AI adoption and firm demand for workers and skills: New insights from Australia

CLAIRE MASON *Data61, Commonwealth Scientific and Industrial Organisation (CSIRO)*
HAOHUI CHEN *Data61, Commonwealth Scientific and Industrial Organisation (CSIRO)*
DAVID EVANS *Data61, Commonwealth Scientific and Industrial Organisation (CSIRO)*

Abstract

The latest Artificial Intelligence (AI) tools can perform some of the complex tasks that highly skilled and well-paid workers perform. In this study, we analyse an Australian dataset of firm job postings to explore the effects of AI adoption on demand for workers and skills. Our findings suggest that AI adoption increases demand for new workers and skills. Both the number of job postings and the number of skills required in job postings grew slightly faster in AI adopting firms than in non-adopting firms, after controlling for firm size, geography and industry. AI exposed occupations did not experience lower demand than non-exposed occupations, unless they were employed in a non-adopting firm. It is not clear whether the stronger demand for new workers in AI adopting firms is due to the need to replace existing workers with new workers (with new skills) or due to growth in the total number of workers. However, our findings counter fears about AI substituting for or deskilling workers and align with the view that the latest AI tools serve to augment, rather than substitute for, human capability.

Keywords: Employment, Labour Demand, Artificial Intelligence, Skills trends

Introduction

As the adoption of Artificial Intelligence (AI) accelerates, so too do concerns about the labour market impacts of AI. Advances in AI in fields such as natural language processing and image recognition mean that AI tools can now perform a range of non-routine cognitive tasks that are normally performed by highly skilled and well-paid workers (Brynjolfsson *et al*., 2017; Felten *et al*., 2019; Tolan *et al*., 2021a; Webb, 2019). These tools are reigniting concerns about loss of jobs (Arntz *et al*., 2016; Chen *et al*., 2022; Priddis *et al*., 2020; White House, 2022) and deskilling of workers (Shiohira, 2021). In this study, we investigate these concerns by comparing workforce and skills trends in firms that have adopted AI and firms that have not. Using a longitudinal job postings data from 4,395 Australian firms, and controlling for differences in firm size, geographic location and industry, we show that firms adopting AI are exhibiting stronger growth in (a) demand for new workers, and (b) demand for skills, than non-adopting firms. In addition, some formerly non-AI occupations in AI adopting firms are transitioning to become AI skilled roles.

AI and the labour market

AI refers to the capability of a system to perform human-like cognitive functions (learning, understanding, reasoning, and interacting) with the aim of obtaining rational outcomes [1, 2]. According to technology-skill complementarity theory, new technologies increase demand for workers whose skills complement the new technology. In the decades between 1980 and 2010, employment growth was concentrated in high-skill roles (Acemoglu and Autor, 2011). Computers and digital technologies made it easy to automate routine cognitive tasks (Autor *et al*., 2003). In line with technology-skill complementary theory, it was the low and middle-skilled workers who performed these routine, cognitive tasks (e.g., clerks, bank tellers, cashiers) who were displaced in earlier waves of automation (Brynjolfsson *et al*., 2018). High-skilled workers had technology-complementary skills (e.g., critical thinking, creativity, manual dexterity and interpersonal skills) that were still needed to perform those tasks that were not yet automatable. For these high-skilled workers, the new technology made them more productive. In addition, the technology created new service delivery opportunities, which in turn required new high-skilled occupations (e.g., software engineers, games developers, digital marketers) to deliver these services.

AI research has progressed to the point where AI tools can perform near to, or better than humans on image recognition, speech recognition, gaming and language translation tasks (Zhang *et al*., 2023). Unlike previous forms of digital technology, AI tools can perform non-routine cognitive tasks, but they still do not match humans in tasks requiring physical ability (Brynjolfsson *et al*., 2018), commonsense reasoning (Davis and Marcus, 2015) and metacognition (Eysenck and Eysenck, 2021; Tolan *et al*., 2021a). Survey data captured by Australia's National AI Centre in 2024 suggests that 35 per cent of large Australian businesses (those with 500 or more employees) have adopted AI (Department of Industry Science and Resources, 2024). The adoption of AI is evident across all industry sectors, although it is more advanced in some sectors (e.g., health, education and manufacturing) than others (e.g., agriculture, forestry and fishing) (Department of Industry Science and Resources, 2024).

To understand how advanced AI tools will affect demand for workers, several groups of researchers have delineated AI capabilities and then investigated which occupations in the labour market traditionally perform tasks that require these capabilities (Brynjolfsson *et al*., 2018; Felten *et al*., 2021, 2018a; Webb, 2019). Occupations that perform tasks that are compatible with current AI capabilities are considered to be more 'exposed' to AI than occupations that perform tasks that AI is not yet capable of performing (Acemoglu *et al*., 2022b). Although their estimates of occupational exposure to AI differ slightly, these researchers all conclude that highly educated and well-paid workers, usually those with high-level cognitive skills (e.g., genetic counsellors, actuaries, teachers, language translators) are most exposed to the latest wave of AI-enabled automation (Brynjolfsson *et al*., 2017; Eloundou *et al*., 2023; Felten *et al*., 2018b; Tolan *et al*., 2021b; Webb, 2019).

Nevertheless, the workforce impacts of AI adoption are difficult to predict because of the uneven rate of development in AI capabilities and the difficulty of unbundling those aspects of a task that an AI can perform from those that still require a human to perform (Brynjolfsson *et al*., 2018). As long as a human is required to perform some aspect of the task, there may be no advantage in using AI to perform the other aspects of the task. Alternatively, if the AI allows the human to work with the AI to perform the task more efficiently, more safely or in a better way, it can be a source of competitive advantage for the firms and workers that use it.

This study investigates whether the adoption of AI has more of a substitution effect (wherein the technology substitutes for the human in performing a task) or more of an augmentation effect (wherein using the technology in a task increases productivity in other tasks, thereby enhancing overall labour productivity) (Loaiza and Rigobon, 2024). One way in which we can answer this question is to monitor how demand for high-skilled workers changes when firms adopt AI. If AI substitutes for workers, demand for workers (especially AI exposed workers) should decline in AI adopting firms relative to non-adopting firms. Alternatively, if AI is being used to augment workers, demand for workers should be as strong, or stronger, in AI adopting firms relative to non-adopting firms.

The skills requirements listed in job postings offer another source of insight into AI's augmentation versus substitution effects. If AI is simply being used to automate some of the tasks that were performed in an exposed occupation, we might see a reduction in skills requirements for the occupation because the worker now only needs to perform those aspects of their work that the AI cannot yet perform. However, if AI is augmenting human worker with its computational power and memory (Loaiza and Rigobon, 2024; Schleiger *et al*., 2024), thereby providing better data or additional insights for humans to draw upon, AI can elevate our human capabilities (Sadiku *et al*., 2021; Yau *et al*., 2021). In this context, AI adoption should enlarge the skills profile of an occupation, since workers remain responsible for their AI-augmented work but now need the skills to work with AI to deliver greater value (Boulus-Rødje *et al.*, 2024; Grimberg and Mason, 2025).

Several studies have already been carried out to investigate the relationship between AI adoption and demand for workers. At the occupational level, researchers report that workers in occupations that are more exposed to the latest advances in AI are experiencing increased demand (Albanesi *et al.*, 2023; Alekseeva *et al.*, 2021; Felten *et al.*, 2019; Green and Lamby, 2023) and even increased wages (Felten *et al.*, 2019; Fossen and Sorgner, 2019). A cross-country study found that demand for highly exposed occupations was only enhanced if workers were in an occupation where computer use is high (Georgieff and Hyee, 2022). However, given that firms adopting AI are still in the minority (Acemoglu *et al.*, 2022a; Borgonovi *et al.*, 2023; Nguyen and Hambur, 2023; Zolas *et al.*, 2020), current trends in demand for AI exposed workers are not likely to reveal the effects of AI unless the analyses focus on AI adopting firms.

Other researchers have investigated workforce impacts of AI by monitoring hiring trends in firms that were recruiting workers with AI relevant skills. Recruitment of workers with AI skills is used as an indicator that a firm is adopting AI. Acemoglu *et al*. (2022b) used job postings to identify firms that were adopting AI and then examined trends in demand for non-AI workers within these firms. They found that after adopting AI, firms posted fewer job advertisements for non-AI workers. Furthermore, when AI adopting firms did advertise roles for non-AI workers, the job postings for AI exposed occupations showed more change in the skills and knowledge sought from these workers.

Babina *et al*. (2024) adopted a slightly different approach, characterising firms according to the proportion of the workforce that were AI skilled. Babina *et al*. found that firms with a high proportion of AI skilled workers showed more growth in employment than firms with a low proportion of AI skilled workers. However, Babina *et al*. did not differentiate between AI skilled and non-AI skilled workers. The positive effects on employment reported by Babina *et al*. may be due to growth in demand for AI skilled workers counterbalancing the negative effects of AI on demand for non-AI workers that were reported by Acemoglu *et al*. (2022b).

Contribution of this study

This study clarifies these conflicting findings. First, we specifically test whether trends in demand for workers and skills differ between AI adopting and non-adopting firms (controlling for firm characteristics such as size, industry and geography). Second, we focus on demand for workers and skills in non-AI skilled occupations, to determine how *existing* occupations are affected by AI adoption. Third, we examine the above effects at the occupational level, so that we can test whether effects of AI adoption on demand for new workers and skills depends on the occupation's AI exposure.

We hypothesised that:

> H1: Firms adopting AI will experience more growth in demand for new workers than non-adopting firms.
>
> H2: Occupations that are more exposed to AI will experience more growth in demand for new workers than occupations that are less exposed to AI
>
> H3: Firms that are adopting AI will experience more growth in demand for skills than firms not adopting AI
>
> H4: The effect of occupational exposure to AI on demand for new workers and skills will be moderated by firms' AI adoption status

Next, the study methodology is described.

Method

Datasets

Job postings

A national database of online job postings was obtained from the labour market platform provider, Adzuna Australia. Adzuna Australia aggregate online job ads from more than a thousand sources in Australia. Their sources include job ads listed directly on the Adzuna Australia platform, ads listed in Australia's major newspapers and cross-postings from other recruitment platforms. The representativeness of the Adzuna Australia job ads has been established through comparison of the geographic and occupational composition of the job ads and the geographic and occupational composition of the Australian labour market reported by the Australian Bureau of Statistics (Evans *et al.*, 2023b). The trends over time in Adzuna Australia online job postings also align with the nationally representative Australian Bureau Statistics (ABS) Job Vacancy Survey (JVS) (Duenser and Mason, 2019). Adzuna Australia's job postings have been used in other studies exploring workforce and skills trends in the Australian labour market (Bratanova *et al.*, 2022; Evans *et al.*, 2024, 2023a; Mason *et al.*, 2023; Zhao *et al.*, 2021) and the coverage of this dataset closely matches the coverage of the Litecast (formerly Burning Glass) job postings (Evans *et al.*, 2023b).

With duplicate job ads (Zhao *et al.*, 2021) and advertisements for unpaid (voluntary) or commission-only roles removed, the Adzuna Australia dataset contained 9,550,441 job postings for the period from 1 January 2016 to 31 December 2023. Employers were identified in job ads using a manually compiled dictionary of 7,372 employer names. This dictionary uses unique text patterns to differentiate the employer name from names of other organisations (or locations) mentioned in job postings that could create false classifications. Using this dictionary, employer names were matched to 25 per cent of the job postings.

The analyses investigating trends in demand for workers and skills are carried out on the subset of job postings that could be matched to an employer. To understand the representativeness of this sample, we compared the geographic, industry and occupation profile of these job postings with the geography, industry and occupational characteristics of the Australian labour force at the time of the 2021 Census. The proportion of workers (according to the 2021 Census (Australian Bureau of Statistics, 2021)) and job postings in each major industry division, major occupation group, and greater capital city statistical area is compared in Table 1, Table 2 and Table 3 respectively. These comparisons reveal that the matched job postings over-represented firms in Transport, Postal and Warehousing and Healthcare and Social Assistance, relative to other industry divisions. From an occupational perspective, machinery operators and drivers and labourers were over-represented. Finally, firms in Sydney and Melbourne were over-represented relative to firms in other locations.

Table 1. Industry profile of job postings compared with 2021 Census employment data

	% of employment (2021 Census)	% of job postings
Agriculture, Forestry and Fishing	2	0
Mining	2	5
Manufacturing	6	3
Electricity, Gas, Water and Waste Services	1	1
Construction	9	3
Wholesale Trade	3	2
Retail Trade	10	9
Accommodation and Food Services	7	5
Transport, Postal and Warehousing	5	15
Information Media and Telecommunications	1	2
Financial and Insurance Services	4	7
Rental, Hiring and Real Estate Services	2	3
Professional, Scientific and Technical Services	8	7
Administrative and Support Services	3	0
Public Administration and Safety	7	8
Education and Training	9	4
Health Care and Social Assistance	15	24
Arts and Recreation Services	2	1
Other Services	4	1

Table 2. Occupation profile of job postings compared with 2021 Census employment data

	% of employment (2021 Census)	% of job postings
Labourers	9	14
Machinery Operators and Drivers	6	33
Sales Workers	8	8
Clerical and Administrative Workers	13	10
Community and Personal Service Workers	12	8
Technicians and Trades Workers	13	8
Professionals	24	16
Managers	14	3

Table 3. Geography of job postings compared with 2021 Census employment data

	% of employment (2021 Census)	% of job postings
Australian Capital Territory	2	3
Rest of NT	0	0
Greater Darwin	1	1
Rest of Tas.	1	0
Greater Hobart	1	0
Rest of WA	2	2
Greater Perth	8	9
Rest of SA	2	1
Greater Adelaide	5	4
Rest of Qld	10	4
Greater Brisbane	10	4
Rest of Vic.	6	3
Greater Melbourne	19	28
Rest of NSW	11	8
Greater Sydney	21	32

AI exposure of occupations

Felten *et al*.'s (2018b) estimates of AI exposure for occupations were used in this study. Felten *et al*. used the Electronic Frontier Foundation (EFF) AI Progress Measurement dataset, which assesses progress in AI in different fields (e.g., image recognition) from blog posts, academic literature and websites. To understand what abilities are used in different occupations, they use the Occupational Information Network (O*NET; National Center for O*NET Development, 2022) database, developed by the US Department of Labour, which identifies 52 distinct abilities, matched to occupations in terms of how important the ability is to the relevant occupation. EFF AI domains were mapped to O*Net abilities to assess the relative effect of advances in AI technology on the different abilities and thus, aggregate across all abilities at the occupation level to create an AI exposure score for each occupation. These occupational exposure scores are available on Github at https://github.com/AIOE-Data/AIOE.

We then translated the AI exposure scores for US Occupations to Australian occupations (ANZSCO four-digit and six-digit codes), using the ANZSCO to International Standard Classification of Occupations (ISCO) and the ISCO to Standard Occupational Classification (SOC) cross-walks to match six-digit ANZSCOs to SOC codes. Due to differences in the granularity of ANZSCO and SOC, some SOC codes map to ANZSCO four-digit codes rather than six-digit codes while others map to ANZSCO four-digit codes. To deal with this inconsistency, AIOE scores for each six-digit ANZSCO were averaged and then assigned to the relevant four-digit ANZSCO code. Using this method, AIOE scores were assigned to 336 of the 358 four-digit ANZSCO occupations. The matches were then reviewed and edited manually, using the SOC and ANZSCO look-up functions, to ensure that matches derived from the cross-walks and aggregation process aligned with similarities in occupation descriptions.

IBISWorld

We also captured firm workforce size data from the IBISWorld Australian Enterprise Profiles database (Australia Enterprise Profiles Report 6287). The IBISWorld Enterprise Wizard provides information on leading Australian and New Zealand enterprises, including ASX and NZX listed companies; public, private and foreign-owned companies; local, state and federal government departments (IBISWorld, 2025). Focusing on the largest 1000 enterprises, we searched for matches between firm names in the IBISWorld list and firm names from the job postings. Matches were confirmed by checking industry classifications (available from both the job postings and the IBISWorld database) were aligned. In those instances where IBISWorld firm statistics had not been updated in 2024, they were excluded from the analyses. Using this method, we were able to obtain workforce size and growth data for 373 of the firms identified from the Adzuna Australia job postings. We compared the profile of firms that were matched to the IBISWorld database on study measures. We found that large enterprises were over-represented in the matched dataset but in terms of industry, geography and AI adoption, the profile of matched firms did not differ significantly from the profile of unmatched firms. To reduce the influence of outliers, the four largest firms were assigned a maximum score that was slightly larger than the fifth largest firm.

Measures

Firm status (AI adopter vs non-adopter)

AI skilled job postings have been used by several researchers to differentiate between firms that are adopting AI and those that are not (Acemoglu *et al.*, 2022b; Alekseeva *et al.*, 2021; Borgonovi *et al.*, 2023; Bratanova *et al.*, 2022). Since the use of AI technology requires specialised skills, demand for AI skills serves as an indicator of firm adoption of AI (Alekseeva *et al.*, 2021). The OECD AI skills dictionary (Borgonovi *et al.*, 2023) was used to identify AI skilled job postings. The great majority of the skills words in this list overlap with the dictionaries used by Acemoglu *et al.* (2022b) and other researchers studying AI adoption and AI skilled workers (Alekseeva *et al.*, 2021; Green and Lamby, 2023). However, the OECD AI skills list is more stringent because it differentiates between generic and specific AI skills. To be identified as an AI skilled job posting, the job posting must contain at least one specific AI skill word (e.g., 'visual image recognition') or two or more generic AI skill words (e.g., 'autonomous driving' and 'artificial intelligence'). However, checks of the data revealed that four of the specific AI skills ('boosting', 'torch', 'screen reader' and 'caffe') were generating a high rate of false positives when used on their own. Consequently, we chose to treat these as generic AI skill words rather than specific AI skill words. If any of a firm's job postings between 2016 and 2019 (T1) included a specific AI skill word or two or more generic AI skill words, the firm was classified as an AI adopter. Otherwise, the firm was classified as a non-adopter.

Firm characteristics (Industry, geography and size)

The industry, geography and size of each firm was also captured from the job postings so that they could be used as control variables. The geographic location of each firm was determined based on the modal location of the jobs being advertised. Location was classified using the ABS Greater Capital City Statistical Area system, which is designed to represent labour markets and the functional area of Australian capital cities (Australian Bureau of Statistics, 2018). Firm size was classified based on the number of job advertisements each firm posted in T1, with firms grouped into deciles[1].

1 In the analyses predicting job postings, the firm size deciles were not included because numbers of job postings (our proxy measure of firm size) were captured in the first step of the analysis.

Demand for workers and skills

To understand the impact of AI on existing occupations, Acemoglu *et al*. (2022b) examined trends in firms' non-AI job postings. That is, they separated out job postings that required AI skills[2]. We adopted the same approach to derive counts of the number of non-AI job postings for each firm in T1 (2016 – 2019) and T2 (2020 – 2023). Due to the high positive skewness of job postings, numbers of non-AI job postings were transformed using the same inverse hyperbolic sine transformation that Acemoglu *et al*. (2022b) used in their analyses.

To capture the number of skills mentioned in each job posting, we used the ESCO skills taxonomy (European Commission, 2019) which contains a dictionary of preferred and alternative labels for more than 13,000 hierarchically organised skills. Job postings were tagged with the relevant Level 2 ESCO skill if they contained the relevant preferred or alternative label. We then calculated the mean number of Level 2 ESCO skills associated with each firm's (or occupation class') job postings in T1 and T2.

Results

Firm adoption of AI

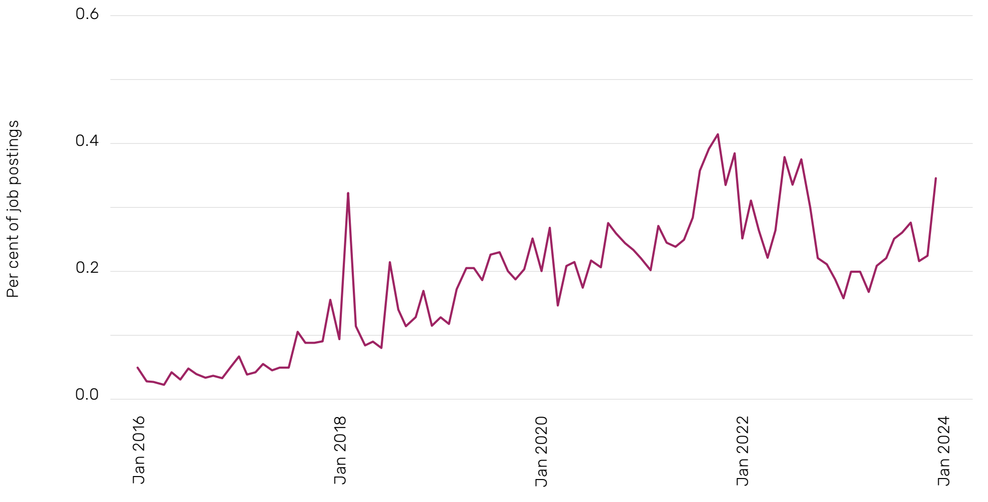
Figure 1 illustrates how the percentage of Australian job postings mentioning AI skills has been changing over time. Between 2016 to 2023, only 0.18 per cent of job postings mentioned AI skills. The OECD published statistics on the proportion of Australian job postings that mentioned AI skills between 2019 and 2022 (Borgonovi *et al*., 2023). When we focus on job postings for the same time period, we find that 0.26 per cent of job postings mentioned AI skills, which is similar to the OECD estimate of 0.30 per cent.

Figure 1 reveals a steady increase in demand for AI skills, despite some short-term fluctuations. Notably, during the period of COVID-19 shut-downs there was an increase in the proportion of AI skilled job postings. There was an additional spike in AI

2 Acemoglu *et al*. (2022b) also excluded firms from the information technology and professional and business services sector (NAICS 51 and 54) on the grounds that these firms were likely to be selling AI products or in the latter case, supporting the integration of AI in production processes. The major industry division ANZSIC classifications for the Adzuna Australia database are less granular so it was not possible to specifically exclude information technology and professional and business services firms. Instead, the analyses were run twice to check that the findings were consistent when all firms from Professional, Scientific and Technical Services major Industry division were excluded from the analysis. Having determined that the findings were consistent, we report the results for all firms.

skilled job postings when the labour market expanded again post-pandemic. It seems that the accelerated digitisation of product and service delivery driven by the pandemic (Calvino *et al*., 2024) heightened demand for AI skilled workers.

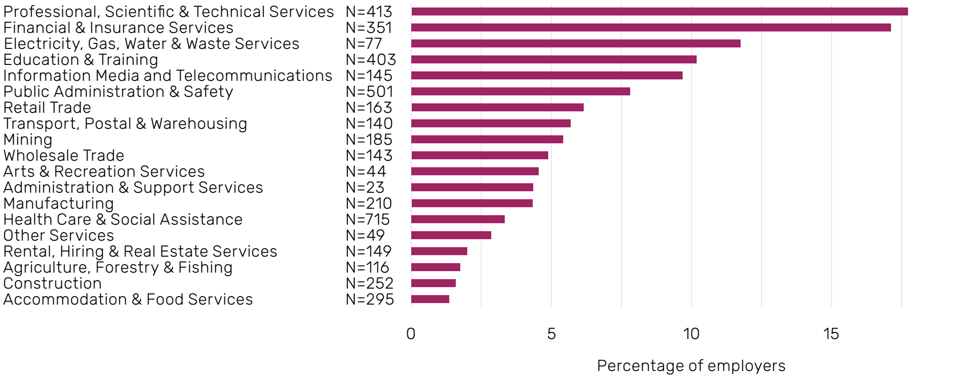
Figure 1. Percentage of job postings requiring AI skills each month (2016 – 2023)

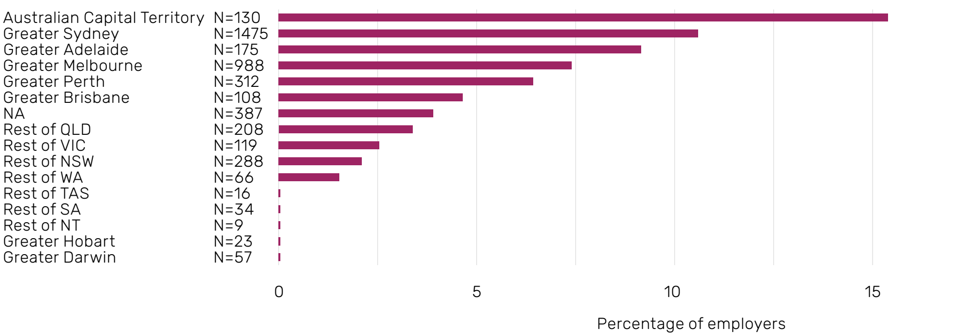


AI skills in job postings were used to differentiate firms that were AI adopters and firms that were not. Firms were categorised as AI adopters if they posted a job ad mentioning one specific or two generic AI skills between 2016 and 2019. Adopting this approach, we identified 322 firms that were adopting AI and 4,073 firms that were not adopting AI at T1.

The observed variability in firm AI adoption across industries and geographies was aligned with previous research. As Figure 2 illustrates, more than 15 per cent of firms in professional, scientific and technical services and financial and insurance services had adopted AI but fewer than 3 per cent of agriculture, forestry and fishing, construction and accommodation and food services firms had adopted AI. These findings are consistent with OCED's cross-country statistics which also found that firms in professional and ICT industries had the most AI skilled job postings and firms in utilities, agriculture, transport, real estate and construction had relatively few AI skilled job postings. The concentration of AI adopting firms in metropolitan regions also aligns with Bratanova *et al*.'s (2022) analysis of Australian AI clusters, which drew upon a wider range of datasets (AI companies, patents and job postings).

Figure 2. Variability in AI adoption by industry and geography at T1 (N denotes the total number of firms represented in the job postings dataset for each industry or geographic location)





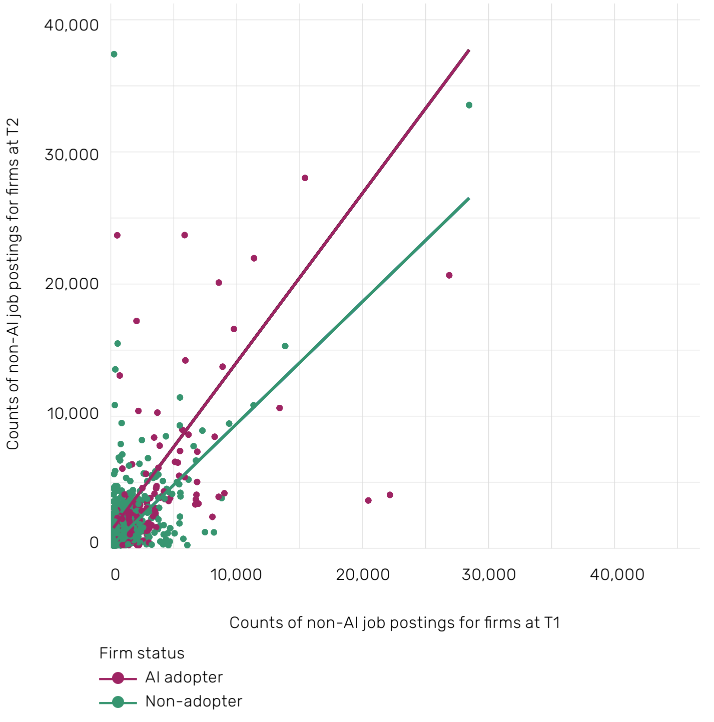
Firm AI adoption and demand for new workers

One of our objectives was to understand whether firms that had adopted AI showed different trends in demand for non-AI workers than firms that had not adopted AI.

To test the effect of AI adoption on demand for non-AI workers, counts of non-AI job postings were captured for firms in both T1 (2016 to 2019) and T2 (2020 to 2023).[3] Figure 3 is based on the counts of job postings for both AI adopting (red) and non-adopting (green) firms at T1 and T2. The steeper regression line for the AI adopting firms reveals that these firms showed a stronger increase in demand for new non-AI workers between T1 and T2.

3 Since the time lag between employer hiring of AI workers and subsequent impacts on demand for non-AI workers is unknown, we tested two alternative timeframes for both T1 (2016-2018 and 2016-2020) and T2 (2019 to 2023 and 2021 to 2023). The findings from these analyses were substantively the same.

Figure 3. Counts of job postings at T1 and T2 within AI adopting and non-adopting firms



The next step was to determine whether the faster growth in demand for new (non-AI) workers in AI adopting firm was statistically significant after controlling for differences in firm geography and industry. The following model was tested:

$$POSTINGS_{i,T2} = \beta_0 + \beta_1 POSTINGS_{i,T2} + \beta_2 Industry_i + \beta_3 Geography_i + \beta_4 AI_i + e_i$$

where:

- $POSTINGS_{i,T2}$ is the (transformed) number of non-AI postings made by firm *i* at T2.
- $POSTINGS_{i,T1}$ is the (transformed) number of postings made by firm *i* at T1.
- AI_i is a binary variable denoting whether firm *i* was an AI adopter (coded 1) or not (coded 0).
- $Industry_i$ is a series of dummy variables denoting the Industry classification (ANZSIC) of firm *i*.
- $Geography_i$ is a series of dummy variables representing firm *i*'s primary geographic location (according to the ABS Greater Capital City Area classification).

- Observations are weighted by the firm's total job postings in T1, meaning that observations from larger firms were given more weight in estimating regression coefficients than were observations from smaller firms (following Acemoglu *et al.*'s (2022b) approach).
- e_i represents unexplained variance in job postings for firm *i* at T2.

In the first step of the analysis, T1 non-AI job postings were entered into the analysis as a predictor of T2 job postings. Controlling for T1 job postings meant that subsequent predictors added to the model were explaining the change in job postings (Cronbach and Furby, 1970; Edwards, 1994). The effects of firm industry and geography were tested in the second step of the analysis. The third step of the analysis was used to test whether the firm's AI adoption status explained change in numbers of job postings made by firms between T1 and T2.

Table 4 shows how the explanatory power of the model improved as additional variables were entered into the analysis. Supporting hypothesis 1, there was a statistically significant ΔR^2 at step 3 when the firm's AI adoption status was entered into the model. The regression weight for the binary variable representing the firm's AI adoption status was β_4 = 36.07 (LLCI = 25.076, ULCI = 47.07). This indicates that non-AI job postings grew 36 per cent faster for AI adopting firms than for non-adopting firms (holding other factors constant).

Table 4. Predicting change in numbers of non-AI postings at the firm level

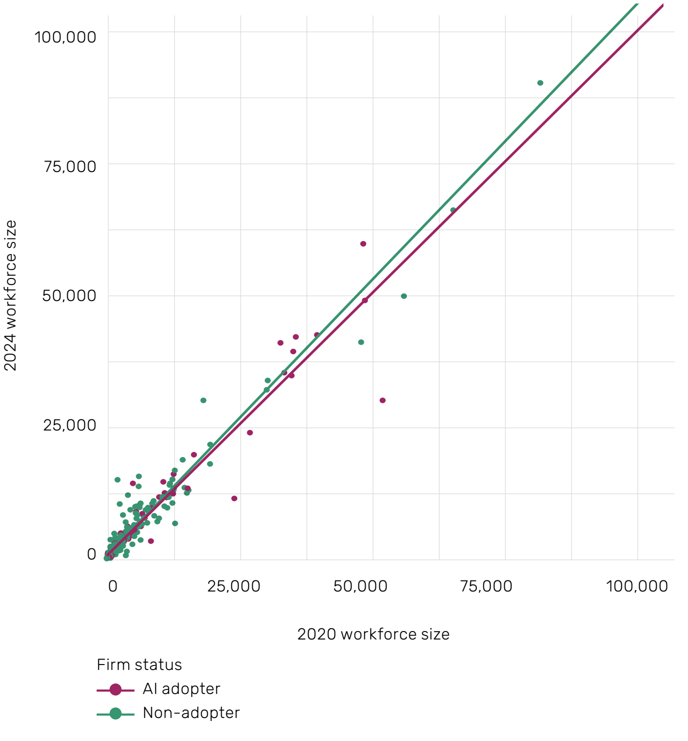
Dependent variable: Firm non-AI postings at T_2			
Predictors in the model	ΔR_{adj}^2	df	F value
Step 1: Firm non-AI postings at T_1	0.52	1,3396	3646.00***
Step 2: + Firm industry, geography and size	0.02	33,3364	8.34***
Step 3: + Firm AI adoption status	0.01	34,3363	41.32***

*** $p < .001$

A limitation of this analysis is the use of job postings as a measure of demand for workers. Job postings reflect demand for *new* workers. If new workers were being recruited to replace existing workers who were being retrenched, the overall size of the workforce might remain unchanged or even decline.

We used the sample of 373 firms that could be matched to an IBISWorld enterprise to investigate whether the faster growth in demand for workers was replicated in the workforce data. This smaller dataset is not representative of Australian employers (it represents the largest Australian enterprises) and the sample was not large enough to allow us to control for the effect of firm industry, geography and size. As Figure 4 reveals, in this sample of large Australian enterprises, AI adopting and non-adopting firms appeared to be growing at the same rate. A regression analysis confirmed that AI adoption did not explain variance in workforce size in 2024 after controlling for workforce size in 2020, β_2 = -200 (LLCI = -866.95, ULCI = 399.27). However, the small and non-representative sample size prevents us from drawing a definitive conclusion from the non-significant result.

Figure 4. Workforce size in 2020 and 2024 for AI adopting and non-adopting firms



Occupational exposure

The job postings also allow us to examine whether hiring trends vary at the occupational-level, due to some occupations being more exposed to AI (H2). In addition, we wanted to investigate whether demand for skills was growing faster in AI exposed occupations (H3) that were employed in AI adopting firms (H4).

Although the goal was to explore trends in job postings and skills requirements for occupations, it was necessary to control for the effects of firm location, industry and size and to test the effect of firm AI adoption. Therefore, the dependent variable was the number of non-AI postings (or the mean skill count for these non-AI postings) at T2 for each occupation class (i.e., for each unique combination of occupation, firm AI adoption status, firm industry, firm geographic location and firm size).

Occupational AI exposure and demand for workers

The following model was used to test whether firm AI adoption and occupational AI exposure explained change in numbers of job postings for each occupation class:

$$O\_POSTINGS_{i,T2} = \beta_0 + \beta_1 O\_POSTINGS_{i,T1} + \beta_2 Industry_i + \beta_3 Geography_i + \beta_4 Size_i + \beta_5 AI_i + \beta_6 AIOE_i + \beta_7 Product_i + e_i$$

where:

- $O\_POSTINGS_{i,T2}$ is the number of non-AI postings for occupation class *i* at T2.
- $O\_POSTINGS_{i,T1}$ is the number of non-AI postings for occupation class *i* at T1.
- $Industry_i$ is a series of dummy variables denoting the Industry classification (ANZSIC major industry division) of the firms employing occupation class *i*.
- $Geography_i$ is a series of dummy variables representing the primary geographic location (Greater Capital City Statistical Area) of the firms employing occupation class *i*.
- $Size_i$ is a series of dummy variables denoting the firm size decile of the firms employing occupation class *i*.
- AI_i is a binary variable denoting the AI adoption status of the firms employing occupation class *i* (coded 1 if the firms were AI adopters and 0 if not).
- $AIOE_i$ is the AI exposure score for occupation class *i*.
- $Product_i$ represents the moderation effect (the product of AI_i and $AIOE_i$).
- Observations are weighted by the firm's total job postings in T1, meaning that observations from larger occupation classes were given more weight in estimating regression coefficients than were observations from smaller occupation classes.
- e_i represents unexplained variance in job postings for occupation class *i* at T2.

The hierarchical approach (controlling for T1 job postings in the first step of the analysis) was used again, so that subsequent predictors were explaining change in job postings for each occupation class.

Table 5 shows how the explanatory power of the model changed as effects were added. AI adoption was added to the model in the third step and explained significant incremental variance (supporting hypothesis one). The measure of AI exposure was added in step four but did not add explanatory power (hypothesis two was not supported). However, hypothesis four was supported. At step 5, the moderation effect added significant (albeit small) explanatory power to the model, $\beta_7 = -6.81$ (LLCI = -9.77, ULCI = -3.85). A simple slopes analysis revealed that there was a negative relationship between occupational AI exposure and growth in job postings in non-adopting firms, slope = −5.12 (t=−5.96, p<.001) but no relationship between AI exposure and growth in job postings in AI adopting firms, slope −0.49 (t=−0.34, p=.74). In other words, the lowest rate of growth in demand for new workers was experienced by AI exposed occupations in non-adopting firms. Among firms not using AI, a one-unit increase in AI exposure is associated with a 5.12 per cent slower rate of growth in job postings for the relevant occupation. Yet in AI adopting firms, the effect of AI exposure on demand for new workers is not significant.

Table 5. Predicting change in non-AI job postings for occupation classes

Dependent variable: Counts of (non-AI) occupational postings at T_2			
Predictors in the model	ΔR_{adj}^2	df	F value
Step 1: Non-AI occupational postings at T_1	0.77	1, 24759	83,000.00***
Step 2: + Firm industry, geography and size	0.03	41, 24718	1102.61***
Step 3: + Firm AI adoption status	0.01	1, 24717	289.42***
Step 4: + Occupational AI exposure	0.00	1, 24716	0.02
Step 5: + AI adoption * AI exposure	0.00	1, 24715	20.36***

*** p < .001

Occupational AI exposure and demand for skills

Our third hypothesis was that skills requirements would be increasing more in AI adopting firms and in our fourth hypothesis we predicted again that the effect of AI exposure on demand for skills would depend on whether the occupation was employed in an AI adopting firm. A second model was used to test these hypotheses. In this model, the dependent variable was the mean number of skills sought in non-AI job postings for an occupation class at T2. As before, the mean number of skills sought in T1 was entered into the analysis at step 1 so that subsequent predictors were explaining growth in skills requirements. The results of these analyses are reported in Table 6.

First, hypothesis three was supported in that AI adopting firms were exhibiting stronger growth in the number of skills required from occupations than were non-adopting firms, β_5 = 0.31 (LLCI = 0.24, ULCI = 0.37). In addition, the effect of AI exposure was significant and demand for skills was growing faster in occupations that were more exposed to AI, β_6 = 0.30 (LLCI = 0.27, ULCI = 0.33). However, the fourth hypothesis was not supported in this instance; the moderation effect was not significant, β_7 = -0.04 (LLCI = -0.02, ULCI = 0.10).

Table 6. Predicting change in skills per non-AI posting for occupation classes

Dependent variable: Mean skills in non-AI postings at T_2			
Predictors in the model	ΔR_{adj}^2	df	F value
Step 1: Skills per non-AI postings at T_1	0.13	1, 24675	3542.00***
Step 2: + Firm industry, geography and size	0.04	41, 24634	27.67***
Step 3: + Firm AI adoption status	0.00	1, 24633	100.66***
Step 4: + Occupational AI exposure	0.02	1, 24632	513.36***
Step 5: + Product (AI adoption * AI exposure)	0.00	1, 24631	1.66

*** $p < .001$

Occupational AI exposure and demand for AI skills

The stronger growth in skills sought in AI adopting firms and AI exposed occupations raises an interesting possibility. One of the new skills that workers in AI adopting firms might need is the ability to work with AI. However, since our methodology excludes job postings that require AI skills, the transition of formerly non-AI occupations into AI-skilled occupations would not be visible in the analyses. Furthermore, by excluding these job postings from our analysis, we could be underestimating the growth in demand for formerly non-AI workers in AI adopting firms.

To explore whether non-AI occupations were evolving to become AI skilled occupations, we revisited the job postings captured from the AI adopting firms, this time counting the number of AI skilled job postings for each occupation class at T1 and T2. As before, the counts of AI skilled job postings were transformed (inverse hyperbolic sine) to reduce the positive skew in the data.

As Table 7 reveals, after controlling for AI skilled job postings at T1 and the effects of industry, geography and firm size, occupational AI exposure was able to explain significant incremental variance in numbers of AI skilled job postings at T2. The regression coefficient for the effect of AI exposure, $\beta_5 = 12.44$ (LLCI = 9.82, ULCI = 15.006), indicates that a difference of one standard deviation in AI exposure was associated with 12.44 per cent more AI skilled postings at T2. That is, occupations were more likely to be transitioning to become AI skilled if they were more exposed to AI. However, although the effect was significant, it was small in magnitude.

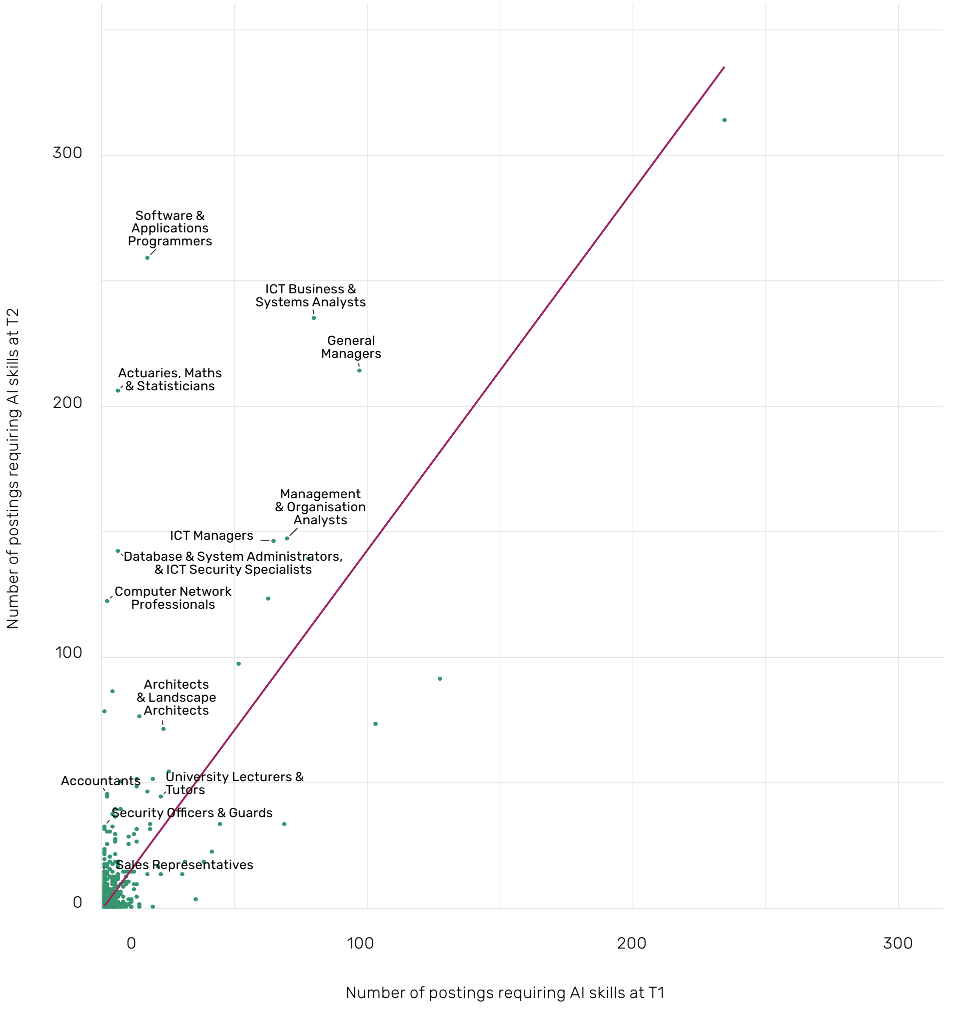
Table 7. Predicting change in numbers of AI skilled job postings for occupation classes in AI adopting firms

Dependent variable: Counts of AI skilled postings at T_2			
Predictors in the model	ΔR_{adj}^2	df	F value
Step1: Occupational AI skilled postings at T_1	0.61	1, 6949	1,0790.00***
Step 2: + Firm industry, geography and size	0.11	36, 6913	79.33***
Step 3: + Occupational AI exposure	0.01	1, 6912	86.79***

*** $p < .001$

For more insight into this AI upskilling trend, the scatterplot in Figure 5 shows how numbers of AI skilled job postings for each occupation class varied between T1 and T2. The steep regression line indicates that numbers of AI skilled job postings were increasing across all occupation classes. Points that land on the y-intercept represent occupations that never required AI skills at T1. Points above the regression line represent occupation classes that were exhibiting faster than average increase in demand for AI skills. Occupation classes that were exhibiting particularly strong AI-upskilling effects have been labelled. Like Alekseeva *et al*. (2021), we find that the trend towards AI upskilling is strongest in IT occupations. Nevertheless, it can be seen in a wide range of occupations, including architects, accountants, sales representatives and security guards.

Figure 5. AI skilled postings at T1 and T2 for occupation classes in AI adopting firms



Discussion

The novel combination of methods used in this study provides a cumulative body of evidence countering concerns about AI being used to substitute for workers and/or deskill jobs. Using longitudinal, national data, we find that firms adopting AI (denoted by the firm posting job advertisements that require AI skills) show slightly faster growth in demand for workers and skills, even after controlling for the effects of firm size, geoography and industry. When we investigated these effects at the occupational level, we found that the number of skills sought in job postings was increasing across the board but it was increasing slightly faster in AI adopting firms and occupations that were exposed to AI. Finally, by analysing demand for AI skills at the occupational level, we discovered that some non-AI skilled occupations were transitioning to become AI skilled workers.

More workers or different workers with more skills?

It is important to acknowledge that higher demand for new workers might not lead to workforce growth. Workforce data was only available for 373 large enterprises and in this sample, AI adoption did not explain rates of growth in the workforce. Given that skills requirements were also increasing faster in AI adopting firms, it is possible that AI adopting firms were posting more jobs advertisements because they they were replacing their existing workers with new workers who had the additional skills required in an AI-augmented workplace. Nevertheless, with job postings and skills requirements increasing slightly faster in AI adopting firms and no evidence that AI adoption was associated with a decline in workforce size, our findings provide confidence that AI is not substituting for or deskilling workers.

Although the effects of AI adoption and AI exposure on existing occupations has been studied before (Acemoglu *et al.*, 2022b; Alekseeva *et al.*, 2021; Felten *et al.*, 2019; Green and Lamby, 2023; Webb, 2019), this study is the first to illustrate that the effect of occupational AI exposure on demand for workers depends on whether or not the relevant occupation is employed in an AI adopting firm. Consequently, our study strengthens the grounds for arguing that it is AI adoption (rather than another factor impacting workers who perform tasks that can now be performed by AI) that underlies the observed effects.

The moderation effect (whereby AI exposure was associated with lower rates of growth but only for workers in non-adopting firms) fits with the notion that advanced AI tools allow AI exposed workers augment their productivity or value add in new ways, providing their firms an advantage in the services and products that these workers help to deliver (Saheb and Saheb, 2023). In non-adopting firms, the same AI exposed occupations are then disadvantaged in their ability to compete for market share relative to their AI-augmented peers, with the result that they experience less growth in job postings. We must acknowledge that these effects, while statistically significant, were weak. Nevertheless, they support the theory that advanced AI tools have more of an augmentation than a substitution effect.

AI adopting firms were not just posting more non-AI job ads, they were also posting job advertisements for AI skilled occupations. Furthermore, some of their AI-exposed but formerly non-AI skilled occupations were transitioning to become AI skilled occupations. The latter effect was slightly stronger in occupations that were exposed to AI, providing further evidence that exposed workers are working with, rather than being displaced by, AI. IT occupations were transitioning fastest, a finding that aligns with global research (Alekseeva *et al.*, 2021; Borgonovi *et al.*, 2023). However, we found several non-IT occupations that were becoming AI skilled. Grinis (2019) argued that the binary classification of occupations into STEM and non-STEM is outdated because STEM skills are now required across a broad range of occupations. The distinction between AI and non-AI workers may also be blurring. Green and Lamby (2023) defined AI workers as those with the skills to develop and maintain AI systems. Our findings reveal that the range of occupations that need to understand and work with AI tools is expanding, encompassing occupations as diverse as security guards, sales representatives and architects.

Limitations

A limitation of this study is the reliance on job postings (and mentions of AI skills in these postings) to determine whether or not a firm is engaging with AI. It may be possible to adopt AI without hiring AI skilled workers if AI development and maintenance is outsourced completely and the use of the AI does not require AI-specific skills. However, the fact that this measure of firm adoption of AI moderated the effect of AI exposure on demand for new workers suggests that this method of differentiating firms that are adopting AI is reasonably effective.

Second, the sample of job postings that could be matched to an employer over-represented some sectors (transport, postal and warehousing, healthcare and social assistance), occupations (machinery operators and drivers and labourers) and locations (Sydney and Melbourne). Since we controlled for the effects of industry, occupation and location in the analyses, this bias in the data should not affect our findings. In addition, firms' geographic location was determined based on where the firm's job postings were located most frequently. In using this approach, we were not able to differentiate between firms that have a national footprint and firms that operating from a single location.

Finally, in adopting Felten *et al.*'s (2018b) AI exposure metrics for the Australian population, we assume that the abilities required in each occupation are the same in the United States and Australia. This assumption is supported by research which found that found that an occupation's exposure to AI varied little, even after taking into account variation in the tasks being performed by workers across different countries (Georgieff and Hyee, 2022). However, our focus on the Australian labour market does limit the generalisability of our findings, since the employment impacts of technology adoption have been found to differ between developed and developing countries (Sharfaei and Bittner, 2024).

Practical implications

Our research suggests that human workers and human skills remain highly sought after in an AI-augmented work environment. Furthermore, the occupations that are most exposed to AI appear to be better off in a firm that adopts AI. The slightly stronger growth in demand for AI exposed workers in AI adopting firms (compared with the same workers in non-adopting firms), along with the significant (albeit small) increase in number of skills required (including AI-related skills) in job postings, align with the argument that more advanced and collaborative AI tools augment (rather than automate) workers (Schleiger *et al*., 2024). The findings validate national policy and investment aimed at educating firms and workers in the effective use of AI (Saheb and Saheb, 2023). Furthermore, our findings reveal key industries (e.g., agriculture, construction, accommodation and food services) and geographic locations (e.g., firms in regional labour markets) that are lagging in terms of AI adoption, offering targets for such efforts.

Directions for further research

Our study focuses on the average effect (across firms) of AI adoption on demand for workers and skills. We note that other researchers have found that the impact of AI adoption in terms of workers' skills depends on the way in which AI is being used (whether to inform a worker's decisions or to direct the worker) and the skill level of the worker (Holm and Lorenz, 2022). Many factors (firm characteristics, type of AI being adopted, type of occupation) could moderate the effects of AI adoption on demand for workers and skills. Elucidating these moderating factors is important, as it may reveal opportunities to strengthen the benefits of AI adoption for both firms and workers.

Finally, we acknowledge that AI adoption is still in its early stages and that workforce impacts may evolve as firms adjust their business processes to the new ways of working that the AI enables (Borgonovi *et al*., 2023). Understanding how ongoing developments in AI systems and business processes are affecting demand for workers and skills requires ongoing research effort.

Conclusion

Although AI tools can now perform some tasks that were traditionally performed by workers in high-skilled and well-paid occupations, our findings counter concerns that they will substitute for workers in AI exposed occupations. We found that AI adopting firms were experiencing slightly stronger growth in job postings than non-adopting firms of the same size, location and industry. In addition, the number of skills required in job postings was increasing slightly faster in AI adopting firms than in non-adopting firms. We conclude that workers who have the skills to use and complement AI remain sought after in an AI-augmented workforce.

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