RESERVE BANK OF AUSTRALIA

Insight 2026-09

Monitoring Early Effects of AI on the Labour Market

Mike Major*

9 November 2026

Insights are short analytical notes in which RBA staff present their own analysis of a range of topics in economics and central banking. The content could align with, extend or even directly challenge the findings of other work undertaken at the Bank.

Disclaimer – The views expressed are those of the authors and should not be interpreted as reflecting or advancing the views of the RBA or its Boards.

© Reserve Bank of Australia
For copyright and disclaimer information, see http://www.rba.gov.au/copyright.

ISSN 3083-1423

Key takeaways

- There is little evidence to date that AI has materially disrupted the Australian labour market, though the timing, scale and direction of any future impacts are highly uncertain.
- There are tentative signs of weaker labour market outcomes in more AI-exposed occupations, particularly for younger workers, but the evidence remains limited.
- Any emerging signs of disruption need to be interpreted cautiously alongside broader cyclical conditions, other structural changes and the potential for AI to also create demand for some types of work.

Motivation

AI adoption could have material implications for the labour market, although the timing, scale and direction of any future impacts are highly uncertain. Moreover, how monetary policy responds to any AI-related change in unemployment depends on whether AI also leads to a change in the non-accelerating inflation rate of unemployment (NAIRU). AI could automate some tasks, augment others by helping individuals work better or faster, create new tasks and jobs, and change the composition of labour demand (see, for example, Acemoglu 2025; Calvino *et al* 2025; Jobs and Skill Australia 2026; Lane 2026). Regular monitoring is therefore important because early signs of adjustment may not be visible in aggregate labour market indicators if they are initially concentrated in particular occupations or cohorts. This note introduces a simple monitoring tool that can help identify where developments look unusual, whether they are concentrated in groups more likely to be exposed to AI, and where deeper analysis may be needed. It focuses on two channels through which AI-related adjustment may first become visible: **occupations with greater exposure** to AI-related tasks, and **young workers and graduates**.

Existing Australian evidence points to limited labour market disruption from AI to date, although there are some tentative signs of weaker outcomes among more AI-exposed occupations, particularly for young workers (Department of Employment and Workplace Relations 2026; Gross 2026; Jobs and Skills Australia 2025; SEEK 2026). While SEEK (2026a) finds some evidence of weaker demand in occupations that are more exposed to automation, it also finds evidence of stronger demand in occupations where AI is more likely to augment human work. This underscores that exposure to AI need not translate into lower labour demand, since some occupations may be complemented by AI. International evidence has also tended to find little evidence of economy-wide effects so far, but some signs of weaker employment and job-finding rates – rather than higher layoffs – for entry-level or younger workers in AI-exposed occupations.[1]

The analysis in this note is deliberately partial and descriptive rather than a causal or general equilibrium assessment. Any signs of adjustment may also reflect broader cyclical conditions or other structural changes in the labour market, and should be considered alongside evidence from the RBA's liaison program or other analysis. Comparisons across occupations or demographic groups may also conceal AI-related effects if adjustment is more broad-based than expected, so these comparisons should be assessed together with aggregate measures.

Occupation-based exposure outcomes

Occupation-level AI exposure measures provide a simple screening tool for identifying early labour market effects of AI, by classifying jobs according to how susceptible their underlying tasks are to automation from AI.[2] I use Jobs and Skills Australia's (JSA 2025) automation exposure mapping by ANZSCO occupation, which is based on Gmyrek *et al* (2023). Occupations are grouped into exposure categories (weighted by employment), with the most exposed occupations – including software developers, clerical workers and administrative workers – reflecting the similarity between their tasks and current AI capabilities. These rankings can then be linked to labour market outcomes before and after the diffusion of generative AI, allowing outcomes to be compared across occupations with different levels of potential AI exposure.[3] I use November 2022 as a benchmark in the following graphs, since this was when ChatGPT first brought generative AI into public use.[4]

A key limitation is that exposure-based measures capture potential task exposure, rather than realised AI adoption or whether firms are actually changing their hiring or wage-setting decisions. High exposure also does not imply displacement. AI exposure can reflect automation, where AI performs tasks in place of workers, or augmentation, where AI assists workers in performing their tasks. Occupations with greater exposure to automation also tend to have greater exposure to augmentation, so the implications for labour demand are not clear-cut (Graph 1).[5] These exposure measures may also be correlated with other factors affecting the

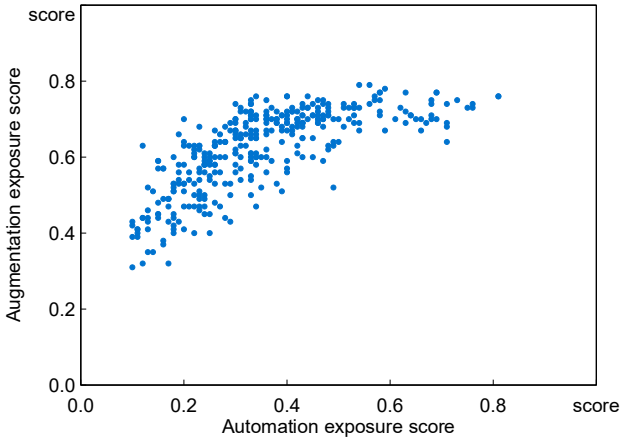
same occupations or cohorts, including post-pandemic changes in work-from-home practices (Lambert and Schindler 2026; Emanuel *et al* 2026) or strength in non-market employment.

Another limitation is that the latest complete occupation data are for February 2026. While partial data are shown for May 2026, changes to the Labour Force Survey methodology and the transition from ANZSCO to OSCA occupation classification mean more recent data (which will be available later in 2026) will require a slightly revised mapping to the AI-exposure classifications used in this analysis.

Graph 1

Occupations by AI Exposure*

Four-digit ANZSCO level



* Exposure is measured on a scale from 0 (lowest) to 1 (highest).
Sources: JSA; RBA.

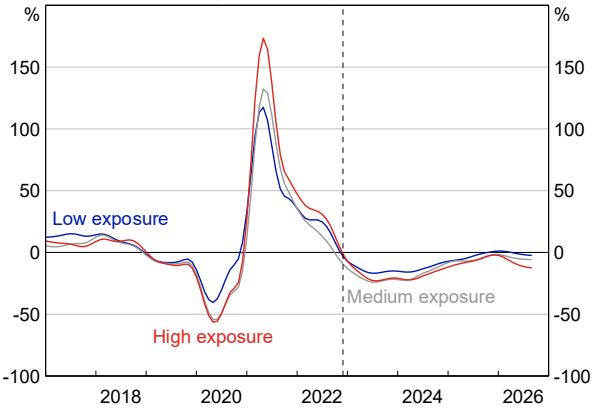
Job advertisements

Job advertisements are useful because they are usually one of the first indicators of shifts in firms' labour demand. JSA and SEEK job ads can be mapped to occupations and therefore exposure groups, allowing labour demand to be compared across jobs with different levels of AI exposure. There is some suggestive evidence in the JSA and SEEK data that the flow of job ads in the most-exposed occupations has slowed a little more than in other occupations (Graphs 2 and 3). The occupations in the most-exposed quintile that contribute most to the decrease in new JSA job ads since November 2022 are general clerks, software and applications programmers, ICT business and systems analysts, call or contact centre workers and receptionists.

Graph 2

SEEK Job Ads by AI Exposure*

Annual growth in new job ads, trend

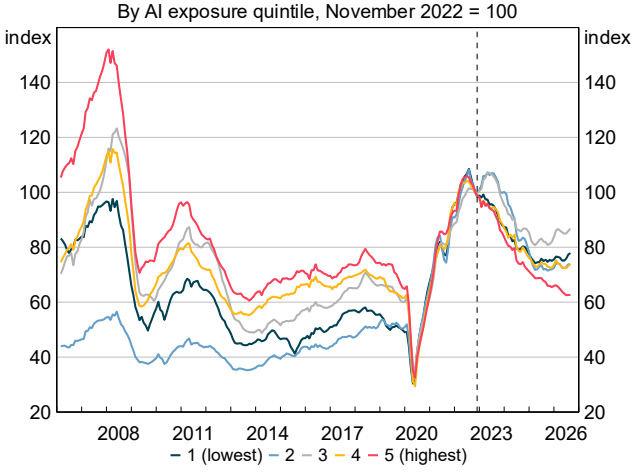


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: RBA; SEEK.

Graph 3

JSA Flow of New Job Ads*

By AI exposure quintile, November 2022 = 100



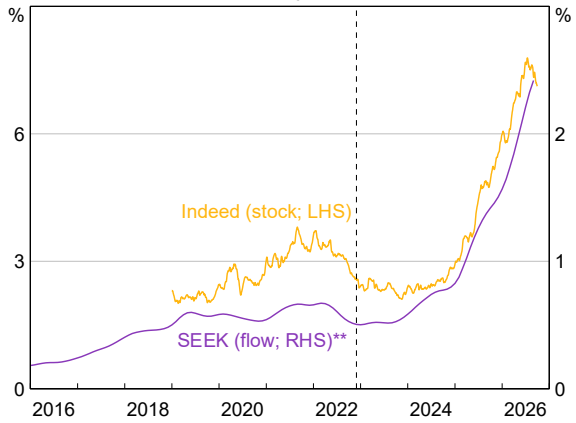
* Dashed line denotes the release of ChatGPT in November 2022.
Sources: JSA; RBA.

SEEK (2026b) and Indeed (Pickering 2026) also provide measures of the share of job ads with AI-related keywords, which have increased rapidly in recent years (Graph 4). These measures suggest rising demand for AI-related skills, but are less informative about whether AI is displacing demand for other types of labour. That said, some of the increase may simply reflect greater use of AI-related terminology in job advertisements rather than genuine changes in skill requirements.

Graph 4

Job Ads Containing AI Terms*

Share of job ads



* Dashed line denotes the release of ChatGPT in November 2022.
** Trend.
Sources: Indeed; RBA; SEEK.

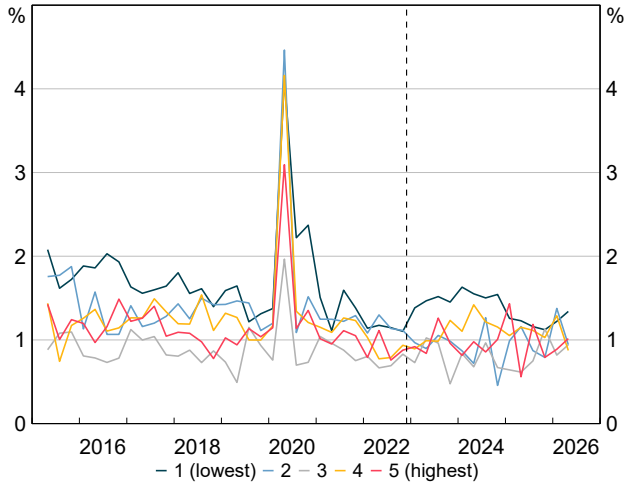
Labour market flows

Labour market flows, such as the job-finding rate, may more quickly identify changes in labour demand than stock measures, such as employment and unemployment (Brynjolfsson *et al* 2026; Maasoum and Lichtinger 2025; Brouillette *et al* 2026). A limitation of these flow measures, however, is that they tend to be volatile. There is little evidence to date of differences in job-finding rates or employment-to-unemployment transition rates across occupations with different AI exposure (Graphs 5 and 6).

Graph 5

Employment-to-Unemployment Transition Rate*

By AI exposure quintile**

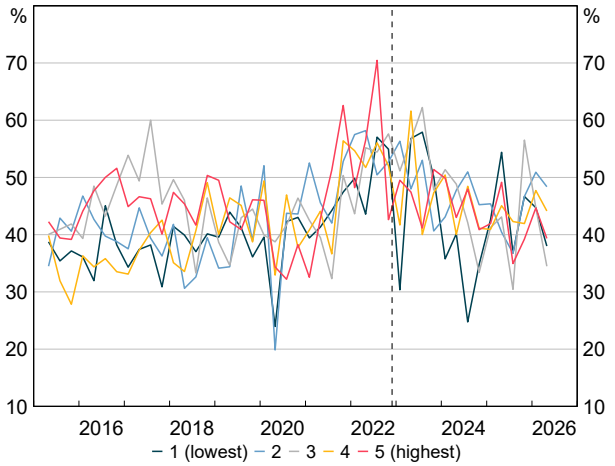


* Share of employed workers who are unemployed in the following quarter.
** Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph 6

Job Finding Rate of Unemployed*

By AI exposure quintile**



* Dashed line denotes the release of ChatGPT in November 2022.
** Share of unemployed who are employed in the following quarter; using subset of unemployed with a previous occupation.
Sources: ABS; JSA; RBA.

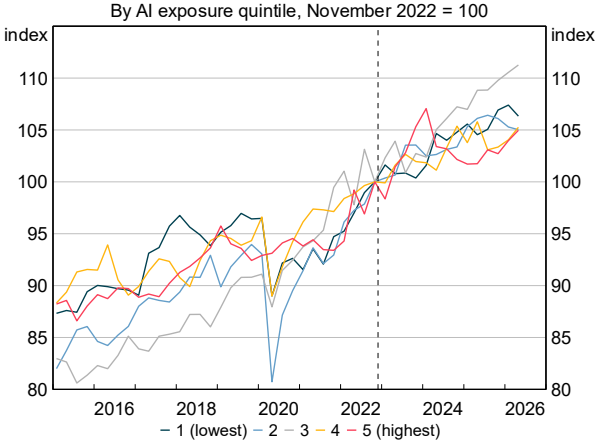
Labour market stocks

Employment growth and total hours worked have been a little weaker in more AI-exposed occupations than in less-exposed occupations over recent years (Graphs 7 and 8). The results are similar when restricting the sample to market-sector occupations, suggesting the strength in non-market employment growth over recent years is not driving the result. The outcomes using the unemployment rate are more tentative, as changes in the unemployment rate can reflect not only shifts in labour demand but also workers' decisions to enter or remain in the labour force.

Graph 7

Employment*

By AI exposure quintile, November 2022 = 100

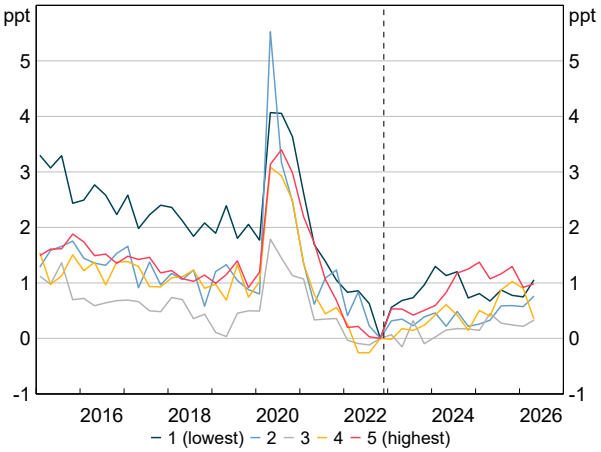


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph 8

Unemployment Rate*

Change relative to November 2022, by AI exposure quintile**



* Using subset of unemployed with a previous occupation.
** Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

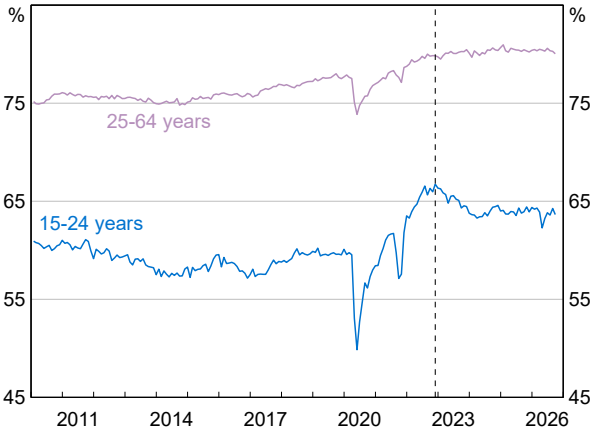
Youth and graduate outcomes

Youth and graduate outcomes may provide an early signal of AI-related adjustment. If firms respond to AI by reducing demand for junior roles, slowing graduate recruitment, or relying less on workers with limited experience, this should be visible in youth outcomes before it is evident in aggregate labour market indicators. Graphs 9–12 suggest softer youth outcomes relative to aggregate outcomes in recent years; however, conditions remain stronger for young workers than prior to the pandemic. Moreover, these measures need to be interpreted cautiously. Youth labour market outcomes are volatile and more cyclical than aggregate series (Dhillon and Cassidy 2018), and the strength in youth employment in 2022 partly reflected the exceptionally tight labour market at that time, as well as the strength in non-market sector employment. Some of the subsequent weakness since 2022 may therefore reflect broader easing in labour market conditions rather than AI adoption.

Graph 9

Employment-to-Population Ratio*

By age group

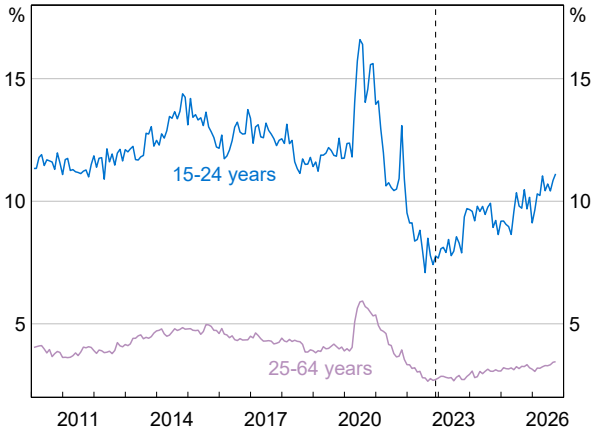


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; RBA.

Graph 10

Unemployment Rate*

By age group

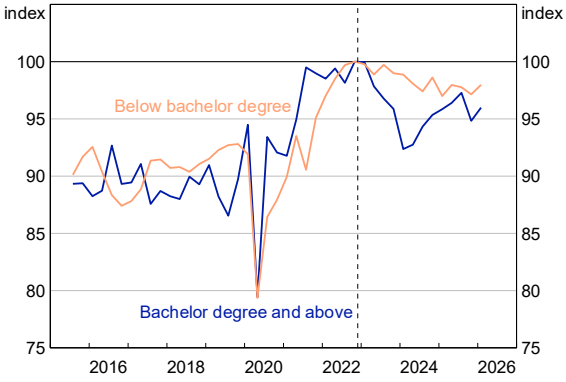


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; RBA.

Graph 11

Employment-to-Population by Education*

20–24-year-olds; November 2022 = 100

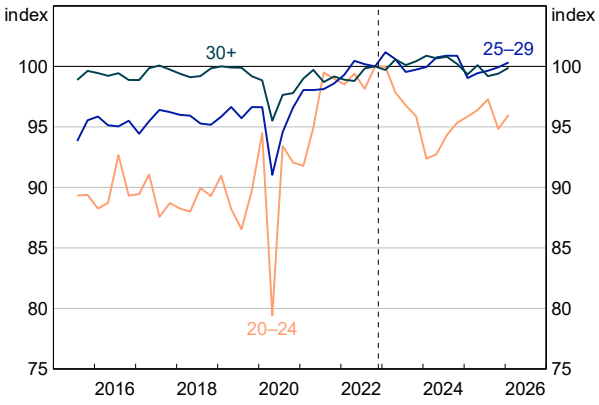


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; RBA.

Graph 12

Employment-to-Population by Age*

Higher education graduates; November 2022 = 100



* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; RBA.

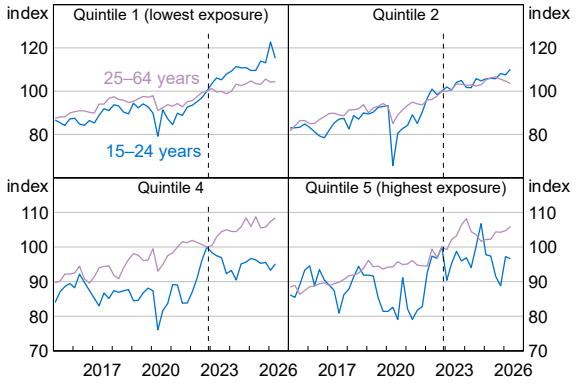
Age and occupation-exposure outcomes

AI-related adjustment may be easier to detect by combining the two monitoring channels: age and occupation-level exposure. The data are volatile, but within the most AI-exposed occupations, younger workers appear to have experienced weaker employment outcomes and larger increases in unemployment than older workers, which is not the case for less AI-exposed occupations (Graphs 13–16). Again, the results are similar when restricting to market-sector occupations.

Graph 13

Employment*

By AI exposure quintile and age, November 2022 = 100

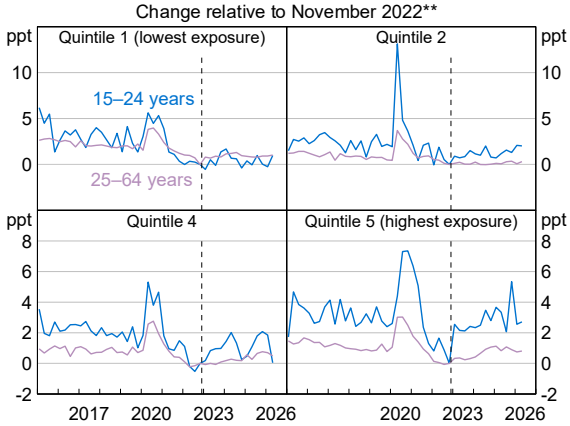


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph 14

Change in Unemployment Rate*

Change relative to November 2022**

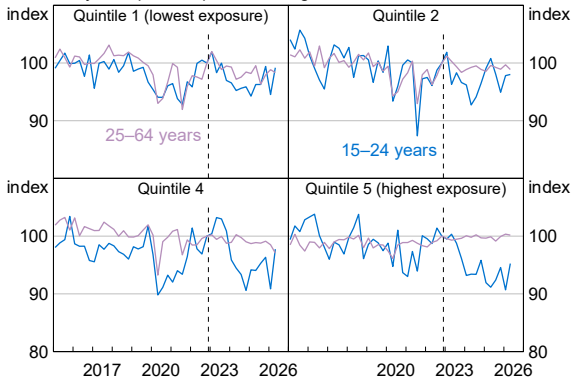


* Using subset of unemployed with a previous occupation.
** Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph 15

Average Hours Per Worker*

By AI exposure quintile and age, November 2022 = 100

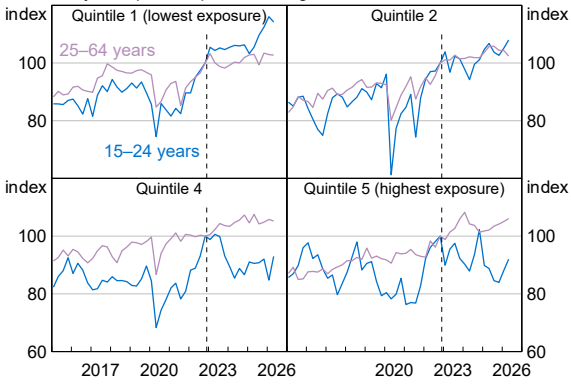


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph 16

Hours Worked*

By AI exposure quintile and age, November 2022 = 100



* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Conclusion

To date, the results point to limited labour market disruption from AI, though there are tentative signs of weaker labour demand and employment outcomes in more AI-exposed occupations, particularly among younger workers. These patterns should not be immediately interpreted as evidence of AI displacement, given exposure measures capture potential rather than realised effects and the same groups may also be affected by other cyclical and structural factors. Moreover, AI may also stimulate demand for some types of work by lowering costs and prices or generating new types of work. Instead, the early signs of labour market adjustment in this note point to areas that the RBA will closely monitor going forward.

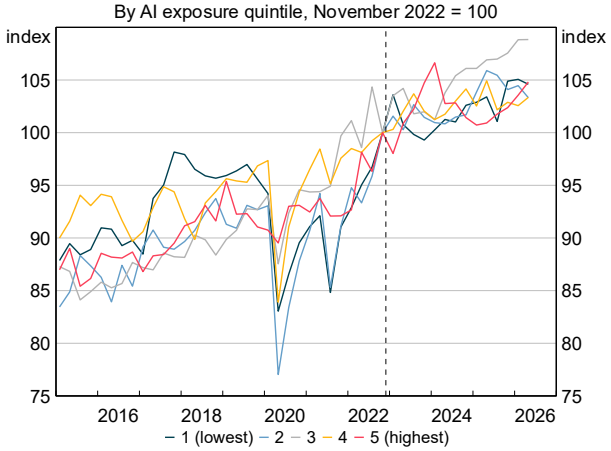
Other indicators can help us understand how AI is affecting labour market outcomes. Adoption evidence is especially important because exposure measures capture potential task impact rather than firms' actual use of AI. Likewise, liaison and external business surveys can more directly indicate whether and how firms are adopting AI and how they are responding (Fernando *et al* 2025). Wages and earnings data could provide additional evidence, though the emerging literature finds limited wage effects so far (Brynjolfsson *et al* 2026; Gross 2026). We will continue to develop our monitoring of the effects of AI on the labour market.

Appendix A: Additional graphs

Graph A.1

Hours Worked

By AI exposure quintile, November 2022 = 100

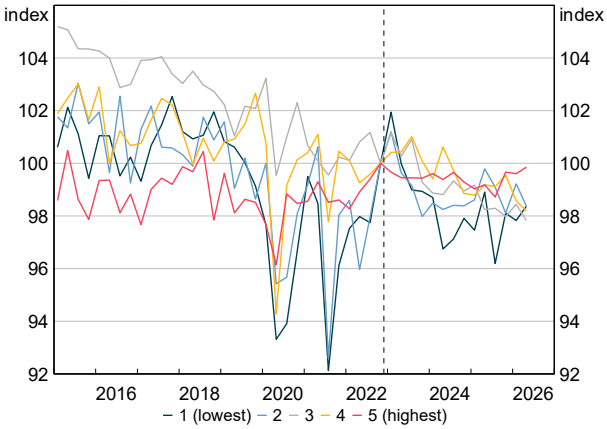


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph A.2

Average Hours Per Worker*

By AI exposure quintile, November 2022 = 100

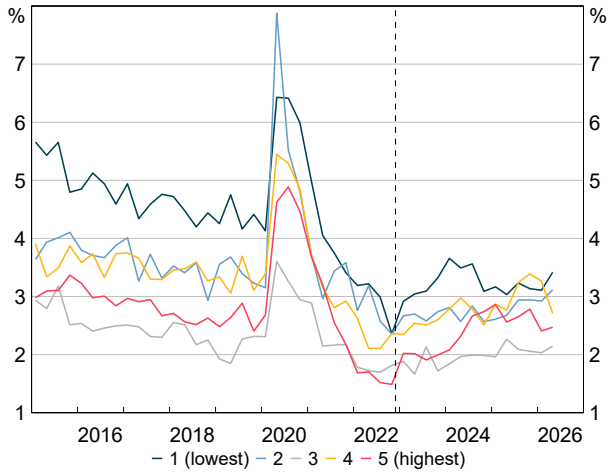


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph A.3

Unemployment Rate*

By AI exposure quintile**

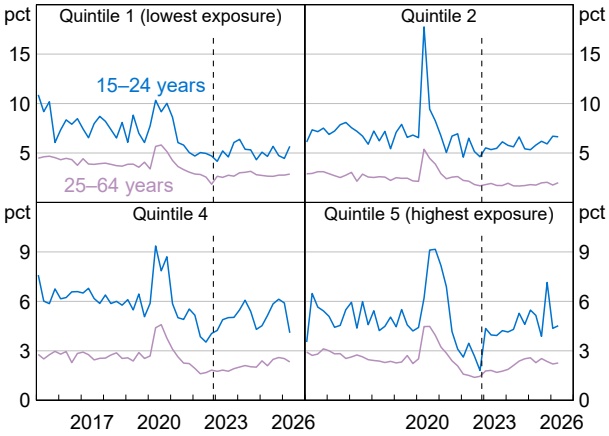


* Using subset of unemployed with a previous occupation.
** Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph A.4

Unemployment Rate*

By AI exposure quintile and age group**

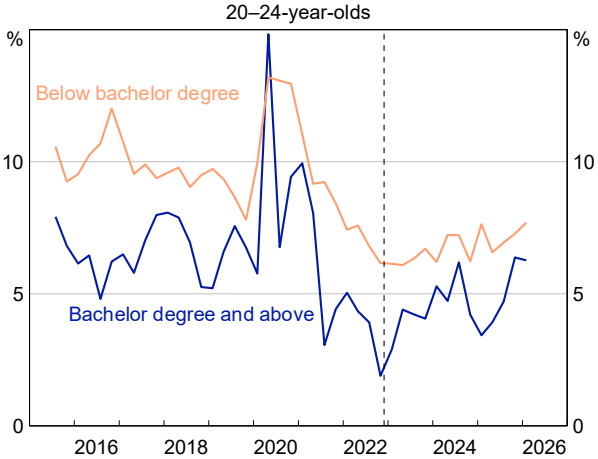


* Using subset of unemployed with a previous occupation.
** Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; JSA; RBA.

Graph A.5

Unemployment Rate by Education*

20–24-year-olds

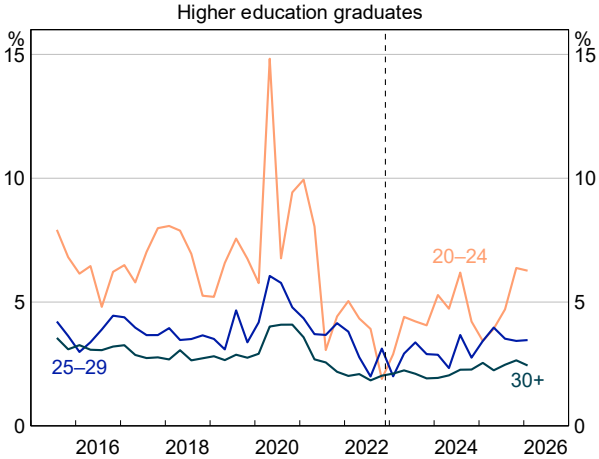


* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; RBA.

Graph A.6

Unemployment Rate by Age*

Higher education graduates



* Dashed line denotes the release of ChatGPT in November 2022.
Sources: ABS; RBA.

References

Abel J, R Deitz, N Emanuel, B Hyman and N Montalbano (2025), 'Are Businesses Scaling Back Hiring Due to AI?', Federal Reserve Bank of New York *Liberty Street Economics*, September.

Acemoglu D, 'The Simple Macroeconomics of AI', *Economic Policy*, 40(211), pp 13–58.

Batten S (2026), 'Is Artificial Intelligence Making Us More Productive? What the UK Industry Data Show', Bank of England *Bank Underground*, August.

Brouillette D, T Dahlhaus and G Galassi (2026), 'Early Signs of AI-driven Adjustments in Canada's Labour Market', Bank of Canada *Sparks at Bank*, August.

Brynjolfsson E, B Chandar and R Chen (2026), 'Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence', Stanford Digital Economy Lab Working Paper, August.

Calvino F, D Haerle and S Liu (2025), 'Is Generative AI a General-purpose Technology? Implications for Productivity and Policy', OECD Artificial Intelligence Paper 40, June.

Del Rio-Chanona RM, E Ernst, R Merola, D Samaan and O Teutloff (2025), 'AI and Jobs – A Review of Theory, Estimates, and Evidence', Working Paper, September.

Department of Employment and Workplace Relations (2026), 'AI and Employment in Australia – Monitoring Framework and Evidence to Date', Report, July.

Dhillon Z and N Cassidy (2018), 'Labour Market Outcomes for Younger People', RBA *Bulletin*, June.

Egan E (2026), 'Generative AI: Degenerative for Jobs?', Bank of England *Bank Underground*, January.

Eloundou T, S Manning, P Mishkin and D Rock (2023), 'GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models', Working Paper, August.

Emanuel N, E Harrington and A Pallais (2026), 'Remote Work Leaves Younger Workers Sidelined', Federal Reserve Bank of New York *Liberty Street Economics*, June.

Felton E, M Raj and R Seamans (2021), 'Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses', *Strategic Management Journal*, 42(12), pp 2195–2217.

Fernando J, K McLoughlin and R Ratnayake (2025), 'Technology Investment and AI: What Are Firms Telling Us?', RBA *Bulletin*, November.

Gmyrek P, J Berg and D Bescond (2023), 'Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality', ILO Working Paper 96, August.

Gmyrek P, J Berg, K Kaminski, F Konopczynski, A Ladna, B Nafradi, K Roslaniec and M Troszynski (2025), 'Generative AI and Jobs: A 2025 Update', ILO Research Brief, May.

Gross Z (2026), 'Kookaburras in the Coal Mine?', *Gross National Product Blog*, 2 June.

Gmyrek P, J Berg and D Bescond (2023), 'Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality', ILO Working Paper 96, August.

Jobs and Skills Australia (2025), 'Our Gen AI Transition – Implications for Work and Skills', Final Overarching Report, August.

Jobs and Skills Australia (2026), 'Pathways to Success – Jobs and Skills', Report, October.

Lambert P and Y Schindler (2026), 'The Broken Ladder: AI, Remote Work, and Early-Career Hiring', University of Warwick Paper, May.

Lane P (2026), 'AI and the Euro Area Economy', Keynote Speech at ECB-SAFE-RCEA International Conference on the Climate-Macro-Finance Interface, Frankfurt, 23 March.

Massoum S and G Lichtinger (2025), 'Generative AI as Seniority-Biased Technological Change: Evidence from U.S. Résumé and Job Posting Data', Wharton Research Paper, September.

Moder I and T Pommer (2026), 'AI and the US Labour Market: Effects on Employment Growth', European Central Bank *Economic Bulletin*, Issue 4/2006.

Pickering C (2026), 'Nothing Artificial About Australian AI Adoption: Business and Government Trends', *Indeed Hiring Lab Insight*, 1 April.

Pizzinelli C, A Panton, M Tavares and M Cazzaniga (2023), 'Labor Market Exposure to AI: Cross-country Differences and Distributional Implications', IMF Working Paper WP/23/216, October.

Schlicht H (2026), 'Canaries in the Column? AI Exposure and the UK's Hiring Slowdown', Bank of England *Bank Underground*, August.

SEEK (2026a), 'AI & Early Careers – How GenAI Is Changing Early-career Hiring in Australia', SEEK *Economist Insight*, September.

SEEK (2026b), 'Employment Report – September'.

Soto P, M Thieu and J Allen (2026), 'The AI Buildout and the Economy: Publicly Available Data to Assess AI's Impact', US Federal Reserve *FEDS Notes*, July.

Endnotes

* I'd like to thank Iris Day, Jonathan Hambur, Kevin Lane, Kate McLoughlin, James Priest and Connor Thrall for their helpful comments.

1 Similar monitoring tools have been introduced in the United States (Soto *et al* 2026; Moder and Pommer 2026; Abel *et al* 2025; Brynjolfsson *et al* 2026), Canada (Brouillette *et al* 2026) and the United Kingdom (Batten 2026; Egan 2026; Schlicht 2026). There is also a rapidly growing literature on the micro effects on AI on work from randomised control trials and field experiments (see Del Rio-Chanona *et al* (2025) for a review).

2 See Felten *et al* (2021); Gmyrek *et al* (2023); Gmyrek *et al* (2025); Eloundou *et al* (2023); and Pizzinelli *et al* (2023).

3 Some estimates of AI effects on the labour market use these exposure-based measures to quantify the number of jobs 'exposed' to AI. These approaches can lead to large estimates of job losses, though often they do not account for possible positive effects of AI.

4 For additional graphs, see Appendix A.

5 The exposure scores are derived from assessments of individual tasks and therefore may not fully capture complementarities between tasks, how tasks are bundled within jobs, or the reallocation of workers to other tasks when some tasks become automated.