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Drivers of AI investment

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EXECUTIVE SUMMARY

IP Australia commissioned the authors of this report to conduct an economic analysis on i) the technology transfer of artificial intelligence (AI) into Australia and its adoption across different industries, and ii) the role of intellectual property (IP) in promoting innovation in AI. Our approach to this assignment is twofold. First, we develop an understanding of AI adopting firms and their characteristics. We then correlate AI adoption with patent activity to explore the importance of IP to these firms. We use the hiring of AI-skilled employees as a proxy for AI capacity building such as inward technology transfer and AI adoption.

For this report, we create a novel database that links international patent data from the Lens patent database with firm microdata constructed from LinkedIn's *Jobs, Company,* and *People* datasets. The process we detail presents a generalisable methodology for mapping technology adoption and innovation that can be applied to other areas of policy interest (e.g., identifying target populations or relevant industry stakeholders for consultation).

For a sample of firms that are hiring in Australia using LinkedIn we collected detailed firm data on their existing skill base, firm demographics and job posting activity. The sample of firms was divided into two groups based on whether or not at the time of data collection they were engaged in hiring staff for AI-related positions (versus general capacity building). We then examine how AI capacity building in the commercial sector correlates with different characteristics of the firm (e.g., size, locations, and company age) and industry[1] using multivariate analyses. Additionally, we draw on patent records from the Lens international patent database to explore whether past innovation activities (patent counts and patent diversity)[2] are associated with AI capacity building.

Key findings

1. AI adoption varies by company demographics and industry

We identified four groups of companies that have a higher tendency to adopt AI technology: (i) large corporations, (ii) small and medium size enterprises (SMEs) with existing AI capacity, (iii) patent-holding firms, and (iv) younger companies. Company attributes such as size and location are correlated with the likelihood of a firm enlarging its AI capacity. In general, there also exists a considerable heterogeneity in AI adoption between firms in different industries. Policymakers can use this information, for example, to identify regions and industries that are particularly well-suited to AI development and target support and investment to these areas; for example, providing access to funding and technical support, promoting entrepreneurship and innovation, and promoting collaboration between firms and universities. From an IP perspective, initiatives could be implemented to streamline the patent application process, offer support for patent examination, and ensure that the IP system remains flexible enough to accommodate the rapidly evolving nature of AI technology.

2. In general, a company holding a patent is a reliable predictor of whether a firm is engaged in AI capacity building

Firms that demonstrate a greater focus on innovation, proxied by being the listed owner of at least one patent, are more likely to increase their involvement with AI in their operations. The identification of patent-holding firms as a group with higher levels of AI adoption also highlights the importance of the IP system in fostering innovation within the AI sector. By safeguarding the IP rights of innovators, the IP system provides a framework for companies to commercialise their inventions and to benefit from their investment in R&D, particularly in areas such as AI.

1 Industry is classified using the Australian and New Zealand Standard Industrial Classification 2006 (ANZSIC). The nineteen primary ANZSIC Divisions are provided in Appendix 1B, Table S1.

2 Patent diversity is assessed using the International Patent Classification (IPC). The eight primary IPC categories are provided in Appendix 1C, Table S3

3. A company's AI capacity building is not related to its scope of patenting activity

A potential source of impact for AI on the patent system is its role in generating new inventions at scale through the novel recombination of ideas. However, at least among firms engaged in patenting activity, in their level of AI capacity building there is no (statistically significant) difference between firms with a broad (or narrow) technological focus, as indicated by diverse (or concentrated) activity across patent classes.

Firms may consider AI capacity building as important for driving innovation across various domains, not just in niche areas, given AI's potential to foster innovation across a wide range of industries and commercial markets. Presently, however, within innovative firms, AI may hold more significance for management and operational aspects than for AI-based innovation. For example, these may include driving productivity improvements through business process enhancements and the automation of customer service functions.

4. Patenting by AI adopters is focused in information and communication technologies and their applications

Companies engaged in AI capacity building are statistically more focused in their patenting on Physics (class G in the International Patent Classification scheme) than a control group of companies engaged in general hiring practices. This class includes subclasses such as 'Computing; Calculating or Counting' (G06) and 'ICT Specially Adapted for Specific Application Fields' (G16).

This technological focus may indicate the use of patents in strategies for appropriating value from AI-related IP. It may also indicate a value-added focus on applying AI to commercialisation – i.e., AI adoption enabling companies to develop novel and innovative applications of AI technology (products, services) within specific industries, markets or problem domains.

5. SMEs are generally less focused on AI capacity building, except for highly specialised technical startups

Overall, SMEs are generally less focused on AI capacity building than general capacity building. However, unlike in the sample more generally, SMEs are more likely to hire additional AI staff if they already possess existing AI staff. This observation suggests the emergence of highly specialized technical start-ups that concentrate on AI development, which may not be adequately captured by patent data alone.

Tests suggest that the relationship between patenting and AI capacity building is not moderated by firm size – the relationship holds both for SMEs in general and for technical startups specialised in AI development. However, as SME are generally underrepresented among patent users in Australia, this finding reinforces the need for policymakers to ensure the IP system is flexible to the needs of AI technology producers and users.

SMEs may use AI for innovative opportunities, but this may not necessarily manifest in seeking patent protection. Instead, some SMEs may opt for trade secrets or leverage the proprietary nature of AI algorithms to reduce time-to-market. This poses a challenge for countries aiming to establish an IP system that effectively supports and safeguards innovation across all industries and business types.

Limitations

Our data does not indicate there are significant performance differences in AI capacity building between SMEs based in Australia and those headquartered overseas. This finding contrasts with existing evidence that Australian firms are lagging behind the global technological frontier. However, it is important to note that the data used in this study to proxy AI capacity building is limited in only capturing job ads for Australian employees. The data may not reflect the full picture of AI capacity building of the companies in our sample. For example, the data may not capture the local hiring of AI workers in the country where a foreign firm is headquartered, which may be where more AI development of products/services occurs for these firms. We acknowledge that our dataset does not encompass the complete universe of a company's employees in the *People/Skills* dataset.

Additionally, our methodology is more likely to capture companies that aim to increase their 'in-house' AI capacity while potentially underrepresenting those that outsource AI effort and functions (e.g., to consultants, contractors or other external technology providers). Moreover, our dataset may not fully represent AI skills and adoption in industries that have a lower reliance on white-collar workers or professionals, as these groups are the predominant users of LinkedIn.

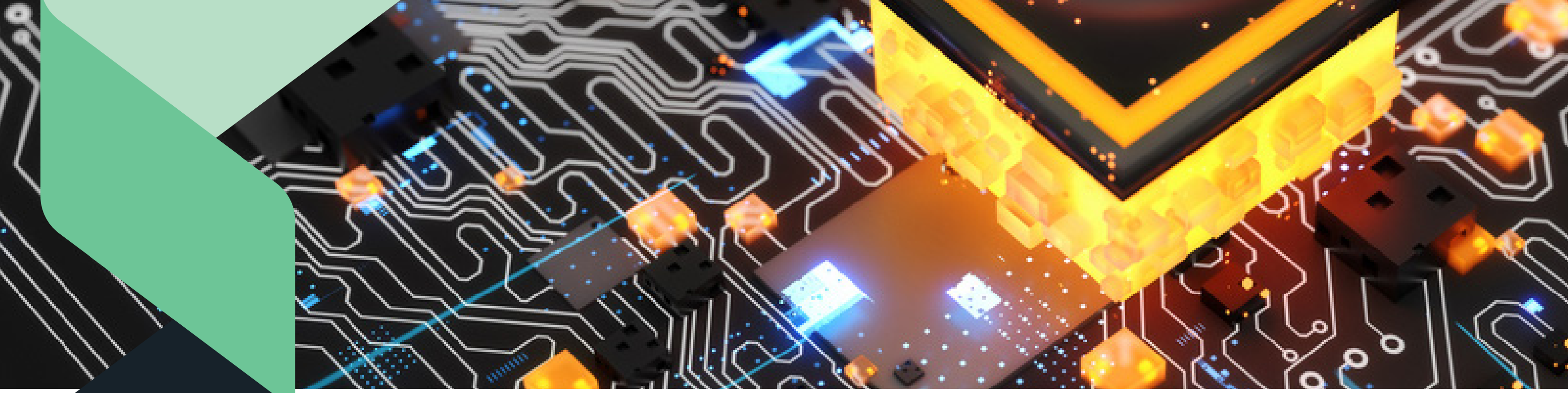
Key policy implications

The key policy implications of this study are twofold. Firstly, it highlights the role of the patent system in the strategies of firms engaged in building capacity in AI. At the same time, it highlights the importance of monitoring the growth of AI beyond the traditional patent regime, exploiting alternative methods to track the adoption of AI and its application to innovation. This is crucial for obtaining a comprehensive understanding of AI development and ensuring that policy frameworks capture the evolving landscape of AI.

Secondly, the study provides a framework for identifying industry stakeholders for consultation regarding appropriate policy settings for AI and IP. This involves engaging with key players in AI adoption, such as AI-related SMEs and younger companies, and understanding their engagement with AI and the IP system. Through supporting targeted consultation, the study aims to support broader efforts to ensure the IP system remains relevant and fit-for-purpose in promoting growth of AI and AI-enabled industry in Australia.

The report concludes with recommendations for data improvement, and for designing and implementing targeted interventions towards AI leaders and laggers identified in this report. This would include connecting leaders and laggers (especially from smaller AI-focused companies with larger companies and AI-lagging SMEs) to facilitate knowledge transfer. It would involve evaluating potential differences at the area (geographical or spatial) level to promote the development of local AI specialisations and skill hubs.

CONTENTS



1. INTRODUCTION

IP Australia commissioned the authors of this report to conduct an economic analysis on i) the technology transfer of artificial intelligence (AI) into Australia and its adoption across different industries and ii) on the role of intellectual property (IP) in promoting innovation in AI. Moreover, based on the analysis, to make recommendations to i) alleviate any barriers to investment, and ii) support drivers of the development and adoption of AI, with a focus on the role of the IP system.

In Section 2, this report describes the background of the project, discusses relevant literature to the current analyses, and outlines the research questions, aims and objectives.

In Section 3, we describe the data collection and preparations necessary to allow the researchers to conduct the analysis. We then present basic observations in Sections 4.1 to 4.5 by providing a set of diagrams and summary statistics that provide initial insights into the drivers and challenges of AI development and adoption.

In Section 4.6, we present insights from structured models using multivariate methods, in particular, regression analysis (linear probability model – specifically, OLS on a binary outcome). We revisit findings from the basic observations, as this method allows us to simultaneously control/test for potential mediators. We present two sets of regression tables; one that focuses on average effects across a variety of facets (e.g., multi-nationality, SMEs, existing AI-staff, industry), and the other that provides the various interaction effects and robustness checks we undertook.

In Section 5, we present a summary of key findings from this report (with policy relevance) and recommendations on how IP Australia may reconsider its data collection process, implement targeted interventions towards different AI leaders and laggers, and explore area-level differences, keeping in mind the geographical nature of innovation. Section 5 also suggests steps for future analysis and how these steps may help to further improve IP Australia's understanding of the key drivers for AI investment and the role of IP in incentivising AI investment. The benefit of this project is in its power to increase the "political analytical capacity" (Giest, 2017, p. 370) for working with and linking patent data to other alternative measures of knowledge and skills diffusion, investment, and development (e.g., job postings).

2. BACKGROUND

IP offices are continuously challenged to understand how new technologies may reshape the innovation process, to ensure the IP system remains fit for purpose, and to appropriately encourage innovation to society's benefit. AI is one such technology that is poised to become a "general purpose technology" (Agrawal et al., 2019; Goldfarb et al., 2022) and, as such, is expected to drive productivity improvements across many sectors and problem contexts. AI has the potential to i) speed up the rate of invention, ii) make inventions cheaper and faster to produce, and iii) expand the range of possibilities for innovation. The open question is whether AI, combined with other frontier technologies (e.g., cloud services, quantum computing, ubiquitous instrumentation)[3] , requires us to rethink how patent systems (and society's institutions, rules/regulations more generally) should best support innovation. This includes understanding the role that IP may play in promoting the development, transfer, and implementation of AI.

"IP are assuming increasing importance, especially for innovative firms… and profiting from knowledge is a crucial aspect of innovation management" (Candelin-Palmqvist et al., 2012, p. 502). Empirical research shows however, "that only a small fraction of innovative companies relies on patents to protect their inventions" (Hall et al., 2013, p. 4). We observe a similar trend in this current study (see Section 4.5). Thus, there is a need to look to alternative sources of data to understand innovation and adoption of AI, and to look for signals on how the IP system may best support such investment and facilitate technology diffusion. IP law itself "comprises a system of policy levers that legislatures tailor and courts interpret in order to promote innovation and protect the integrity of markets" (Menell & Scotchmer, 2007, p. 1475; see also Ernst & Mishra, 2021). With AI emerging in the innovation process, much discussion has centred on the issue of whether AI can or should be named as inventors on patents (see e.g., De Costa & Carrano, 2017; Tripathi & Ghatak, 2018; Li & Koay, 2020; Thomas & Murdick, 2020; Adde & Smith, 2021). However, a broader framing asks (e.g., see working paper, de Rassenfosse et al., 2022): What protections and disclosure requirements are needed to stimulate innovation, considering the ease with which AI models may be replicated (e.g., reverse engineering), and the challenges comprehending how AI models work (i.e., black-box nature)? What are the best mechanisms to encourage knowledge transfer? And how is exchange (knowledge, skills, tech) between AI developers and implementers best facilitated? Further, how should AI patent protection be enforced in the court system?

Potential challenges arising from the emergence of AI include the volume of applications for patents that may result from the application of AI to innovation (and the stresses this place on patent examiners) and the distributed nature of AI development (and complications this presents for determining liability, e.g., in the case of faults, biases).[4] Putting these aside, AI systems that can generate patentable inventions still need to satisfy patentability requirements such as novelty, non-obviousness, and disclosure requirements. The non-obviousness criterion is that patents should only be awarded for inventions that would not easily occur to a person having ordinary skill in the art (PHOSITA). This criterion in particular might need re-consideration in the face of AI-enabled or AI-generated innovations. For example, does the person having ordinary skill in the art (PHOSITA) also have AI-capability?

[3] See also e.g., Bloom et al., (2021), Zhang et al. (2022), Arnold et al. (2020), for alternative lists, definitions, and perspectives of disruptive and emerging technologies related to and/or enabled by AI. See also e.g., Smoch (2008) regarding the WIPO technology concordance table linking the International Patent Classification (IPC) symbols with thirty-five fields of technology (see Table 2 on pages 9-10). See e.g., Liu et al. (2021) and Bickley et al. (2022) for alternative keywords for different types of AI, according to function and/or foundational theoretical basis or perspective.

[4] The volume of patent applications and stressors this place on examination systems requires to re-think the calibration of temporary/automatic rights assignment and the potential for automation or augmentation of examination services and examiners' tasks and functions (e.g., initial screening, flagging problematic patents), among other factors. The distributed nature of AI develop could allow errors to cascade through networks of ill-defined liability and code development. However, the openness (of code, data, etc) of current development online encourages reproducibility, at the same time as opening pandoras box for maladaptive uses.

In the case of AI-generated inventions, should obviousness be considered in relation to the PHOSITA (again, with or without AI capacity) or in relation to another normally skilled AI system? In addition, and of particular relevance for the case of AI, are the subject matter limitations on patentability (e.g., restrictions around the patentability of computer-implemented inventions).

Other challenges for AI in the discovery process include:

- AI does not explain how or what it has learned. In other words, it does not reflect upon what it discovers and, hence, humans need to monitor and potentially regulate the machine's operations (human-in-the-loop), raising questions around creativity and inventorship.
- AI is imprecise – models or insights are not typically derived from a theoretical understanding about the relationship between a property and an effect, but AI nonetheless identifies partial relationships – which may make it harder to establish links from AI systems to prior art.
- AI has a keen ability to detect aspects of reality that humans have not been able to detect (connections that can elude humans). Thus, by removing human-driven expertise, intuition, and insights, experimental results may become more important for AI-driven discovery. Knowledge of which data and what representation of that data to use as training data becomes key for effective disclosure and replication.
- Many AI models carry a sense of impenetrability: an inability to look under the hood and provide explanations of the decisions the network makes. This challenges the normal disclosure requirements of IP (and hence diffusion of technology and ideas).

Taking a broader lens of AI policy (beyond the IP system), Agrawal et al. (2019) suggest that AI diffusion across and within countries could also be driven by privacy laws (e.g., around data access, storage/localisation, repurposing, de-identification), trade agreements (e.g., mandating privacy, labour, environmental standards), and legal liability laws (e.g., strength and consistency of the application of tort law to AI technologies).

Looking abroad, we see a variety of policy responses to AI (Paunov et al., 2019). Namely, those that support digital technology adoption and diffusion (e.g., testing facilities, business advisory services) and those that facilitate co-operation and open digital innovation (e.g., collaborative innovation labs, open innovation tools, matchmaking and networking events, access to expertise/advanced infrastructure for start-ups). Indeed, many countries (e.g., China (Roberts et al., 2020); see also Zhang et al., 2022) are setting ambitious AI targets and strategy; looking to claim their own slice of the technology advancements that AI is poised to bring forward (e.g., China (Roberts et al., 2020); see also Zhang et al., 2022)

IP also has implications for job mobility[5], which patent data alone struggles to identify and where job posting data presents significant potential. For instance, Melero et al. (2020) find that patenting reduces the likelihood of inventor mobility – by up to 42% for each patent granted – by making human capital more specific to the firm. They argue that patents reduce the inventor's ability to replicate an innovation elsewhere, but also that patents increase the inventor's value to her employer, particularly where the inventor's involvement is important to bringing the innovation to market. Patents may also shift the incentive to invest in human capital development (e.g., training and skills/knowledge development) from the employer to the employee. Results are strongest in the case of discrete technologies, like chemicals and pharmaceuticals, for which patent effectiveness is greater. Still, it would be interesting and pertinent to see if the effect holds for company-level AI hiring and employees' skills development within certain industries in Australia.

Recent work focusing on Australia has provided evidence that while progress at the technological frontier has remained strong, the gap between firms at the global frontier and other 'laggards' within an industry has grown over time. In considering key drivers, it has been argued that 'laggards' are slower to adopt cutting-edge technologies and processes and are also slower to catch-up to the global frontier than they have been historically (Andrews et al., 2022). Even more recently, Bahar and Lane (2022) built on this evidence base by analysing a sample of 8.5 million Australian job ads (collated by Lightcast[6]) over the 2012 to 2020 period. They report that ads referencing machine learning (ML)/AI and cloud computing (in the job ad text description) have become more evenly distributed across Australian industries over time. However, by reducing diffusion to a single value, they leave less well-explored the diversity of investment into AI by different industries and sectors. They also do not consider the existing skill-base of companies, instead focusing on skills-needs identified from job ad postings.

[5] See e.g., recent work published in chapter 8 of the 2023 IP Australia report.
[6] A.k.a. Emsi Burning Glass. See website for more detail: https://lightcast.io/about/data.

This report builds on existing evidence by exploring AI capacity building by firms (identified from job ads) and how this relates to a firm's demographics, existing AI capacity base, patenting activity (identified by firms' current active and pending patents) and innovation focus (wide/narrow). The paper explores 'self-selection' effects (i.e., the decision by firms to select into developing AI capacity, including whether to further specialise in AI if you already have AI staff/capacity.

This paper exploits a novel database that links international patent data from the Lens patent database with firm microdata we construct from LinkedIn jobs, company, and people datasets. This allows us to explore industry and firm differences in current and aspirational skill bases, proxied by job ad posting and current employee self-nominated skills. This also allows us to explore the importance of IP to firms focused on AI-hiring (compared to General-hiring) and along various facets (e.g., company demographics, existing skill base, location of headquarters). The approach helps us explore AI innovation in Australia and the challenges/ drivers of continued AI investment across Australian industries. What we find is that AI capacity has been developed across most industries in Australia, but capacity is more pronounced in industries with a strong technology focus such as information and communication technologies and professional services. This is indicated by job advertisements as the skills of current employees of firms captured by our data. More importantly, we are also able to identify innovation by firms operating in the field of AI by including patent data in our analysis.

2.1 Aims and objectives

In this report, we aim to uncover insights on the relationship between IP and investment in skills development for frontier technologies, with a focus on AI in Australian companies. We document the differences between different types of organisations (e.g., small and new vs established firms) and sectors. Using novel linked data, we document the extent that AI is adopted in Australia highlighting differences by industry, company size, location, and year founded. We map the AI skills base within Australian firms and industries based on a snapshot of LinkedIn job postings and analyse their AI skills needs based on a snapshot of LinkedIn job advertisements.

We look for signals of the importance of IP to firms investing in AI development and implementation by appealing to the Lens patent database. In particular, we examine whether AI adoption (proxied by the extent a company is hiring AI staff) is stronger in i) those companies with currently active or pending patents, indicating an innovation focus (relative to peers without patents) ii) SMEs (relative to larger corporates), and iii) companies with existing AI capacity (relative to those without existing capacity).

In addressing our broader research aim, we illustrate what empirical evidence derived from online big data can contribute for policy, practice, and research, supplementing more traditional IP data and survey methods. Such data provides a unique lens on the development and diffusion of AI across Australian companies and industries, and discusses current trends bridging economic, legal, and operational perspectives.

3. METHODOLOGY

3.1 Data description

We construct a novel linked dataset based on a 2022 snapshot of companies' demographics, Australian job advertisements and employee skills profiles from LinkedIn. We match by company name the companies provided by LinkedIn to applicants in national and international patent records from the Lens patent database. We briefly describe the data collection process for each source in turn below. See Appendix 1 for further detail on data collection and linking.

LinkedIn

We first collect a snapshot[7] of 1000 job advertisement postings returned by our query to LinkedIn including the keyword "*Artificial Intelligence*" and with the job location set to "*Australia*". We refer to this as the Jobs dataset. Next, we extract the unique LinkedIn company IDs from the *Jobs* dataset and use them to retrieve company microdata such as industry (manually coded to align with the 19 primary ANZSIC06 industry divisions), staff count, headquarters location, and country(ies) of operation. We call this the *Companies* dataset.

Using the same list of unique company identification numbers (IDs), we retrieve a sample population of company employees. These have people IDs that we can use to retrieve employee microdata such as job title and skills (i.e., a list of self-nominated skills that are publicly listed on employees' LinkedIn profiles); a.k.a. the *People/Skills* dataset. We make no claim to have collected the complete universe of company employees in the *People/Skills* dataset. Moreover, our methodology is likely to capture companies that aim to increase their 'in-house' AI capacity but might underrepresent those that outsource AI effort and function to consultants, contractors, or other external technology providers. Moreover, our methodology only captures a subset of companies and employees and a snapshot of job postings at a discrete point in time. Only a subset of the business and employee populations uses LinkedIn to recruit and network.

To examine how patterns of AI hiring vary across industries and firms, we compare the sample of companies with AI-related job ads to a benchmark sample of companies engaged in general hiring. Specifically, we replicate the process above (retrieving *Jobs, Companies* and *People/Skills*) using a general search in which we do not include a keyword parameter in the search for job advertisements. This provides a baseline measure to explore the relative focus of companies and industries on hiring for AI skills, accounting for general hiring patterns. The search for AI job ads and general job ads was undertaken on 28 August and 2 September 2022, respectively. While these job ad lists were not necessarily constructed to be exclusive sets at the outset, we found only one job listing was captured in both samples.

Next, using the *People/Skills* LinkedIn datasets, we classify whether the employees are "AI-skilled" or not. This binary distinction is based on whether the skills listed in the employee's profile contain at least one AI-related keyword (e.g., "Boosting," "Computer Vision," "Convolutional Neural Network"). We adopt the skills keywords (any of the artificial intelligence, natural language processing, neural networks, ML, robotics, or visual image recognition dictionaries of keywords) presented in the Stanford AI Index 2022 report (Zhang et al., 2022). In doing so, we can explore the relationship between having existing AI capacity and the decision to post job advertisements to hire additional AI employees (i.e., self-selection effects).

[7] At the current stage, this analyses only provides a once-off snapshot in terms of both time period and only a relatively small snippet or sample population of the entire possible LinkedIn job posting activities, companies, and people (i.e., an estimated 48.7% of Australian population or 12.7 of 25.89 million Australians LinkedIn users in April 2022 – see e.g., https://www.smperth.com/resources/linkedin/linkedin-statistics/). It would be interesting and valuable to explore longitudinal data on job postings across individual companies and industries, as well as collecting a more complete documentation of companies' current and previous employees to help characterise the relationship between inventor and employee mobility and company behaviours over time (e.g., patenting, market focus, employer-employee and company-investor relations, investment in knowledge/skill development, profits, market share, and R&D investment, industry-academic partnerships and collaboration, and so on).

Lens

Using the list of company names from the *Company* LinkedIn datasets (AI and general combined), we query the Lens patent database[8] to retrieve total counts of patent records where the company is the current owner of the patent in the Lens database. We facet these total counts by the 8 main technology categories in the International Patent Classification scheme (A-H, all[9]), legal status (expired, active, pending, all[5]) and jurisdiction (patents held in Australia, patents held in anywhere in the world[5]). This allows us to examine companies' field(s) of innovation (distribution across companies and diversity within firm), the companies' patent histories (volume, present, emerging), and the location of patenting (within Australia vs outside Australia). In the current paper, we consider only active and pending patents. We derive measures of patent diversity based on the patent count data from Lens.

3.2 Analysis

First, we seek to understand characteristics of AI capacity building/adopting firms. Using the LinkedIn *Jobs, Companies* and *People/Skills* datasets, we present descriptive results that map AI-hiring across (i) industry (ANZIC06 divisions), (ii) company size, (iii) company location, and (iv) company age in Sections 4.1 to 4.4 (respectively). We examine whether the hiring of AI staff is associated with the firm's current AI capacity, and whether this relationship varies depending on the company's characteristics.
We calculate the share of job ad postings for all companies across all facets combined.

In the second half of the results section, we seek to understand the association between patent behaviour and AI adoption by firms. We compare the AI-hiring and General-hiring samples of companies, looking at their) patent class diversity and ii) IPC classes of patents by industry (Section 4.5.2). Lastly, we present regression analyses exploring the effects of different company facets on the probability of a firm hiring AI staff (as opposed to general staff), controlling for other factors (Section 4.6). We introduce to the regression analysis interaction terms between different facets (namely[10] , *AUS HQ*SMEs* and *SMEs*Exist AI-staff*) to explore potential multiplicative effects. We perform robustness checks using the number of AI staff per company instead of the binary variable – whether a company has AI-skilled staff or not. This does not qualitatively change our insight that, in general, companies with existing AI capacity are less likely to hire additional AI staff.

[8] Refer to Lens API documentation: https://docs.api.lens.org/. In particular, see 'Getting Started', 'Request / Patent Request', and 'Response / Patent Response'.
[9] 'all' is the total count of all unique patent records by company. This uses the '*' wildcard operator in the relevant dimension facet of the search criteria (e.g., jurisdiction of patent record, legal status of patent record) to provide the baseline measure for a crude proxy of the diversity of a company's patent classification combinations.
[10] AUS HQ = Australian Headquarters, Exist AI-staff = this company has at least one AI-skilled employee.

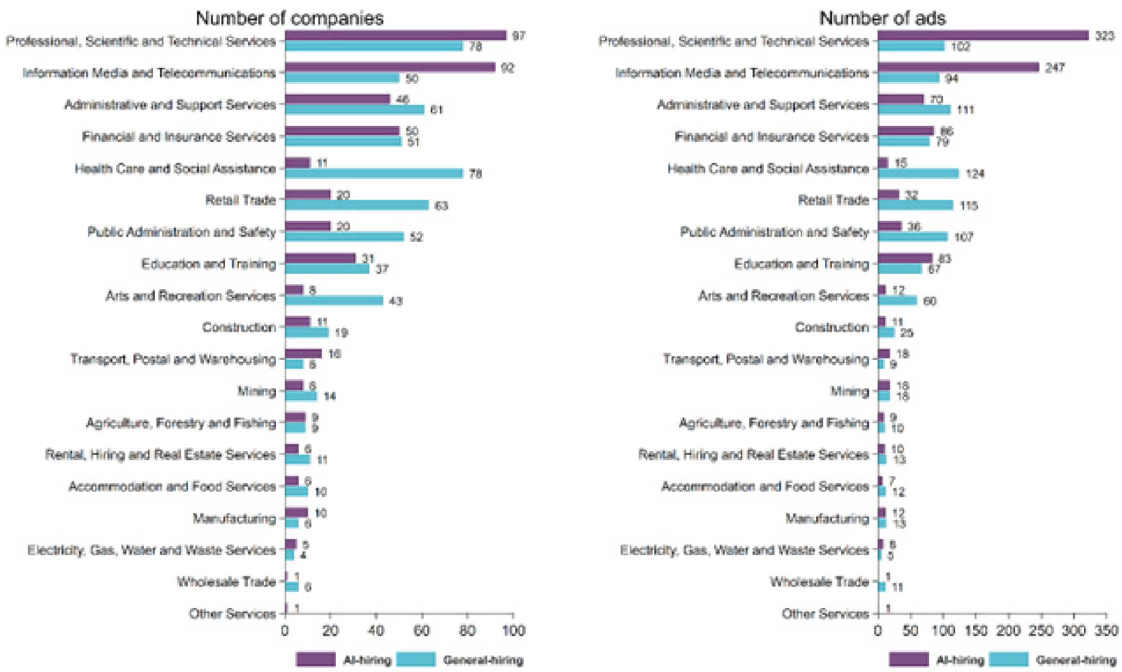
4 FINDINGS

4.1 Industry

Overall, we find there are 448 and 600 unique company IDs obtained from the AI and general ad searches, respectively. This means that *fewer companies are responsible for more AI ads than for general ads* (i.e., more concentrated pool of potential companies/employers), given both searches return a maximum 1000 job ad postings.

Looking at the industry comparisons (Fig. 1 left), we see that in the *Professional, Scientific and Technical Services and Information Media and Telecommunications* industries, there are more companies from the sample of AI hirers than from the general sample. Conversely, industries such as *Health Care and Social Assistance, Retail Trade, Public Administration and Safety, and Arts and Recreation Services* have relatively fewer companies expanding AI capacity compared to the number of firms hiring 'general' employees. Similar patterns hold when comparing the number of job ad postings by industry (Fig 1. right).

Fig. 1: Counts of unique company IDs (left) and job ad postings (right) in AI-hiring and General-hiring samples, by ANZSIC industry.

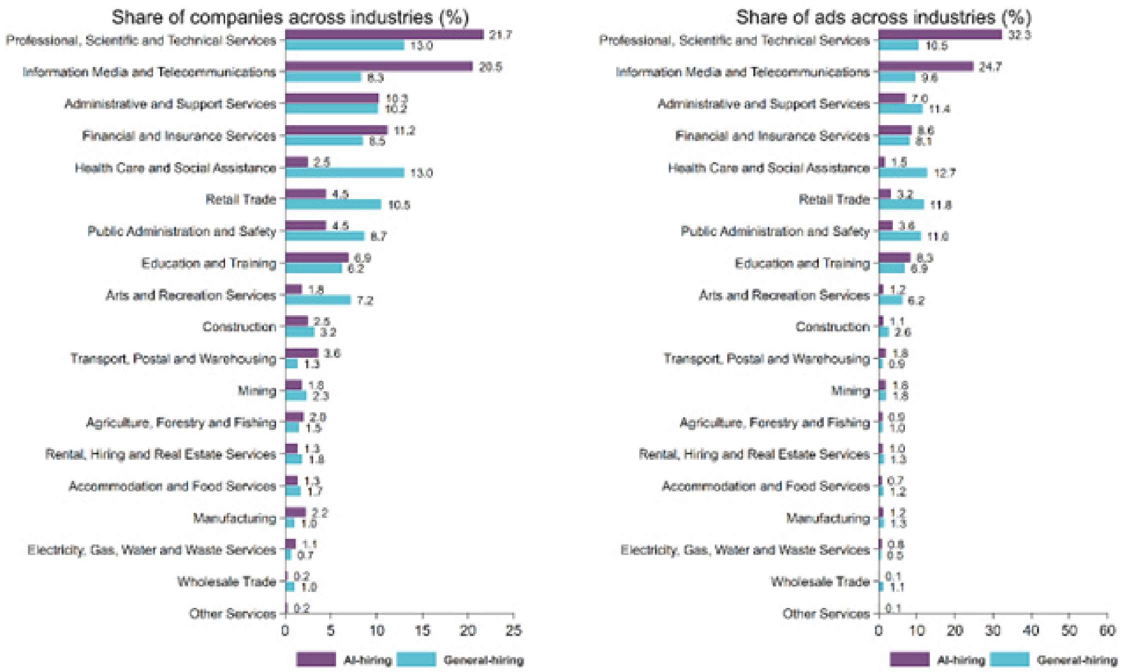


Now taking the share of companies (Fig. 2 left) and job ad postings (Fig. 2 right), we can see the comparison across industries more clearly. We define this share as the proportion of total companies (or job postings) in a sample which originate from an industry division. Similar conclusions can be drawn to those reported above. For example, the *Information Media and Telecommunications* sector accounts for 20.5% of the 448 companies posting AI-hiring ads, compared to only 8.3% of the 600 companies posting any hiring ads. The difference in share is 12.2 percentage points, highlighting the relative focus on AI hiring in this sector[11].

[11] At least that is what is captured by this job ads posting snippet/snapshot in time. See recommendation 2 in Section 4.3.3 for discussion on longitudinal data collection and undertaking of more structural analyses.

Health Care and Social Assistance (Q) has the largest 'AI-gap' with only 2.5% of companies posting AI-hiring ads compared to the general hiring baseline of 13%. The difference in share is -10.5 percentage points. This suggests that, relatively speaking, *Health Care and Social Assistance* (Q) companies in our dataset currently focus more of their efforts on general capacity building as opposed to AI capacity building and investment, keeping in mind the very 'hands-on' and human-centred nature of healthcare provision. The difference in share is reported in Table 1.

Fig. 2: Industry shares of unique company IDs (left) and job ad postings (right) in AI-hiring and General-hiring samples.



Whilst Table 1 provides interesting insights, the results should be interpreted with caution for industries with lower shares of job ad posting (e.g., *Other services, Wholesale trade, Utility services*) as their lower frequency may skew the effect sizes. Also, some industries (*e.g., Construction, Retail trade, Warehousing*) may typically advertise for lower-skilled, lower-paid jobs through means other than LinkedIn and other online sources (e.g., word of mouth, newspaper classifieds, Facebook or other social media posts through company page). LinkedIn job posts may under-represent general hiring within these industries, so the results presented here may overstate their focus on AI-hiring. See Zhu et al. (2018) for discussion and further insights about the LinkedIn data (global comparison), produced via the World Bank Group-LinkedIn partnership:

> "LinkedIn data are best at representing skilled labour in the knowledge-intensive, and tradable sectors… Although LinkedIn may have better coverage in developed than developing countries, there are certain knowledge-intensive and tradable sectors, such as information and communication; professional, scientific, and technical activities; financial and business services; arts and entertainment; manufacturing; and mining and quarrying, that have good LinkedIn coverage globally" (p. 4).

Thus, for knowledge-intensive sectors in particular, LinkedIn data could allow comparable benchmarking of performance across geographical locations (which we do not address in this report); for example, in mapping the performance of Australian firms against those abroad, or for mapping the distributive effects of IP policy and interventions across different locations/cities/states within Australia.

Table 1. Difference between an ANZSIC industry's share of companies in the AI-hiring samples and its share of companies in the control sample.

Code	Industry	PPD*
J	Information Media and Telecommunications	**12.2**
M	Professional, Scientific and Technical Services	**8.7**
K	Financial and Insurance Services	**2.7**
I	Transport, Postal and Warehousing	**2.3**
C	Manufacturing	**1.2**
P	Education and Training	0.7
A	Agriculture, Forestry and Fishing	0.5
D	Electricity, Gas, Water and Waste Services	0.4
S	Other Services	0.2
N	Administrative and Support Services	0.1
H	Accommodation and Food Services	-0.4
B	Mining	-0.5
L	Rental, Hiring and Real Estate Services	-0.5
E	Construction	-0.7
F	Wholesale Trade	**-0.8**
O	Public Administration and Safety	**-4.2**
R	Arts and Recreation Services	**-5.4**
G	Retail Trade	**-6**
Q	Health Care and Social Assistance	**-10.5**

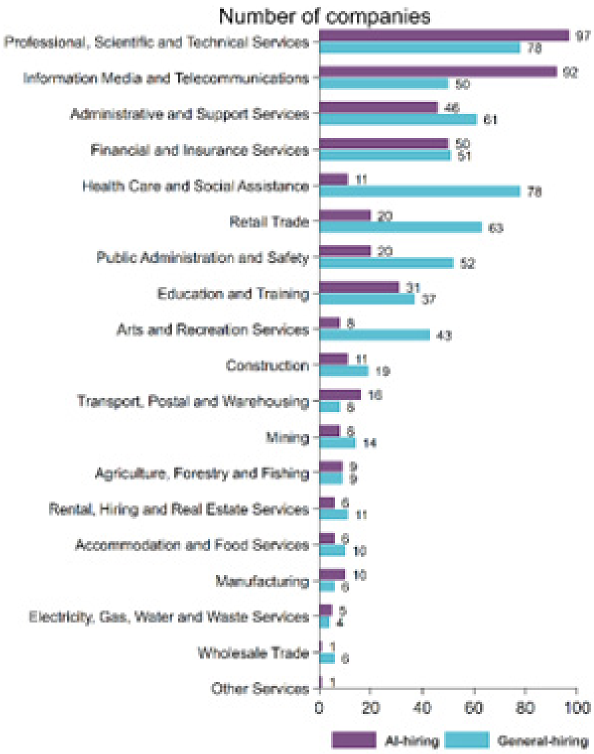
* PPD – Percentage point difference.

4.1.1 Firms with existing AI capacity by industry

We next explore whether, across different industries, those companies investing in AI are building on existing AI capacity or are "laggards" seeking to catch-up to early AI adopters. To explore such 'self-selection' effects, we compare the share of companies with existing AI staff that are hiring for AI skills vs the share engaged in general hiring (i.e., AI capacity vs. general capacity building). For example, among companies in the *Information Media and Telecommunications* (J) sector that posted AI-hiring ads, 18.5% have existing AI-staff, while only 12% of those were hiring generally. Not only are ICT firms (generally) more focused on AI capacity building, but they are also continuing to build on existing AI capacity.

Interestingly, for *Financial and Insurance Services* (K), there is a larger share of companies with existing AI staff who are hiring 'generally' (17.6%) than are hiring for AI staff (10%). In light of Table 1, this may indicate that some companies in this sector are approaching saturation of AI employees, re-focusing their efforts on recruiting for more general or 'human-facing' positions (e.g., customer service) rather than continuing to build AI capacity. The positive PPD in Table 1 could potentially reflect catch-up by laggard firms within the *Financial and Insurances Services* industry.

Fig. 3: Self-selection of companies by industry



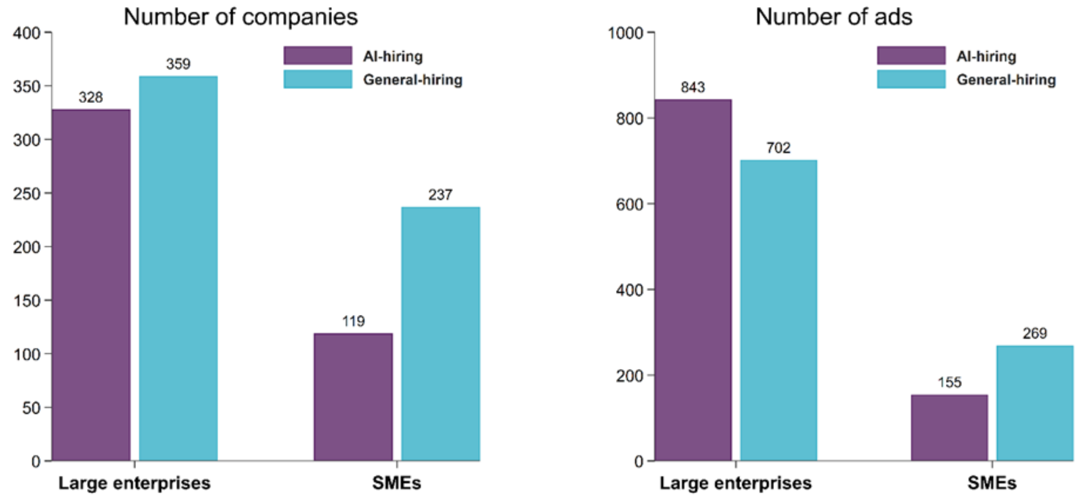
Again, this figure and the insights that can be drawn from it should be interpreted with caution, due to concerns about the representativeness of the data.

4.2 Company size

When looking at company size, we define SMEs as companies with less than 200 staff count in the *Companies* dataset. Large enterprises are defined as any company with more than or equal to 200 staff count.

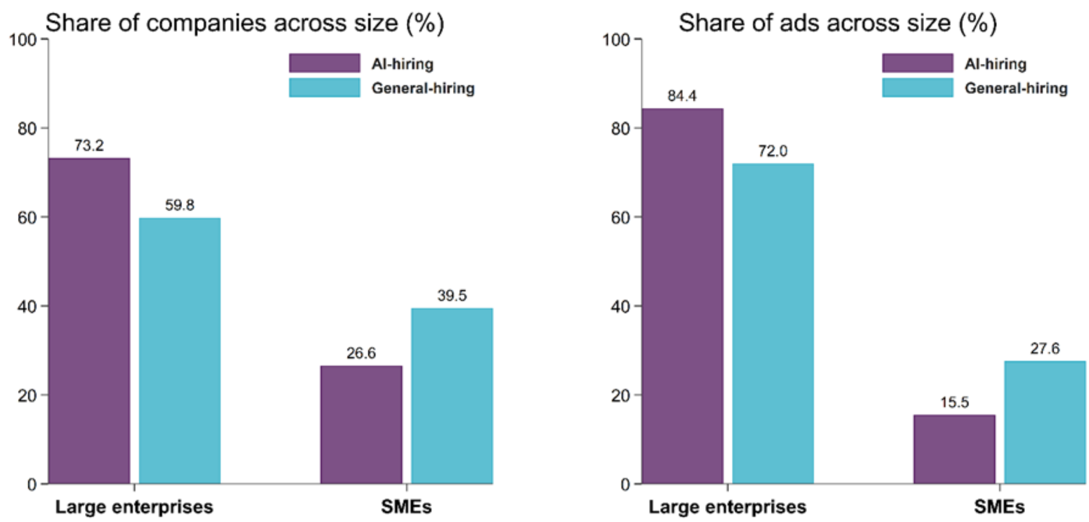
There seems to be a minor subset set of large companies and SMEs engaged in hiring AI-staff. For the same sample size of 1000 ads, we get a smaller set of companies in both categories (Fig. 4 left). This could also be due to the companies posting more AI-related positions (Fig. 4 right). Large companies are posting relatively more ads hiring AI-staff, compared to SMEs, but also compared to their own general hiring activity. For example, large companies are posting, on average, 2.57 AI ads compared to 1.96 general ads (ratio of 1.3 to 1), while SMEs are posting 1.3 AI ads compared to 1.14 general ads (ratio of 1.14 to 1). This likely reflects differences in access to resources/affordances (economic, management/supervisory, etc.) and hence, differences in ability to recruit generally as well as for more specific skills and knowledge (e.g., AI skills and expertise).

Fig. 4: Counts of unique company IDs (left) and job ad postings (right) in AI-hiring and General-hiring samples, by company size, proxied by staff count.



Normalising the count of companies, in Figure 5 we report the share of companies in a size category engaged in AI and general capacity building. We again see that large companies are relatively more dominating in the AI-hiring space. For example, 73.2% of the companies we find hiring AI staff are large companies, compared to 59.8% found in general hiring ads. The share of ads across size (Fig. 5 right) tells a similar story to Fig. 4 above – SMEs are, in this data snapshot, currently more focused on general capacity building.

Fig. 5: Shares of unique company IDs (left) and job ad postings (right) in AI-hiring and General-hiring samples linked to companies of different size.

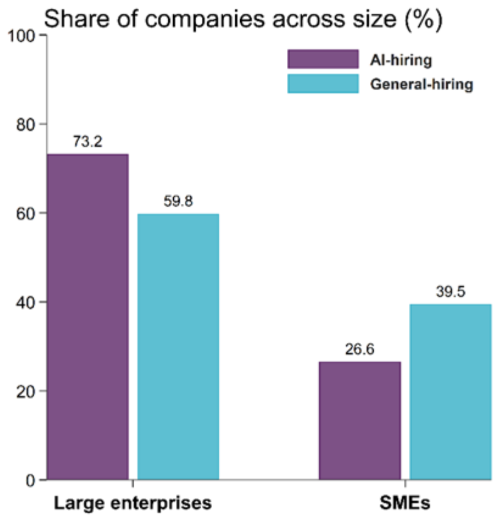


4.2.1 Firms with existing AI capacity by company size

Here we explore whether large enterprises with existing AI capacity are more likely to hire additional AI staff, compared to smaller enterprise with existing AI capacity (see Fig. 6). We find that only 16.5% of large companies hiring AI-staff have existing AI-staff (a sign that those who don't are trying to catch up), compared to 20% of the large companies in the sample of general hirers. Conversely, SMEs seem to specialise – those hiring AI-staff are more likely to have existing AI capability than those drawn from the general sample.

Nevertheless, from a methodological standpoint, this finding could reflect data limitations: for each company, the data provides a potentially incomplete sample of staff (limited to ~1000 records) on the basis of which existing AI skills have been identified. For larger companies, there is likely to have a smaller sample of the total population of workers at that company, so they are potentially less likely to identify existing AI skills even where those skills may exist within the organisation (e.g., locally or abroad).

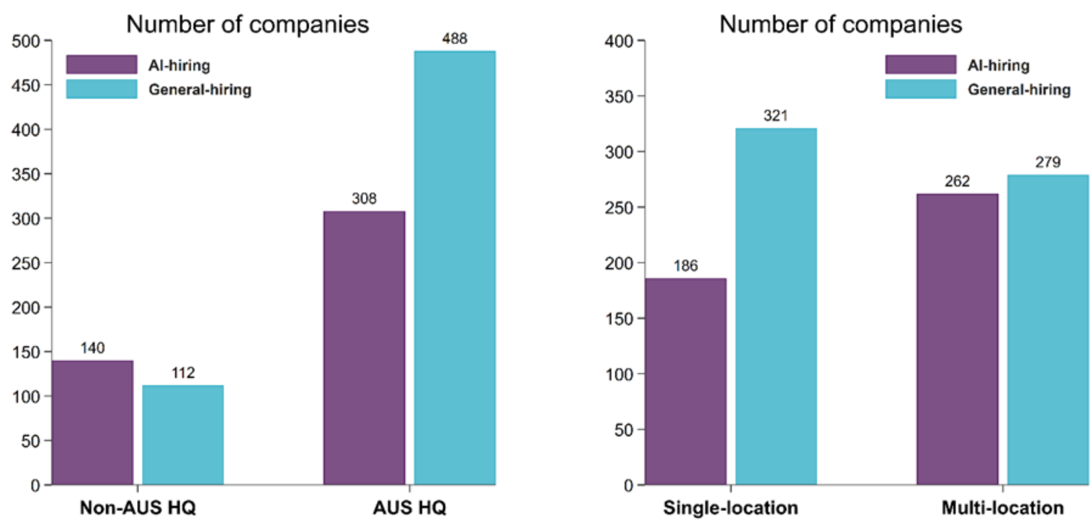
Fig. 6: Self-selection of companies by company size, proxied by staff count.



4.3 Company location

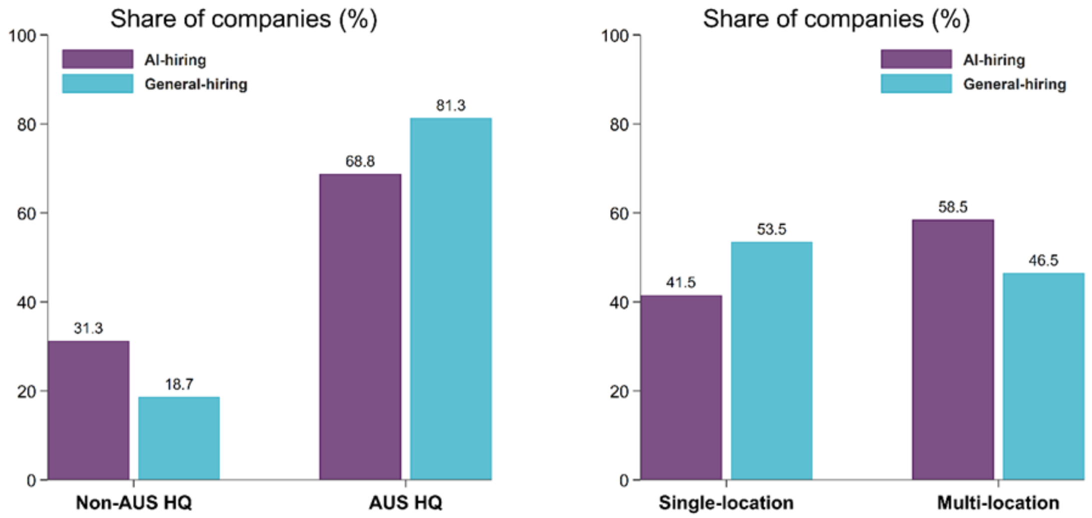
Overall, most of the companies in the sample dataset have their HQ in Australia, but the share is smaller among AI-hiring firms compared to general hiring firms (140:308 compared to 112:488 – see Fig. 7 left). This is again a potential sign that Australian firms are less AI-active. Likewise, companies that operate in multiple countries (multinational corporations) are more likely to hire AI-staff (Fig. 7 right). If AI companies have a relatively strong global focus and international operations, then a harmonised global approach to AI patent policy, developed through international engagement and cooperation, is especially important.

Fig. 7: Counts of unique company IDs in AI-hiring and control samples, by location (Australian vs non-Australian HQ (left), single- vs multi-location (right)).



Again, it visually looks like AI-hiring is stronger among companies with HQ outside Australia or operating in multiple locations, compared to AUS HQ or single location companies (see Fig. 8). This potentially reflects redundancy in roles or human expertise required when a company extends itself across geographical boundaries: the geographical distribution of business can introduce redundancy in roles (e.g., sales manager, software engineer etc.) across locations. Unique context-specific challenges and opportunities arise in the businesses' interactions with the local environment and ecosystem over time which requires to develop local capability. Such challenges include communication losses or inequalities in information, knowledge, or skills of businesses' employees when operating across multiple locations. Local capability building, in turn, requires additional (local) management to make up for communication losses in corporate culture, norms, rules and regulations, for example. The result may also be a function of large firms being more likely to be multinational firms and hire more staff.

Fig. 8: Shares of unique company IDs in AI-hiring and General-hiring samples linked to companies with Australian vs non-Australian HQs (left) or single- vs multi-location (right).



4.3.1 Firms with existing AI capacity by company location

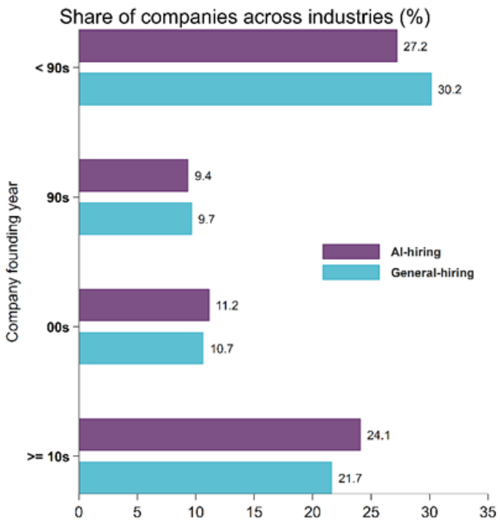
In general, we find that non-AUS HQ (Fig. 9 left) and multi-location firms (Fig. 9 right) are more likely to have existing AI-staff, whether or not they are from the AI-hiring ad sample or General-hiring ad sample. Interestingly, 'general hiring' firms with non-AUS HQ have the highest proportion of existing AI-staff in their sampled workforces. This may suggest AI capacity maturity or saturation in these firms, hence the current focus on general capacity building as opposed to AI capacity building.

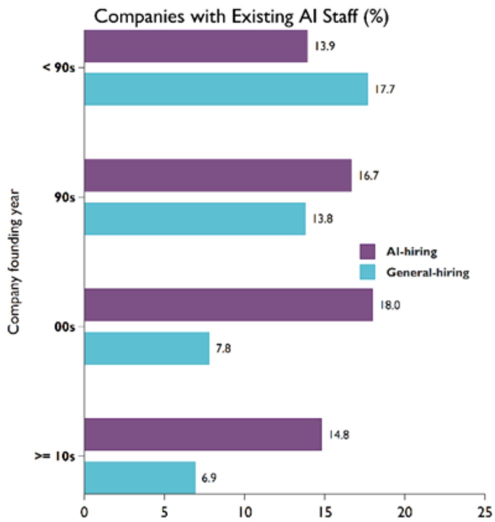
Fig. 9: Self-selection of companies by location.

4.4 Company age

Overall, approximately 28% of the companies in our sample (293 out of 1048 – similar across General-hiring and AI-hiring sets) do not list their founding year and so, we drop these instances for this analysis. Looking to Fig. 10 (right), we see that the most well-established (< 1990s) and youngest (>= 2010s) companies account for over half of the AI job ads in our sample. The left panel of Fig. 10, however, shows that the most well-established companies with existing AI capability are relatively more focused on general capacity than AI capacity building in our sample, perhaps indicating they have reached some level of maturity or saturation. In contrast, for companies in all other age groups (1990s, 2000s, 2010s), where they already have existing AI skills, knowledge, experience co-residing with their employees, they appear to be focused on increasing AI specialisation.

Fig. 10: Shares of unique company IDs in AI-hiring and control samples linked to companies of different age (based on ranges of founding years) (right) and self-selection of companies (right) by founding year.





4.5 Patenting behaviour

We first descriptively explore if there is any relationship between companies' AI-hiring focus and the number of patents they hold, as well as the relative focus of our companies on the Australian IP market (i.e., their focus on patenting in Australia vs overseas). Next, we examine the co-occurrence of unique IPC classes in active/pending patents, highlighting differences between patents held by companies in the AI-hiring and General-hiring samples, to understand the technological focus of AI adopters in patenting. We explore the diversity (or concentration) of active/pending patents across IPC classes for AI-hiring and general-hiring companies. For patents falling into two (or more) IPC classes, we allow them to be double counted.

According to Boden (1998), AI techniques can be used to create new ideas by exploring conceptual spaces, producing novel combinations of new ideas, and enabling the generation of previously impossible ideas through transformations. Wu et al. (2020) report a statistically significant complementary relationship between firms' data analytics use/capacity and diverse re-combination of patent classes, as measured by patents' backward citations. We explore whether the proposed relation between AI and combinatorial creativity (Boden, 1998) holds up when proxied by the distribution and diversity of the firms' IPC classification counts. More generally, this verifies whether there is a difference in the importance of AI in the innovation process for firms with narrow (concentrated) or wide (diverse) innovation focus.

We measure patent class diversity using two simple metrics (admittedly, a narrow approach to diversity[12]). First, we count the number of WIPO IPC classifications in which the company holds a patent. Second, we calculate the Shannon's entropy, which we define as $-\sum_{i=1}^{8} p(i) * \ln(p(i))$, where p(i) is the share of patents in IPC c++lass i relative to the total number of patents the company holds (active and pending only). A higher Shannon's entropy value means patents are held in more diverse IPC classes.

[12] For Leinster (2021) and Page (2017) (among others, e.g., Rao, 1982; Stirling, 2007), diversity is much deeper than just counting some sort of distribution (individual species, typed connections on networks, etc.) and computing the Shannon entropy. Measuring the distance or similarity/relatedness between species is also crucial to take into account.

In the extreme case, a maximum Shannon's entropy means patents are uniformly distributed in all eight WIPO classes. On the other end of extremes, low Shannon's entropy represents a sole focus on one or very few categories of innovation. In general, we do not find evidence to suggest any difference between firms with wide or narrow innovation focus in terms of their current AI capacity building in Australia.

4.5.1 Patenting by AI-hiring vs General-hiring firms

Overview

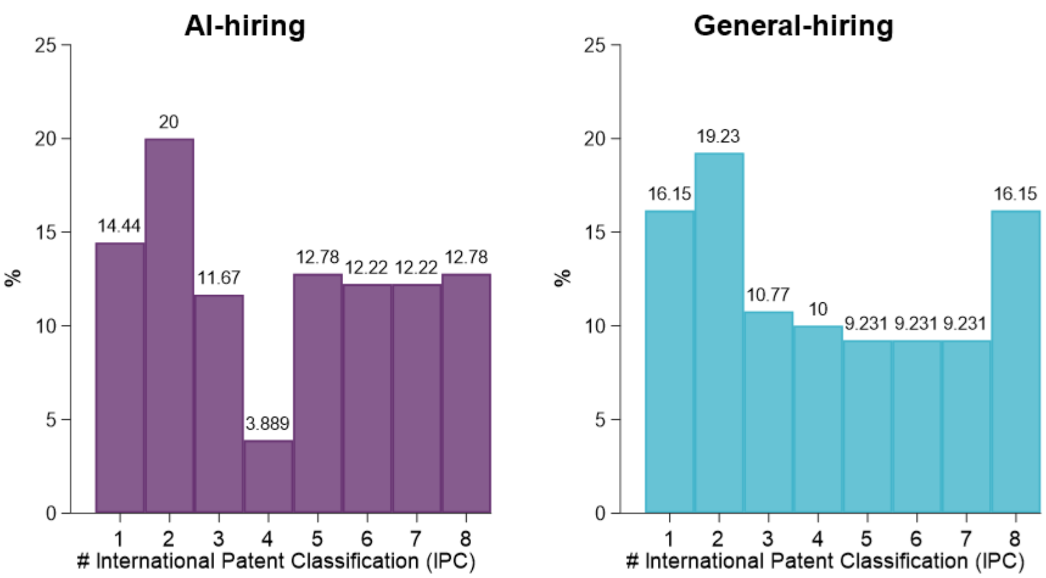
Most companies in our dataset do not hold a patent (n=671). However, the non-patent holding share of companies is larger in the 'General-hiring' sample (71.5%) than the sample hiring AI-staff (54%). For those companies with at least one patent (n=310), the mean and median are 1894 and 30 patents (raw patent count, not patent families – counting patents held anywhere in the world), respectively. This shows the distribution of patents is highly skewed; you either hold a lot of active or pending patents or few/any at all. AI-hiring companies (with at least one patent, n=206) also hold more patents on average (as well as the median) relative to General-hiring companies (n=171), potentially reflecting the use of AI as a direct input into the innovation process, or the complex nature of AI technologies. These are key findings: on average, companies engaged in AI capacity building are more likely to own patents than companies in the general sample. Also, focusing on those companies that own patents, those engaged in AI capacity building own more patents on average than companies in the general sample.

Moreover, just over half (52.6%) of the companies found to own a patent hold at least one patent in Australia, including 87 companies in the AI-hiring sample and 76 companies in the General-hiring sample. This is consistent with prior evidence describing the Australian market as an international breeding ground for AI patents. For example, Leusin et al., (2020) measure both the extent that a country attracts 'AI patents coming from abroad' and produces 'AI patents going abroad.' Australia's status as an international breeding ground for AI patents reflects both its promising market potential for AI exploitation and relevant AI development that is exploited in promising foreign markets, outcomes that are reliant on efficient IP protection.

Diversity

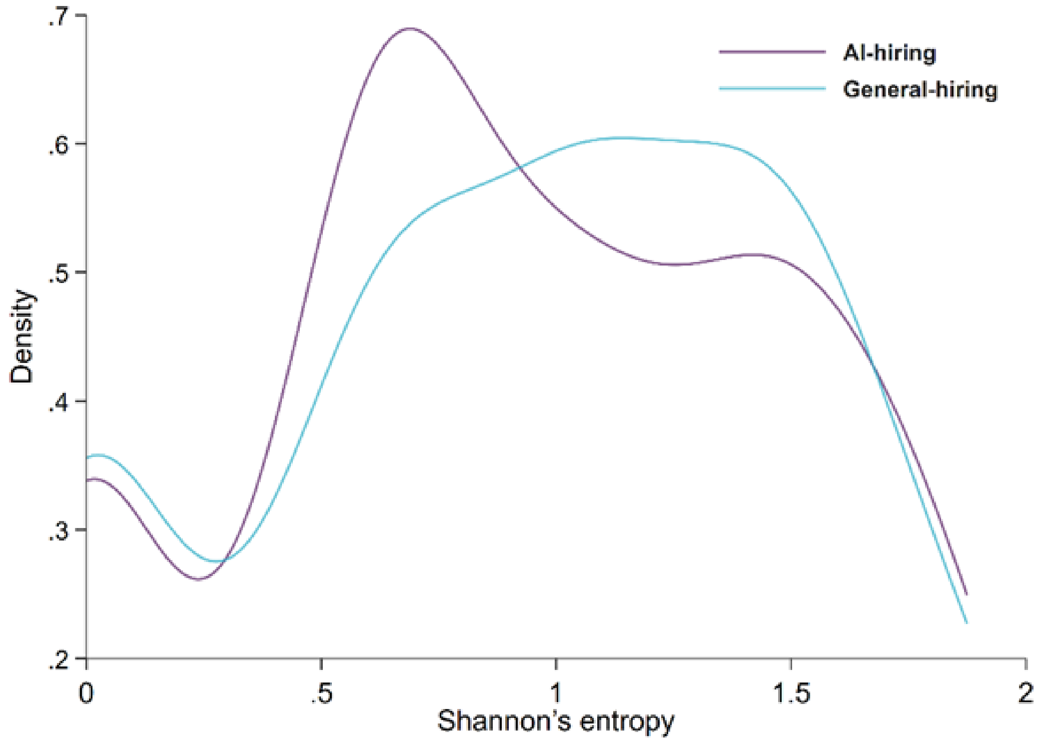
For the 310 patent-holding companies, the average number of IPC classes counted across all of their patents equals 4.3 (SD = 2.45; Median = 4). We do see a visual difference between companies in the *AI-hiring* (left) and the *General-hiring* (right) samples, in the extent their patents are distributed across a number of IPC classes (see Fig. 11). However, these differences are not statistically significant at the 95% confidence level (p=0.401). It is important to note that Fig. 11 shows the distributions of the number of different patent classes held by patent-holding companies, rather than the aggregated counts of each patent class in the sample (which is explored in the next section).

Fig. 11: Distribution of the number of IPC classes in which companies hold patents (anywhere in the world), for the AI-hiring (left) and General-hiring (right) samples.



In terms of Shannon's entropy (see Fig. 12) – wherein a higher value of Shannon's entropy indicates more IPC class diversity or dispersion, and a lower value indicates more IPC class concentration – we find that the difference between the means of the AI-hiring and General-hiring samples is not statistically significant (p=0.596). Diversity in innovation focus does not appear to influence much the decision to build AI capacity, and AI capacity building is not clearly linked to technological diversity in patent output, based on our sample.

Fig. 12: Shannon's entropy of the patents held by patent-holding companies in the AI-hiring (blue) and General-hiring (red) samples.



For the subset of companies holding at least one Australian patent, most held patents in only one WIPO class. Again, there is no statistically significant difference between the AI-hiring (left) and General-hiring (right) samples. We also did not find any statistically significant differences in the number of IPC classes (or Shannon's entropy) between companies with existing AI staff and those without. This result is consistent using data from the pooled sample or from the two subsamples (see Table 2).

Fig. 13: Distribution of the number of IPC classes in which companies hold patents (anywhere in the world) for companies which hold at least one patent in Australia, for the AI-hiring (left) and General-hiring (right) samples.

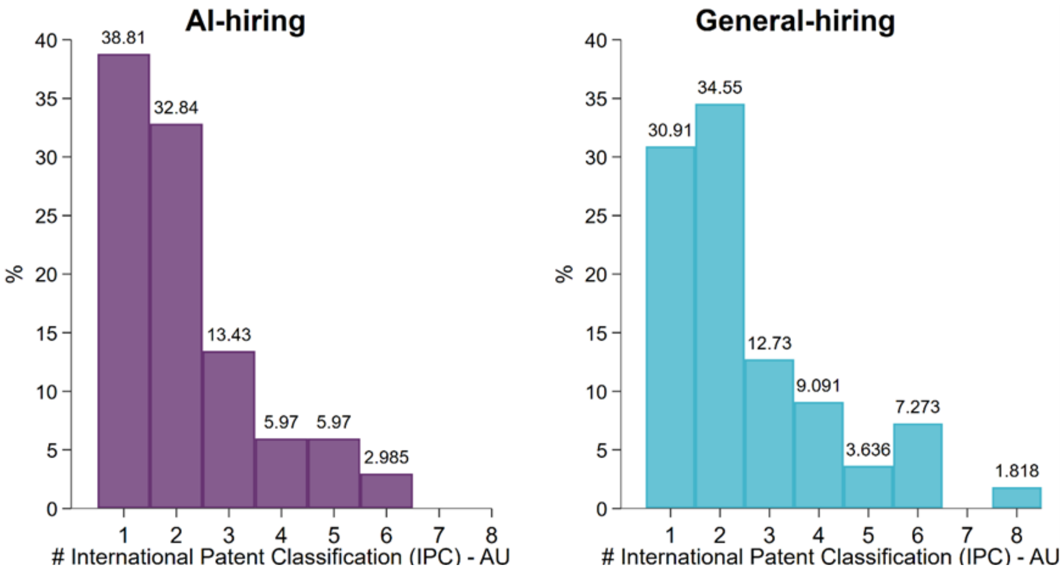


Table 2. Difference between companies with and without existing AI staff.

	Number of IPC classes	Shannon's Entropy
Pooled	z = -0.006, p = 0.996	t = -0.323, p = 0.747
AI-hiring companies	z = -0.113, p = 0.911	t = -0.755, p = 0.451
General-hiring companies	z = 0.160, p = 0.875	t = 0.374, p = 0.709

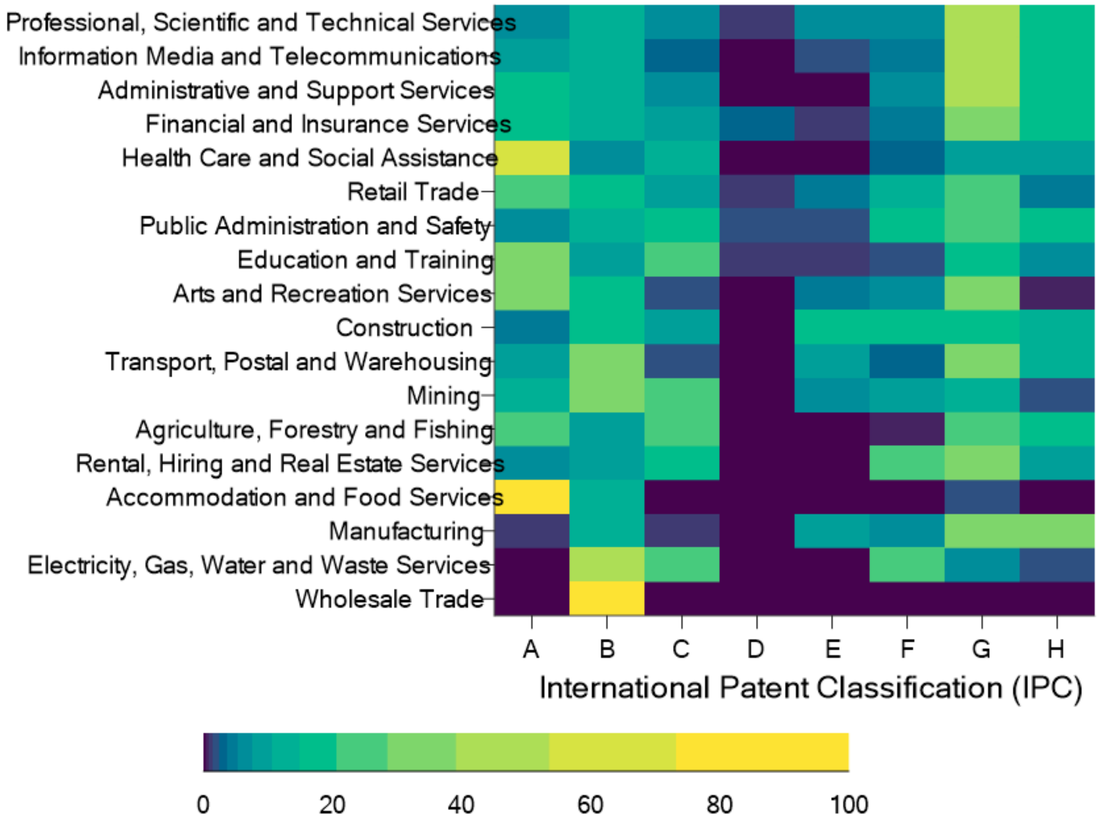
Notes: For the number of IPC classes, we use the ranksum test. For Shannon's entropy, we use a two-sample t-test.

Taken together, these descriptive insights provide preliminary evidence that patent diversity (or concentration) is a poor predictor of AI-hiring or capacity building. Firms with narrow or wide innovation focus, indicated by their patent output, do not behave differently in terms of their current AI capacity building – AI capacity building is not more or less important for niche innovators than for generalists in our sample.

4.5.2 Patenting by industry and IPC classifications

Next, we examine relationships between a company's industry and the IPC classes in which it holds patents (active and pending). Figure 14 presents a heatmap showing, for each industry, the share of patents held by companies in that industry assigned to each of the eight broad IPC classes, based on the full pooled dataset. For companies that hold patents, their technological focus varies by industry, as would be expected, with strong patenting across patent classes A (Human Necessities), B (Performing Operations; Transporting) and G (Physics). There are also some intuitive relations that visually present themselves in the heatmaps, for example, Accommodation and Food Services with patent class A, Healthcare and Social Assistance with patent class A, and Wholesale Trade with patent class B. For brevity, we include separate (industry-patent class) heatmaps for the AI-hiring and General-hiring companies in Appendix 4.

Fig. 14: Heatmap (pooled sample) showing average share of total patents from an industry assigned to each WIPO IPC class.



Next, we test for statistically significant differences between AI-hiring and General-hiring companies in their mean share of patents held within each IPC classification (see Table 3), to provide statistical evidence of whether AI-hiring and General-hiring firms differ in their technological focuses when patenting. We only find statistical significance for G (Physics), suggesting that (on average) those companies currently hiring AI employees are more focused on innovations/markets in this domain. This makes sense as this IPC category includes a range of AI-enabling and AI- related technologies, e.g., optics (G02), computing and calculating or counting (G06), information storage (G11), and information and communication technology adapted for specific application fields (G16). See Table S3 in Appendix 1C for the full list of IPC sub-categories.

Table 3. T-tests to determine if there is a significant difference in innovation focus between AI-hiring and General-hiring companies, proxied by their mean share of patents held in WIPO IPC classes.

		AI-hiring	General	t	p
A	Human Necessities	20.71	19.75	0.25	0.81
B	Performing Operations; Transporting	17.51	17.25	0.07	0.95
C	Chemistry; Metallurgy	10.93	11.66	-0.28	0.78
D	Textiles; Paper	0.51	0.40	0.65	0.52
E	Fixed Constructions	2.75	4.18	-0.97	0.34
F	Mechanical Engineering; Lighting; Heating; Weapons; Blasting	6.32	10.92	-1.32	0.21
G	**Physics**	**29.36**	**21.57**	**2.03****	**0.06**
H	Electricity	11.92	14.27	-1.08	0.29

4.6 Regression approach

Next, we conduct regression analysis using the binary outcome variable AI-hiring (1 if the company has posted an AI-hiring ad, 0 otherwise). We employ a linear probability model (OLS on a binary outcome) and note that modelling with probit does not change the results qualitatively. Bear in mind that the variables denoting whether a company has an AUS HQ, is multi-location (i.e., operates in more than one office or location, potentially as a multi-national), as well as the variable identifying SMEs are somewhat correlated (hence, confounding), and therefore, these results should be interpreted with caution.

4.6.1 Drivers of AI adoption

First, based on the estimated results, SMEs are less likely (on average) to post AI-hiring ads in our sample (models 1-3, Table 4 and models 6-9, Table 5). Second, having existing AI-staff within a company (in our sample) tends to discourage AI-hiring (perhaps having achieved sufficient AI capacity) in that the effect is not statistically significant on average (models 1-5, Table 4 and model 6, Table 5). This could also reflect increased AI-specific hiring by lagging companies trying to catch up with AI.

Third, companies that have patents are more likely to be investing in AI by hiring AI staff (model 2, Table 4 and models 6-9, Table 5). This insight can support the view (De Costa & Carrano, 2017) that companies are increasingly turning to IP rights to protect the value of their investment in AI, such as when adding AI features to existing products and services or creating new AI-based offerings. However, for companies with at least one patent, patent class diversity has no clear impact on AI-hiring. This result aligns with the findings from the previous section (Section 3.5).

Table 4. OLS regression – general/average effects, no interaction effects.

Dep. Var. = AI-hiring	(1)	(2)	(3)	(4)	(5)
AUS HQ	-.0619*	-.022	-.0217	-.0048	2.1e-04
	(.0375)	(.0393)	(.0403)	(.0635)	(.0613)
Multi-location	.0281	.0226	.0259	.1131*	.1128*
	(.0305)	(.0305)	(.0305)	(.0626)	(.0635)
SMEs	-.1605***	-.1398***	-.1458***	-.1379	-.14
	(.0343)	(.0345)	(.0345)	(.0932)	(.093)
Existing AI-staff	-.0375	-.0462	-.0419	-.0489	-.049
	(.0425)	(.0422)	(.0423)	(.0662)	(.0662)
ABS industry					
Information Media and Telecommunications (J)	.0648	.073	.0717	-.0844	-.0843
	(.0544)	(.0542)	(.0544)	(.085)	(.0849)
Administrative and Support Services (N)	-.0772	-.0545	-.0662	-.3582**	-.3541**
	(.0628)	(.0629)	(.0627)	(.1669)	(.1681)
Financial and Insurance Services (K)	-.0908	-.0867	-.0873	-.1931*	-.1932*
	(.0615)	(.0612)	(.0618)	(.1025)	(.1025)
Health Care and Social Assistance (Q)	-.4412***	-.4248***	-.435***	-.5579***	-.5552***
	(.0517)	(.0517)	(.0516)	(.1079)	(.1085)
Retail Trade (G)	-.3293***	-.314***	-.3213***	-.1815	-.1803
	(.0597)	(.0587)	(.0594)	(.1338)	(.1332)
Public Administration and Safety (O)	-.3033***	-.275***	-.2936***	-.3994**	-.3933**
	(.0684)	(.0688)	(.0688)	(.1969)	(.1952)
Education and Training (P)	-.1296*	-.151**	-.1623**	-.1508	-.1456
	(.0711)	(.0695)	(.0703)	(.1068)	(.1067)
Arts and Recreation Services (R)	-.4013***	-.377***	-.3827***	-.4095**	-.41**
	(.0601)	(.0599)	(.0603)	(.1779)	(.1778)
Construction (E)	-.2273**	-.2261**	-.2263**	-.3915**	-.3918**
	(.0947)	(.0955)	(.0946)	(.1558)	(.1568)

Dep. Var. = AI-hiring	(1)	(2)	(3)	(4)	(5)
Transport, Postal and Warehousing (I)	.0816	.0808	.0826	-.3588**	-.3581**
	(.1048)	(.1114)	(.1093)	(.165)	(.1644)
Mining (B)	-.2736**	-.279***	-.2832***	-.3143**	-.3129**
	(.1083)	(.1058)	(.1043)	(.1548)	(.1552)
Agriculture, Forestry and Fishing (A)	-.0371	-.0266	-.0287	-.0437	-.0433
	(.1239)	(.1244)	(.1267)	(.2465)	(.2448)
Rental, Hiring and Real Estate Services (L)	-.2217*	-.2067	-.2093*	-.2675	-.2703
	(.1296)	(.1285)	(.1266)	(.2643)	(.2669)
Accommodation and Food Services (H)	-.2156*	-.1901	-.1903	-.3936	-.3995
	(.1225)	(.1249)	(.1229)	(.2544)	(.256)
Manufacturing (C)	.0434	.035	.0274	.0158	.0196
	(.1296)	(.1278)	(.1276)	(.177)	(.176)
Electricity, Gas, Water and Waste Services (D)	-.026	-.0111	-.0204	-.2738	-.2732
	(.1681)	(.1716)	(.1687)	(.4124)	(.4152)
Wholesale Trade (F)	-.4038**	-.3876***	-.3887**	.4316***	.4298***
	(.1579)	(.1396)	(.1539)	(.1032)	(.1098)
Other Services (S)	.3726***	.4181***	.3977***		
	(.0447)	(.0463)	(.0454)		
Have patent		.1269***			
		(.0374)			
# WIPO classes			.0205***	.0036	
			(.0074)	(.0128)	
Shannon's entropy					.0055
					(.0548)
Constant	.6613***	.5813***	.5981***	.6979***	.71***
	(.0494)	(.0555)	(.0549)	(.0992)	(.0965)
Observations	1043	1043	1043	310	310
R^2	0.148	0.159	0.155	0.131	0.131

Notes: Robust standard errors in parentheses. The symbols *, **, * represent statistical significance at the 10%, 5%, and 1%, respectively.**

4.6.2 Interaction effects and robustness checks

In Table 5, we further examine the relationship between our variables and other robustness checks. In model 6, we substitute the dummy variable 'Exist AI-staff', denoting that a company has at least one staff member with AI skills, with a continuous variable denoting the number of existing AI-staff in a company within our sample population. In model 7, we control for the age of the company (where the reference group is companies founded before the 1990s , also note the drop in observations due to not all companies providing the founding date on their company LinkedIn profile).

In model 8, we include an interaction between 'AUS HQ' and 'SMEs' to test whether Australia-based SMEs are less likely to hire AI staff (compared to non-Australia-based SMEs). In model 9, we include an interaction term between 'SMEs' and 'Exist AI-staff' to see if SMEs with existing AI-staff act differently from those without. In model 10 and 11, we interact the dummy variable for whether a company holds patents with the dummy variable for whether it is an SME (model 10) or whether it has existing AI-staff (model 11).

Finally, in model 12, we include the three-way interaction term between 'SMEs', 'Exist AI-staff' and 'Have patent' to test whether SMEs with existing AI-staff and who hold a patent act differently from those who do not hold a patent. This provides a pathway to test for the importance of IP to AI-skilled SMEs investing in continued AI development and/or implementation.

Table 4. OLS regression – general/average effects, no interaction effects.

Dep. Var. = AI-hiring	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AUS HQ	-.0197	.004	-.0271	-.0249	-.0212	-.0219	-.0233
	(.0395)	(.0506)	(.0434)	(.039)	(.0396)	(.0393)	(.0394)
Multi-location	.0227	.0221	.0223	.0287	.0224	.0226	.0284
	(.0305)	(.0358)	(.0306)	(.0303)	(.0305)	(.0305)	(.0304)
SMEs	-.1381***	-.1989***	-.1654*	-.1698***	-.137***	-.1396***	-.1642***
	(.0341)	(.0428)	(.0925)	(.0349)	(.0363)	(.0346)	(.0375)
Have patent	.1296***	.1841***	.126***	.1246***	.1305***	.1283***	.127***
	(.0377)	(.0448)	(.0376)	(.037)	(.0412)	(.041)	(.0461)
# Existing AI-staff	-.0023						
	(.0023)						
Exist AI-staff		*-.0414*	-.0461	-.1109**	-.046	-.0431	-.1263**
		(.051)	(.0422)	(.0442)	(.0422)	(.0544)	(.0586)
Company found							
90s		*.0303*					
		(.0544)					
00s		*.0589*					
		(.0521)					
>= 10s		*.1276****					
		(.0468)					
Interactions							
*AUS HQ*SMEs*			.0292				
			(.0975)				
*SMEs*Exist AI-staff*				.4293***			.4305***
				(.1085)			(.1254)
*SMEs*Have patent*					-.0179		-.0479
					(.0914)		(.0958)
*Have patent*Exist AI-staff*						-.0075	.0336
						(.0865)	(.0912)
*SMEs*Exist AI-staff *Have patent*							.0478
							(.2633)
Constant	*.5726****	*.4984****	.5847***	.5844***	.5792***	.5807***	.582***
	(.055)	*(.071)*	(.057)	(.055)	(.0565)	(.056)	(.0571)
ABS Industry FE	*Yes*	*Yes*	Yes	Yes	Yes	Yes	Yes
Observations	*1043*	*752*	1043	1043	1043	1043	1043
R^2	*0.159*	*0.168*	0.159	0.170	0.159	0.159	0.170

Notes: Robust standard errors in parentheses. The symbols *, **, *** represent statistical significance at the 10%, 5%, and 1%, respectively.

We first find that using the number of AI-staff instead of a binary indicator does not change the results (model 6) – having existing AI-staff within a company tends to discourage further AI-hiring. Importantly, we see that younger companies (founded after the 2010s) are more likely to hire AI staff than most established companies (model 7), reflecting relatively greater attention or exposure to AI.

Further, SMEs with existing AI-staff are more likely to hire more AI-staff than other SMEs. Conversely, large companies with existing AI-staff are less likely to hire additional AI-staff than other large companies (model 9). Together this suggests increased AI specialisation by AI-based SMEs, and possibly more AI-based start-ups entering in recent years since, e.g., as ML and deep learning really took off in the mid-2010s.

Moreover, Australian-based and non-Australian-based SMEs are similarly likely to hire AI-staff in Australian locations (model 8). This could reflect Australia's international market appeal for providers of AI (and related technologies) and desires to invest in Australia. It may also reflect slower uptake and adoption of AI by Australian SMEs.

We do not find any mediation effects of company characteristics on the relationship between AI adoption and patenting (number of patents and patent class diversity). Further, we do not find significance for the two-way and three-way interaction effects testing whether the link between AI adoption and patenting is greater for SMEs ('SMEs*Have patent') or for SMEs specialised in AI ('SMEs *Exist AI-staff*Have patent') in models 10, 11 and 12. This suggests that SMEs (relative to large firms) that hold a patent are not much different from firms that do not hold a patent, in terms of current AI-hiring or capacity building in our sample. In other words, despite the finding that holding a patent, in general, increases the likelihood of AI capacity building, for SMEs there is no difference in the AI-hiring of firms with and without patents. This could also reflect the lower engagement of SMEs with the patent system more generally (e.g., due to resource constraints, focus on time to market).

5 CONCLUSIONS AND RECOMMENDATIONS

This study highlights the role of the patent system in the strategies of firms engaged in building capacity in AI. At the same time, it highlights the importance of monitoring the growth of AI beyond the traditional patent regime, exploiting alternative methods to track the adoption of AI and its application to innovation.

The LinkedIn job posting approach, combined with the Lens patent data, provides a novel approach for analysing and monitoring trends in IP, investment, and skills development for frontier technologies. It presents an attractive, viable complement to more traditional patent and company microdata due to the volume, velocity and variety of the data it draws upon. However, care must be taken in interpreting raw results, as data adjustment/correction may be required to help balance quantity-quality trade-offs.

5.1 Target interventions towards AI leaders/laggers

IP offices and researchers should not shy away from the complexity of studying the innovation patterns of emerging technologies and the challenges (cue opportunity) this presents. By separating out the heterogeneity in adoption across industries and faceting company microdata along dimensions such as size, location, patent behaviour, and others, we can more accurately analyse and monitor trends (emerging, sustained) in different sub-populations. This could also help government more generally to identify groups of companies or people that are negatively impacted by market failures, quantify their gains or losses, and correct market failures (where there are effective policy instruments) including by designing appropriate and timely compensation policies (where there is a reasonable national interest to doing so).

The process we detail in this report presents a generalisable methodology for mapping research and development that can also be applied to other areas of policy interest (e.g., identifying target populations). The power of such "finger on the pulse" monitors of the economy (using alternative data sources) is that we can use them to diagnose issues in the 'here and now' and design targeted compensation measures and interventions to correct these issues.

As a first step (low-hanging fruit) based on the findings of this current report, we recommend targeting SMEs who do not have existing AI-staff to encourage them to engage more with AI, to prevent them from falling further behind the AI frontier. For example, where there is a proven business case to do so, this might include adopting AI techniques from others in the same industry. Laggers should be encouraged to explore whether it could be worth adopting or applying AI across different business/operational roles and functions guided by what other AI leaders (firms, industries) have done.

Another target group to focus on are industries that we identified as i) behind the AI hiring curve (e.g., health care and social assistance, retail trade, public administration and safety) to help them catch up, or ii) ahead of the curve (e.g., information media and telecommunications, professional, scientific and technical services, financial and insurance services, transport, postal and warehousing, manufacturing) to foster their development and encourage diffusion from problems/applications within these leading AI-hiring industries to related problems or applications in lagging industries (see Table 6 in Section 4.1). Connecting AI laggers with leaders (e.g., those identified as having an innovation focus and existing AI-staff) can help facilitate knowledge transfer and development of local AI specialisations and skill hubs.

5.2 Improve data available on AI development, transfer and implementation

Our analysis relied on only a snapshot of job ad postings and current employees in time. This data cannot say much about the dynamics or temporal elements of firms' skills-bases and needs. Longitudinal data collection on companies and companies' employees would enable researchers to track trends over time in employee mobility, skill penetration, knowledge generation, and knowledge/skills flows across industries and companies with different characteristics. For example, such data could enable monitoring of the 'ordinary skill in the art' of AI across different industries, domains, technologies, etc.

We recommend implementing an automated, frequent or intermittently scheduled data collection to capture additional data points on our base set of AI-hiring and General-hiring companies over time. Job posting data can be retrieved via methods detailed in this report. In particular, searching for all job posts by each company. This could be done by either i) setting 'companies' – see API documentation – to the complete list of unique company IDs in our *Companies* dataset to retrieve all jobs for all companies (keeping in mind the limit of 1000 results returned by LinkedIn's Voyager API), or ii) setting, for each company in the *Companies* dataset, values on the variable 'companies' to the company's id and retrieving all jobs for that company (this would take much longer to run the script but provide more coverage).

Keep in mind the job market is a two-sided market: employees and employers both search for each other, directly or through intermediaries (e.g., hiring agencies/HR firms). By appealing to more extensive (temporal) datasets of job posting across companies, we could also explore whether a company's IP and innovation openness make a firm more attractive to prospective employees and job seekers (e.g., with openness proxied by community outreach (e.g., company follower count), whether full text is shared or through text analysis (readability, authenticity) of full text). It would be pertinent to appeal to a broad range of data/proxies either via commercial providers or open/publicly accessible data. However, care should always be taken to construct only census-like sources of aggregate behaviour which preserve individual privacy.

It could also be useful to extend this mapping approach to other related and enabling/enabled frontier and digital technologies (e.g., mobile technologies, quantum computing, distributed ledgers, internet of things, remote sensing, etc.) to explore their co-evolution over time. This could be done by appealing to patent-level metadata from the complete list of firms' patents (see e.g., Schmoch, 2008; Arnold et al., 2020; Bloom et al., 2021; Zhang et al., 2022) and also via the skills and job posting approaches we and others (Bahar & Lane, 2022) demonstrate.

5.3 Explore area-level differences

Our analysis did not stipulate or explore job posting locations beyond the need for a job posting to be for position in Australia. However, it is well known that innovation and specialisations can cluster in geographical space (e.g., innovation hubs and regions) and over time. For example, such clustering is observed in high-paying, high-skilled positions in pioneer locations, in local ecosystems of universities, high-skilled labour pools, and (pioneer) firms (Bloom et al., 2021). As such, it would be useful from a policy perspective to explore any geographical/spatial effects in the industries' response to AI, including at a state- or city-level, and assess any differences or spillovers not accounted for in our current analysis.

We also recommend exploring regional factors represented by job postings analysed by city and state. Policymakers and researchers could explore job mobility across different locations in Australia, for example, to explore interactions between AI-skill mobility and city- or state-level regulation, standards, and other (human) aspects such as socio-economic situation, culture, liveability, etc. (see, for example, Zwetsloot et al., 2021).

5.4 Use the mapping of AI capabilities and innovation to inform strategic initiatives

Mapping AI capabilities and innovation can help to identify areas where investment and collaboration are needed to drive growth and competitiveness. The presented work provides information on where to focus such investments – with respect to industries as well as locations.

Besides identifying locations in Australia where AI capability may be agglomerated, mapping emerging and established firm capabilities and formal innovative activity can be used to connect sites of R&D strength with firms actively demonstrating need for related technology and skills. In complement to the function of a successful IP system, this data tool can be used to connect potential partners from industry and research in strategic programs directed at building industry capacity. Strategic initiatives can be tailored for different industries, and designed for different types of businesses, including SMEs, large enterprises, national and multinational corporations.

The multi-faceted approach to mapping AI capabilities and innovation presented in this work provides a more comprehensive picture of the current landscape, including the strengths and weaknesses of businesses with different characteristics (industry, size, age, location) in AI jobs, skills, and innovation. By drawing on a diverse range of data sources, decision-makers can gain a more complete understanding of the innovation landscape and the trends shaping the development of AI technology. By leveraging this information, decision-makers can support the development of new AI technologies and applications, foster innovation in the field, and drive the growth of the AI sector(s) in Australia.

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APPENDIX 1: DATA SOURCE AND LINKING

The analysis presented in this report is based on analysis of two primary sources:

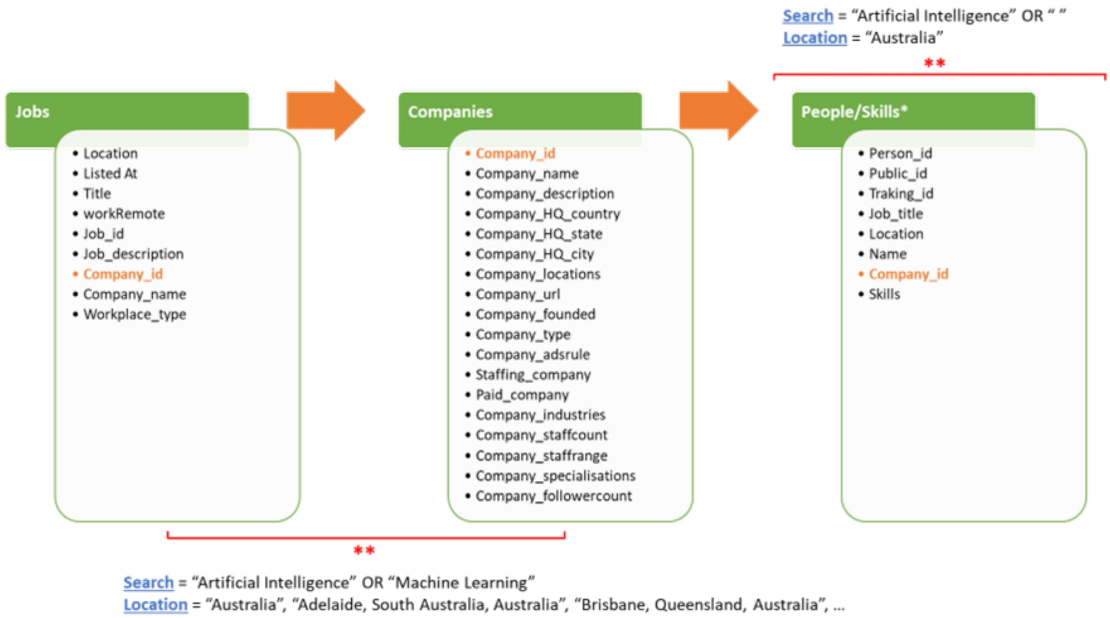
1. LinkedIn — Jobs, Companies, People/Skills Datasets.
2. Lens — Patent Record Counts.

Appendix 1A: *LinkedIn Jobs, Companies* and *People/Skills datasets*

We leverage the work of Tom Quirk[13] to interact with LinkedIn's Voyager endpoints, allowing us in some sense to automatically communicate and interact with the LinkedIn website and retrieve detailed microdata on job advertisements, companies, and people/skills.

Fig. S1 illustrates graphically the LinkedIn data collection process and key job search criteria used (keyword and location).

Fig. S1: LinkedIn Data Collection Process and Job Search Criteria.



Essentially, the LinkedIn data collection process and search criteria is:

1. "Search Jobs" for keywords = Artificial Intelligence OR Machine Learning in location_name = Australia, Brisbane, Canberra, etc. (returns job_id, time listed, title, work_remote).
2. Using the job_id's from 1, "Get Job" and retrieve detailed job information (returns description, company_id, company name, workplace type, etc.).
3. Using the company_id's from 2, "Get Company" and retrieve detailed company information (returns company_id, industry, staff count, staff range, specialties, LinkedIn follower count, location of HQ, etc.).
4. Using the company_id's from 3, "Search People" with current_company = company_id's for those who are currently working at company (returns person_id, title, company_id, location, name, etc.).
5. Using the person_id's from 4, "Get Profile Skills" and retrieve self-listed skills.

[13] See https://github.com/tomquirk/linkedin-api. Additional documentation at https://linkedin-api.readthedocs.io/.

APPENDIX 1B: INDUSTRY MATCHING — LINKEDIN TO ANZIC06

LinkedIn industries[14] are manually mapped to the ANZIC06 industry divisions (see Table S1), a common frame of reference also adopted by the Australian Bureau of Statistics (ABS), using rule-based coding.

Table S1. ANZIC 2006 (ANZIC06) division code ranges.

ID	ANZSIC06 Division Name	Code Range
A	Agriculture, Forestry and Fishing	0100-0599
B	Mining	0600-1099
C	Manufacturing	1100-2599
D	Electricity, Gas, Water and Waste Services	2600-2999
E	Construction	3000-3299
F	Wholesale Trade	3300-3899
G	Retail Trade	3900-4399
H	Accommodation and Food Services	4400-4599
I	Transport, Postal and Warehousing	4600-5399
J	Information Media and Telecommunications	5400-6099
K	Financial and Insurance Services	6200-6499
L	Rental, Hiring and Real Estate Services	6600-6799
M	Professional, Scientific and Technical Services	6900-7099
N	Administrative and Support Services	7200-7399
O	Public Administration and Safety	7500-7799
P	Education and Training	8000-8299
Q	Health Care and Social Assistance	8400-8799
R	Arts and Recreation Services	8900-9299
S	Other Services	9400-9699

Source: https://www.abs.gov.au/statistics/classifications/australian-and-new-zealand-standard-industrial-classification-anzsic/2006-revision-2-0/numbering-system-and-titles#codes-and-titles, accessed 7 September 2022.

[14] See: https://learn.microsoft.com/en-us/linkedin/shared/references/reference-tables/industry-codes-v2.

The ANZIC06-LinkedIn industry mapping is given in Table S2.

Table S2. ANZIC06-LinkedIn mappings.

LinkedIn Industry Name	**ANZIC06 Division**
Food & Beverages	Accommodation and Food Services
Food Production	Accommodation and Food Services
Wine and Spirits	Accommodation and Food Services
Facilities Services	Administrative and Support Services
Staffing and Recruiting	Administrative and Support Services
Dairy	Agriculture, Forestry and Fishing
Environmental Services	Agriculture, Forestry and Fishing
Farming	Agriculture, Forestry and Fishing
Maritime	Agriculture, Forestry and Fishing
Renewables & Environment	Agriculture, Forestry and Fishing
Computer Games	Arts and Recreation Services
Entertainment	Arts and Recreation Services
Gambling Facilities and Casinos	Arts and Recreation Services
Leisure, Travel & Tourism	Arts and Recreation Services
Sports	Arts and Recreation Services
Events Services	Arts and Recreation Services
Health, Wellness & Fitness	Arts and Recreation Services
Publishing	Arts and Recreation Services
Hospitality	Arts and Recreation Services
Motion Pictures & Film	Arts and Recreation Services
Music	Arts and Recreation Services
Recreational Facilities & Services	Arts and Recreation Services
Building Materials	Construction
Construction	Construction
Machinery	Construction
Shipbuilding	Construction
E-learning	Education and Training
Education Management	Education and Training
Higher Education	Education and Training
Research	Education and Training
Primary/Secondary Education	Education and Training
Professional Training & Coaching	Education and Training
Utilities	Electricity, Gas, Water and Waste Services
Banking	Financial and Insurance Services
Financial Services	Financial and Insurance Services
Insurance	Financial and Insurance Services
International Trade & Development	Financial and Insurance Services
Venture Capital & Private Equity	Financial and Insurance Services
Capital Markets	Financial and Insurance Services
Investment Banking	Financial and Insurance Services
Hospital & Health Care	Health Care and Social Assistance
Individual & Family Services	Health Care and Social Assistance

LinkedIn Industry Name	**ANZIC06 Division**
Medical Device	Health Care and Social Assistance
Non-profit Organization Management	Health Care and Social Assistance
Pharmaceuticals	Health Care and Social Assistance
Biotechnology	Health Care and Social Assistance
Civic & Social Organization	Health Care and Social Assistance
Mental Health Care	Health Care and Social Assistance
Broadcast Media	Information Media and Telecommunications
Information Services	Information Media and Telecommunications
Information Technology & Services	Information Media and Telecommunications
Internet	Information Media and Telecommunications
Libraries	Information Media and Telecommunications
Online Media	Information Media and Telecommunications
Telecommunications	Information Media and Telecommunications
Computer & Network Security	Information Media and Telecommunications
Media Production	Information Media and Telecommunications
Automotive	Manufacturing
Electrical & Electronic Manufacturing	Manufacturing
Furniture	Manufacturing
Industrial Automation	Manufacturing
Semiconductors	Manufacturing
Mining & Metals	Mining
Oil & Energy	Mining
Outsourcing/Offshoring	Other Services
Accounting	Professional, Scientific and Technical Services
Architecture & Planning	Professional, Scientific and Technical Services
Aviation & Aerospace	Professional, Scientific and Technical Services
Chemicals	Professional, Scientific and Technical Services
Civil Engineering	Professional, Scientific and Technical Services
Computer Software	Professional, Scientific and Technical Services
Design	Professional, Scientific and Technical Services
Human Resources	Professional, Scientific and Technical Services
Law Practice	Professional, Scientific and Technical Services
Management Consulting	Professional, Scientific and Technical Services
Market Research	Professional, Scientific and Technical Services
Marketing & Advertising	Professional, Scientific and Technical Services
Mechanical Or Industrial Engineering	Professional, Scientific and Technical Services
Legal Services	Professional, Scientific and Technical Services
Public Relations & Communications	Professional, Scientific and Technical Services
Defense & Space	Public Administration and Safety
Executive Office	Public Administration and Safety
Government Administration	Public Administration and Safety
Public Safety	Public Administration and Safety
Law Enforcement	Public Administration and Safety
Security & Investigations	Public Administration and Safety
Government Relations	Public Administration and Safety

LinkedIn Industry Name	**ANZIC06 Division**
Military	Public Administration and Safety
Political Organization	Public Administration and Safety
Public Policy	Public Administration and Safety
Real Estate	Rental, Hiring and Real Estate Services
Apparel & Fashion	Retail Trade
Business Supplies & Equipment	Retail Trade
Consumer Goods	Retail Trade
Consumer Services	Retail Trade
Cosmetics	Retail Trade
Retail	Retail Trade
Computer Hardware	Retail Trade
Consumer Electronics	Retail Trade
Luxury Goods & Jewelry	Retail Trade
Packaging & Containers	Retail Trade
Airlines/Aviation	Transport, Postal and Warehousing
Logistics & Supply Chain	Transport, Postal and Warehousing
Transportation/Trucking/Railroad	Transport, Postal and Warehousing
Wholesale	Wholesale Trade
Paper & Forest Products	Wholesale Trade

Source: Manually-coded mapping from LinkedIn industry name to ANZIC06 division.

APPENDIX 1C: IPC FRAMEWORK

Table S3. International Patent Classification (IPC) framework – the 8 primary IPC categories.

ID	Category Name	Sub-Classes
A	Human Necessities	Includes agriculture (A01), foodstuffs, tobacco (A21-4 personal or domestic articles (A41-7, e.g., clothing, jewellery, furniture), health and life-saving (A61-62), leisure and amusement (A63), and other (A99).
B	Performing Operations, Transporting	Includes functions such as separating and mixing (i.e., B01-9), shaping (B21-33), printing (B41-4), transporting (B60-68), e.g., vehicles, rail, conveying, hoisting), microstructural/nano technology (B81-2), and other (B99).
C	Chemistry, Metallurgy	Includes chemistry (C01-14), metallurgy (C21-35, C30), combinatorial technology (C40), and other (C99).
D	Textiles, Paper	Includes textiles or flexible materials not otherwise provided for (D01-07), paper (D21), and other (D99).
E	Fixed Constructions	Includes building (E01-06, e.g., construction of roads, hydraulic engineering, foundations, water/sewage, locks/keys/safes, doors/windows) and earth or rock drilling and mining (E21), and other (E99).
F	Mechanical Engineering, Lighting, Heating, Weapons	Includes engines or pumps (F01-04), engineering in general (F15-7), lighting and heating (F21-8), weapons and blasting (F41-2), and other (F99).
G	Physics	Includes measuring and testing (G01), optics (G02), photography/cinematography/etc. (G03), horology (G04), controlling and regulating (G05), computing and calculating or counting (G06), checking-devices (G07), signalling (G08), educating/advertising/cryptography (G09), musical instruments and acoustics (G10), information storage (G11), instrument details (G12), information and communication technology adapted for specific application fields (G16), nuclear physics and engineering (G21), and other (G99).
H	Electricity	Includes basic electrical elements (H01), generation and conversion or distribution of electric power (G02), basic electronic circuity (H03), electric communication technique (H04), electric techniques not otherwise provided for (H05), and other (H99).

Source: https://www.wipo.int/classifications/ipc/en/, accessed 16 October 2022.

APPENDIX 2: COUNTS AND SHARES OF JOB ADS BY COMPANY LOCATIONS

Fig. S2: Counts of unique company IDs by AUS vs Non-AUS HQ (left) by single- vs multi-location (right).

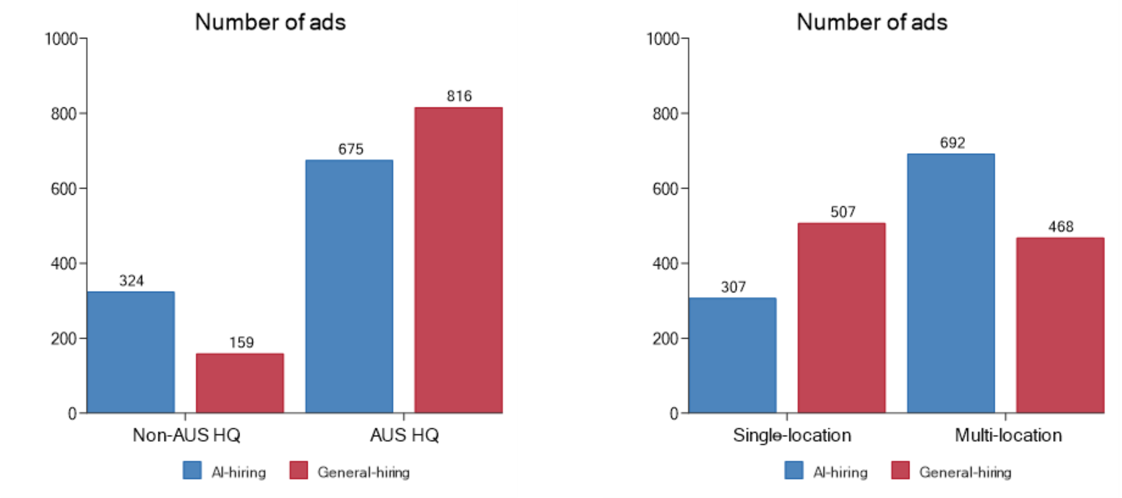
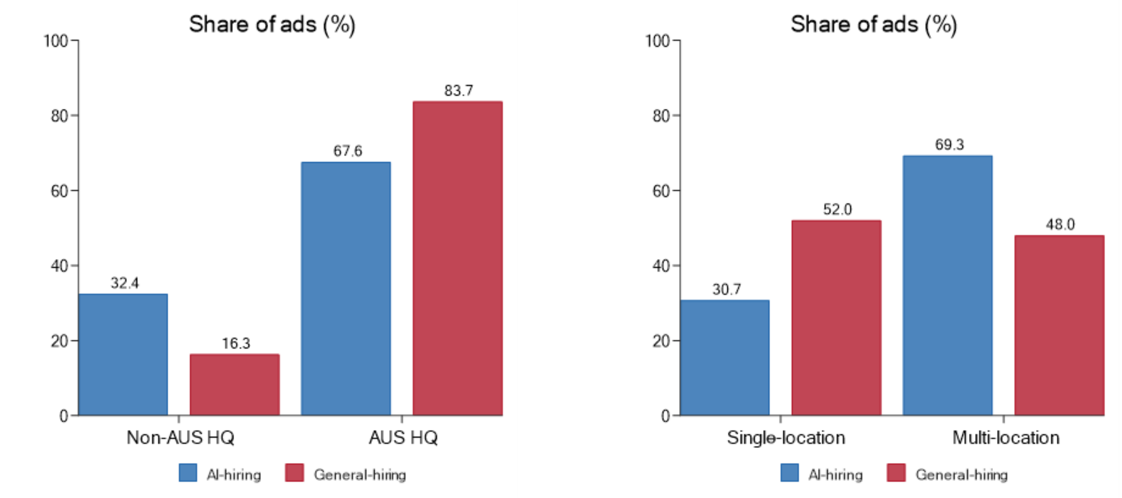


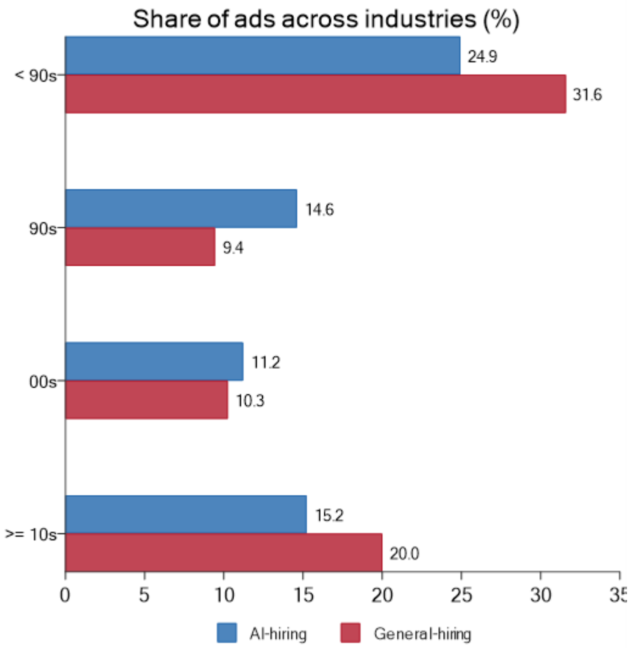
Fig. S3: Shares of unique company IDs by AUS vs Non-AUS HQ (left) by single- vs multi-location (right).



APPENDIX 3: SHARE OF JOB ADS BY COMPANY AGE

Here, we sum the share of job ads by company age, aggregating by companies' industry instead of raw company counts. Here more recently founded companies aren't doing so well in terms of raw counts of AI job ads. This is likely driven by company size (smaller resources).

Fig. S4: Shares of job ad IDs across industries by founding year.



APPENDIX 4: SHARE OF PATENT IN EACH WIPO CLASS, BY ABS INDUSTRY AND AI ADOPTION STATUS

Fig. S5: Heatmap (AI-hiring) - Average share of patent in each WIPO IPC class, by ABS industry.

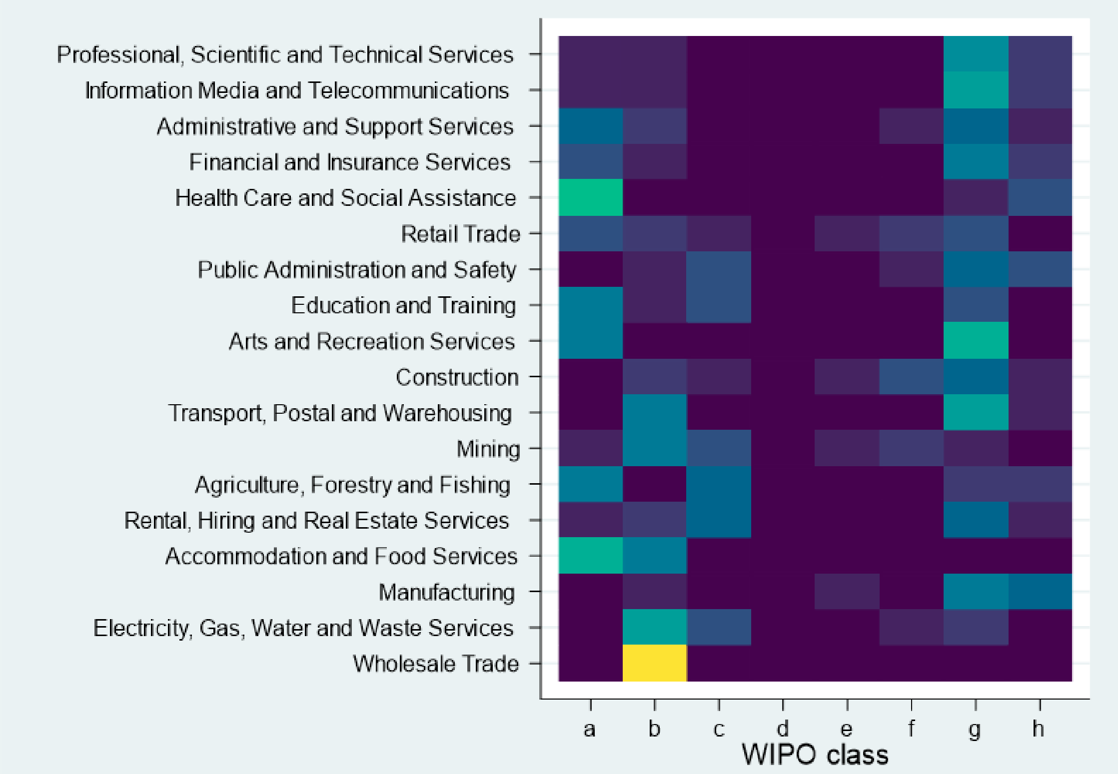
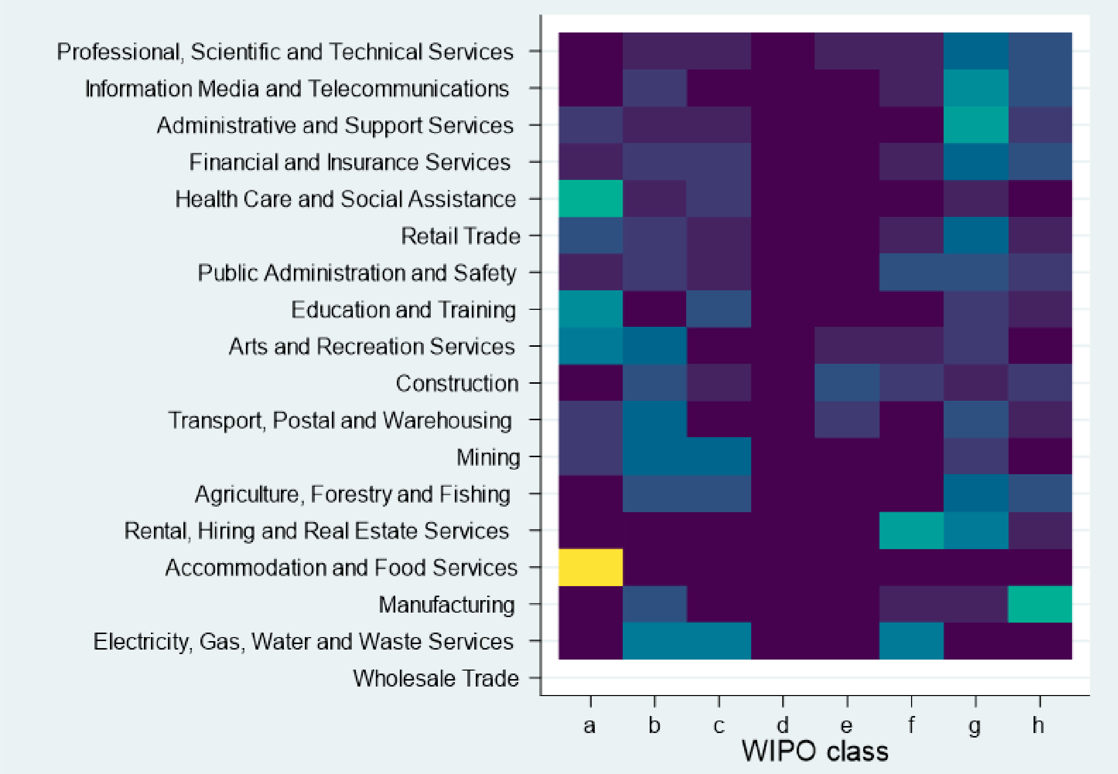


Fig. S6: Heatmap (General-hiring) - Average share of patent in each WIPO IPC class, by ABS industry.

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