Research Article

AI Adoption and Firm Demand for Workers and Skills: Insights from Online Job Postings

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The latest Artificial Intelligence (AI) tools can perform some of the complex tasks that highly skilled and well-paid workers perform. To investigate their effects on demand for workers and skills, we compared hiring trends in Australian firms that were adopting AI and those that were not. Job postings grew significantly faster in firms that had adopted AI, even after controlling for firm size, geography and industry. This accelerated growth in job postings included occupations that were highly exposed to AI. The number of skills sought in job postings was also growing faster for AI exposed occupations, especially if they were being recruited by AI adopting firms. Some formerly non-AI skilled roles were transitioning to become AI skilled roles. These findings suggest that AI tools are now being used to augment rather than replace workers and that efforts to promote AI adoption and upskilling benefit both workers and firms.

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1. Introduction

As the adoption of 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 were traditionally performed by highly skilled and well-paid workers[1][2][3][4]. These tools are reigniting concerns about loss of jobs[5][6][7][8] and deskilling of workers[9]. In this study, we investigate whether these concerns are warranted by comparing workforce and skills trends in firms that have adopted AI and firms that have not. Using a

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longitudinal data from 3,539 Australian firms, and controlling for differences in firm size, geographic location and industry, we show that firms that are adopting AI show stronger growth in demand for new workers and demand for skills than do non-adopting firms. Even occupations that highly exposed to the latest AI technology are experiencing sustained demand and faster upskilling when they are employed in AI adopting firms.

1.1. Developments in AI

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]. AI now performs near to or better than humans on image recognition, speech recognition, gaming and language translation tasks[10]. In contrast, there has been little progress in AI applications with physical and psychomotor abilities such as social interaction and metacognition[4]. Several groups of researchers have delineated these new AI capabilities and then investigated which occupations in the labour market traditionally perform tasks that require these abilities. Although their estimates of occupational exposure to AI differ slightly, they 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 this new wave of AI-enabled automation[1][3][11][12][13].

1.2. AI and the labour market

AI adoption can affect demand for workers in a variety of ways. On the one hand, by automating some of the tasks that highly educated workers traditionally perform, AI could reduce demand for these workers and/or the earnings that they can attract[14]. On the other hand, by lowering the cost of production, the adoption of AI could strengthen consumer demand and in consequence, increase demand for workers who perform the tasks that are not automated. The adoption of AI can also have a positive impact on demand for workers by enabling new services and products to be delivered that require human input. In this way, previous waves of technology development have led to the emergence of new occupations[15] and (alongside decline in some occupations) growth in the labour market overall[16][17].

As well as creating new occupations, AI can change the skills profile of existing occupations. In the decades between 1980 and 2010, employment growth was concentrated in high-skill roles[18]. Arguably this trend will continue because highly skilled workers will be needed to match and complement the new standards of output that the technology enables. However, new evidence suggests that the latest AI tools might allow lower-ability workers to achieve standards of performance that formerly were only achieved by higher-ability workers. Workers who were previously less competent at the tasks that generative AI tools support are experiencing the greatest gains in productivity and quality from using these tools[19][20][21][22]. Brynjolfssen et al.[23] explain this 'skills-leveling' effect by arguing that generative AI tools capture and disseminate the patterns of behaviour that characterize the most productive workers, thus allowing more workers to achieve the same levels of productivity. These early findings suggest that more advanced AI tools could create more productivity benefits for low and middle-skilled workers.

On the other hand, reliance on advanced AI tools could lead to workers becoming less skilled[24][25]. When AI is used to automate tasks that previously required a high level of expertise and knowledge, workers may lose this expertise and knowledge. Over-reliance on AI to generate ideas and content might eventually weaken human creativity and critical thinking skills[25][26][27]. It is therefore important to understand not just how the adoption of AI affects demand for workers but also whether the range of skills sought from workers is narrowing or enlarging.

Several studies have already been carried out to investigate how adoption of these more advanced AI tools is affecting 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[2][28][29][30] and even increased wages[2][31]. 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[32]. However, given that firms adopting AI are still in the minority[33][34][35][36], current trends in demand for workers do not tell us how the adoption of AI will affect exposed occupations.

Other researchers have investigated workforce impacts of AI by monitoring hiring trends in firms that were recruiting workers with AI-relevant skills. Analysing job postings from January 2014 to June 2019, Bessen et al.,[37] used a spike in hiring for software developers to infer when a firm was investing in technology such as AI. They found that, after hiring more software developers, the job ads posted by the firm showed an increase in the mean number of skills requested and wages offered. In addition, the types of roles being advertised shifted towards occupations that required college degrees and cognitive skills (whether routine or non-routine). Acemoglu et al.[38] also used job postings to identify firms that were adopting AI and then examined trends in demand for non-AI workers within

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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. Their research suggests that AI adoption reduces demand for workers who do not have AI skills and requires them to acquire new skills. However, Acemoglu et al. and Bessen et al. only examined changes in hiring patterns in firms adopting AI or other automation technologies. They did not compare hiring trends over the same period for non-adopting firms.

Babina et al.[39] adopted a slightly different approach, characterizing 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, like Bessen et al., Babina et al. did not differentiate between AI skilled and non-AI skilled workers. The positive effects on employment reported by Bessen et al. and Babina et al. may be due to growth in demand for AI-skilled workers, masking the negative effects of AI on demand for non-AI workers that were reported by Acemoglu et al.

1.3. Contribution of this study

This study helps to clarify 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. Finally, we provide more up-to-date information about the effects of AI adoption. Earlier AI tools were only capable of performing routine and rule-based tasks. More advanced capabilities (such as the ability to perform non-routine, cognitive tasks) became possible through advances in AI research occurring since 2010 or thereabouts[40][41]. Therefore, earlier studies of AI adopting firms (especially studies with a longitudinal design spanning several years) may well reflect workforce impacts associated with less advanced AI tools. Examining the effects of AI adoption with more up-to-date data increases the likelihood that AI adopting firms in the dataset were using advanced AI tools.

We hypothesized that:

- H1: Firms adopting AI will experience greater change in demand for new workers than non-adopting firms.

- H2: Occupations that are more exposed to AI will experience greater change in demand for new workers than occupations that are less exposed to AI
- H3: Occupations that are more exposed to AI will experience greater change in demand for skills than occupations that are less exposed to AI
- H4: The effect of occupational exposure to AI on demand for new workers and skills will differ between AI adopting and non-adopting firms.

Figure 1 illustrates the study design and the effects observed in the data schematically. In this figure, each bubble represents a job posting from one of two groups of firms. Differences in the size, geographic location and industry of the firms are controlled for. However, firms in group A (represented by the dark blue and light blue job postings) posted some job advertisements at T1 (between 2016 and 2019) that required AI skills. Blue job postings are therefore posted by AI adopting firms. Firms in group B (represented by the dark red and light red job postings) did not post any AI skilled job postings between 2016 and 2019 and they are classified as non-adopters.

Since each job posting is for a specific occupation, it is assigned an AI exposure score (based on Felten et al.'s[42] estimates). Job postings that are positioned higher on the y axis are for occupations that are highly exposed to AI (because AI tools have at least some of the abilities required in these occupations). Job postings that are low on the y axis are less exposed to AI. The x axis represents the date when the job advertisement was posted. Job advertisements that were posted between 2016 and 2019 are aggregated to provide counts of job ads (and skills mentioned in job ads) for T1. Similarly, job advertisements posted between 2020 and 2023 are aggregated to provide T2 measures of job postings and skills counts.

The primary focus of this study are the non-AI skilled (dark blue or dark red) job postings for each firm at both T1 and T2. As the figure illustrates, both AI adopting and non-adopting firms posted more job advertisements at T2 than in T1. However, growth in demand for new workers was stronger amongst the AI adopting firms. In non-adopting firms, highly exposed occupations experienced weaker growth in job postings but in AI adopting firms, highly exposed occupations did not experience a decline in demand. Instead, in AI adopting firms, job postings for highly exposed occupations were requiring more skills, with some formerly non-AI occupations transitioning to become AI-skilled occupations.

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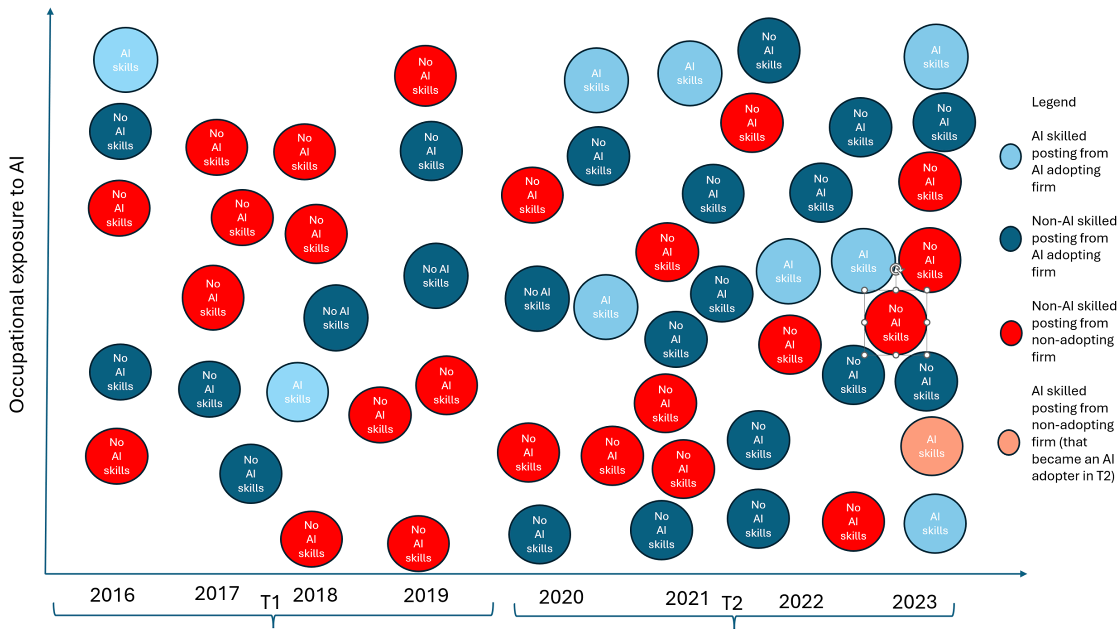

Figure 1. *Visual representation of the study design and findings*

In summary, firms adopting AI were exhibiting faster growth in demand for new workers and (unlike non-adopting firms) this growth in demand was equally strong for AI exposed occupations as it was for less AI exposed occupations. However, job postings for AI exposed occupations in AI adopting firms were showing faster than average skills growth, perhaps because new skills are required to work with and add value to the AI.

In the next section, we describe the study method in more detail.

2. Method

2.1. Datasets

2.1.1. Job postings

The 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

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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[43]. The trends over time in Adzuna Australia online job postings also align with the nationally representative Australian Bureau Statistics (ABS) Job Vacancy Survey (JVS)[44]. Adzuna Australia's job postings have been used in other studies exploring workforce and skills trends in the Australian labour market[45][46][47][48][49] and the coverage of this dataset closely matches the coverage of the Lightcast (formerly Burning Glass) job postings[43].

With duplicate job ads[48]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 4,861 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 22% of the job postings in the Adzuna Australia database.

2.1.2. *AI exposure of occupations*

Felten et al.'s[11] 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[50].) 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 fur-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.

2.2. Measures

2.2.1. 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[30][36][38][49]. Since the use of AI technology requires specialised skills, demand for AI skills serves as an indicator of firm adoption of AI[30]. The OECD AI skills dictionary[36] 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.[38] and other researchers studying AI adoption and AI-skilled workers[29][30]. However, the OECD AI skills list is more stringent because it differentiates between generic and specific AI skills. An AI-skilled job posting was defined as containing 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 three 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.

2.2.2. 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[51]. Firm size was classified based on the number of job advertisements each firm posted in T1, with firms grouped into deciles[1].

2.2.3. Demand for workers and skills

To understand the impact of AI on existing occupations, Acemoglu et al.[38] examined trends in firms' non-AI job postings. That is, they excluded 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.[38] used in their analyses.

To capture the number of skills mentioned in each job posting we used the ESCO skills taxonomy[52] which contains a dictionary of preferred and alternative labels for more than 13,000 hierarchically organized 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.

3. Results

3.1. Firm adoption of AI

Figure 2 illustrates how the percentage of Australian job postings mentioning AI skills has been changing over time. Between 2016 to 2023, only 0.18% of job postings mentioned AI skills. This figure is lower than the statistics for Australia (which hover around 0.30%) published by the OECD[36]. Our lower estimates reflect the longer timeline (demand for AI has been increasing over time) and the fact that we treated some of the OECD 'specific' AI skill words (specifically "boosting", "torch", "screen reader" and "caffe") as 'generic' AI skill words because they were generating a high number of false positives.

There has been 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-skilled job postings when the labour market expanded again post-pandemic. It seems that the accelerated digitization of product and service delivery driven by the pandemic[53] heightened demand for AI skilled workers.

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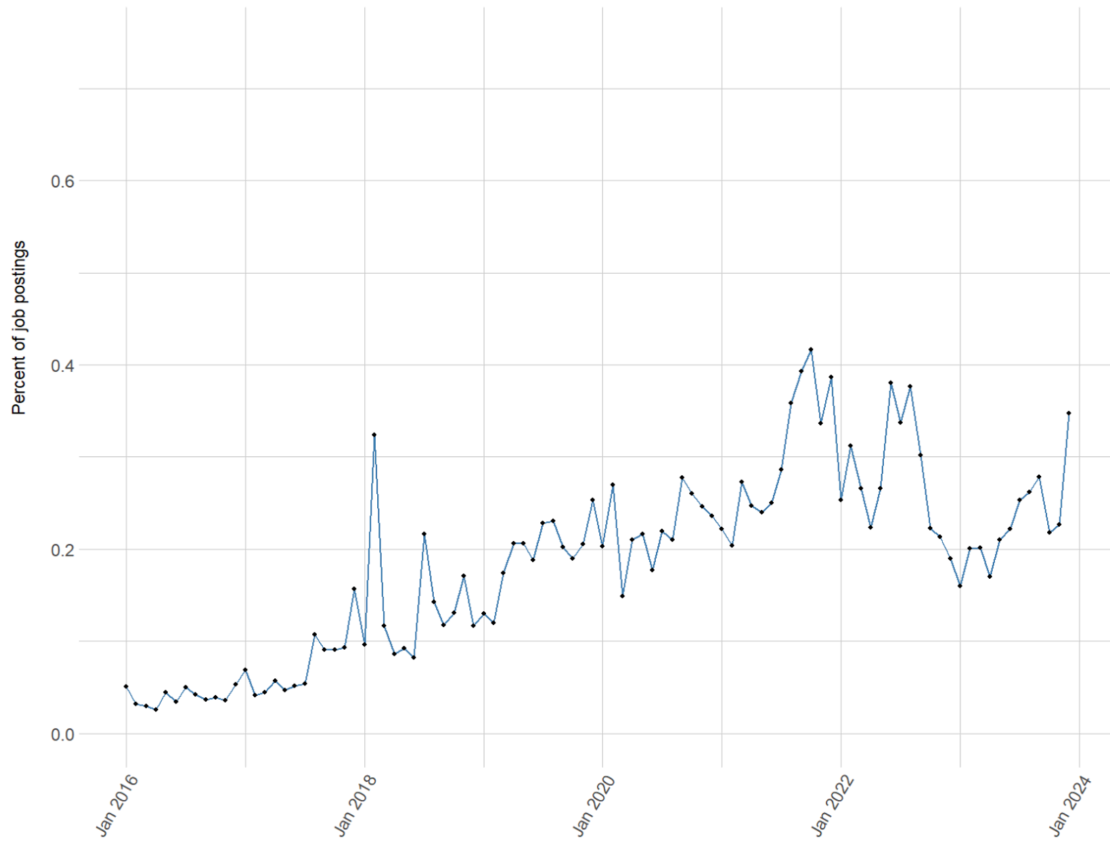

Figure 2. *Percent of job postings requiring AI skills each month (2016 – 2023)*

AI skills in job postings were used to differentiate firms that were AI adopters and firms that were not. Firms were categorized 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 258 firms that were adopting AI and 3,281 firms that were not adopting AI at T1.

The observed variability in firm AI adoption across industries and geographies aligns with previous research. As Figure 3 illustrates, more than 15% of firms in professional, scientific and technical services or financial and insurance services had adopted AI but fewer than 2% of construction firms had adopted AI. These findings align 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

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al.'s[49] analysis of Australian AI clusters, which drew upon a wider range of datasets (AI companies, patents and job postings).

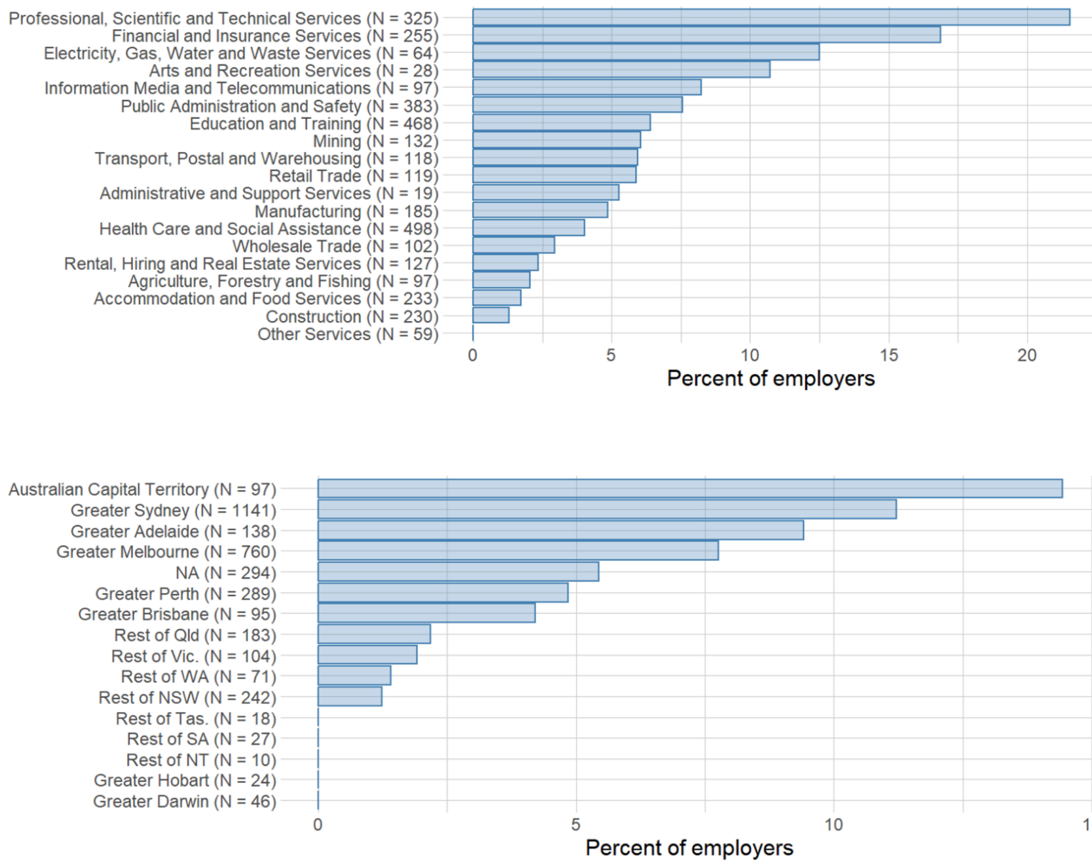

Figure 3. *Variability in AI adoption by industry and geography at T1 (N denotes the total number of firms represented in the job postings dataset for each industry or geographic location).*

3.1.1. Firm AI adoption and demand for new workers

One of the research 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 4 is based on the counts of job postings for both AI adopting (black) and non-adopting (blue) 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.

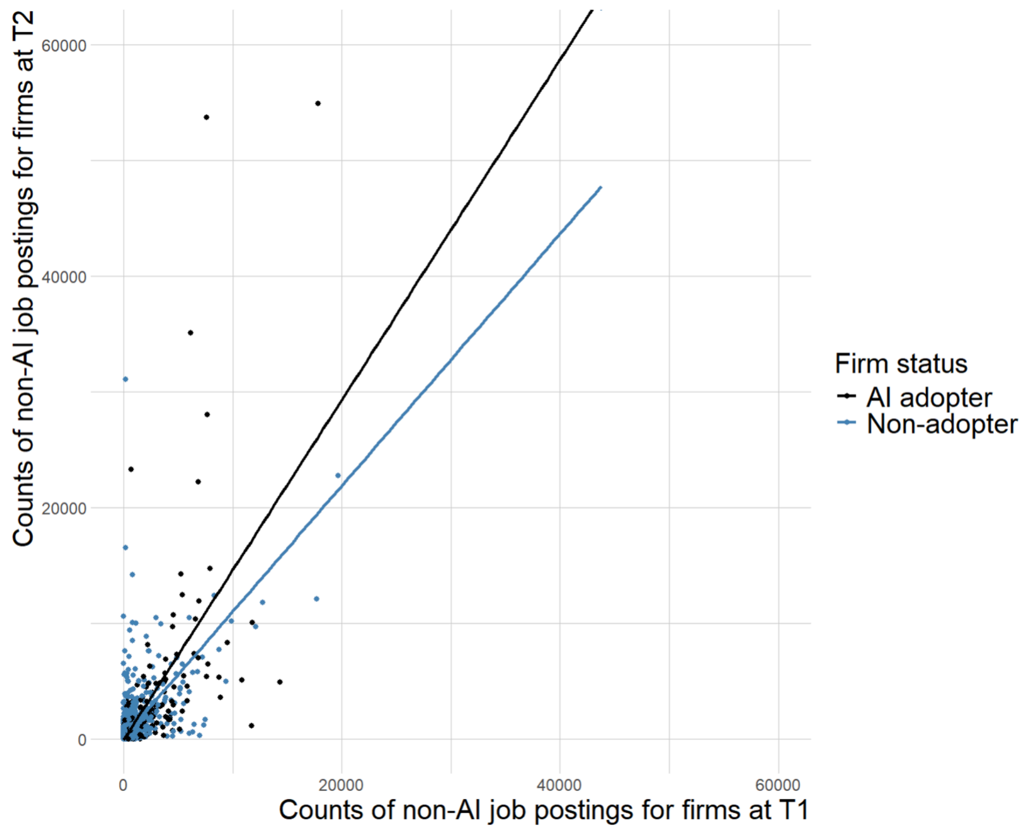

Figure 4. *Counts of job postings at T1 and T2 within AI adopting and non-adopting firms*

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:

$$\text{POSTINGS}_{i,T2} = \beta_0 + \beta_1\text{POSTINGS}_{i,T1} + \beta_2\text{Industry}_i + \beta_3\text{Geography}_i + \beta_4\text{AI}_i + e_i$$

where:

- $\text{POSTINGS}_{i,T2}$ is the (transformed) number of non-AI postings made by firm *i* at *T2*.
- $\text{POSTINGS}_{i,T1}$ 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)

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- 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 (in line with Acemoglu et al.'s[38] analyses).
- 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[54][55]. 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 1 shows how the explanatory power of the model improved as additional variables were entered into the analysis. Supporting hypothesis 1, there was a 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 = 24.41 (LLCI = 14.01, ULCI = 34.81). This indicates that non-AI job postings grew 24% faster for AI-adopting firms than for non-adopting firms (holding other factors constant).

Dependent variable: Firm non-AI postings at T2			
Predictors in the model	**ΔR_{adj}^2**	**df**	**F value**
Step1: Firm non-AI postings at T1	0.60	1, 2744	4128.00^{***}
Step 2: + Firm industry, geography and size	0.03	32, 2712	9.00^{***}
Step 3: + Firm AI adoption status	0.01	1, 2711	21.18^{***}

Table 1. *Predicting change in numbers of non-AI postings*

*** *p <.001*

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3.2. Occupational exposure

At the firm level, AI adoption was associated with stronger growth in demand for new workers. The next step was to investigate whether this effect differed for occupations that were more exposed to AI (H2). In addition, we wanted to investigate whether demand for skills was growing faster (or more slowly) 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). In total, 37,304 occupation classes were identified in the dataset.

3.2.1. Occupational AI exposure and demand for workers

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

$O\_POSTINGS_{,T2} = \beta_0 + \beta_{10} O\_POSTINGS_{i,T1} + \beta_2 Industry_i + \beta_3 Geography_i + \beta_4 Size_i + \beta_5 AI_i + \beta_6 AIOE_i + \beta_7 Product_i + e_i$

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) of the firms employing occupation class *i.*
- $Geography_i$ is a series of dummy variables representing the primary geographic location (Greater Capital City 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 $AIOE_i$).

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- 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 *T*2.

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. Occupational AI exposure was added to the model in the fourth step of the analysis and it significantly improved model fit, supporting Hypothesis 2 (see Table 2). Occupations that were more exposed to AI experienced weaker growth in job postings, β_6 = -4.62 (LLCI = -6.28, ULCI = -2.96). However, the moderation effect was also significant, β_7 = 3.59 (LLCI = 0.84, ULCI = 6.33). Figure 5 illustrates how the effect of AI exposure on occupational job postings varied. It reveals that the decline in demand for more AI exposed workers was largely confined to non-adopting firms.

The very low (but statistically significant) ΔR_{adj}^2 associated with these predictors is still practically significant because effects for occupation classes apply to multiple job postings (on average, there were 34 non-AI job postings for each occupation class at T1 and 65 at T2). The regression coefficients indicate that an occupation class that is a standard deviation above the mean for AI exposure would experience 4.62% fewer job postings than an occupation class with average AI exposure (when all other factors were held constant). However, if that occupation class was employed in an AI-adopting firm, the decline in job postings would be mitigated by 3.59%.

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Dependent variable: Counts of (non-AI) occupational postings at T_2			
Predictors in the model	**ΔR_{adj}^2**	**df**	**F value**
Step1: Non-AI occupational postings at T_1	0.82	1, 23692	111,300.00***
Step 2: + Firm industry, geography and size	0.03	41, 23651	115.27***
Step 3: + Firm AI adoption status	0.00	1, 23650	235.71***
Step 4: + Occupational AI exposure	0.02	1, 23649	23.39***
Step 5: + AI adoption * AI exposure	0.00	1, 23648	6.57*

Table 2. *Predicting change in non-AI job postings for occupation classes*

*** *p <.001*

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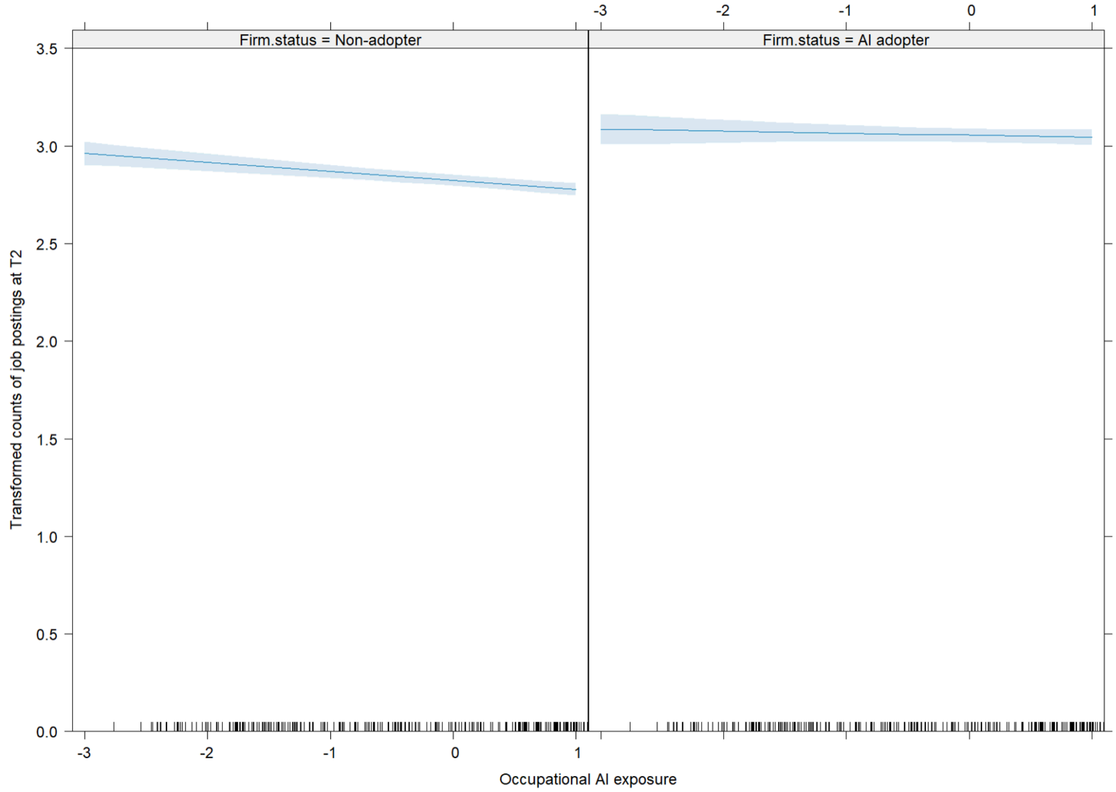

Figure 5. *The moderating effect of AI adoption on the relationship between AI exposure and changing demand for new workers*

3.2.2. Occupational AI exposure and demand for skills

A second model was used to test whether firm adoption of AI and occupational exposure to AI was related to changes in demand for skills. In this model, the dependent variable was the mean number of skills sought in non-AI job postings for an occupation class at T2 and the mean number of skills sought in T1 was entered into the analysis at step 1. The results of these analyses are reported in Table 3.

The analysis supported hypothesis 3. AI adopting firms were exhibiting stronger growth in the number of skills required from occupations, β_5 = 0.14 (LLCI = 0.07, ULCI = 0.21) than were non-adopting firms. In addition, hypothesis 4 was supported. Demand for skills was growing faster in occupations that were more exposed to AI, β_6 = 0.26 (LLCI = 0.23, ULCI = 0.29). However, the hypothesized moderation effect (H5) was also significant. The effect of AI occupational exposure was moderated by firm AI adoption, β_7 = 0.07 (LLCI = 0.01, ULCI = 0.13). If the occupation was being

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advertised by an AI adopting firm rather than a non-adopting firm, there was a further 0.07% increase in the mean number of skills sought in job postings (see Figure 6 for a visual illustration of this effect). In other words, AI exposed occupations experienced more growth in the number of skills sought by employers, if the firm recruiting these workers was an AI adopter.

Dependent variable: Mean skills in non-AI postings at T_2			
Predictors in the model	**ΔR_{adj}^2**	**df**	**F value**
Step1: Skills per non-AI postings at T_1	0.11	1, 23597	3019.00***
Step 2: + Firm industry, geography and size	0.03	41, 23556	18.83***
Step 3: + Firm AI adoption status	0.00	1, 23555	20.63***
Step 4: + Occupational AI exposure	0.01	1, 23554	388.43***
Step 5: + Product (AI adoption * AI exposure)	0.00	1, 23553	4.71*

Table 3. *Predicting change in skills per non-AI posting for occupation classes*

*** *p <.001*

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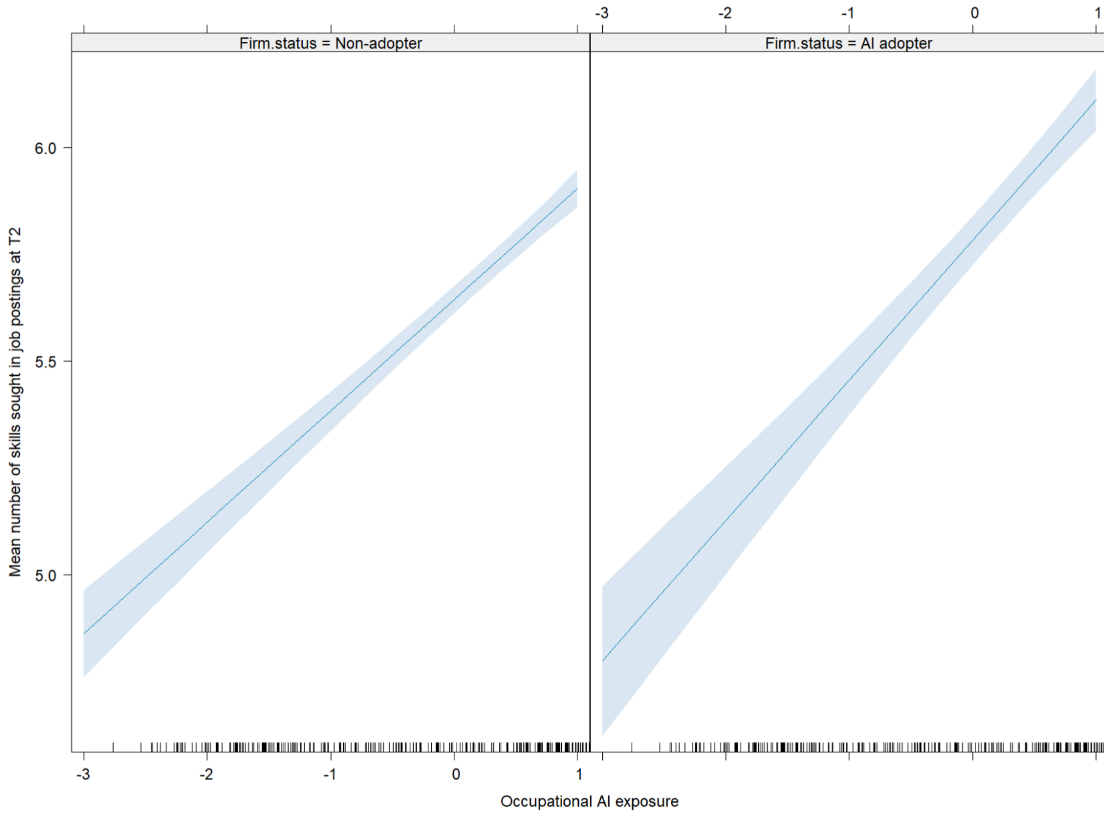

Figure 6. *The moderating effect of AI adoption on the relationship between AI exposure and demand for skills*

3.2.3. Occupational AI exposure and demand for AI skills

The stronger growth in skills sought from AI exposed occupations by AI adopting firms raises an interesting possibility. One of the new skills AI exposed 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 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.

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As Table 4 Predicting change in AI-skilled job postings for occupation classesTable 4 reveals, after controlling for AI skilled job postings at T1 and the effects of industry, geography and firm size, AI exposure was able to explain a significant incremental variance in numbers of AI skilled job postings at T2. The regression coefficient for the effect of AI exposure was β_5 = 8.36 (LLCI = 5.73, ULCI = 11.00), indicating that a difference of one standard deviation in AI exposure was associated with 8.36% more AI skilled postings at T2. That is, demand for AI skills was increasing across all occupation classes in AI adopting firms but the increase in demand was most evident for occupations that were highly exposed to AI.

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	0.62	1, 6308	10100.00^{***}
Step 2: + Firm industry, geography and size	0.06	35, 6273	40.12^{***}
Step 3: + Occupational AI exposure	0.01	1, 6272	38.68^{***}

Table 4. *Predicting change in AI-skilled job postings for occupation classes in AI adopting firms*

*** *p <.001*

For more insight into this AI upskilling trend, the scatterplot in Figure 7 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 above zero landing on the y axis represent occupation classes that were transitioning from non-AI skilled (at T1) to having at least some AI skilled job postings at T2. Points above the regression line represent occupation classes that were exhibiting faster than average increase in demand for AI skills. For illustrative purposes, some of the occupation classes that were exhibiting particularly strong AI-upskilling effects have been labelled. Like Alekseeva et al.[30], 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 teachers, architects, graphic designers, metal fitters, mechanics and security guards.

doi.org/10.32388/LAVWIY.2

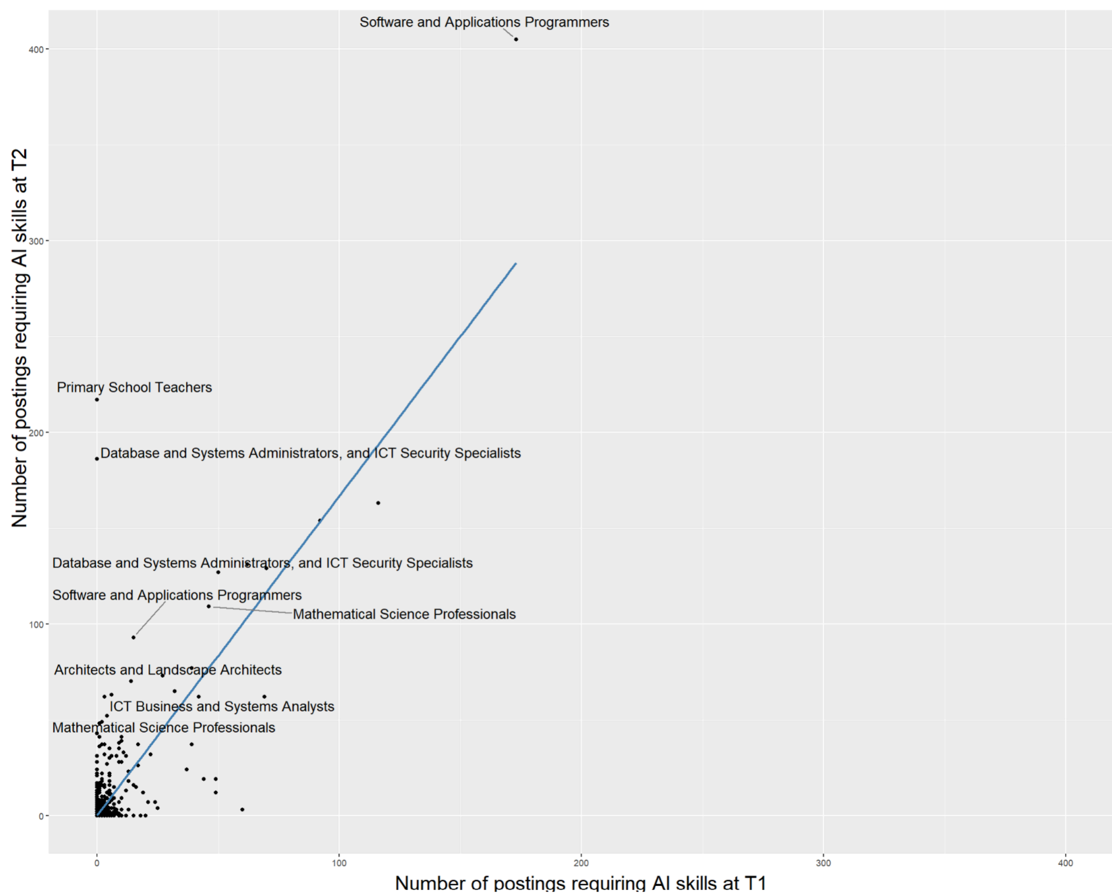

Figure 7. *AI skilled postings at T1 and T2 for occupation classes in AI adopting firms*

4. Discussion

This study found that the adoption of AI within a firm (denoted by the firm posting job advertisements that require AI skills) was associated with stronger demand for new workers. After controlling for firm size, industry and geography, firms that were adopting AI between 2016 and 2019 showed 24% stronger growth in demand for non-AI workers than non-adopting firms. Furthermore, even AI exposed occupations remained in strong demand within these AI adopting firms. AI adopting firms also showed stronger growth in the number of skills sought in job postings, especially if the job posting was for an AI exposed occupation. In some instances, traditionally non-AI skilled occupations were transitioning to become AI skilled workers, suggesting that the new wave of AI tools allow workers to *use* AI to augment their capability rather than being replaced by it. In comparison, in non-adopting firms, demand for new workers, particularly demand for AI exposed workers, was growing

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more slowly. Similarly, the number of skills sought in job postings was growing less strongly in non-adopting firms.

4.1. Firms adopting AI are hiring more workers

Our study contributes to the literature by strengthening the evidence that firm AI adoption increases demand for non-AI workers (even in occupations that are highly exposed to AI). Although the effects of AI adoption and AI exposure on existing occupations has been studied before[2][3][38], this study is the first to illustrate that the effect of occupational AI exposure 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.

Our estimate of AI's job creation effects is conservative because we focused on job postings that did not mention AI skills. AI adopting firms were not just posting more non-AI job ads, they were also posting AI skilled job advertisements. On average, AI adopting firms advertised 2 AI-skilled roles in T1 and 5 AI-skilled jobs at T2, in addition to the growth in non-AI skilled job postings.

Adoption of new technology may be associated with increased demand for new workers because the technology-adopting firms gain market share at the expense of the non-adopting firms[56]. If AI exposed occupations are able to augment their productivity or value add in new ways when their firm adopts AI, it would give their firms an advantage in the services and products that these workers help to deliver. Such an effect would explain the weaker growth in job postings for AI exposed occupations in non-adopting firms. In non-adopting firms, AI exposed occupations would be at a disadvantage relative to their AI-augmented peers in AI adopting firms.

4.2. Skills demand is increasing for AI exposed workers in AI adopting firms

We also found that the number of skills sought in job postings was increasing faster in AI adopting firms, especially in AI exposed occupations. Acemoglu et al.[38] found that AI exposed occupations exhibited greater change in the skills listed in job postings, and that the growth in new skills exceeded the decline in existing skills. However, their study only examined skills trends in AI adopting firms. Our study strengthens the evidence that AI adoption is a driver of increasing skills demand because it shows that the number of skills required in AI exposed occupations is increasing faster in AI-adopting firms than in non-adopting firms.

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We also discovered some formerly non-AI roles (often those with high occupational exposure to AI) that were transitioning to become AI-skilled roles. This effect was strongest in IT occupations, a finding that aligns with global research[30][36]. However, our research identifies several non-IT occupations where some firms now seek AI skills in these roles. Grinis[57] 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[29] defined AI workers as those with the skills to develop and maintain AI systems (whilst acknowledging that there is uncertainty around who is using AI directly in their jobs). 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, architects, teachers and mechanics.

4.3. Limitations

A limitation of our 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 we found that our measure of firm adoption of AI moderated the effect of AI exposure on demand for occupations suggests that this method of differentiating firms that are adopting AI is reasonably effective.

Second, in adopting Felten et al's[11] 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 a study that drew upon data from 23 countries and found that an occupation's exposure to AI varied little, even after taking into account variation in the tasks being performed by workers across these countries[32]. 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[58], perhaps because firms in developed countries tend to have higher absorptive capacity[59][60].

Finally, we interpret the growth in job postings and skills demand for AI adopting firms as evidence of AI promoting growth and upskilling. An alternative explanation is that the adoption of AI requires new skills, thereby displacing existing workers and creating demand for new workers who have these new skills. This alternative explanation cannot explain why AI adopting firms also showed stronger growth

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in demand for workers in non-exposed occupations. Nevertheless, to rule out this alternative explanation for our findings, it would be useful to compare turnover levels in AI adopting and non-adopting firms.

4.4. Practical implications

This study adds to a growing body of evidence attesting to the positive effects of AI on employment at the firm level[39][61]. It also provides an explanation for the negative effects on demand for non-AI workers that was reported by Acemoglu et al.[38] since we found that focusing on non-AI job postings fails to capture demand for workers in existing occupations that are transitioning to become AI-skilled roles. Our research suggests that even with the adoption of increasingly advanced AI tools, demand for new workers and more skills (including AI skills) continues to grow, supporting national policy and investment aimed at encouraging AI adoption and AI skills development[4].

Our findings also suggest that the occupations that are most exposed to new AI tools are better off in a firm that adopts the new AI tools. The stronger growth in demand for exposed workers in AI adopting firms (compared with the same workers in non-adopting firms), along with the increase in number of skills required (including AI-related skills) in job postings suggest that the latest AI tools augment the work of exposed occupations, creating competitive advantage for the firm and the workers who use them. These findings validate national policy and investment aimed at educating firms and workers in the effective use of AI[56]. 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.

4.5. Directions for further research

Future research could extend these findings by comparing training investment and worker turnover in AI adopting and non-adopting firms. In addition, research focusing on the adoption of generative AI tools would provide a means of focusing the study of AI adoption on widely used AI tools that are known to be capable of performing non-routine cognitive tasks. We attempted to gain early insight into these effects by focusing on job postings that mentioned generative AI skills but there were not enough job postings mentioning ‘generative AI’ (or related skills terms) in the first half of 2023 to provide sufficient statistical power for quantitative analyses.

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[36]. Understanding how ongoing developments in AI systems and business processes are affecting demand for workers and skills requires ongoing research effort.

4.6. Conclusion

Although AI tools can now perform certain tasks that were traditionally performed by workers in high-skilled and well-paid occupations, the adoption of these tools appears to augment rather than displace the occupations that are most exposed to this new wave of AI. Our study revealed that AI adopting firms were experiencing 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 for AI exposed occupations was increasing faster in AI adopting firms than in non-adopting firms. Our findings suggest that initiatives aimed at supporting the adoption of AI and development of AI-relevant skills for AI-exposed occupations will enable both firms and workers to flourish in the era of AI-assisted production.

Statements and Declarations

Declarations of interest

The authors have nothing to declare.

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Data availability

Data will be made available on request.

Footnotes

[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.

[2] Acemoglu et al.[38] 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.

[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.

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