

What impact has AI had on wage inequality?

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Key findings

- Over the past few decades, technological change has contributed to increases in wage inequality across OECD countries, and rapid advances in Artificial Intelligence (AI) raise questions as to whether these trends will continue. However, evidence for the period 2014-18 suggests that AI did not, so far, alter the gap between high- and low-wage occupations.
- There is some indication, however, that higher exposure to AI may be associated with lower inequality between high- and low-wage workers within occupations.
- Over the period analysed, wage inequality declined most in occupations most exposed to AI, such as: Business Professionals; Legal, Social and Cultural Professionals; Managers; and Science & Engineering Professionals. This is consistent with more recent evidence that AI may reduce productivity differences between workers in certain occupations.
- These greater reductions in wage inequality within occupations exposed to AI have not so far translated into similar reductions in the wage gaps between men and women, or between younger and older workers.

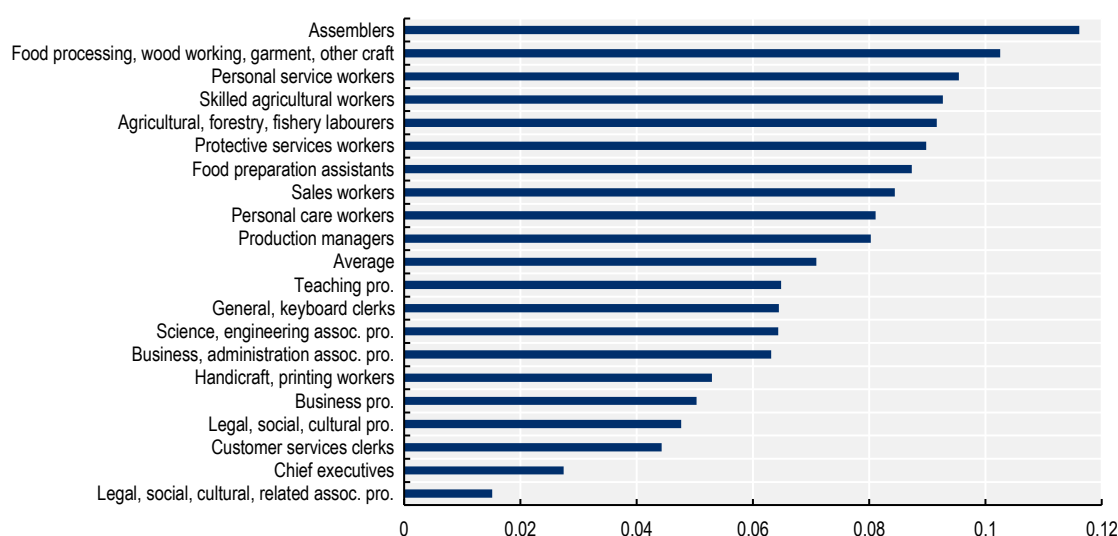
So far, AI has not affected the gap between high and low-wage occupations

Real wages grew in most occupations over the period 2014-18, as OECD economies recovered from the financial crisis. Interestingly, contrary to previous trends, the gap between high- and low-wage occupations narrowed over this period. Wage growth tended to be lowest in some high-skilled occupations, such as Legal, social, cultural professionals (4.8%) and related associate professional occupations (1.5%), as well as Chief executives (2.7%) and Business professionals (5%) (Figure 1). By contrast, wage growth was strongest in some low-skilled occupations, such as Assemblers (11.6%), Food processing, wood working, garment and other craft occupations (10.3%) and Personal service workers (9.5%). This was largely driven by adjustments in minimum wages to protect the standard of living of low-wage workers against inflation (Araki et al., 2023^[1]). There is no indication that these changes have been driven by AI. Indeed, new OECD research (Georgieff, 2024^[2]) suggests there was no association between wage growth in a particular

occupation and the level of exposure of that occupation to AI. Occupational exposure to AI is a cross-country measure derived from that developed by Felten, Raj and Seamans (2019^[3]) for the United States – a measure of the degree to which occupations rely on abilities in which AI has made the most progress. An advantage of this measure is that it is available for 36 occupations in the 19 countries considered. However, it also has some drawbacks: it only captures the *potential* automation of tasks that is *directly related to the capabilities of AI* – it does not capture the potential automation of tasks where AI is only an enabler of other technologies.

Figure 1. In most occupations, real wages have grown between 2014 and 2018

2014-18 log change in real average wage by occupation, simple averages across countries (selected occupations)



Source: Based on Georgieff (2024^[2]), "Artificial intelligence and wage inequality", <https://doi.org/10.1787/bf98a45c-en>.

AI may be reducing wage inequality within occupations

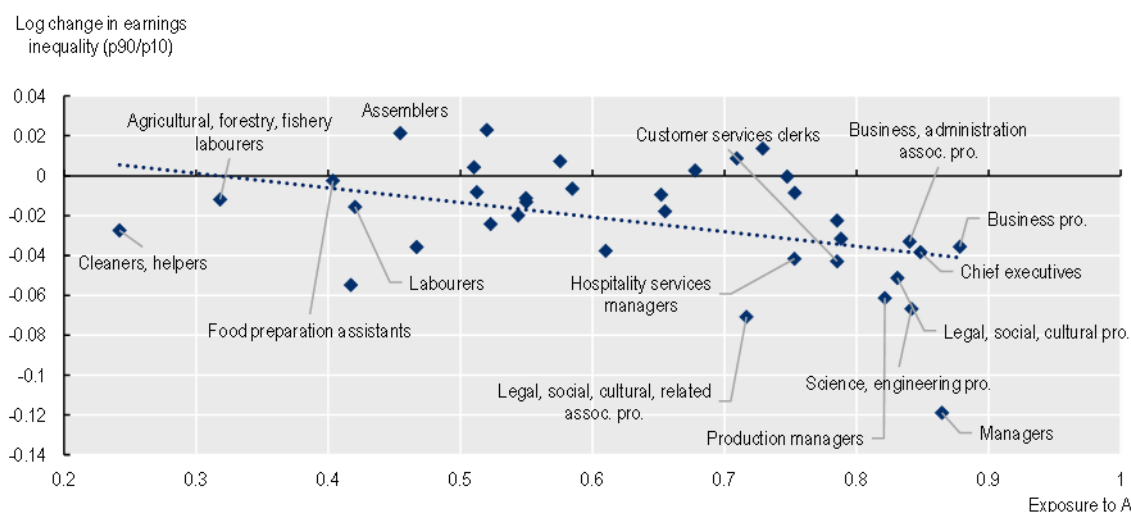
At the same time, inequality declined *within* most occupations over the period 2014-18 and it declined more in occupations most exposed to AI (Figure 2), such as Business Professionals; Legal, Social and Cultural Professionals; Managers; and Science & Engineering Professionals.

This early finding is consistent with other emerging evidence that AI may reduce productivity differences between workers in certain occupations (Brynjolfsson, Li and Raymond, 2023^[4]; Choi and Schwarcz, 2023^[5]; Dell'Acqua et al., 2023^[6]; Haslberger, Gingrich and Bhatia, 2023^[7]; Noy and Zhang, 2023^[8]; Peng et al., 2023^[9]). One possible explanation is that low performers have more to gain from using AI because AI systems are trained to embody the more accurate practices of high performers (Brynjolfsson, Li and Raymond, 2023^[4]). However, AI can also reduce performance differences within an occupation through a "selection effect", i.e. if low performers have to leave their job because they are unable to adapt to AI tools by shifting their activities to tasks that AI cannot automate.

While wage inequality has increased less (or reduced more) within the occupations most exposed to AI, there is no indication that AI has reduced wage gaps between men and women in those occupations, nor between young and prime age workers.

Figure 2. Wage inequality has increased less (or fallen more) within the occupations most exposed to AI

Occupation level log change in hourly wage inequality (2014 to 2018) and exposure to AI (early 2010s), simple averages across countries



Note: The chart shows the change in the p90/p10 ratio for each occupation against that occupation's exposure to AI (averaged across the 19 countries analysed). The negative relationship between AI exposure and growth in wage inequality remains statistically significant in multivariate regressions when a number of controls for other factors are included in the analysis. A one standard deviation increase in AI exposure (i.e. the difference in exposure between managers and sales workers) is associated with 1.5 percentage points lower growth in the p90/p10 ratio.

Source: Based on Georgieff (2024^[2]), "Artificial intelligence and wage inequality", <https://doi.org/10.1787/bf98a45c-en>.

OECD and policymakers should keep monitoring the impact of AI on wage inequality

While there is some evidence of an association between AI exposure and wage inequality within occupations, it is hard to say at this point whether this relationship is causal (i.e. that AI causes lower wage inequality). Still, the findings suggest that the most productive workers may play a key role in providing machine learning algorithms with examples of good practices. Compensation for top performers for the data they provide to train AI systems will therefore be essential for firms to attract these workers and make the most of AI. In addition, the greater productivity benefits for low performers suggest that training policies could benefit from targeting lower-skilled workers who are able to use AI.

The associations (or lack of them) were observed during a period when AI adoption was still relatively low and more recent advances in generative AI had not yet occurred. OECD and policymakers should keep monitoring the impact of AI on wages, productivity and skills needs in the future, as well as the consequences for labour demand, wage setting policies and inequality (Council of Economic Advisers, 2024^[10]).

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Explore further

Read the related working paper:

Georgieff, A. (2024), “Artificial intelligence and wage inequality”, *OECD Artificial Intelligence Papers*, No. 13, OECD Publishing, Paris, <https://doi.org/10.1787/bf98a45c-en>.

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Contact

Stijn BROECKE (✉ stijn.broecke@oecd.org)

Alexandre GEORGIEFF (✉ alexandre.georgieff@oecd.org)

This policy brief contributes to the OECD's Artificial Intelligence in Work, Innovation, Productivity and Skills (AI-WIPS) programme, which provides policymakers with new evidence and analysis to keep abreast of the fast-evolving changes in AI capabilities and diffusion and their implications for the world of work. The programme aims to help ensure that adoption of AI in the world of work is effective, beneficial to all, people-centred and accepted by the population at large. AI-WIPS is supported by the German Federal Ministry of Labour and Social Affairs (BMAS) and will complement the work of the German AI Observatory in the Ministry's Policy Lab Digital, Work & Society. For more information, visit <https://oecd.ai/work-innovation-productivity-skills> and <https://denkfabrik-bmas.de/>.



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