# Differentiating artificial intelligence capability clusters in Australia

Bratanova, Alexandra and Pham, Hien and Mason, Claire and Hajkowicz, Stefan and Naughtin, Claire and Schleiger, Emma and Sanderson, Conrad and Chen, Caron and Karimi, Sarvnaz

Commonwealth Scientific and Industrial Research Organisation (CSIRO)

31 May 2022

# Differentiating artificial intelligence capability clusters in Australia

PRE - PRINT

31 May 2022

Alexandra Bratanova*, Hien Pham, Claire Mason, Stefan Hajkowicz, Claire K Naughtin, Emma Schleiger, Conrad Sanderson, Caron Chen and Sarvnaz Karimi

**Abstract**

We demonstrate how cluster analysis underpinned by analysis of revealed technology advantage can be used to differentiate geographic regions with comparative advantage in artificial intelligence (AI). Our analysis uses novel datasets on Australian AI businesses, intellectual property patents and labour markets to explore location, concentration and intensity of AI activities across 333 geographical regions. We find that Australia's AI business and innovation activity is clustered in geographic locations with higher investment in research and development. Through cluster analysis we identify three tiers of AI capability regions that are developing across the economy: 'AI hotspots' (10 regions), 'Emerging AI regions' (85 regions) and 'Nascent AI regions' (238 regions). While the AI hotspots are mainly concentrated in central business district locations, there are examples when they also appear outside CBD in areas where there has been significant investment in innovation and technology hubs. Policy makers can use the results of this study to facilitate and monitor the growth of AI capability to boost economic recovery. Investors may find these results helpful to learn about the current landscape of AI business and innovation activities in Australia.

**Keywords:** Artificial intelligence, cluster, revealed technology advantage, regional innovation, Australia.
**JEL classification codes:** O310, O330, O380, R120

**Authors' affiliation:**
Commonwealth Scientific and Industrial Research Organisation (CSIRO), Brisbane, Queensland, Australia
*Corresponding author. Email: Alexandra.bratanova@data61.csiro.au.
Address: Level 7, STARS Building, 296 Herston Rd, Herston Queensland 4029, Australia

**Funding:** This work was supported by the CSIRO's Data61.

**Acknowledgments:** We would like to thank students from RMIT - Nikhita Singh Shiv Kalpana and Prerit Miglani who helped set up the data collection and analysis at the early stages of this research. We are grateful to Adzuna Australia for providing permission to use their job ads data.

## 1 Introduction

The world has arguably entered an artificial intelligence (AI) race, with AI seen as a promise for a productivity uplift and economic growth [1]. According to modeling by the McKinsey Global Institute, AI will grow global economic output by US$13 trillion between 2018 and 2030 [2]. Some experts argue the impact of AI will extend beyond the economic domain, affecting how people think, act, interact with machines and with each other [3-5]. In Australia specifically, AI adoption is helping to transform economic sectors (e.g., mining, health, agriculture) [6], which will likely continue with future technological advances [7-10].

In this context, governments worldwide, including Australia, are making substantial investments to support the development of AI capability [6, 11]. Since Canada's first national AI strategy in 2017 [12], over 700 AI policy initiatives have been developed across 60 countries and territories. Australia committed to the development of AI capability through the Australian National AI Roadmap (2019) [6] and Australia's Artificial Intelligence Action Plan (2021). Australia's AI Action Plan includes AU$124 million of budget investment in 2021-22 to enhance the leadership of Australia in AI development and adoption [11]. Australian states and territories have included AI into their regional development priorities [13-16]. In terms of private investment in AI, Australia is among the top twelve nations globally [17]. However, these investments may need to be targeted effectively to achieve their desired benefits. National, state and local governments globally and in Australia want to know whether AI development and adoption could boost the recovery and growth of their regional economies. They are asking questions on where regions stand in the AI domain and what actions are required to ensure they are not left behind in the emerging international and national AI economies [18].

In this paper, we take the first step towards addressing these questions for Australian regions. We examine the location and concentration of AI business and innovation activities to explore the emerging geography of AI in Australia. To do this, we apply clustering algorithms to metrics of AI activity, and profile geographic regions in terms of their AI capability. Through this analysis we identify three tiers of regions: tier 1 'AI hotspots', tier 2 'Emerging AI regions', and tier 3 'Nascent AI regions'. The 'AI hotspots' represent 10 Australian regions with the highest concentration of AI activities both in innovation and business domains. These are the regions where AI patents are being filed, new AI companies started and AI jobs advertised. The 'emerging AI regions' are the 85 regions with a substantial level of AI activities, but below the level of tier 1 regions. There is less AI activity and it tends to be limited to either innovation or business domains. Finally, the 'nascent AI regions' include 238 regions with very limited evidence of AI related innovation or business activities.

The motivation for our geography and cluster analysis is as follows. Since the 1980s, an increasing number of conceptual and applied economic models have demonstrated the importance of place-specific factors as determinants of regional economic growth and sources of comparative advantage for regions [19], despite ongoing globalisation. Michael Porter defines this "paradox" as follows: "the enduring competitive advantages in a global economy lie increasingly in local things—knowledge, relationships, motivation—that distant rivals cannot match" [20]. Regions have been shown to evolve from the seeds of applied research into innovation hubs and innovation systems [21] when supported by appropriate and targeted policy settings as well as investment in research and education [22].

For AI specifically, it has been previously shown that there is substantial variation in the development and adoption of AI both across and within national boundaries [18]. There is evidence that while AI development is widespread, it tends to be concentrated in specific geographic locations. For example, Toney and Flagg [23] analysed AI-related job ads in the United States and showed that AI jobs are concentrated in particular states, with California having more than twice the number of AI jobs than any other state and Washington D.C. having the highest proportion of AI-job ads relative to its population size. A recent report by researchers from Brookings Institution looked at seven measures of AI capacity across US regions; it concluded that AI activity was highly concentrated in a shortlist of regions called 'superstar metro areas' and 'early adopter hubs' [18].

The contributions of this paper are threefold. Firstly, despite the growing interest in AI development and adoption in Australia, little is published on the distribution of AI activities across geographical areas. While there is a growing body of research literature exploring various aspects of AI in Australia, most of these studies focus on the application of AI to specific scientific and technical challenges [24]. Some provide case studies of AI adoption in specific industries [25, 26]. Very few studies were found providing an overarching analysis of AI activity in Australia [27], while none were found exploring the issues of the location, concentration and specialisation of AI activities across Australian geographical areas. In this work, different from other studies, we look at Australia's granular level geographical areas to determine the comparative regional advantages and clusters of AI business and innovation activity. Specifically, we calculate revealed technology advantage (RTA) indices and perform cluster analysis for 3 Statistical Area Level 3 (SA3) geographical regions of Australia [28].

Secondly, to the best of our knowledge this study represents the first of its kind in that we employ a clustering algorithm to complement the comparative advantage analysis. We start by determining each region's comparative advantage in AI development and adoption by calculating revealed technology advantage (RTA) indices. We then conduct cluster analysis to define tiers of AI activities across the Australian geographies. Here RTA indices are used as part of the input variables; other input variables include the economic characteristics of the regions and the total number of AI activities by category. Our composite method of analysis allows us to determine areas of higher concentration of AI activities both in absolute and relative terms. It allows us to combine several datasets in a way that optimises our ability to differentiate regions.

Thirdly, in this work we construct and apply a novel combination of datasets to assess AI-related business and innovation activity. The business activity in AI within Australia is traced using data from Crunchbase, the Australian Business Registry (ABR), Australian Bureau of Statistics (ABS), combined with data on online job advertisements (ads) obtained from Adzuna Australia and CSIRO's Data61 [29]. Innovation activity is traced through patent data from IP Australia. While researchers commonly use patent and research publications data to track and measure AI activities [3, 30], we argue that substantial AI innovation and adoption happens in private companies and start-ups, and cannot be captured solely by research publications and patents activity. Therefore, this paper extends prior work by including data on business activity.

The rest of the paper is organized into five sections. Section 2 provides a background analysis of AI in Australia and a review of economic studies on regional aspects of technological innovation and comparative advantage. Section 3 summarises the research methodology, data sources, data preparation, and validation. Section 4 describes our findings, which are discussed in Section 5. Section 6 concludes the paper by summarising the main contributions of the research, identifying implications for policy and industry activity in this space and sets up directions for future research.

## 2 Background: Innovation as a geographic phenomenon, regional comparative advantage

Regional economists, economic geographers and planners have long shown that successful new technology investments need to be closely linked to the economic traditions and historical strengths of regions [31, 32]. These theories are based upon concepts and models of regional endogenous development [33, 34], territorial innovation models [31, 35], regional innovation systems [36, 37], and learning regions [38-40]. These models are particularly useful in local development policy as they stress the critical importance of local factors for economic growth and development, including local human capital, local business culture, educational system, infrastructure, and existing production systems [41].

Several schools of thoughts emerged from this work, including the new industrial spaces concept (stressing the relationship between technical innovation, location and industrial organisation), and the industrial district school (showing the relationship between long-term economic growth and the quality of formal and informal social, economic and political relations within districts) [42, 43]. The ideas of geographical and domain specialisations in technology innovation have been well developed in the literature on smart specialisation [44]. This approach has then been embedded in numerous national and regional policies, especially across Europe [45, 46]. While there is an ongoing debate in the literature on the validity and application challenges of smart specialisation and related concepts [47-50], there is an agreement that a cornerstone for regional innovation policy is the understanding of regional innovation patterns, traditional knowledge base and capabilities [22].

In this respect, innovation is often viewed as a regional phenomenon, with restricted resources and collaborative networks being key factors that weigh into firms' innovation activity [19]. Prior research has shown that the development of innovation systems is effective when supported by regional specialisation [19, 51-53]. Geographical concentration of economic and innovative activities creates favorable conditions for technology incubation and the acceleration of regional comparative advantage [54]. While the concentration of public and private resources on selected technological priorities and R&D can foster new economic activity, technology development, dissemination, adaptation, and adoption [55].

It is not yet clear whether these principles apply to general-purpose technologies like AI (which includes machine learning). One potential hypothesis is that the concentration of resources can boost dissemination and adoption of general-purpose technologies across the economy, as well as stimulate new business and innovation activity [54, 55]. An empirical study conducted in European countries showed that the availability of general-purpose technology knowledge in a region increases the capacity of the region to acquire new technological specialisations, increase the portfolio of new technologies, and master technological advantages [56]. This work suggests that regional clustering may be beneficial in growing the broad adoption and use of AI across the economy.

The motivation for this paper is therefore to explore if there exists regional concentration of AI activities in Australia, identify whether regions are building a comparative advantage in a specific AI activity or field and how we can measure it.

Two approaches that are often taken in the literature to identify when a region has a comparative advantage in a particular innovation activity and how this activity is distributed geographically are (i) revealed technology advantage (RTA) analysis, and (ii) cluster analysis.

Revealed technology advantage (RTA) is broadly applied by researchers in the studies discovering regional trends and relative specialisations in technology domains [57]. RTA aids in the discovery of regional trends and relative specialisations in technology domains [57]. European Commission uses similar indicator – Revealed comparative advantage to explore comparative advantage in AI and regional thematic specialisation [58]. In this research, we used the RTA approach sourced from OECD [3] to explore the relative regional concentration of Australian AI business and innovation activity. As discussed in detail in Section 3, we measured AI business and innovation activity as the number of AI patent application counts, AI companies and AI job ads.

The current study also implemented a cluster analysis to identify the geographical areas where AI activity is concentrated across Australia. A ‘cluster’ is defined as a concentration of connected companies and institutions that operate in the same domain [20]. The importance of clustering to foster regional economic development and innovation is well defined in the economic literature [59-63]. Industry clustering in Australia has been well studied. Many regions, states, cities, and local areas have established plans and policies to encourage development of regional clusters [64-66].

As we explain in the next section, we adopt a composite approach and extend the cluster analysis by including RTA indices as inputs along with the traditional economic indicators. Our clusted analysis therefore draws upon economic parameters, RTA indices, and absolute number of AI activities by categories within each geographical region. This allowed us to capture intensity of AI activities together with relative comparative advantages in AI activities within clusters.

# 3 Data and methodology

AI is a broad term that covers a range of established and emerging technologies and there are numerous definitions of AI in the literature. In this paper we follow the definition of AI provided in the Australian AI Roadmap as “a collection of interrelated technologies used to solve problems autonomously and perform tasks to achieve defined objectives, in some cases without explicit guidance from a human being” [6].

Our analysis drew upon data from Crunchbase, the Australian Bureau of Statistics (ABS), the Australian Business Register (ABR), IP Australia, Adzuna Australia online job ads and company websites. The combination of these datasets provided a fine-grained information of business and innovation activities across Australian AI domain. To identify AI-related activities, we used text mining and a set of AI-related terms developed by OECD to identify AI-related business and innovation activities between 2015 and 2019 [30, 67]. The geographical aspects of the analysis were implemented for Australian geographical areas of Statistical Area Level 3 (SA3) classification [28]. The following section outlines the procedures undertaken for data search and preparation.

## 3.1 Datasets and measures

### *3.1.1 Identifying AI businesses in Australia*

Crunchbase and ABR data is used to identify companies who are engaged in AI business activity. Crunchbase arguably has access to the most comprehensive dataset on venture activities and startup companies globally [68]. It has also been broadly used in AI related research [17, 67]. There were 1,532,432 companies globally in the Crunchbase database at the time of this research, including over 29,000 Australian organisations. We used the dictionary of 180 AI-related terms developed by the OECD (see Appendix A) to identify companies in the Crunchbase database that included these terms in their titles or short description [30, 67]. Given that we were interested in recent AI developments as an index for future opportunities, the analysis was limited to businesses registered between 2015 and 2019.

This initial search identified 598 AI businesses in Australia. Where the geographic location or registration status of businesses was missing from the results, the ABR Australian Business Number (ABN) Lookup tool was used to obtain these details [69]. The ABR ABN Lookup tool is an Australian Government database which stores business and organisation details for all registered businesses in Australia. The location of each business is determined based on the postcode of the main business address. More detail on the preparation and validation of AI business activity data is provided in Appendix B. The final list of Australian AI businesses included 327 entities.

#### *3.1.2 Identifying AI patent activity*

The data on patents filed by Australian applicants was sourced from IP Australia, Australia's national intellectual property agency. The same search strategy that was used for identifying AI-related Australian businesses was used for identifying AI patents. Postcodes were sourced from the patent holder details registered by IP Australia. The priority date (the earliest filling date) was used as the date of the patent application as this is the closest time to when the invention occurs. The final patent dataset included 3,643 applications.

#### *3.1.3 Identifying businesses and organisations hiring AI talent*

The job advertisements (ads) data was sourced from Adzuna Australia, an aggregator of online job ads. The Adzuna job search engine has been operating in Australia since 2013; it captures job ads from over one thousand sources and has been used in research focused on skills in the digital economy critical for Australian future prosperity [70, 71]. The dataset aligns well with the geographic, occupation and industry composition of the Australian labour market [72]; it aggregates job ads data from multiple sources and applies algorithms to remove the duplicate job ads [73]. The dataset has a relatively high occupation and industry sector labelling, compared to comparable datasets [74].

The described above datasets of activities are referred to in this paper as 'AI activities' for clarity of explanations. However, strictly speaking the more suitable term could be AI-related activities, i.e., AI-related businesses, AI-related patents and AI-related job ads.

#### *3.1.4 Identifying regional innovation activity*

The innovation data was collected from the ABS [75], including R&D expenditure, skilled labour, total labour force, number of research institutes, and the total number of businesses. We used the perpetual inventory method [76, 77] to calculate the stock variables R&D investment series. We followed Australian Bureau of Statistics (ABS) and assumed a 10% depreciation rate for R&D and patent stocks [78]. All economic data (R&D expenditure, R&D stock) were deflated using Consumer Price Index reported by the World Bank with 2010 being the base year [79]. The final data set provided comprehensive AI measures for 333 SA3 regions in Australia. We excluded all SA3 regions with missing values on R&D expenditure and labour force. The summary statistics for the set of combined variables are reported in Appendix C.

### 3.2 Methodology

To investigate the location and concentration of AI development and adoption across regions in Australia, we performed the analysis in two stages: (i) analysis of revealed technology advantage to determine relative performance of regions in AI activities, and (ii) cluster analysis to explore regional strengths and AI hubs.

At the second stage, for cluster analysis we used RTA indices as input variables along with economic characteristics of the regions and absolute number of AI activities in each region.

### *3.2.1 Stage 1: Revealed technology advantage index*

Revealed technology advantage (RTA) was used to identify the regions with comparative advantages in AI [3]. We calculated three sets of RTA indices for Australian SA3 regions, using data for AI company, AI patent and AI job ads. Specifically, we used:

$$RTA_{iT}^{p} = \frac{n_{iT}^{p} \ / \sum_T n_{iT}^{p}}{\sum_i n_{iT}^{p} / \sum_i \sum_T n_{iT}^{p}} \quad (1)$$

where, $p$ denotes the group of RTA indices – RTA for AI companies, RTA for AI patents, or RTA for AI job ads; $n_{iT}^{p}$ - value of the parameter under consideration (number of AI companies, number of AI patents applications or number of AI job ads) for region *i* for technology *T*. For *T* we used three values – AI companies, patents and job ads versus and all other counts in these categories. The numerator represents share of the parameter under consideration (AI companies, patents or job ads) in all business, patent or job ads count for the region *i*. The denominator represents the share of AI companies, patents or job ads among all companies, patents or job ads across all regions.

### *3.2.2 Stage 2: Cluster analysis*

Before conducting the cluster analysis, the global Moran's I [80] index was calculated. The Moran's I statistic measures the spatial autocorrelation based on both location and value. In other words, the statistic examines the extent to which the AI-related activities in one region are associated with the same activities in its neighbouring areas. Moran's I statistic is calculated as (2):

$$I = \frac{N}{S_0} \frac{\sum_i^N \sum_j^N w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_j - \bar{x})^2} \ (2)$$

In (2), $x_i$ ($i=1,\dots,N$) are the AI-related values for $N$ SA3 regions, $\bar{x}$ is the sample mean and $w_{ij}$ is the spatial weight of each neighbouring polygon. $N$ is the total number of SA3 regions in the sample. For simplicity, each neighboring polygon is assigned an equal weight. The value for the Moran's I statistic lies in the interval [-1,1]. A positive Moran's I statistic implies that there exists a positive spatial autocorrelation of the variable across units in the sample. Moran's I test is also used to check the spatial autocorrelation across units.

Cluster analysis was applied to detect and analyse similarities/dis-similarities in the performance of AI activities at the regional level. Clustering is a widely used unsupervised learning algorithm that can categorise observations into meaningful, homogeneous groups [81]. The distance between clusters (between-cluster variance) should be maximised while the distance among a cluster's members (within-cluster variance) should be minimised [82].

The most popular clustering method is k-means clustering. However, this method suffers from a lack of robustness when a single outlying data point is placed arbitrarily far away [83]. This problem was clearly identifiable in our dataset given the concentration of AI activities in some SA3 regions. To address this issue, we used the trimmed k-means method and an algorithm developed by L.García-Escudero et al [84] to perform the clustering. It allowed us to handle an α (*alpha*) proportion of outlying data to guarantee the robustness of the results. Trimming allows the removal of a fraction α of the "most outlying" data. The α outlining observation then serves as a separate cluster. We used "crisp clustering" approach whereby observations were either assigned to one cluster or to a separated group of the α fraction of most "outlying" observations.

Before performing the cluster analysis, the correlation matrix was calculated to check the correlation across variables. All variables were normalised and rescaled to improve the efficiency and accuracy of the clustering algorithm[1].

The robustness of clustering is dependent on the choice of the number of clusters ($k$) and the trimming proportion (α). We chose the optimal number of clusters and trimming proportion based on the classification trimmed likelihood curves as recommended by L.García-Escudero et al. [84]. The choice of $k$ was also re-examined in a hierarchical clustering exercise. In particular, the centroid, average and Ward algorithm were used, and the dendrograms were plotted to determine the initial number of clusters. We also re-examined the choice of $k$ using Elbow and Silhouette plot [85].

The optimal number of clusters suggested was two and the group of outliers were considered as a separate cluster. The three cluster groups defined three tiers of AI activities in Australia. The trimming proportion was set to $\alpha = 0.03$. The plots of the obtained classification trimmed likelihood curves, Elbow and Silhouette plots are presented in Appendix D.

To test the robustness of the clustering method we conducted several statistical checks. Firstly, we assessed how the cluster result changed with the adjustment of trimming proportion value by changing α from 0.01 to 0.05. Second, we conducted cluster-weighted chi-squared test for given probabilities with variance estimation followed Gregg et al [86]. The low p-value of the test confirmed the validity of cluster methodology to our data. We also checked the sensitivity of the cluster result on the choice of variables. The latter was conducted by removing one of the AI-related variables. Our findings remained consistent with all these adjustments, indicating that they are robust.

# 4 Analysis

## 4.1 Correlation analysis

To explore the relationships between the various measures of AI activity, we started with a correlation analysis across all nine indicators of regional AI activity and innovation. AI-focused measures (number of job ads requiring AI talent, number of AI businesses, number of AI patents) correlate more strongly with one another than they do with the more general measures of regional innovation activity, indicating that AI-related innovation can be differentiated from innovation activity in general. Nevertheless, there is significant correlation between AI activity and regional innovation metrics, e.g., the number of research institutes, R&D stock of the region (see Figure 1).

[1] The following formula was used to transform all variables to values between 0 and 1: $x_{normalized} = \frac{x - \min(x)}{\max(x) - \min(x)}$. We rescaled all variables to a mean of 0 and standard deviation of 1 as follows: $x_{rescaled} = \frac{x_{normalized} - mean(x_{normalized})}{sd(x_{normalized})}$, where $sd(x)$ is the standard deviation of $x$.

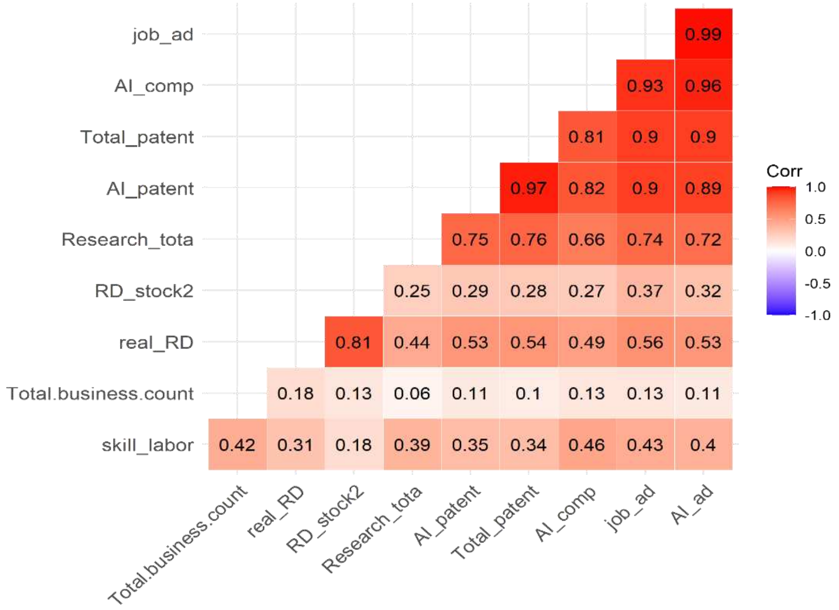



*Figure 1 Correlation matrix for all variables.*

## 4.2 Analysis of revealed technology advantage (RTA)

The RTA indices show the relative position of SA3 regions on the AI activity measure. The values of RTA equal or greater than 1 imply that a region has a relative advantage in AI in a particular group of activity. The relative advantage does not imply that the region is developing or adopting more AI than other regions. It means that relative to all other activities, the region is better at developing or adopting AI or that there is a higher concentration of AI business and/or innovation activities in that region.

Table 1 shows the proportion of regions with RTA values above 1 across Australian states and territories. South Australia (SA) has the highest number of SA3 regions that have relative advantage in developing AI patents and AI companies, followed by Victoria (VIC), New South Wales (NSW), Queensland (QLD). ACT, on the other hand, leads the country in the proportion of SA3 regions with relative advantage in AI job ads in the analysed period.

*Table 1 Number and proportion of SA3 regions with RTA greater than 1 across Australian states and territories.*

| Group of AI activity | Indicator | NSW | VIC | QLD | SA | WA | TAS | NT | ACT |
|---|---|---|---|---|---|---|---|---|---|
| AI patent | # of regions | 23 | 17 | 18 | 9 | 4 | - | - | 2 |
| | % of state regions | 25.3% | 26.2% | 22.0% | 32.1% | 11.8% | 0.0% | 0.0% | 20.0% |
| AI company | # of regions | 20 | 9 | 13 | 7 | 2 | 1 | - | 1 |
| | % of state regions | 22.0% | 13.8% | 15.9% | 25.0% | 5.9% | 6.7% | 0.0% | 10.0% |
| AI job ad | # of regions | 6 | 6 | 6 | 2 | 1 | 1 | 1 | 3 |
| | % of state regions | 6.6% | 9.2% | 7.3% | 7.1% | 2.9% | 6.7% | 11.1% | 33.3% |

Figure 2 maps the performance of Australian SA3 regions on the three AI-related RTA indices. Table 2 lists the top 10 SA3 regions for patent, company, and job ads RTA indices. Only seven SA3 regions in Australia have RTA values greater than 1 in all three indices. These are North Sydney – Mosman (NSW), Adelaide city (SA), Chatswood-Lane Cove (NSW), Port Phillip (VIC), Monash (VIC), Brisbane Inner (QLD) and Brisbane Inner-North (QLD).

Interestingly, many regions with a high RTA index in AI patents and AI job ads are regions outside the state capital areas. That may indicate a potential for further development of AI in regional Australia. All obtained RTAs are provided in Appendix E.

*Table 2 Top ten SA3 regions for patent, company, and job ad RTA indices.*

| **AI patent RTA** | | | **AI company RTA** | | | **AI job ads RTA** | | |
|---|---|---|---|---|---|---|---|---|
| **SA3 region** | **State** | **RTA** | **SA3 region** | **State** | **RTA** | **SA3 region** | **State** | **RTA** |
| Canada Bay | NSW | 26.1 | Sydney Inner City | NSW | 50.9 | Barkly | NT | 7.6 |
| Caboolture Hinterland | QLD | 23.2 | Brisbane Inner – North | QLD | 19.2 | Sherwood - Indooroopilly | QLD | 6.0 |
| Barwon - West | VIC | 18.4 | Melbourne City | VIC | 18.3 | Kenmore - Brookfield – Moggill | QLD | 4.5 |
| Marrickville - Sydenham – Petersham | NSW | 18.0 | North Sydney – Mosman | NSW | 9.9 | Creswick - Daylesford – Ballan | VIC | 4.0 |
| Bathurst | NSW | 14.4 | Warringah | NSW | 9.4 | Port Phillip | VIC | 1.9 |
| Murray River - Swan Hill | VIC | 12.5 | Brisbane Inner | QLD | 8.6 | Ryde - Hunters Hill | NSW | 1.9 |
| Prospect – Walkerville | SA | 11.4 | Tweed Valley | NSW | 5.9 | Kiama - Shellharbour | NSW | 1.8 |
| The Gap – Enoggera | QLD | 9.5 | Gosford | NSW | 5.5 | Sydney Inner City | NSW | 1.8 |
| Kalamunda | WA | 8.6 | Adelaide City | SA | 5.4 | Salisbury | SA | 1.7 |
| Blue Mountains | NSW | 7.4 | Cairns – South | QLD | 5.1 | Central Highlands (Tas.) | TAS | 1.6 |

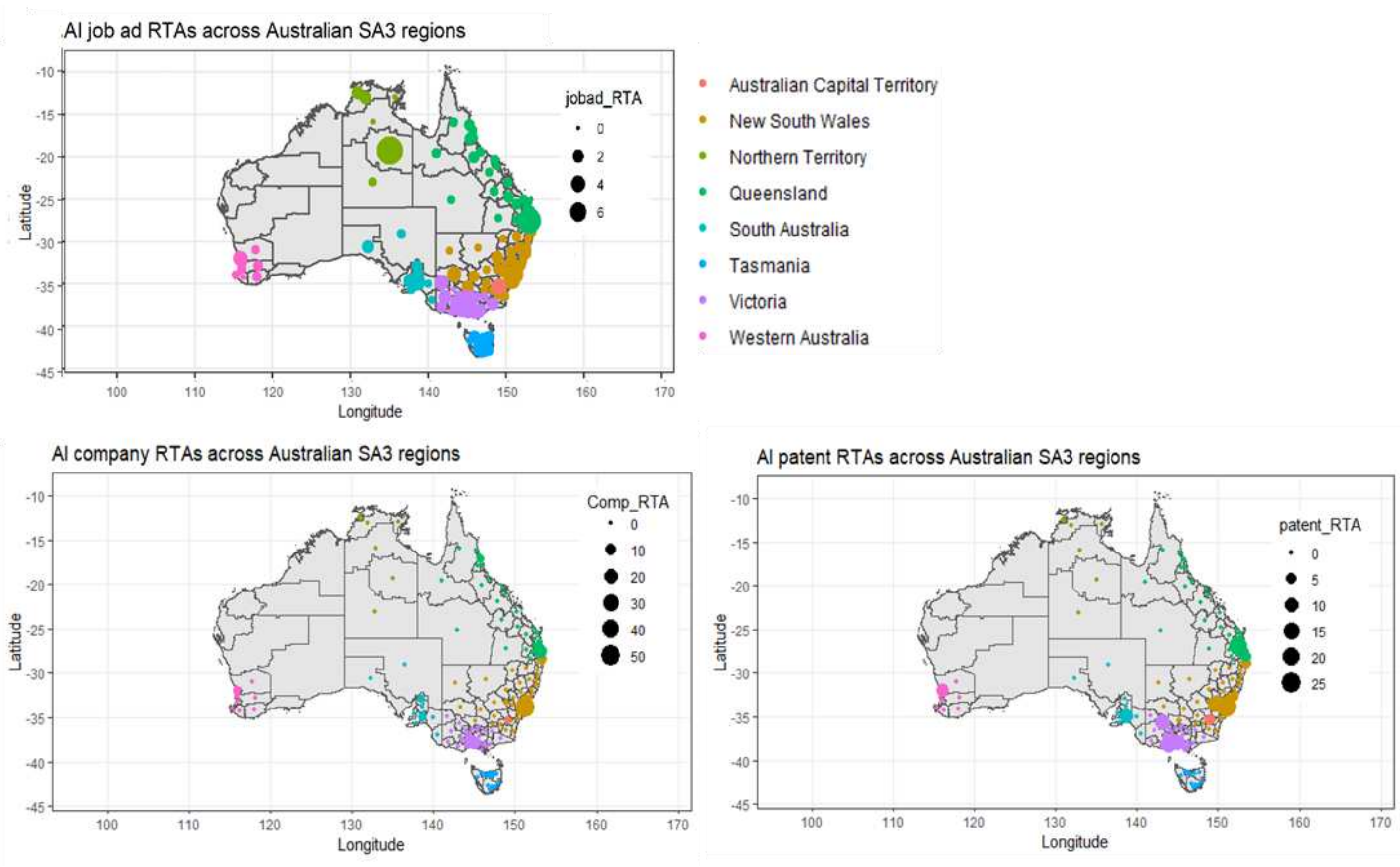



*Figure 2 AI-related RTA indices by group of activities across SA3 regions in Australia*

### 4.3 Cluster analysis

We used the Moran's I statistic to investigate the geographical concentration of AI-related activities. The Moran's I index values for AI patents, job ads and number of AI companies and associated RTA indices are presented in Table 3. The positive values of the Moran's I statistics confirm the positive spatial autocorrelation of AI activities across SA3 regions in Australia, confirming the observations from the maps in Figure 2 that AI activities tend to cluster in a small number of regions in Australia. A stronger spatial correlation was observed for the 'jobad_RTA' parameter which measures the relative advantage of regions in generating AI-related jobs. The same exercise was conducted with various contiguity matrices (considering first and second order neighboring matrices). The results also confirmed the geographical autocorrelation of AI-related indicators across regions in Australia, which is the initial indicator of clustering of AI activities in Australia.

*Table 3 Moran's I statistic and test for spatial autocorrelation.*

| Parameter | Moran's I statistics | P-value | Standard deviation |
|---|---|---|---|
| patent_RTA | 0.3916 | 0.01*** | 1.95 |
| jobad_RTA | 0.73665 | 0.01*** | 2.35 |
| Comp_RTA | 0.49153 | 0.02** | 2.02 |
| AI_patent | 0.3943 | 0.45 | 0.11 |
| AI_jobad | 0.4123 | 0.044** | 2.88 |
| AI_comp | 0.43009 | 0.01*** | 2.1 |

*Note: *** statistically significant at 1% level of confidence interval; ** statistically significant at 5% level of confidence interval.*

Next, the cluster analysis was conducted. We used information relating to both R&D inputs of regions (value of R&D expenditure, R&D stock, the number of skilled workers and the number of research institutes) and AI-related indicators. In this exercise, both the level of concentration (intensity of the activities) and the relative comparative advantage (RTA indices) were considered.

Cluster analysis allowed us to identify three tiers of AI activity: the first one comprised of 'hotspot' regions with much higher value in AI measures compared to other regions, while the other two cluster groups (tiers) were categorized using the k-means algorithm. Table 4 shows summary statistics for SA3 regions in each tier. The joint F-statistic for the F-test shows that all of the AI measure varied significantly between the three tiers or clusters.

***Tier 1 'AI hotspots'***

The AI hotspots tier includes 10 SA3 regions. These AI hotspot regions observed the highest concentration of AI activities in terms of AI patent applications, number of AI companies and AI-related job ads and/or highest RTAs in AI-related activities. The number of AI patent applications of these regions is 22 times and 110 times higher than those recorded in tier 2 and 3, respectively. Similarly, the gaps for AI job ads between tier 1 and tiers 2 and 3 are 28 and 180 times, respectively. These regions also stand out for their high level of investment in R&D. On average, regions in AI hotspots spent 12 times more in R&D expenditure than regions in tier 2, and 30 times more than the tier 3 regions. There are also more research institutes in tier 1 regions, compared to the rest of the nation.

Most of the hotspot regions are located in the metropolitan areas such as Sydney Inner City, Melbourne City, Brisbane Inner, Adelaide City. However, there are also regions outside states' central business districts, although still in the greater capital city regions, such as The Gap–Enoggera in Queensland, Port Phillip in Victoria or Marrickville - Sydenham–Petersham in New South Wales.

***Tier 2 'Emerging AI regions'***

The level of AI-related activities in the 'emerging AI regions' is notably lower then in 'AI hotspots'. The number of AI companies in the regions of this tier are on average 3% of those in the first tier. The number of AI-related job ads and patents is considerably lower, representing approximately 1% of those in 1$^{st}$ tier regions. In terms of broader economic measures, the tier 2 regions are behind the regions in tier 1 in R&D investment and in the number of research institutes. However, these regions have a comparable proportion of skilled labor and workforce to the regions in the AI hotspot tier.

The distribution of emerging AI regions varies across Australian states. In Victoria, 28 regions (43% of all VIC SA3 regions) are in this tier. Around 29 regions (32%) of NSW and 10 regions (29%) of WA are also categorized in this group. Tasmania has no regions in this tier, while only around 10 regions (10%) in Queensland are categorized as emerging AI areas.

***Tier 3 'Nascent AI regions'***

The majority of the regions in Australia (238 out of 333 regions) are categorized in this tier. There is very limited evidence on AI related activities in the regions of the tier 3. The mean number of AI patents is just 20% of that in tier 2, and 0.5% of tier 1. Similarly, the number of AI-related job ads in these regions equals to 16% of that in regions of tier 2, and only 0.3% of those in tier 1. In terms of general economic measures, tier 3 regions are characterised by limited R&D investment and labour resources.

*Table 4 Summary statistics for SA3 regions in each cluster*

| Variable | N | Mean | SD | N2 | Mean.2 | SD.2 | N.3 | Mean.3 | SD.3 | Test |
|---|---|---|---|---|---|---|---|---|---|---|
| **Cluster** | **Tier 1** | | | **Tier 2** | | | **Tier 3** | | | |
| real_RD | 10.00 | 716.99 | 693.59 | 85 | 59.82 | 90.03 | 238.00 | 23.85 | 106.07 | F=99.191*** |
| RD_stock2 | 10 | 14420.82 | 18380.28 | 85 | 792.60 | 2361.96 | 238 | 241.14 | 1174.70 | F=82.994*** |
| skill_labor | 10 | 25.85 | 22.56 | 85 | 27.06 | 7.52 | 238 | 9.19 | 4.75 | F=239.902*** |
| Research_tota | 10 | 13.20 | 18.69 | 85 | 4.15 | 3.73 | 238 | 2.06 | 2.32 | F=40.16*** |
| patent_RTA | 10 | 8.70 | 9.97 | 85 | 1.27 | 1.77 | 238 | 0.61 | 2.13 | F=47.187*** |
| jobad_RTA | 10 | 1.03 | 0.57 | 85 | 0.54 | 0.59 | 238 | 0.33 | 0.70 | F=7.482*** |
| Comp_RTA | 10 | 9.75 | 16.26 | 85 | 1.04 | 1.85 | 238 | 0.26 | 0.86 | F=50.699*** |
| AI_comp | 10 | 12.05 | 22.35 | 85 | 1.01 | 1.94 | 238 | 0.12 | 0.34 | F=46.962*** |
| AI_patent | 10 | 105.62 | 209.67 | 85 | 4.77 | 12.62 | 238 | 0.95 | 10.70 | F=39.771*** |
| AI_ad | 10 | 2634.30 | 4883.12 | 85 | 91.27 | 206.60 | 238 | 14.64 | 39.06 | F=49.762*** |

# 5 Discussion and limitations

The analysis demonstrated that AI-related measures of innovation (counts of AI companies, AI patents and AI job ads) are strongly correlated with one another and that they are less strongly correlated with general measures of innovation (investment in R&D, number of research-oriented organisations in the region, level of skilled labor in the region). These findings suggest that it is meaningful to characterise regions in terms of their AI performance and that this can be differentiated from other forms of regional innovation. Nevertheless, the AI business and innovation activity in Australia tends to concentrate in clusters in areas with higher R&D investments.

The cluster analysis revealed that the hotspots of Australian AI development and adoption today are located around the central metropolitan areas of the states' capital cities. The largest business districts of the country (Sydney Inner and Melbourne City) observe the highest total number of AI activities in business, patents, and jobs. This result is not surprising given the relative novelty of AI. We expect that in the future as AI adoption increases, this concentration would become less evident with the diffusion of AI as a general purpose technology [87]. However, before that happens and as AI becomes increasingly important, if the regional comparative advantage in AI is still concentrated in the greater capital cities, then the disparity between cities and regions in AI development and adoption migh further exacerbate.

At the same time regions in Western Australia have the highest average R&D input. However, fewer patents and job ads in AI were recorded in WA regions, compared to ACT, VIC, and NSW. This highlights the differences in the development of AI across Australian states and territories. This indicates that high R&D investments is likely a necessary, but insufficient condition for AI development in the geographical areas.

The emerging tier 2 AI regions identified through the cluster analysis are of particular interest, The level of AI activity here is lower than in tier 1, but substantial as captured by the AI measured in our cluster analysis.  These regions have the potential for AI growth within regional Australia and should not be overlooked by decision makers at the state and local government levels. Interestingly, there are also multiple regions outside the capital cities which performed well on RTAs for patents and job ads. These regions, along with tier 2 regions, can be considered high potential for regional AI development. These are the areas where business activity is more likely to emerge outside of the capital centers.

Analysis of comparative advantage through RTA indices provided insights into the location and relative concentration of AI activities in Australia. South Australia appeared as a state with relative comparative advantage in AI in regards to the relative concentration of AI patent and AI company activities, while ACT had a relatively higher concentration of AI jobs compared to other states. When all three parameters are considered, seven regions nationwide stand out: Adelaide city in SA, Chatswood-Lane Cove and North Sydney – Mosman in NSW, Port Phillip and Monash in VIC, and Brisbane Inner and Brisbane Inner-North in QLD.

Three regions stand out with the top performance on RTAs as well as in the cluster analysis: Adelaide City (SA), Brisbane Inner-North (QLD) and Port Phillip (VIC). A closer look at the activities of these leading regions reveals interesting stories. Adelaide (SA) is a well-known hub of AI research institutions with a history of digital technology innovation, including the work of Defence Science and Technology Group [88]. It is the home to Australian Institute for Machine Learning, MITbigdata Living Lab by Massachusetts Institute of Technology, the Australian Research Centre for Interactive and Virtual Environments at the University of South Australia, and the Australian Cyber Collaboration Centre (ACCC). Global tech leaders Amazon Web Services, Google Cloud, Accenture recently opened regional centers in Adelaide [16]. Many of these are operating from Adelaide's innovation hub Lot Fourteen. Brisbane Inner-North in Queensland is a home to another innovation and technology hub – The Precinct, which was developed under the Advance Queensland initiative of Queensland Government targeting and effectively attracting start-up and technology companies in the region. This region also includes Herston Health Precinct with the state's largest health research hospital [89, 90]. The third region is Port Phillip, which has positioned itself as a hub for interactive digital media and games development [91] with a vision to become games capital of Victoria [92]. These patterns show how the leading regions in AI activity in Australia are associated with targeted hub development initiatives. These are several examples of how an innovation hub approach can contribute to AI development and adoption, although further detailed analysis would be required to prove that this conclusion can be generalised.

There is an ongoing argument among researchers whether leadership in AI is possible and required for Australia to prosper in the future. Some support the technology-adopter position, while other argue that there is an imperative for Australia to aggressively pursue globally recognised leadership positions in AI through bold and critical strategic actions to capture productivity and economic growth potential [93].The vision of the Australia's Artificial Intelligence Action Plan is for Australia to be a global leader in AI development and adoption [11]. AI is a complex and diverse technology field where policy and investment decisions are hard to make. For policy makers to leverage further development of capability in AI and potential upgrade to world leading roles in AI requires detailed understanding of existing strengths before bold courses can be set, policies developed, and strategic actions taken.

This paper contributes to the understanding of existing activities and strength in AI in Australia, the location and concentration of AI development and adoption across the country. This analysis can support national, regional, and local governments in their initiatives to build and expand the national AI ecosystem and make better decision about locations of AI hubs and centers, better understand local skills and talent needs and shortages, seek and attract potential industry partner organisations. The performance of the regions on RTA indices and in cluster analysis can become one of the criteria for government investment decisions, for example in the initiatives such as '*Catalysing the Artificial Intelligence Opportunity in Our Regions*' [94], part of the Australian Government AI Action Plan [11].

We acknowledge that the geography of AI innovation is more complex than a regional growth model can capture and is constantly changing. Policy making and effective investment would require systematic research and monitoring system to capture growth opportunities, understand and leverage traditional knowledge base of the regions, enhance knowledge transfer including scientific and professional labour mobility between the regions [22].

***Limitations of the analysis, data availability and quality***

While every effort was made to collect and prepare the data and perform the analysis, there are limitations of this study that need to be acknowledged when interpreting and using the results.

- Business data is sourced from Crunchbase, which covers a substantial number of companies. While it is arguably the best available dataset on venture activities and startup companies globally and is broadly used in AI related research [17, 67], it is not comprehensive, complete and error-free [95]. Manual verification of companies' data showed that for many companies recorded in the Crunchbase database, some details (e.g., addresses, employee count) were missing, dated or incorrect. Crunchbase also has a limited representation across world regions and has limited ability to compare timeseries data. Furthermore, we acknowledge that the use of the head quarter location can only be indicative to the location of AI activities. There could be companies in our dataset where AI activities happen outside the headquarter region or where multiple offices with AI activities are present but not accounted for in this research.
- AI is a buzzword today. We acknowledge that some activities tracked in our datasets would not be called AI if the AI technology was not as 'hyped' as it is now. For example, startup companies in ICT industry could have used AI-related terms in the company description to make it more attractive to potential investors.
- There are several international organisations, research institutions and individual researchers who undertake similar analysis across the regions of the world with various focuses and using various datasets. The results of this study are critically sensitive to the key search terms that define AI and to the datasets used at the time of research. Results of this study might not be directly comparable to similar studies and reports on related topics.
- The analysis relies on datasets that might contain outdated information. We assume that at the time of registration of a company in ABR and at the time of the entry of companies' details into Crunchbase, company details were correct and up to date. However, we acknowledge that at the time of research some of the details can be outdated. Although we performed a manual verification of the details for most of the companies, some were missing websites, others had multiple locations in Australia and/or around the world. The data on regional distribution of companies is therefore not complete, but the best available at the time of this research.

# 6 Conclusions

As a general-purpose technology, AI has the potential to boost economic growth and productivity across the globe, change business models, transform science, and change the way we live and work. Australia investment in AI is among the top 12 nations globally. Since the National AI Roadmap launch, Australia is committed to increase its presence, and grow its AI capability, including an ecosystem of AI agents, developers, talent, and commercial applications.

In this work, in line with the ideas of territorial innovation models, we focus on the analysis of the landscape of Australian AI business and innovation activities at the local level. We look specifically at Australian geographical areas to explore the regional technology advantage in AI and map clusters of AI business and innovation activity. We draw upon a set of national-level databases that each provides insight into separate facets of AI activity and adoption. We use Crunchbase and the Australian Business Register to identify and geo-locate companies that are engaged in AI business activity. We use the IP Australia database to identify companies that are patenting AI technology. We used Innovation metrics published by the Australian Bureau of Statistics to identify regional variation in Research and Development activity and workforce skills. Finally, we use online job ads captured by Adzuna Australia to identify companies that are hiring AI talent. Each dataset allows us to match the relevant activity to a specific geographic SA3 region. We then use cluster analysis and identify three tiers of AI activity that allow us to meaningfully categorise regional 'AI hotspots', 'emerging AI regions', and 'nascent AI regions'. The first tier comprises the leading 10 SA3 regions. The second tier consists of 85 SA3 regions that are catching up in terms of AI activities. The regions of the second tier demonstrated moderate engagement in AI activities with the level of activities much lower than those in the first tier. The third tier is the biggest one, it includes 238 SA3 regions where the observed AI activities were minimal. Three regions stand out nationwide (Port Phillip, Brisbane Inner-North and Adelaide City) providing examples of effective innovation hub developments that contributed to the formation of AI hotspots.

The results of this paper are important for decision-makers looking to grow effective AI capability in Australia that is well connected with established regional economic and social strengths. For researchers this paper provides a straightforward and transparent method to analyse business activities in conjunction with patent and job market activities in AI technology domain. The paper contributes to the literature on regional innovation clusters and AI technology development and adoption.

The next step for this research would be to analyse the sectoral specialisation of Australian business and innovation activities in the AI domain. This may allow to determine industry areas for potential technological specialisation for targeted AI capability development. Potential further research would be beneficial to distinguish the regions with the potential for AI development versus AI adoption to examine the factors underpinning the success of 'AI hotspot' regions. More detailed micro-economic analysis at firm level would also complement this research and provide insights into the individual cases of AI development and applications. Specifically, further research could be done to analyse the returns on investment in AI activities and AI companies.

# APPENDIX

## A. Search keywords

Search keywords applied to define AI companies are provided below. The list is sourced from OECD Science Technology and Industry Working Paper [67]. For the purposes of this study, we used 180 keywords as per the list below. The list has been adopted from OECD except for several terms that are subsequent to more general categories used in the search.

> action recognition; activity recognition; adaboost; adaptive boosting; adversarial network; ambient intelligence; ant colony; artificial intelligence; association rule; autoencoder; autonomic computing; autonomous vehicle; autonomous weapon; backpropagation; Bayesian learning; bayesian network; bee colony; blind signal separation; bootstrap aggregation; brain computer interface; brownboost; chatbot; classification tree; cluster analysis; cognitive automation; cognitive computing; cognitive insight system; cognitive modelling; collaborative filtering; collision avoidance; community detection; computational intelligence; computational pathology; computer vision; cyber physical system; data mining; decision tree; deep belief network; deep learning; dictionary learning; dimensionality reduction; dynamic time warping; emotion recognition; ensemble learning; evolutionary algorithm; evolutionary computation; face recognition; facial expression recognition; factorisation machine; feature engineering; feature extraction; feature learning; feature selection; firefly algorithm; fuzzy c; fuzzy environment; fuzzy logic; fuzzy number; fuzzy set; fuzzy system; gaussian mixture model; gaussian process; genetic algorithm; genetic programming; gesture recognition; gradient boosting; graphical model; gravitational search algorithm; hebbian learning; hierarchical clustering; high-dimensional data; high-dimensional feature; high-dimensional input; high-dimensional model; high-dimensional space; high-dimensional system; image classification; image processing; image recognition; image retrieval; image segmentation; independent component analysis; inductive monitoring; instance-based learning; intelligence augmentation; intelligent agent; intelligent classifier; intelligent geometric computing; intelligent infrastructure; Kernel learning; K-means; latent dirichlet allocation; latent semantic analysis; latent variable; layered control system; learning automata; link prediction; logitboost; long short term memory (LSTM); lpboost; machine intelligence; machine learning; machine translation; machine vision; madaboost; MapReduce; Markovian; hidden Markov model; memetic algorithm; meta learning; motion planning; multi task learning; multi-agent system; multi-label classification; multi-layer perceptron; multinomial naïve Bayes; multi-objective optimisation; naïve Bayes classifier; natural gradient; natural language generation; natural language processing; natural language understanding; nearest neighbour algorithm; neural network; neural turing; neuromorphic computing; non negative matrix factorisation; object detection; object recognition; obstacle avoidance; pattern recognition; pedestrian detection; policy gradient methods; Q-learning; random field; random forest; rankboost; recommender system; regression tree; reinforcement learning; relational learning; rough set; rule learning; rule-based learning; self-organising map; self-organising structure; semantic web; semi-supervised learning; sensor fusion; sentiment analysis; similarity learning; simultaneous localisation mapping; single-linkage clustering; sparse representation; spectral clustering; speech recognition; speech to text; stacked generalisation; stochastic gradient; supervised learning; support vector regression; swarm intelligence; swarm optimisation; temporal difference learning; text mining; text to speech; topic model; totalboost; trajectory planning; trajectory tracking; transfer learning; trust region policy optimisation; unmanned aerial vehicle; unsupervised learning; variational inference; vector machine; virtual assistant; visual servoing; xgboost.

## B. Australian AI company data preparation steps

ABR search was followed up by a manual cross-check of the companies' details through the company websites. As a result of cross-checking and manual analysis 133 companies were excluded from the list based on the following grounds. The details of excluded companies by the reasons of exclusion as well as further data cleaning procedures are provided below.

1. **76** companies with no active ABN and no website were found and excluded from the list. This includes the cases where no website was found, website link recorded on the company's Crunchbase profile was not working, or the website link returned some irrelevant or insecure webpage. Notably in few cases there were companies with no website, but with an active ABN and an active Crunchbase registration (marked as 'operating' on Crunchbase). For these companies if AI-related activities could be traced (online media articles, LinkedIn profile, Facebook pages), the companies were kept in the list of Australian AI companies.
2. Companies that are clearly operating in the fields non-related to AI. There were **54** such companies. Those companies included motorcycle companies, virtual assistance providers (e.g., call center operators), computer hardware retailers and repair services, technology news portals and educational providers.
3. Rebranded and acquired companies: companies that were rebranded or acquired but continued operations within the same domain in Australia (as defined in the company description on Crunchbase), were included in the list of Australian AI companies. New company name or the name of acquisitor were placed in brackets next to the original company name as per Crunchbase registry. Similarly, when Crunchbase record referred to a product (e.g., software package or a single technology solution), the title of the parent organisation was put in brackets and company retained in the list. However, when acquisitions resulted in company closing, shutting down of the website, substantially changing the domain of operations, or shifting all operations overseas, these companies were excluded from the list. There were 3 companies excluded from the list on this ground.

- *Postcodes*

To explore the regional distribution of Australian AI companies, we obtained the postcodes for each company from Crunchbase, ABR and the companies' websites. The postcodes search on Crunchbase was done through API. ABR data was collected through the application of *ABN Lookup tool*, while website searches were performed manually. Where there were discrepancies between postcodes from different data sources, we preferred website postcodes to Crunchbase record and Crunchbase record to ABR record. In three cases where none of the three data sources contained details on the postcodes, we contacted companies directly via emails to seek their assistance with identification of their office location(s). All three companies responded and provided their current addresses.

Where only PO Box postcodes were available on Crunchbase, we used the postcode from website or ABR record. Where websites contained details of multiple offices in Australia, we used the postcode of the head office (when available) or of the office top in the list.

- *Employee count*

Data on employee count was sourced from Crunchbase for the validated list of Australian AI companies. Where estimates were not available, the data was complemented from companies' LinkedIn profiles. The total number of companies with recorded employee count was 426.

## C. Summary statistics

*Table C1. Summary statistics for SA3 regions in Australia.*

| Variable | N | Mean | Std..Dev. | Min | Pctl..25 | Pctl..75 | Max |
|---|---|---|---|---|---|---|---|
| R&D expenditure | 333 | 54.563 | 207.644 | 0.145 | 4.308 | 28.048 | 2254.817 |
| R&D stock | 333 | 826.375 | 4107.909 | 0.573 | 21.966 | 212.229 | 52298.174 |
| skill labor | 333 | 13.894 | 10.105 | 0.069 | 6.672 | 19.143 | 75.883 |
| Other labor | 333 | 25.155 | 15.91 | 0.226 | 14.288 | 31.921 | 87.197 |
| Research Institute | 333 | 2.925 | 4.572 | 0 | 1 | 4 | 55 |
| AI company | 333 | 1.403 | 13.508 | 0 | 0 | 0.008 | 234.99 |
| AI patent | 333 | 9.672 | 96.394 | 0 | 0 | 0.646 | 1619.993 |
| Total Patent | 333 | 3064.702 | 32288.297 | 0 | 37.182 | 200.715 | 513337.606 |
| Total business | 333 | 13.645 | 124.678 | 0 | 3.061 | 9.07 | 2285.464 |
| Job Ad | 333 | 2208.239 | 22314.645 | 0 | 21.5 | 195.5 | 369880 |
| AI job ad | 333 | 48.943 | 501.727 | 0 | 0 | 2 | 8198 |

*Table C2. Statistic summaries for Australian states and territories.*

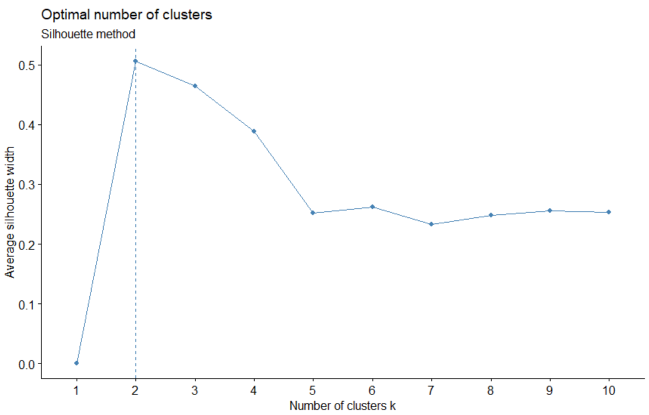
| Variable | N | Mean | SD | N | Mean | SD | N | Mean | SD | N | Mean | SD. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| State / Territory | Australian Capital Territory | | | New South Wales | | | Northern Territory | | | Queensland | | |
| R&D expenditure | | 9.972 | 8.6 | 89 | 72.461 | 256.677 | 9 | 6.903 | 16.886 | 82 | 30.422 | 99.009 |
| R&D stock | 8 | 55.019 | 57.975 | 89 | 678.622 | 2785.4 | 9 | 35.656 | 92.206 | 82 | 735.768 | 3601.323 |
| skill labor | 8 | 11.954 | 7.61 | 89 | 16.729 | 11.803 | 9 | 5.286 | 4.464 | 82 | 10.934 | 6.295 |
| Other labor | 8 | 17.962 | 13.124 | 89 | 29.558 | 16.33 | 9 | 9.606 | 7.327 | 82 | 21.369 | 11.062 |
| Research Institute | 8 | 6.375 | 7.633 | 89 | 3.202 | 4.483 | 9 | 4.778 | 3.962 | 82 | 1.671 | 2.178 |
| AI company | 8 | 0.25 | 0.462 | 89 | 1.315 | 7.485 | 9 | 0 | 0 | 82 | 0.415 | 1.533 |
| AI patent | 8 | 23.375 | 55.335 | 89 | 5.933 | 43.636 | 9 | 0 | 0 | 82 | 1.28 | 5.445 |
| Total Patent | 8 | 1989.79 | 3940.3 | 89 | 2095.467 | 17352.5 | 9 | 11.249 | 14.008 | 82 | 204.498 | 441.831 |
| Total business | 8 | 6.377 | 5.946 | 89 | 8.399 | 9.027 | 9 | 1.188 | 1.593 | 82 | 5.395 | 3.729 |
| Job Ad | 8 | 405.25 | 662.8 | 89 | 2046 | 15553.6 | 9 | 163 | 371.257 | 82 | 521.988 | 2431.652 |
| AI job ad | 8 | 14.25 | 23.279 | 89 | 47.281 | 386.124 | 9 | 2.556 | 6.948 | 82 | 10.122 | 44.559 |

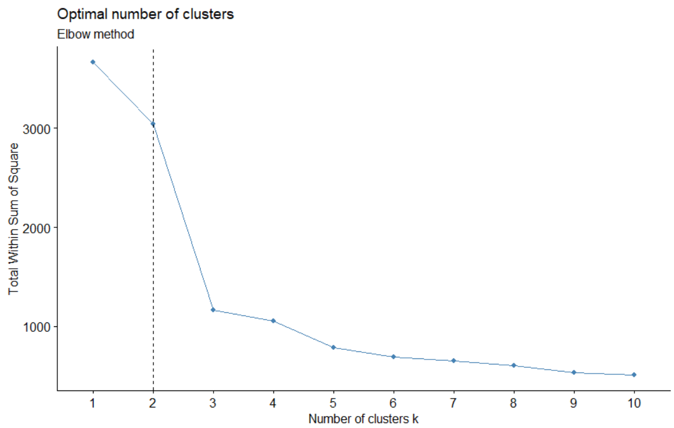
*Table C3. Statistic summaries for Australian states and territories (cont).*

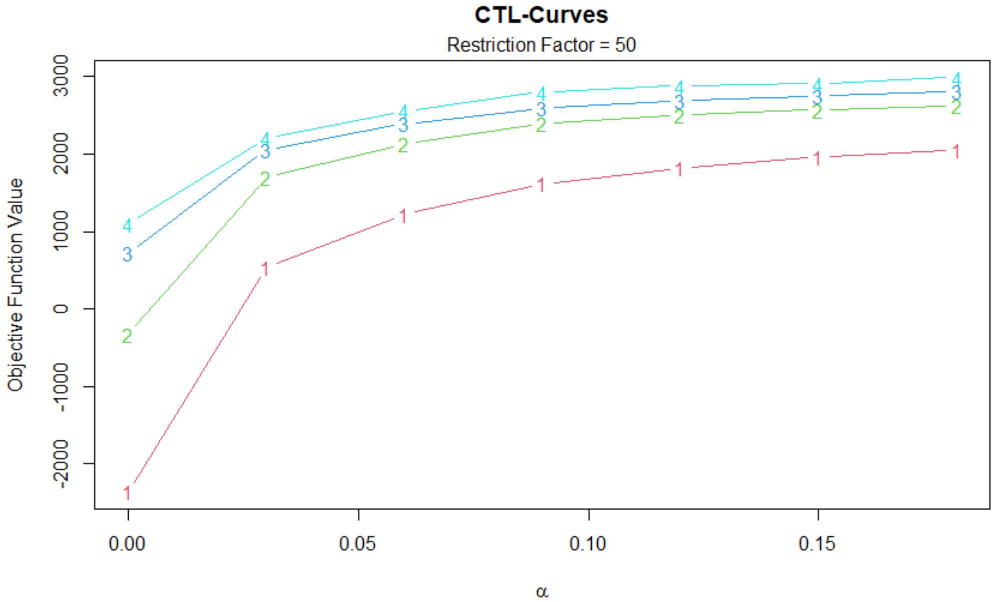
| Variable | N | Mean | SD | N | Mean | SD | N | Mean | SD | N | Mean | SD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| State / Territory | South Australia | | | Tasmania | | | Victoria | | | Western Australia | | |
| R&D expenditure | 28 | 19.266 | 23.787 | 15 | 9.125 | 6.688 | 65 | 80.745 | 275.792 | 27 | 117.47 | 311.359 |
| R&D stock | 28 | 151.465 | 239.5 | 15 | 53.712 | 58.0 | 65 | 1012.6 | 2913.8 | 27 | 3089.158 | 11022.068 |
| skill labor | 28 | 10.797 | 6.208 | 15 | 5.972 | 4.371 | 65 | 18.044 | 10.738 | 27 | 18.237 | 11.342 |
| Other labor | 28 | 21.243 | 12.94 | 15 | 12.06 | 7.036 | 65 | 31.682 | 18.122 | 27 | 31.278 | 17.348 |
| Research Institute | 28 | 3.607 | 3.871 | 15 | 2.133 | 2.85 | 65 | 3.985 | 7.059 | 27 | 2.259 | 2.28 |
| AI company | 28 | 0.357 | 0.841 | 15 | 0.067 | 0.256 | 65 | 0.954 | 3.912 | 27 | 0.333 | 0.999 |
| AI patent | 28 | 0.821 | 1.833 | 15 | 0 | 0 | 65 | 10.968 | 68.567 | 27 | 2.37 | 9.668 |
| Total Patent | 28 | 170.535 | 254.4 | 15 | 29.333 | 17.56 | 65 | 4153.7 | 30487.316 | 27 | 690.889 | 2524.441 |
| Total business | 28 | 4.463 | 2.673 | 15 | 2.672 | 1.922 | 65 | 9.681 | 7.467 | 27 | 7.549 | 5.973 |
| Job Ad | 28 | 403.714 | 1682.5 | 15 | 57.667 | 79.49 | 65 | 1706.8 | 11517.9 | 27 | 635.556 | 2741.429 |
| AI job ad | 28 | 10.036 | 44.277 | 15 | 0.867 | 1.187 | 65 | 36.169 | 247.925 | 27 | 14 | 61.678 |

## D. Cluster analysis robust checks

- Choose k
- Choose $\alpha$
- Robust tests: reweighted chi squared test of independence




## E. RTA index and cluster allocations for Australian SA3 regions

*Note: Color coding is applied to visually distinguish regions with higher values of RTAs (green) through medium (yellow) and to low RTA values (red). Each column is color-coded separately.*

| **SA3 regions** | | | **RTA index values** | | | **Tiers:** 1 – AI hotspot 2 – Emerging AI regions 3 - Nascent AI regions |
|---|---|---|---|---|---|---|
| **SA3 name** | **State or territory** | **SA3 code** | **Patent activity** | **Business activity (AI companies)** | **Job ads** | |
| Goulburn - Yass | New South Wales | 10101 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Queanbeyan | New South Wales | 10102 | 0.00000 | 0.00000 | 0.04855 | 3 |
| Snowy Mountains | New South Wales | 10103 | 0.00000 | 0.00000 | 0.08247 | 3 |
| South Coast | New South Wales | 10104 | 0.00000 | 0.00000 | 0.22721 | 3 |
| Goulburn - Mulwaree | New South Wales | 10105 | 0.00000 | 0.00000 | 0.52456 | 3 |
| Young - Yass | New South Wales | 10106 | 0.00000 | 0.00000 | 0.40641 | 3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Gosford | New South Wales | 10201 | 4.54713 | 5.53591 | 0.27589 | 2 |
| Wyong | New South Wales | 10202 | 0.00000 | 2.10256 | 0.20154 | 2 |
| Bathurst | New South Wales | 10301 | 14.38713 | 0.00000 | 0.29324 | 3 |
| Lachlan Valley | New South Wales | 10302 | 0.00000 | 0.00000 | 0.10283 | 3 |
| Lithgow - Mudgee | New South Wales | 10303 | 0.10653 | 0.00000 | 0.11499 | 3 |
| Orange | New South Wales | 10304 | 0.04927 | 1.46791 | 0.22698 | 3 |
| Clarence Valley | New South Wales | 10401 | 0.00000 | 0.00000 | 0.08548 | 3 |
| Coffs Harbour | New South Wales | 10402 | 0.00000 | 0.00000 | 0.04904 | 3 |
| Bourke - Cobar - Coonamble | New South Wales | 10501 | 0.00000 | 0.00000 | 0.06576 | 3 |
| Broken Hill and Far West | New South Wales | 10502 | 0.00000 | 0.00000 | 0.07862 | 3 |
| Dubbo | New South Wales | 10503 | 0.00000 | 0.00000 | 0.63080 | 3 |
| Lower Hunter | New South Wales | 10601 | 0.04469 | 0.03823 | 0.09008 | 3 |
| Maitland | New South Wales | 10602 | 0.00000 | 0.00000 | 0.16886 | 3 |
| Port Stephens | New South Wales | 10603 | 2.88914 | 0.00000 | 0.29512 | 3 |
| Upper Hunter | New South Wales | 10604 | 0.00000 | 0.00000 | 0.37908 | 3 |
| Dapto - Port Kembla | New South Wales | 10701 | 4.01338 | 0.00000 | 0.16900 | 3 |
| Kiama - Shellharbour | New South Wales | 10703 | 0.00000 | 0.00000 | 1.84926 | 2 |
| Wollongong | New South Wales | 10704 | 0.00000 | 0.00000 | 0.54565 | 2 |
| Great Lakes | New South Wales | 10801 | 0.00000 | 0.00000 | 0.11893 | 3 |
| Kempsey - Nambucca | New South Wales | 10802 | 0.00000 | 0.00000 | 0.03254 | 3 |
| Lord Howe Island | New South Wales | 10803 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Port Macquarie | New South Wales | 10804 | 0.00000 | 0.00000 | 0.30518 | 3 |
| Taree - Gloucester | New South Wales | 10805 | 0.00000 | 0.00000 | 0.02747 | 3 |
| Albury | New South Wales | 10901 | 0.00000 | 0.00000 | 0.08692 | 3 |
| Lower Murray | New South Wales | 10902 | 0.00000 | 0.00000 | 1.36342 | 3 |
| Upper Murray exc. Albury | New South Wales | 10903 | 0.31741 | 0.00000 | 0.78139 | 3 |
| Armidale | New South Wales | 11001 | 0.00000 | 0.00000 | 0.37041 | 3 |
| Inverell - Tenterfield | New South Wales | 11002 | 0.00000 | 0.00000 | 0.23532 | 3 |
| Moree - Narrabri | New South Wales | 11003 | 0.00000 | 0.00000 | 0.06053 | 3 |
| Tamworth - Gunnedah | New South Wales | 11004 | 0.00000 | 0.00000 | 0.17038 | 3 |
| Lake Macquarie - East | New South Wales | 11101 | 0.00000 | 0.66421 | 0.13831 | 2 |
| Lake Macquarie - West | New South Wales | 11102 | 0.00000 | 0.00000 | 0.38470 | 3 |
| Newcastle | New South Wales | 11103 | 0.01734 | 0.00000 | 0.57387 | 2 |
| Richmond Valley - Coastal | New South Wales | 11201 | 5.68051 | 0.00000 | 0.04156 | 3 |
| Richmond Valley - Hinterland | New South Wales | 11202 | 0.00000 | 0.00000 | 0.15696 | 3 |
| Tweed Valley | New South Wales | 11203 | 0.00000 | 5.92531 | 0.07319 | 3 |
| Griffith - Murrumbidgee (West) | New South Wales | 11301 | 0.00000 | 0.00000 | 0.46569 | 3 |
| Tumut - Tumbarumba | New South Wales | 11302 | 0.00000 | 0.00000 | 0.10777 | 3 |
| Wagga Wagga | New South Wales | 11303 | 0.00000 | 0.00000 | 0.20393 | 3 |
| Shoalhaven | New South Wales | 11401 | 0.00000 | 0.00000 | 0.06604 | 3 |
| Southern Highlands | New South Wales | 11402 | 0.00000 | 0.00000 | 0.39548 | 3 |
| Baulkham Hills | New South Wales | 11501 | 0.35884 | 2.57197 | 0.62083 | 2 |
| Dural - Wisemans Ferry | New South Wales | 11502 | 0.00000 | 1.55005 | 0.73412 | 3 |
| Hawkesbury | New South Wales | 11503 | 0.00000 | 0.00000 | 0.09975 | 3 |
| Rouse Hill - McGraths Hill | New South Wales | 11504 | 0.00000 | 0.00000 | 0.05991 | 3 |
| Blacktown | New South Wales | 11601 | 2.82375 | 0.00408 | 0.33728 | 2 |
| Blacktown - North | New South Wales | 11602 | 0.00597 | 0.00107 | 0.07555 | 3 |
| Mount Druitt | New South Wales | 11603 | 0.00000 | 0.00000 | 0.29483 | 3 |
| Botany | New South Wales | 11701 | 0.00000 | 0.00000 | 0.45460 | 3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Marrickville - Sydenham - Petersham | New South Wales | 11702 | 17.95162 | 0.61931 | 0.59053 | 1 |
| Sydney Inner City | New South Wales | 11703 | 0.79726 | 50.90683 | 1.77387 | 1 |
| Eastern Suburbs - North | New South Wales | 11801 | 1.50201 | 0.00000 | 0.41843 | 2 |
| Eastern Suburbs - South | New South Wales | 11802 | 1.51682 | 0.87042 | 0.49229 | 2 |
| Bankstown | New South Wales | 11901 | 0.00000 | 2.51703 | 0.17771 | 2 |
| Canterbury | New South Wales | 11902 | 0.00000 | 0.00352 | 0.05994 | 3 |
| Hurstville | New South Wales | 11903 | 0.00000 | 0.00000 | 0.16794 | 2 |
| Kogarah - Rockdale | New South Wales | 11904 | 0.00000 | 0.00000 | 0.29623 | 2 |
| Canada Bay | New South Wales | 12001 | 26.09220 | 0.00010 | 0.28399 | 1 |
| Leichhardt | New South Wales | 12002 | 2.07940 | 0.49081 | 0.29331 | 3 |
| Strathfield - Burwood - Ashfield | New South Wales | 12003 | 1.77253 | 1.65705 | 0.74060 | 2 |
| Chatswood - Lane Cove | New South Wales | 12101 | 1.29979 | 2.18922 | 1.45589 | 2 |
| Hornsby | New South Wales | 12102 | 2.09116 | 0.21246 | 0.18664 | 2 |
| Ku-ring-gai | New South Wales | 12103 | 3.56444 | 4.50776 | 0.22266 | 2 |
| North Sydney - Mosman | New South Wales | 12104 | 3.20643 | 9.89605 | 1.52847 | 2 |
| Manly | New South Wales | 12201 | 3.53136 | 2.48237 | 0.28535 | 3 |
| Pittwater | New South Wales | 12202 | 1.09206 | 3.45415 | 0.37271 | 3 |
| Warringah | New South Wales | 12203 | 0.19070 | 0.00000 | 0.76902 | 2 |
| Camden | New South Wales | 12301 | 0.00000 | 0.00000 | 0.24943 | 3 |
| Campbelltown (NSW) | New South Wales | 12302 | 2.28861 | 2.90461 | 0.19072 | 2 |
| Wollondilly | New South Wales | 12303 | 0.19526 | 0.00000 | 0.41840 | 3 |
| Blue Mountains | New South Wales | 12401 | 7.41001 | 0.00000 | 0.53487 | 2 |
| Penrith | New South Wales | 12403 | 0.00000 | 0.00000 | 0.17773 | 2 |
| Richmond - Windsor | New South Wales | 12404 | 0.00000 | 0.00000 | 0.29276 | 3 |
| St Marys | New South Wales | 12405 | 0.00000 | 0.00000 | 0.03302 | 3 |
| Auburn | New South Wales | 12501 | 5.91037 | 0.00000 | 0.35332 | 2 |
| Carlingford | New South Wales | 12502 | 4.91609 | 0.00150 | 0.37849 | 3 |
| Merrylands - Guildford | New South Wales | 12503 | 0.98581 | 1.24934 | 0.18704 | 2 |
| Parramatta | New South Wales | 12504 | 2.51852 | 1.44242 | 0.53373 | 2 |
| Pennant Hills - Epping | New South Wales | 12601 | 0.81733 | 0.20087 | 0.34132 | 3 |
| Ryde - Hunters Hill | New South Wales | 12602 | 0.00116 | 1.39968 | 1.87138 | 2 |
| Bringelly - Green Valley | New South Wales | 12701 | 0.00000 | 0.00000 | 0.39444 | 3 |
| Fairfield | New South Wales | 12702 | 0.00000 | 0.00000 | 0.16874 | 2 |
| Liverpool | New South Wales | 12703 | 0.00000 | 1.46508 | 0.13259 | 3 |
| Cronulla - Miranda - Caringbah | New South Wales | 12801 | 0.00000 | 0.00000 | 0.28405 | 2 |
| Sutherland - Menai - Heathcote | New South Wales | 12802 | 0.00000 | 0.00000 | 0.19508 | 2 |
| Ballarat | Victoria | 20101 | 5.31256 | 0.00000 | 0.57443 | 2 |
| Creswick - Daylesford - Ballan | Victoria | 20102 | 0.00000 | 0.01191 | 4.03207 | 3 |
| Maryborough - Pyrenees | Victoria | 20103 | 0.00000 | 0.00000 | 0.32938 | 3 |
| Bendigo | Victoria | 20201 | 0.00000 | 0.00000 | 0.72777 | 3 |
| Heathcote - Castlemaine - Kyneton | Victoria | 20202 | 0.00000 | 4.34549 | 0.00000 | 3 |
| Loddon - Elmore | Victoria | 20203 | 0.00000 | 0.00000 | 0.33408 | 3 |
| Barwon - West | Victoria | 20301 | 18.43371 | 0.00000 | 0.00000 | 3 |
| Geelong | Victoria | 20302 | 0.97704 | 0.00000 | 0.68681 | 2 |
| Surf Coast - Bellarine Peninsula | Victoria | 20303 | 0.03325 | 0.00000 | 0.38546 | 3 |
| Upper Goulburn Valley | Victoria | 20401 | 0.00000 | 0.00000 | 0.22401 | 3 |
| Wangaratta - Benalla | Victoria | 20402 | 0.00000 | 0.00000 | 0.13750 | 3 |
| Wodonga - Alpine | Victoria | 20403 | 0.00000 | 0.00000 | 0.13728 | 3 |
| Baw Baw | Victoria | 20501 | 0.00000 | 0.00000 | 0.13638 | 3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Gippsland - East | Victoria | 20502 | 0.00000 | 0.00000 | 0.67238 | 3 |
| Gippsland - South West | Victoria | 20503 | 1.47168 | 0.00000 | 0.20387 | 3 |
| Latrobe Valley | Victoria | 20504 | 0.00000 | 0.00000 | 0.95351 | 3 |
| Wellington | Victoria | 20505 | 0.00000 | 0.00000 | 0.17520 | 3 |
| Brunswick - Coburg | Victoria | 20601 | 4.68886 | 0.31850 | 0.16180 | 2 |
| Darebin - South | Victoria | 20602 | 0.00000 | 0.00000 | 0.08547 | 3 |
| Essendon | Victoria | 20603 | 0.00000 | 0.00000 | 0.49401 | 3 |
| Melbourne City | Victoria | 20604 | 0.70057 | 18.34032 | 1.49882 | 1 |
| Port Phillip | Victoria | 20605 | 1.74068 | 2.10683 | 1.88045 | 1 |
| Stonnington - West | Victoria | 20606 | 0.00000 | 0.66133 | 0.51862 | 2 |
| Yarra | Victoria | 20607 | 0.50200 | 4.81451 | 1.11221 | 2 |
| Boroondara | Victoria | 20701 | 2.64195 | 2.11195 | 0.90375 | 2 |
| Manningham - West | Victoria | 20702 | 0.00000 | 0.00000 | 0.17058 | 3 |
| Whitehorse - West | Victoria | 20703 | 6.18930 | 0.00000 | 0.77511 | 2 |
| Bayside | Victoria | 20801 | 1.96540 | 0.00000 | 0.39895 | 2 |
| Glen Eira | Victoria | 20802 | 1.33337 | 3.33940 | 0.26357 | 2 |
| Kingston | Victoria | 20803 | 0.00172 | 0.00000 | 0.25420 | 2 |
| Stonnington - East | Victoria | 20804 | 0.00000 | 1.32438 | 0.26482 | 3 |
| Banyule | Victoria | 20901 | 1.81307 | 0.00000 | 0.61620 | 2 |
| Darebin - North | Victoria | 20902 | 1.82639 | 2.67974 | 0.19584 | 2 |
| Nillumbik - Kinglake | Victoria | 20903 | 0.00000 | 0.00000 | 0.16704 | 3 |
| Whittlesea - Wallan | Victoria | 20904 | 0.54883 | 0.00000 | 0.29928 | 2 |
| Keilor | Victoria | 21001 | 0.00117 | 0.00000 | 0.04117 | 3 |
| Macedon Ranges | Victoria | 21002 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Moreland - North | Victoria | 21003 | 0.69029 | 0.41537 | 0.27179 | 3 |
| Sunbury | Victoria | 21004 | 0.00000 | 0.00000 | 0.38466 | 3 |
| Tullamarine - Broadmeadows | Victoria | 21005 | 0.35443 | 0.00000 | 0.44846 | 2 |
| Knox | Victoria | 21101 | 0.34971 | 0.89780 | 0.52265 | 2 |
| Manningham - East | Victoria | 21102 | 0.12395 | 0.00000 | 0.54312 | 3 |
| Maroondah | Victoria | 21103 | 0.62612 | 0.46355 | 0.37656 | 2 |
| Whitehorse - East | Victoria | 21104 | 0.00574 | 0.80652 | 0.34828 | 3 |
| Yarra Ranges | Victoria | 21105 | 0.00000 | 0.69918 | 0.12503 | 2 |
| Cardinia | Victoria | 21201 | 0.06552 | 0.00000 | 0.08658 | 3 |
| Casey - North | Victoria | 21202 | 2.51560 | 0.00000 | 0.16199 | 2 |
| Casey - South | Victoria | 21203 | 0.39384 | 0.00000 | 0.40586 | 2 |
| Dandenong | Victoria | 21204 | 1.08396 | 0.00000 | 0.23272 | 2 |
| Monash | Victoria | 21205 | 2.29936 | 2.36206 | 1.43444 | 2 |
| Brimbank | Victoria | 21301 | 0.00000 | 0.00000 | 0.29271 | 2 |
| Hobsons Bay | Victoria | 21302 | 0.00000 | 0.42906 | 0.90430 | 2 |
| Maribyrnong | Victoria | 21303 | 2.30193 | 0.00000 | 0.35693 | 2 |
| Melton - Bacchus Marsh | Victoria | 21304 | 0.00000 | 0.00000 | 0.05038 | 2 |
| Wyndham | Victoria | 21305 | 0.00000 | 0.00000 | 0.17647 | 2 |
| Frankston | Victoria | 21401 | 0.00000 | 0.00000 | 0.10601 | 2 |
| Mornington Peninsula | Victoria | 21402 | 1.16634 | 0.00000 | 0.70488 | 2 |
| Grampians | Victoria | 21501 | 0.00000 | 0.00000 | 0.93455 | 3 |
| Mildura | Victoria | 21502 | 0.00000 | 0.00000 | 1.20596 | 3 |
| Murray River - Swan Hill | Victoria | 21503 | 12.53704 | 0.00000 | 0.00000 | 3 |
| Campaspe | Victoria | 21601 | 0.00000 | 0.00000 | 0.18624 | 3 |
| Moira | Victoria | 21602 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Shepparton | Victoria | 21603 | 0.00000 | 0.00000 | 0.18839 | 3 |
| Glenelg - Southern Grampians | Victoria | 21701 | 0.00000 | 0.00000 | 0.41993 | 3 |
| Warrnambool | Victoria | 21704 | 0.00000 | 0.00000 | 0.09396 | 3 |
| Capalaba | Queensland | 30101 | 0.00000 | 0.00000 | 0.30296 | 3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Cleveland - Stradbroke | Queensland | 30102 | 0.00000 | 0.00000 | 0.08211 | 3 |
| Wynnum - Manly | Queensland | 30103 | 0.00292 | 1.51429 | 0.44789 | 3 |
| Bald Hills - Everton Park | Queensland | 30201 | 0.00000 | 1.42224 | 0.22863 | 3 |
| Chermside | Queensland | 30202 | 0.00000 | 2.17049 | 0.55423 | 3 |
| Nundah | Queensland | 30203 | 0.00000 | 0.91836 | 0.20423 | 3 |
| Sandgate | Queensland | 30204 | 0.00000 | 1.63530 | 0.17185 | 3 |
| Carindale | Queensland | 30301 | 1.70906 | 0.24918 | 0.20685 | 3 |
| Holland Park - Yeronga | Queensland | 30302 | 3.09796 | 0.00000 | 0.70306 | 2 |
| Mt Gravatt | Queensland | 30303 | 5.24056 | 0.70097 | 0.46604 | 3 |
| Nathan | Queensland | 30304 | 0.68380 | 0.00000 | 0.09801 | 3 |
| Rocklea - Acacia Ridge | Queensland | 30305 | 0.00000 | 0.00000 | 0.13962 | 3 |
| Sunnybank | Queensland | 30306 | 0.97873 | 1.01408 | 0.08339 | 3 |
| Centenary | Queensland | 30401 | 0.02931 | 0.00000 | 0.08689 | 3 |
| Kenmore - Brookfield - Moggill | Queensland | 30402 | 0.00000 | 0.00000 | 4.45615 | 2 |
| Sherwood - Indooroopilly | Queensland | 30403 | 0.27599 | 0.00000 | 6.03558 | 3 |
| The Gap - Enoggera | Queensland | 30404 | 9.51501 | 0.00000 | 0.94716 | 1 |
| Brisbane Inner | Queensland | 30501 | 1.87955 | 8.64870 | 1.14049 | 2 |
| Brisbane Inner - East | Queensland | 30502 | 0.98488 | 1.99056 | 1.54112 | 3 |
| Brisbane Inner - North | Queensland | 30503 | 1.74603 | 19.18668 | 1.10286 | 1 |
| Brisbane Inner - West | Queensland | 30504 | 6.22559 | 3.05401 | 0.40618 | 2 |
| Cairns - North | Queensland | 30601 | 0.00000 | 0.74277 | 0.20520 | 3 |
| Cairns - South | Queensland | 30602 | 0.00000 | 5.11013 | 0.14967 | 2 |
| Innisfail - Cassowary Coast | Queensland | 30603 | 0.00000 | 0.00000 | 0.06586 | 3 |
| Port Douglas - Daintree | Queensland | 30604 | 0.00000 | 0.00000 | 0.48957 | 3 |
| Tablelands (East) - Kuranda | Queensland | 30605 | 0.00000 | 0.00000 | 0.47994 | 3 |
| Darling Downs (West) - Maranoa | Queensland | 30701 | 0.00000 | 0.00000 | 0.10913 | 3 |
| Darling Downs - East | Queensland | 30702 | 0.00000 | 0.00000 | 0.19242 | 3 |
| Granite Belt | Queensland | 30703 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Central Highlands (Qld) | Queensland | 30801 | 0.00000 | 0.00000 | 0.19564 | 3 |
| Rockhampton | Queensland | 30803 | 0.00000 | 0.00000 | 0.26915 | 2 |
| Biloela | Queensland | 30804 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Gladstone | Queensland | 30805 | 0.00000 | 0.00000 | 0.43735 | 3 |
| Broadbeach - Burleigh | Queensland | 30901 | 4.27941 | 0.00000 | 0.31914 | 3 |
| Coolangatta | Queensland | 30902 | 0.00000 | 0.00000 | 0.12832 | 3 |
| Gold Coast - North | Queensland | 30903 | 2.37469 | 0.00000 | 0.16025 | 3 |
| Gold Coast Hinterland | Queensland | 30904 | 0.00000 | 0.03862 | 1.00258 | 3 |
| Mudgeeraba - Tallebudgera | Queensland | 30905 | 1.99468 | 0.00000 | 0.18379 | 3 |
| Nerang | Queensland | 30906 | 0.00000 | 0.91148 | 0.00000 | 3 |
| Ormeau - Oxenford | Queensland | 30907 | 0.00795 | 0.00000 | 0.13325 | 3 |
| Robina | Queensland | 30908 | 2.47934 | 0.00206 | 0.19718 | 3 |
| Southport | Queensland | 30909 | 1.17179 | 0.00000 | 0.34915 | 3 |
| Surfers Paradise | Queensland | 30910 | 2.21878 | 1.81950 | 0.05506 | 3 |
| Forest Lake - Oxley | Queensland | 31001 | 0.61983 | 0.00000 | 0.19915 | 3 |
| Ipswich Hinterland | Queensland | 31002 | 0.00000 | 0.00000 | 0.40341 | 3 |
| Ipswich Inner | Queensland | 31003 | 0.00000 | 0.00000 | 0.08464 | 3 |
| Springfield - Redbank | Queensland | 31004 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Beaudesert | Queensland | 31101 | 0.00000 | 0.00000 | 0.10340 | 3 |
| Beenleigh | Queensland | 31102 | 0.00000 | 0.00000 | 0.17702 | 3 |
| Browns Plains | Queensland | 31103 | 0.00000 | 0.00000 | 0.41360 | 3 |
| Jimboomba | Queensland | 31104 | 0.00000 | 0.00000 | 0.41384 | 3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Loganlea - Carbrook | Queensland | 31105 | 3.79358 | 0.00000 | 0.11099 | 3 |
| Springwood - Kingston | Queensland | 31106 | 1.53197 | 0.00000 | 0.15399 | 3 |
| Bowen Basin - North | Queensland | 31201 | 0.00000 | 0.00000 | 0.14772 | 3 |
| Mackay | Queensland | 31202 | 0.00000 | 0.00000 | 0.04890 | 2 |
| Whitsunday | Queensland | 31203 | 0.00000 | 0.00000 | 0.22794 | 3 |
| Bribie - Beachmere | Queensland | 31301 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Caboolture | Queensland | 31302 | 0.00000 | 0.00000 | 0.20997 | 3 |
| Caboolture Hinterland | Queensland | 31303 | 23.21151 | 0.00000 | 0.20855 | 1 |
| Narangba - Burpengary | Queensland | 31304 | 0.00000 | 0.00000 | 0.20822 | 3 |
| Redcliffe | Queensland | 31305 | 0.00000 | 0.00000 | 0.14577 | 3 |
| Hills District | Queensland | 31401 | 4.81546 | 3.64495 | 0.00000 | 2 |
| North Lakes | Queensland | 31402 | 0.00000 | 0.00000 | 0.16784 | 3 |
| Strathpine | Queensland | 31403 | 0.00000 | 0.00000 | 0.26506 | 3 |
| Far North | Queensland | 31501 | 0.00000 | 0.00000 | 0.24795 | 3 |
| Outback - North | Queensland | 31502 | 0.00000 | 0.00000 | 0.24597 | 3 |
| Outback - South | Queensland | 31503 | 0.00000 | 0.00000 | 0.12989 | 3 |
| Buderim | Queensland | 31601 | 0.00000 | 0.00000 | 0.12051 | 3 |
| Caloundra | Queensland | 31602 | 0.00000 | 0.00000 | 0.09196 | 3 |
| Maroochy | Queensland | 31603 | 0.00000 | 1.35763 | 0.09148 | 3 |
| Nambour - Pomona | Queensland | 31604 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Noosa | Queensland | 31605 | 0.00000 | 0.26209 | 0.36501 | 3 |
| Sunshine Coast Hinterland | Queensland | 31606 | 2.76370 | 0.00000 | 0.13012 | 3 |
| Nambour | Queensland | 31607 | 0.00000 | 0.06433 | 0.15415 | 3 |
| Toowoomba | Queensland | 31701 | 0.00000 | 0.00000 | 0.23446 | 2 |
| Charters Towers - Ayr - Ingham | Queensland | 31801 | 0.00000 | 0.00000 | 0.53615 | 3 |
| Townsville | Queensland | 31802 | 0.00000 | 0.00000 | 0.18690 | 2 |
| Bundaberg | Queensland | 31901 | 0.00000 | 0.00000 | 0.12388 | 3 |
| Burnett | Queensland | 31902 | 0.00000 | 0.00000 | 0.39274 | 3 |
| Gympie - Cooloola | Queensland | 31903 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Hervey Bay | Queensland | 31904 | 0.00000 | 0.00000 | 0.13576 | 3 |
| Maryborough | Queensland | 31905 | 0.00000 | 0.00000 | 0.17185 | 3 |
| Adelaide City | South Australia | 40101 | 2.55139 | 5.44654 | 1.11916 | 1 |
| Adelaide Hills | South Australia | 40102 | 0.00000 | 0.00000 | 0.08479 | 3 |
| Burnside | South Australia | 40103 | 0.00000 | 1.46799 | 0.07791 | 3 |
| Campbelltown (SA) | South Australia | 40104 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Norwood - Payneham - St Peters | South Australia | 40105 | 0.00000 | 4.46527 | 0.26458 | 3 |
| Prospect - Walkerville | South Australia | 40106 | 11.35536 | 0.00000 | 0.00000 | 3 |
| Unley | South Australia | 40107 | 1.94889 | 4.50576 | 0.29739 | 3 |
| Gawler - Two Wells | South Australia | 40201 | 0.00000 | 0.00000 | 0.46784 | 3 |
| Playford | South Australia | 40202 | 0.00000 | 0.00000 | 0.37539 | 3 |
| Port Adelaide - East | South Australia | 40203 | 0.00000 | 0.00000 | 0.25676 | 3 |
| Salisbury | South Australia | 40204 | 0.00000 | 0.00000 | 1.71225 | 2 |
| Tea Tree Gully | South Australia | 40205 | 0.00000 | 0.00000 | 0.16128 | 3 |
| Holdfast Bay | South Australia | 40301 | 2.98296 | 0.00000 | 0.18641 | 3 |
| Marion | South Australia | 40302 | 3.91534 | 1.05239 | 0.39552 | 2 |
| Mitcham | South Australia | 40303 | 1.87436 | 1.46579 | 0.68593 | 2 |
| Onkaparinga | South Australia | 40304 | 1.46872 | 0.00112 | 0.31409 | 2 |
| Charles Sturt | South Australia | 40401 | 0.10860 | 0.00000 | 0.34606 | 2 |
| Port Adelaide - West | South Australia | 40402 | 2.94960 | 0.00000 | 0.26979 | 3 |
| West Torrens | South Australia | 40403 | 1.22474 | 0.00000 | 0.47503 | 3 |
| Barossa | South Australia | 40501 | 0.00000 | 0.00000 | 0.67860 | 3 |
| Lower North | South Australia | 40502 | 0.00000 | 0.00000 | 0.44492 | 3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Mid North | South Australia | 40503 | 0.00000 | 4.22758 | 0.47989 | 3 |
| Yorke Peninsula | South Australia | 40504 | 0.00000 | 0.00000 | 0.82155 | 3 |
| Eyre Peninsula and South West | South Australia | 40601 | 0.00000 | 0.00000 | 0.81281 | 3 |
| Outback - North and East | South Australia | 40602 | 0.00000 | 0.00000 | 0.22451 | 3 |
| Fleurieu - Kangaroo Island | South Australia | 40701 | 0.00000 | 0.00000 | 0.21306 | 3 |
| Limestone Coast | South Australia | 40702 | 0.00000 | 0.00000 | 0.05442 | 3 |
| Murray and Mallee | South Australia | 40703 | 0.00000 | 0.00000 | 0.06405 | 3 |
| Augusta - Margaret River - Busselton | Western Australia | 50101 | 0.00000 | 0.00000 | 0.09747 | 3 |
| Bunbury | Western Australia | 50102 | 0.00000 | 0.00000 | 0.21164 | 3 |
| Manjimup | Western Australia | 50103 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Mandurah | Western Australia | 50201 | 0.00000 | 0.00000 | 0.03999 | 3 |
| Cottesloe - Claremont | Western Australia | 50301 | 2.78599 | 0.89807 | 0.97194 | 1 |
| Perth City | Western Australia | 50302 | 1.18939 | 1.72152 | 0.76982 | 2 |
| Bayswater - Bassendean | Western Australia | 50401 | 0.00000 | 0.00841 | 0.61435 | 3 |
| Mundaring | Western Australia | 50402 | 0.00136 | 0.00000 | 0.10711 | 3 |
| Swan | Western Australia | 50403 | 0.00000 | 0.00000 | 0.15026 | 2 |
| Joondalup | Western Australia | 50501 | 0.00000 | 0.00000 | 0.32472 | 2 |
| Stirling | Western Australia | 50502 | 0.00000 | 1.05469 | 0.70200 | 2 |
| Wanneroo | Western Australia | 50503 | 0.00000 | 0.00000 | 0.15589 | 2 |
| Armadale | Western Australia | 50601 | 0.00000 | 0.00000 | 0.19257 | 3 |
| Belmont - Victoria Park | Western Australia | 50602 | 3.00712 | 0.00000 | 0.31614 | 3 |
| Canning | Western Australia | 50603 | 0.00000 | 0.00000 | 0.36612 | 2 |
| Gosnells | Western Australia | 50604 | 0.00000 | 0.00000 | 0.18704 | 2 |
| Kalamunda | Western Australia | 50605 | 8.56278 | 0.00000 | 0.14880 | 3 |
| Serpentine - Jarrahdale | Western Australia | 50606 | 0.00000 | 0.00000 | 0.33275 | 3 |
| South Perth | Western Australia | 50607 | 0.00000 | 0.00000 | 1.18731 | 3 |
| Cockburn | Western Australia | 50701 | 0.00000 | 0.79240 | 0.41039 | 2 |
| Fremantle | Western Australia | 50702 | 0.00000 | 0.20989 | 0.21232 | 3 |
| Kwinana | Western Australia | 50703 | 0.00000 | 0.00000 | 0.39530 | 3 |
| Melville | Western Australia | 50704 | 0.00000 | 0.17106 | 0.51168 | 2 |
| Rockingham | Western Australia | 50705 | 0.00000 | 0.00000 | 0.23417 | 2 |
| Albany | Western Australia | 50901 | 0.00000 | 0.00000 | 0.28291 | 3 |
| Wheat Belt - North | Western Australia | 50902 | 0.00000 | 0.00000 | 0.12717 | 3 |
| Wheat Belt - South | Western Australia | 50903 | 0.00000 | 0.00000 | 0.30276 | 3 |
| Kimberley | Western Australia | 51001 | 0.00000 | 0.00000 | 0.26422 | 3 |
| East Pilbara | Western Australia | 51002 | 0.00000 | 0.00000 | 0.11713 | 3 |
| West Pilbara | Western Australia | 51003 | 0.00000 | 0.00000 | 0.20820 | 3 |
| Esperance | Western Australia | 51101 | 0.00000 | 0.00000 | 0.06676 | 3 |
| Gascoyne | Western Australia | 51102 | 0.00000 | 0.00000 | 0.08263 | 3 |
| Goldfields | Western Australia | 51103 | 0.00000 | 0.00000 | 0.05196 | 3 |
| Mid West | Western Australia | 51104 | 0.00000 | 0.00000 | 0.09708 | 3 |
| Brighton | Tasmania | 60101 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Hobart - North East | Tasmania | 60102 | 0.00000 | 0.00000 | 0.26045 | 3 |
| Hobart - North West | Tasmania | 60103 | 0.00000 | 0.00000 | 0.07538 | 3 |
| Hobart - South and West | Tasmania | 60104 | 0.00000 | 0.00000 | 0.11558 | 3 |
| Hobart Inner | Tasmania | 60105 | 0.00000 | 0.00000 | 0.46598 | 3 |
| Sorell - Dodges Ferry | Tasmania | 60106 | 0.00000 | 0.00000 | 0.75507 | 3 |
| Launceston | Tasmania | 60201 | 0.00000 | 4.78239 | 0.39497 | 3 |
| Meander Valley - West Tamar | Tasmania | 60202 | 0.00000 | 0.01957 | 0.24715 | 3 |
| North East | Tasmania | 60203 | 0.00000 | 0.00000 | 0.62008 | 3 |
| Central Highlands (Tas.) | Tasmania | 60301 | 0.00000 | 0.00000 | 1.60127 | 3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Huon - Bruny Island | Tasmania | 60302 | 0.00000 | 0.00000 | 0.16506 | 3 |
| South East Coast | Tasmania | 60303 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Burnie - Ulverstone | Tasmania | 60401 | 0.00000 | 0.00000 | 0.64548 | 3 |
| Devonport | Tasmania | 60402 | 0.00000 | 0.00000 | 0.10554 | 3 |
| West Coast | Tasmania | 60403 | 0.00000 | 0.00000 | 0.05082 | 3 |
| Darwin City | Northern Territory | 70101 | 0.00000 | 0.00000 | 0.36746 | 3 |
| Darwin Suburbs | Northern Territory | 70102 | 0.00000 | 0.00000 | 0.71547 | 2 |
| Litchfield | Northern Territory | 70103 | 0.00000 | 0.00000 | 0.44747 | 3 |
| Palmerston | Northern Territory | 70104 | 0.00000 | 0.00000 | 0.24383 | 3 |
| Alice Springs | Northern Territory | 70201 | 0.00000 | 0.00000 | 0.16634 | 3 |
| Barkly | Northern Territory | 70202 | 0.00000 | 0.00000 | 7.58816 | 3 |
| Daly - Tiwi - West Arnhem | Northern Territory | 70203 | 0.00000 | 0.00000 | 0.62518 | 3 |
| East Arnhem | Northern Territory | 70204 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Katherine | Northern Territory | 70205 | 0.00000 | 0.00000 | 0.00000 | 3 |
| Belconnen | Australian Capital Territory | 80101 | 0.00000 | 0.90307 | 1.07097 | 2 |
| Fyshwick - Pialligo - Hume | Australian Capital Territory | 80103 | 0.00000 | 0.00408 | 0.00000 | 3 |
| Gungahlin | Australian Capital Territory | 80104 | 0.00000 | 0.00000 | 0.04446 | 3 |
| North Canberra | Australian Capital Territory | 80105 | 2.28431 | 0.00069 | 1.04440 | 2 |
| South Canberra | Australian Capital Territory | 80106 | 0.00000 | 1.61445 | 1.50336 | 3 |
| Tuggeranong | Australian Capital Territory | 80107 | 0.00000 | 0.00001 | 0.44309 | 3 |
| Weston Creek | Australian Capital Territory | 80108 | 0.00000 | 0.00002 | 0.15331 | 3 |
| Woden | Australian Capital Territory | 80109 | 4.47959 | 0.00000 | 0.00000 | 3 |
| Molonglo | Australian Capital Territory | 80110 | 0.00000 | 0.00002 | 0.00000 | 3 |

**Data Availability Statement:**
The data that support the findings of this study is available on request from the corresponding author.

**Ethics:**
No sensitive or personal data was collected or used in the research associated with this paper.

**Declaration of Interest:**
None. No potential conflict of interest was reported by the authors.

## References

[1] T. H. Davenport and R. Ronanki, "Artificial intelligence for the real world " *Harvard Business Review,* vol. Reprint R1801H (January-February 2018), 2018.
[2] J. Bughin, J. Seong, J. Manyika, M. Chui, and R. Joshi, "Notes from the AI frontier: Modeling the impact of AI on the world economy. Discussion paper," McKinsey Global Institute.
[3] H. Dernis, P. Gkotsis, N. Grassano, S. Nakazato, M. Squicciarini, B. van Beuzekom*, et al.*, "World Corporate Top R&D investors: Shaping the Future of Technologies and of AI. A joint JRC and OECD report. ," Office of the European Union, Luxembourg2019.
[4] A. Annoni, P. Benczur, P. Bertoldi, B. Delipetrev, and et al, " Artificial Intelligence: A European Perspective," Publications Office of the European Union, Luxembourg2018.
[5] OECD, "OECD.AI Policy Observatory: Investments in AI. Venture Capital," OECD.AI Policy Observatory2021.
[6] S. Hajkowicz, S. Karimi, T. Wark, C. Chen, M. Evans, N. Rens*, et al.*, "Artificial intelligence: Solving problems, growing the economy and improving our quality of life.," CSIRO Data61, Australia2019.
[7] Forbes Technology Council, "16 Business And Industry Functions Being Transformed By AI," *Forbes,* vol. 9 September 2021, 2021.
[8] N. Ismail, "AI predictions: how AI is transforming five key industries " *Information Age,* vol. 4 September 2019, 2019.
[9] S. Akter, K. Michael, M. R. Uddin, G. McCarthy, and M. Rahman, "Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics," *Annals of Operations Research,* vol. 308, pp. 7-39, 2022/01/01 2022.
[10] A. Ashtaiwi, "Artificial Intelligence is Transforming the World Development Indicators," in *2020 IEEE / ITU International Conference on Artificial Intelligence for Good (AI4G)*, 2020, pp. 122-128.
[11] DISER, "Australia's Artificial Intelligence Action Plan (www.industry.gov.au)," Department of Industry, Science, Energy and Resources, Australian Government2021.
[12] T. Dutton, B. Barron, and G. Boskovic, *Building an AI world. Report on national and regional AI strategies*, 2018.
[13] DTIS, "Hub to supercharge Queensland's AI economy (DTIS news 7 May 2021)," Department of Tourism, Innovation and Sport, Queensland Government2021.
[14] NSW Government, "AI Strategy," New South Wales Government2021.
[15] Victoria State Government, "Backing Victoria as a leading AI technology destination (Media release 16 February 2021)," Victoria State Government2021.
[16] DTI, "Adelaide aims high with AI initiative (Government of South Australia news 20 May 2021)," Department for Trade and Investment, Government of South Australia2021.
[17] HAI Stanford University, "Artificial Intelligence Index Report 2021," Human-Centered Artificial Intelligence Stanford University2021.
[18] M. Muro and S. Liu, "The geography of AI: Which cities will drive the artificial intelligence revolution?," Brookings2021.
[19] B. T. Asheim and A. Isaksen, "Regional Innovation Systems: The Integration of Local 'Sticky' and Global 'Ubiquitous' Knowledge," *The Journal of Technology Transfer,* vol. 27, pp. 77-86, 2002/01/01 2002.
[20] M. Porter, "Clusters and the New Economics of Competition (p.78)," *Harvard Business Review,* vol. Nov./Dec., pp. 77-90, 1998.
[21] A. Muscio, "From regional innovation systems to local innovation systems: Evidence from Italian industrial districts," *European Planning Studies,* vol. 14, pp. 773-789, 2006/07/01 2006.
[22] R. Camagni and R. Capello, "Regional Innovation Patterns and the EU Regional Policy Reform: Towards Smart Innovation Policies," in *Seminal Studies in Regional and Urban Economics: Contributions from an Impressive Mind*, R. Capello, Ed., ed Cham: Springer International

Publishing, 2017, pp. 313-343.
[23] A. Toney and M. Flagg, "U.S. Demand for AI-Related Talent," Center for Security and Emerging Technology (CSET)2020.
[24] K. Aziz, M. M. Haque, A. Rahman, A. Y. Shamseldin, and M. Shoaib, "Flood estimation in ungauged catchments: application of artificial intelligence based methods for Eastern Australia," *Stochastic Environmental Research and Risk Assessment,* vol. 31, pp. 1499-1514, 2017/08/01 2017.
[25] F. Flanagan and M. Walker, "How can unions use Artificial Intelligence to build power? The use of AI chatbots for labour organising in the US and Australia," *New Technology, Work and Employment,* vol. 36, pp. 159-176, 2021.
[26] P. Henman, "Improving public services using artificial intelligence: possibilities, pitfalls, governance," *Asia Pacific Journal of Public Administration,* vol. 42, pp. 209-221, 2020/10/01 2020.
[27] T. Yigitcanlar, N. Kankanamge, M. Regona, A. Ruiz Maldonado, B. Rowan, A. Ryu*, et al.*, "Artificial Intelligence Technologies and Related Urban Planning and Development Concepts: How Are They Perceived and Utilized in Australia?," *Journal of Open Innovation: Technology, Market, and Complexity,* vol. 6, p. 187, 2020.
[28] ABS, "Australian Statistical Geography Standard (ASGS): Volume 1 - Main Structure and Greater Capital City Statistical Areas, July 2016," Australian Bureau of Statistics2016.
[29] C. Mason, C. Chen, S. Wan, K. Trinh, A. Duenser, R. Sparks*, et al.*, "Australian Skills Dashboard," Commonwealth Scientific and Industrial Research Organisation2022.
[30] S. Baruffaldi, et al,, "Identifying and measuring developments in artificial intelligence: Making the impossible possible," *OECD Science, Technology and Industry Working Papers , No. 2020/05,,* vol. OECD Publishing, Paris, 2020.
[31] F. Moulaert and F. Sekia, "Territorial Innovation Models: A Critical Survey," *Regional Studies,* vol. 37, pp. 289-302, 2003/05/01 2003.
[32] M. J. Andrews and A. Whalley, "150 years of the geography of innovation," *Regional Science and Urban Economics,* p. 103627, 2021/01/25/ 2021.
[33] R. J. Barro and S.-i.-M. Xavier, "Convergence," *Journal of Political Economy,* vol. 100, pp. 223-251, 1992.
[34] R. Stimson, R. R. Stough, and P. Nijkamp, *Endogenous Regional Development*: Edward Elgar Publishing, 2011.
[35] D. Doloreux, J. Gaviria de la Puerta, I. Pastor-López, I. Porto Gómez, B. Sanz, and J. M. Zabala Iturriagagoitia, "Territorial innovation models: to be or not to be, tha" s the question," *Scientometrics,* vol. 120, pp. 1163 - 1191, 2019.
[36] A. Agrawal, I. Cockburn, A. Galasso, and A. Oettl, "Why are some regions more innovative than others? The role of small firms in the presence of large labs," *Journal of Urban Economics,* vol. 81, pp. 149-165, 2014/05/01/ 2014.
[37] A. Agrawal and I. Cockburn, "The anchor tenant hypothesis: exploring the role of large, local, R&D-intensive firms in regional innovation systems," *International Journal of Industrial Organization,* vol. 21, pp. 1227-1253, 2003/11/01/ 2003.
[38] OECD, *Learning to Innovate: Learning regions*, 2002.
[39] B. T. Asheim, "Learning Regions," in *International Encyclopedia of Human Geography*, R. Kitchin and N. Thrift, Eds., ed Oxford: Elsevier, 2009, pp. 172-178.
[40] R. Rutten and F. Boekema, *The Learning RegionFoundations, State of the Art, Future*: Edward Elgar Publishing, 2007.
[41] A. Jungmittag, "Innovations, technological specialisation and economic growth in the EU," *International Economics and Economic Policy,* vol. 1, pp. 247-273, 2004/12/01 2004.
[42] S. Brusco, "The Emilian model: productive decentralisation and social integration," *Cambridge Journal of Economics,* vol. 6, pp. 167 - 184, 1982.
[43] A. Rinaldi, "The Emilian Model Revisited: Twenty Years After," *Business History,* vol. 47, pp. 244-266, 2005/04/01 2005.
[44] D. Foray, "From smart specialisation to smart specialisation policy," *European Journal of*

*Innovation Management,* vol. 17, pp. 492-507, 2014.
[45] OECD, "Innovation-driven Growth in Regions: The Role of Smart Specialisation " Organisation for Economic Co-operation and Development2013.
[46] European Commission, "European Structural and Investment Funds 2014-2020: Official texts and commentaries," European Commission, European Union2015.
[47] C. Gianelle, F. Guzzo, and K. Mieszkowski, "Smart Specialisation: what gets lost in translation from concept to practice?," *Regional Studies,* vol. 54, pp. 1377-1388, 2020/10/02 2020.
[48] R. Hassink and H. Gong, "Six critical questions about smart specialization," *European Planning Studies,* vol. 27, pp. 2049-2065, 2019/10/03 2019.
[49] M. Di Cataldo, V. Monastiriotis, and A. Rodríguez-Pose, "How 'Smart' Are Smart Specialization Strategies?," *JCMS: Journal of Common Market Studies,* vol. n/a, 2020.
[50] C. Veldhuizen, B. Wilson, L. Coenen, L. Goedegebuure, and M. Schoen, "State of the Art Review of Smart Specialisation in Europe," Melbourne Sustainable Society Institute, The University of Melbourne 2018.
[51] B. T. Asheim, R. Boschma, and P. Cooke, "Constructing Regional Advantage: Platform Policies Based on Related Variety and Differentiated Knowledge Bases," *Regional Studies,* vol. 45, pp. 893-904, 2011/07/01 2011.
[52] P. Cooke, "'Introduction. Origins of the Concept,' in H.-J. Braczyk et al. (eds.), Regional Innovation Systems," 1998.
[53] F. Tödtling and M. Trippl, "One size fits all?: Towards a differentiated regional innovation policy approach," *Research Policy,* vol. 34, pp. 1203-1219, 2005/10/01/ 2005.
[54] A. Ciffolilli and A. Muscio, "Industry 4.0: national and regional comparative advantages in key enabling technologies," *European Planning Studies,* vol. 26, pp. 2323-2343, 2018/12/02 2018.
[55] D. Foray and X. Goenaga, "The Goals of Smart Specialisation (S3 Policy Brief Series). JRC Scientific and Policy Reports," European Comission2013.
[56] S. Montresor and F. Quatraro, "Regional Branching and Key Enabling Technologies: Evidence from European Patent Data," *Economic Geography,* vol. 93, pp. 367-396, 2017/08/08 2017.
[57] OECD, *OECD Science, Technology and R&D Statistics: Revealed technology advantage in selected fields*: OECD Science, Technology and R&D Statistics (database), 2021.
[58] EC, "AI Watch. G3: AI areas of specialisation: comparative advantage in AI thematic areas," European Commission2022.
[59] OECD, "Boosting Innovation: The Cluster Approach," Organisation for Ecomonic Co-operation and Development1999.
[60] G. Swann, M. Prevezer, and D. Stout, *The Dynamics of Industrial Clustering: International Comparisons in Computing and Biotechnology*: Oxford University Press, 1998.
[61] M. Enright, "'Regional clusters and firm strategy', in Business Networks: Prospects for Regional Development, Eds. U. Staber, N. Schaefer & B. Sharma, de Gruyter, Berlin and New York," 1996.
[62] P. Maskell, "Towards a Knowledg… based Theory of the Geographical Cluster," *Industrial and Corporate Change,* vol. 10, pp. 921-943, 2001.
[63] OECD, "Innovative Clusters: Drivers of National Innovation Systems " Organisation for Economic Co-operation and Development2001.
[64] M. J. Enright and B. H. Roberts, "Regional Clustering in Australia," *Australian Journal of Management,* vol. 26, pp. 65-85, 2001/08/01 2001.
[65] B. H. Roberts, "The Role of Industry Clusters in Driving Innovation and Competitiveness of Regions," *RDA National Forum 2018, Australian Capital Territory* vol. 16-17th August, 2018.
[66] S. Hajkowicz, A. Reeson, D. Evans, A. Bratanova, and L. Cameron, "Industry Growth Opportunities: A technical report to support the Western Parkland City Economic Development Strategy. A research report for the New South Wales Government by CSIRO Data61 Insights," CSIRO, Australia2021.
[67] S. Baruffaldi, B. van Beuzekom, H. Dernis, D. Harhoff, N. Rao, and et al., "Identifying and measuring developments in artificial intelligence: Making the impossible possible. OECD Science,

Technology and Industry Working Papers 2020/05," OECD2020.
[68] Crunchbase, "About Crunchbase: Search less. Close more (www.crunchbase.com)," 2022.
[69] ABR, *ABN Lookup tool*: Australian Business Register, Australian Government, 2021.
[70] J. O. Atherton, A. Bratanova, and B. Markey-Towler, "Who Is the Blockchain Employee? Exploring Skills in Demand Using Observations from the Australian Labour Market and Behavioural Institutional Cryptoeconomics," *The Journal of The British Blockchain Association,* vol. 3, 2020.
[71] S. Hajkowicz, A. Reeson, L. Rudd, A. Bratanova, L. Hodgers, C. Mason*, et al.*, "Tomorrow's Digitally Enabled Workforce: Megatrends and scenarios for jobs and employment in Australia over the coming twenty years," CSIRO, Brisbane, Australia2016.
[72] A. Duenser and C. Mason, "Evaluating online job ads as indicators of demand for new workers: Characterising strengths and weaknesses," CSIRO, Canberra2019.
[73] Y. Zhao, C. Chen, and C. Mason, "A Framework for Duplicate Detection from Online Job Postings " *The 20th IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (14-17 December 2021),* 2021.
[74] H. C. Yanchang Zhao, Claire Mason, Andrew Reeson, Shanae Burns and David Evans,, "Comparison of Online Job Ads Data – Adzuna vs Burning Glass," *CSIRO publishing,* 2021.
[75] ABS, "Data.gov.au: SA3 Regional Innovation Data, 2009 to 2016," Australian Bureau of Statistics, Australian Government2022.
[76] B. H. Hall and J. Mairesse, "Exploring the relationship between R&D and productivity in French manufacturing firms," *Journal of Econometrics,* vol. 65, pp. 263-293, 1995/01/01/ 1995.
[77] M. Berlemann and J.-E. Wesselhöft, "Estimating Aggregate Capital Stocks Using the Perpetual Inventory Method: A Survey of Previous Implementations and New Empirical Evidence for 103 Countries," *Review of Economics,* vol. 65, pp. 1-34, 2014.
[78] ABS, "Information Paper: Implementation of new international statistical standards in ABS National and International Accounts, September 2009. Chapter 6: Research & Development," Australian Bureau of Statistics2009.
[79] The World Bank, "The World Bank Data: Consumer price index (2010 = 100)," The World Bank2022.
[80] P. A. P. Moran, "Notes on Continuous Stochastic Phenomena," *Biometrika,* vol. 37, pp. 17-23, 1950.
[81] J. D. C. James M. Lattin, Paul E. Green,, *Analyzing Multivariate Data*. Pacific Grove, CA: Thomson Brooks/Cole, 2003.
[82] J. F. Hair Jr., W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis* vol. 7. Essex, England: Pearson Education Limited, 2014.
[83] L. A. García-Escudero, A. Gordaliza, C. Matrán, and A. Mayo-Iscar, "A review of robust clustering methods," *Advances in Data Analysis and Classification,* vol. 4, pp. 89-109, 2010/09/01 2010.
[84] L. García-Escudero, A. Gordaliza, C. Matrán, and A. Mayo, "A general trimming approach to robust Cluster Analysis," *The Annals of Statistics,* vol. 36, pp. 1324-1345, 06/01 2008.
[85] N. G. Malika Charrad, Veronique Boiteau, Azam Niknafs,, "NbClust: An R package for determining the relevant number of clusters in a data set," *Journal of Statistical Software,* vol. 61, October 2014 2014.
[86] M. Gregg, S. Datta, and D. Lorenz, "Variance estimation in tests of clustered categorical data with informative cluster size," *Statistical Methods in Medical Research,* vol. 29, pp. 3396-3408, 2020/11/01 2020.
[87] D. A. Comin, M. Dmitriev, and E. Rossi-Hansberg, "The Spatial Diffusion of Technology. NBER Working paper 18534," *National Bureau of Economic Research,* 2012.
[88] Department of Defence, "About Defence Science and Technology Group," Department of Defence, Australian Government2022.
[89] Queensland Government, "A place for innovation: Queensland innovation places strategy. Discussion paper," Advance Queensland, Queensland Government2021.

[90] Queensland Government, "The Precinct," Advance Queensland, Queensland Government2021.
[91] City of Port Phillip. (2022). *Games Port Phillip (www.portphillip.vic.gov.au)*.
[92] City of Port Phillip, "Games Action Plan," City of Port Phillip2020.
[93] M.-A. Williams, "The artificial intelligence race: Will Australia lead or lose?," *Journal and Proceedings of the Royal Society of New South Wales,* vol. 152, 2019.
[94] Australian Government, "Catalysing the Artificial Intelligence Opportunity in Our Regions Round 1," Business, Australian Government2022.
[95] E. Ingham, "CrunchBase is such a valuable startup analysis tool, but the problem is it has no filter," *Forbes,* vol. 5 November 2014, 2014.