Active job-search methods: in particular a change from registration to contact with the public employment service in France (2002/03) and Spain (2000/01).
 - Duration of active job search: In Australia (2014/15), the duration of unemployment has been replaced by duration of job search. In Belgium (2010/11), the duration of job search has been changed from an unlimited duration to previous four weeks including the survey reference week. In Chile (2009/10), the duration of active job search has been shortened from last two months to previous four weeks including the survey reference week.
 - Availability to work criterion: In Sweden (2004/05), the work availability criterion changed from the reference week to two weeks from the reference week to be consistent with the operational definition in other EU countries. In Chile, the work availability criterion did not exist prior to 2010 in the Encuesta Nacional de Empleo (ENE) and was introduced in the Nueva Encuesta Nacional de Empleo (NENE) since April 2010. It has been fixed to two weeks from the end of the reference week.
 - Persons on lay off considered as employed instead of unemployed: Norway (2005/06).
 - Other minor changes: Australia (2000/01) and Poland (2003/04).
- **Changes in the questionnaire with impact on employment and unemployment estimates:** Germany (2010/11): new questionnaire design ensures better coverage of small jobs. This led to a higher-than-normal annual employment increase. Impact on employment and unemployment statistics in New Zealand (2015/16) with the inclusion of army personnel. Spain (2004/05): impact on employment and unemployment and impact on unemployment estimates in Norway (2005/06) and Sweden (2004/05).
- **Change from seasonal to calendar quarters:** Switzerland (2009/10) and the United Kingdom (2005/06). However, there is no break in series between 2005 and 2006 for the United Kingdom as calendar quarter based historical series are available since 1992.
- **Introduction of new EU harmonised questionnaire:** Sweden (2004/05) and Türkiye (2003/04).
- **Change in lower age limit from 16 to 15 years:** Iceland (2008/09), Norway (2005/06) and Sweden (2006/07).
- **Change in lower age limit from 15 to 16 years:** Italy (2007/08).
- **Change in data collector in Denmark since the first quarter of 2017:** the LFS response rate increased and resulted in a significant break in series between 2016 and 2017.
- In Norway, as of 2006 age is defined as years reached at the survey reference week, instead of completed years at the end of the year, as in previous years.
- **Inclusion of population controls based on census results in the estimation process:** Mexico (2009/10) and Türkiye (2006/07).
- In Japan, data for Table J on temporary employees has a break in series between 2013 and 2017.

Table A. OECD unemployment rates

As a percentage of civilian labour force

<https://stats.oecd.org/Index.aspx?QueryId=119413>

Table B1. Employment/population ratios by selected age groups – Total

As a percentage of the population in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120204>

<https://stats.oecd.org/Index.aspx?QueryId=119603> (time series)

Table B2. Employment/population ratios by selected age groups – Men

As a percentage of the population in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120205>

<http://stats.oecd.org//Index.aspx?QueryId=120064> (time series)

Table B3. Employment/population ratios by selected age groups – Women

As a percentage of the population in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120206>

<http://stats.oecd.org//Index.aspx?QueryId=120065> (time series)

Table C1. Labour force participation rates by selected age groups – Total

As a percentage of the population in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120207>

<http://stats.oecd.org//Index.aspx?QueryId=120066> (time series)

Table C2. Labour force participation rates by selected age groups – Men

As a percentage of the population in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120208>

<http://stats.oecd.org//Index.aspx?QueryId=120067> (time series)

Table C3. Labour force participation rates by selected age groups – Women

As a percentage of the population in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120209>

<http://stats.oecd.org//Index.aspx?QueryId=120068> (time series)

Table D1. Unemployment rates by selected age groups – Total

As a percentage of the total labour force in each age group

<http://stats.oecd.org/Index.aspx?QueryId=120210>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=120069)

Table D2. Unemployment rates by selected age groups – Men

As a percentage of the total labour force in each age group

<http://stats.oecd.org/Index.aspx?QueryId=120225>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=120070)

Table D3. Unemployment rates by selected age groups – Women

As a percentage of the total labour force in each age group

<http://stats.oecd.org/Index.aspx?QueryId=120226>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=120072)

Table E. Employment/population ratios by educational attainment, latest year

Persons aged 25-64, as a percentage of the population in each gender

<http://stats.oecd.org/Index.aspx?QueryId=119284>

Table F. Labour force participation rates by educational attainment, latest year

Persons aged 25-64, as a percentage of the population in each gender

<http://stats.oecd.org/Index.aspx?QueryId=119410>

Table G. Unemployment rates by educational attainment, latest year

Persons aged 25-64, as a percentage of the labour force in each gender

<http://stats.oecd.org/Index.aspx?QueryId=119411>

Table H1. Incidence and composition of part-time employment

Persons aged 15 and over, percentages

<http://stats.oecd.org/Index.aspx?QueryId=120227>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=119416)

Table H2. Women's share in part-time employment

Percentages

<http://stats.oecd.org/Index.aspx?QueryId=119415>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=120228)

Table I1. Incidence and composition of involuntary part-time employment

Persons aged 15 and over, percentages

<http://stats.oecd.org/Index.aspx?QueryId=120229>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=119429)

Table I2. Involuntary part-time employment as a share of part-time employment

Persons aged 15 and over, percentages

<http://stats.oecd.org/Index.aspx?QueryId=120230>

[\(time series\)](https://stats.oecd.org/Index.aspx?QueryId=119604)

Table J1. Incidence and composition of temporary employment

As a percentage of dependent employment in each age group

<http://stats.oecd.org/Index.aspx?QueryId=120231>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=119431)

Table J2. Women's share in temporary employment

As a percentage of dependent employment in each age group

<http://stats.oecd.org/Index.aspx?QueryId=120244>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=119432)

Table K1. Incidence of job tenure shorter than 12 months – Total

As a percentage of total employment in each age group

<http://stats.oecd.org/Index.aspx?QueryId=120245>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=119609)

Table K2. Incidence of job tenure shorter than 12 months – Men

As a percentage of total employment in each age group

<http://stats.oecd.org/Index.aspx?QueryId=120246>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=120167)

Table K3. Incidence of job tenure shorter than 12 months – Women

As a percentage of total employment in each age group

<http://stats.oecd.org/Index.aspx?QueryId=120247>

[\(time series\)](http://stats.oecd.org/Index.aspx?QueryId=120168)

Table L. Average annual hours actually worked per person in employment

National accounts concepts unless otherwise specified (Hours per person per year)

<http://stats.oecd.org//Index.aspx?QueryId=120248>

<http://stats.oecd.org/Index.aspx?QueryId=119612> (time series)

Table M1. Incidence of long-term unemployment, 12 months and over – Total

As a percentage of total unemployment in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120249>

<http://stats.oecd.org//Index.aspx?QueryId=120074> (time series)

Table M2. Incidence of long-term unemployment, 12 months and over – Men

As a percentage of total unemployment in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120250>

<http://stats.oecd.org//Index.aspx?QueryId=120073> (time series)

Table M3. Incidence of long-term unemployment, 12 months and over – Women

As a percentage of total unemployment in each age group

<http://stats.oecd.org//Index.aspx?QueryId=120251>

<http://stats.oecd.org/Index.aspx?QueryId=119613> (time series)

Table N1. Real average annual wages

Average wages in 2022 USD PPPs

<http://stats.oecd.org//Index.aspx?QueryId=124081>

Table N2. Real average annual wage growth

Real wage growth of average gross annual wages per full-time equivalent employee, in 2022 constant prices

<http://stats.oecd.org//Index.aspx?QueryId=124065>

Table O1. Earnings dispersion

<http://stats.oecd.org//Index.aspx?QueryId=120252>

<http://stats.oecd.org/Index.aspx?QueryId=119440> (time series)

Table O2. Incidence of high and low pay

<http://stats.oecd.org//Index.aspx?QueryId=120253>

<http://stats.oecd.org/Index.aspx?QueryId=119605> (time series)

Table P1. Relative earnings – Gender gap

<http://stats.oecd.org/Index.aspx?QueryId=119449> (time series)

Table P2. Relative earnings – Age gap<http://stats.oecd.org/Index.aspx?QueryId=119448> (time series)**Table Q1. Public expenditure in labour market programmes**<http://stats.oecd.org//Index.aspx?QueryId=120256><https://stats.oecd.org/Index.aspx?QueryId=119611> (time series)**Table Q2. Participant stocks in labour market programmes**<http://stats.oecd.org//Index.aspx?QueryId=120258><http://stats.oecd.org/Index.aspx?QueryId=119451> (time series)**Table R1. Real hourly minimum wages**

Statutory minimum wages in constant 2021 prices at 2021 USD Purchasing Power Parities (PPPs) for private consumption expenditures

<http://stats.oecd.org//Index.aspx?QueryId=120151>**Table R2. Minimum wage relative to mean and median earnings**

As a percentage of median earnings of full-time employees

<http://stats.oecd.org//Index.aspx?QueryId=120152>**Table S. Trade union density**

As a percentage of the number of employees

<http://stats.oecd.org//Index.aspx?QueryId=120156>**Table T. Collective bargaining coverage**

As a percentage of eligible employees with the right to bargain

<http://stats.oecd.org//Index.aspx?QueryId=120158>**Table U1. Strictness of employment protection – Individual and collective dismissals (regular contracts)**

Index varying from 0 to 6, from the least to the most stringent

<http://stats.oecd.org//Index.aspx?QueryId=120159>**Table U2. Strictness of employment protection – Temporary contracts**

Index varying from 0 to 6, from the least to the most stringent

<http://stats.oecd.org//Index.aspx?QueryId=120160>

OECD Employment Outlook 2023

ARTIFICIAL INTELLIGENCE AND THE LABOUR MARKET

The 2023 edition of the *OECD Employment Outlook* examines the latest labour market developments in OECD countries. It focuses, in particular, on the evolution of labour demand and widespread shortages, as well as on wage developments in times of high inflation and related policies. It also takes stock of the current evidence on the impact of artificial intelligence (AI) on the labour market. Progress in AI has been such that, in many areas, its outputs have become almost indistinguishable from that of humans, and the landscape continues to change quickly, as recent developments in large language models have shown. This, combined with the falling costs of developing and adopting AI systems, suggests that OECD countries may be on the verge of a technological revolution that could fundamentally change the workplace. While there are many potential benefits from AI, there are also significant risks that need to be urgently addressed, despite the uncertainty about the short- to medium-term evolution of AI. This edition investigates how to get the balance right in addressing the possible negative effects of AI on labour market outcomes while not stifling its benefits.



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