

# **Changing Labour Market Dynamics in Australia: Skill Shortages, Job Transitions, and Artificial Intelligence Technology Adoption**

**by Nikolas Dawson**

Thesis submitted in fulfilment of the requirements for  
the degree of

**Doctor of Philosophy**

under the supervision of  
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## CERTIFICATE OF ORIGINAL AUTHORSHIP

I, *Nikolas Dawson* declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the *School of Computer Science, Faculty of Engineering & IT* at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution. This research is supported by the Australian Government Research Training Program.

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## ABSTRACT

The Australian labour market is in the midst of significant structural changes. Emerging technologies, such as Artificial Intelligence (AI), are changing the demands for skills and tasks within jobs. Additionally, the economic crisis induced by COVID-19, in conjunction with other factors, have accelerated these adjustments. Three major issues for the Australian labour market are (1) skill shortages, (2) job transitions, and (3) AI adoption at the firm-level. This thesis by compilation addresses each of these issues in a series of four standalone papers. The first paper puts forward a range of indicators to detect skill shortages from a longitudinal dataset of online job advertisements (ads). The second paper develops a machine learning model that accurately predicts skill shortages from job ads data and employment statistics. The third paper conducts an in-depth case study of the journalism jobs crisis in Australia, examining both the changes in labour demand (using job ads) and labour supply (using employment statistics) from 2012-2020. Last, the fourth paper develops a novel method to measure the similarity between sets of skills from real-time job ads data. These similarity measures are then combined with other labour market variables to build a ‘Job Transitions Recommender System’ that accurately predicts transition pathways between occupations, validated against a longitudinal household survey. The same skills set similarity method is then used to construct a measure of new technology adoption in labour markets, showcasing AI.



## DEDICATION

*To my wife, Emma, for her ongoing love, patience, and support.*



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Undertaking doctoral research has been both the hardest and most rewarding endeavour of my career thus far. It has been a marathon to complete and a roller-coaster of emotions. While working towards my doctorate has developed skills and knowledge that I'll carry forward in my career, it has also taught me a significant lesson: *the most important thing to do is to think for yourself*. This is the foundation of great research or creating anything new of lasting value. A lesson that is simple to preach but difficult to practice.

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Central to all of the research papers that I present in this thesis are job advertisements data, which have been generously provided by Burning Glass Technologies (BGT). Therefore, I would like to acknowledge and thank BGT for granting access to these data that enabled this research. Specifically, I would like to thank Bledi Taska and Davor Miskulin from BGT for establishing the data sharing agreement and for their valuable feedback on the various papers.

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6. Dawson, N., and MA Rizioiu. 2020. "Coronavirus Infecting Australian Jobs: Vacancy Rates down since Early February." The Conversation, March 22, 2020. <http://theconversation.com/coronavirus-infecting-australian-jobs-vacancy-rates-down-since-early-february-134234>.

Table 1: Papers and contributions by co-authors.

Title	Lead Author	Co-Author 1	Co-Author 2	Co-Author 3
Adaptively Selecting Occupations to Detect Skill Shortages from Online Job Ads.	Nikolas Dawson	<b>Dr. Marian-Andrei Rizioiu</b> , Lecturer at UTS and Ph.D. co-supervisor – assisted with the design of the research, data analysis, and manuscript editing.	<b>Dr. Benjamin Johnston</b> , Senior Lecturer at UTS and Ph.D. co-supervisor – provided feedback and technical assistance.	<b>Distinguished Professor Mary-Anne Williams</b> , UTS and Ph.D. supervisor – assisted with data collection and provided feedback.
Predicting Skill Shortages in Labor Markets: A Machine Learning Approach.	Nikolas Dawson	<b>Dr. Marian-Andrei Rizioiu</b> , Lecturer at UTS and Ph.D. co-supervisor – assisted with the design of the research, data analysis, and manuscript editing.	<b>Dr. Benjamin Johnston</b> , Senior Lecturer at UTS and Ph.D. co-supervisor – provided feedback and technical assistance.	<b>Distinguished Professor Mary-Anne Williams</b> , UTS and Ph.D. supervisor – assisted with data collection and provided feedback.
Layoffs, Inequity and COVID-19: A Longitudinal Study of the Journalism Jobs Crisis in Australia from 2012 to 2020.	Nikolas Dawson	<b>Dr. Sacha Molitorisz</b> , Lecturer at UTS – assisted with the design of the research, preparation of the manuscript, and journalism-specific expertise.	<b>Dr. Marian-Andrei Rizioiu</b> , Lecturer at UTS and Ph.D. co-supervisor – assisted with the design of the research, data analysis, and manuscript editing.	<b>Peter Fray</b> , Managing Editor at Private Media – assisted with the design of the research.
Skill-driven Recommendations for Job Transition Pathways.	Nikolas Dawson	<b>Dr. Marian-Andrei Rizioiu</b> , Lecturer at UTS and Ph.D. co-supervisor – assisted with the design of the research, data analysis, and manuscript editing.	<b>Distinguished Professor Mary-Anne Williams</b> , UTS and Ph.D. supervisor – assisted with data collection and provided feedback.	

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**[Peter Fray]**



## TABLE OF CONTENTS

<b>List of Publications</b>	<b>ix</b>
<b>List of Figures</b>	<b>xix</b>
<b>List of Tables</b>	<b>xxv</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Identified research gaps . . . . .	3
1.2 Aims and contributions of this research . . . . .	4
1.3 Thesis structure: A Ph.D. by compilation of papers . . . . .	6
<b>2 Literature Review</b>	<b>9</b>
2.1 Australia's changing labour market . . . . .	9
2.1.1 Australia's labour market performance . . . . .	10
2.1.2 The changing nature of employment and skills in Australia's work- force . . . . .	12
2.1.3 Labour Market Programmes: supporting displaced workers to tran- sition . . . . .	17
2.2 Job transitions & skill mismatches . . . . .	25
2.2.1 Occupational mobility and job transitions . . . . .	25
2.3 AI & its impacts on labour markets . . . . .	30
2.3.1 Defining AI . . . . .	31
2.3.2 Categorising the Extent of AI . . . . .	32
2.3.3 Research Trends & Subsets of AI . . . . .	33
2.3.4 Drivers of Recent AI Advancements . . . . .	36
2.3.5 AI as the Next General Purpose Technology . . . . .	38
2.3.6 Projecting the Economic Impacts of AI . . . . .	40

## TABLE OF CONTENTS

---

2.3.7	Creative Destruction: Long-term relationship between technology and jobs . . . . .	44
2.3.8	AI and Inequality . . . . .	49
2.3.9	AI Adoption . . . . .	55
2.4	Positioning this research . . . . .	58
<b>3</b>	<b>Paper 1 - Adaptively selecting occupations to detect skill shortages from online job ads</b>	<b>59</b>
3.1	Introduction . . . . .	60
3.2	Related Work & Limitations . . . . .	63
3.3	Skill similarity and sets of related skills . . . . .	64
3.4	DSA occupations and categories . . . . .	65
3.5	Detecting Skill Shortages from Job Ads . . . . .	66
3.5.1	Variables for detecting skill shortages . . . . .	68
3.5.2	Predict job ad posting . . . . .	69
3.6	Discussion . . . . .	70
3.7	Conclusions and Future Research . . . . .	73
3.8	Supplementary Materials . . . . .	75
3.8.1	Australia's looming DSA Shortfall . . . . .	75
3.8.2	Limitations of Online Job Ads Data . . . . .	75
3.8.3	Challenges with Classifying Occupations . . . . .	76
3.8.4	DSA Skill Demands . . . . .	76
3.8.5	Time Series Forecasting with Prophet . . . . .	77
3.8.6	Evaluating performance . . . . .	78
3.8.7	DSA Skills List . . . . .	79
<b>4</b>	<b>Paper 2 - Predicting Skill Shortages in Labor Markets: A Machine Learning Approach</b>	<b>81</b>
4.1	Introduction . . . . .	82
4.2	Related Work & Limitations . . . . .	85
4.2.1	Measuring Labor Shortages . . . . .	85
4.2.2	Economic Costs of Skill Shortages . . . . .	87
4.3	Data and Methods . . . . .	88
4.3.1	Data sources and constructed features . . . . .	88
4.3.2	Quantify skill importance for occupations . . . . .	90
4.3.3	Predictive Setup for Skill Shortages . . . . .	91

4.4	Results . . . . .	93
4.4.1	Profiling the Skills Shortage Prediction dataset . . . . .	94
4.4.2	Skill importance levels for Data Scientists. . . . .	96
4.4.3	Predict Skill Shortages . . . . .	97
4.4.4	Feature Importance for Predicting Skill Shortages . . . . .	98
4.5	Discussion . . . . .	99
4.6	Conclusion and Future Work . . . . .	101
4.7	Supplementary Materials . . . . .	102
4.7.1	Cyclical and Structural Factors Affecting Skill Shortages . . . . .	102
4.7.2	Oversampling . . . . .	103
4.7.3	Performance metrics . . . . .	104
4.7.4	Using a standardized occupation taxonomy – ANZSCO. . . . .	104
4.7.5	Summary of constructed features . . . . .	105
4.7.6	Feature correlation analysis . . . . .	106
<b>5</b>	<b>Paper 3 - Layoffs, Inequity and COVID-19: A Longitudinal Study of the Journalism Jobs Crisis in Australia from 2012 to 2020</b>	<b>107</b>
5.1	Introduction . . . . .	108
5.2	Related Work & Background . . . . .	110
5.3	Data & Methods . . . . .	115
5.3.1	Data Sources . . . . .	115
5.3.2	Skill Similarity . . . . .	116
5.4	Jobs Data Analysis and Results . . . . .	117
5.4.1	Posting Frequency & Employment levels . . . . .	117
5.4.2	Salaries . . . . .	119
5.4.3	Trend Analysis & Predictability . . . . .	121
5.4.4	Gender . . . . .	122
5.4.5	Location . . . . .	123
5.4.6	Education & Experience . . . . .	124
5.4.7	Employment Type . . . . .	124
5.4.8	Journalism Skills . . . . .	125
5.5	Discussion . . . . .	127
5.5.1	Volatility of journalism jobs . . . . .	127
5.5.2	Gender Wage Gap . . . . .	130
5.5.3	Location . . . . .	131



## TABLE OF CONTENTS

---

5.5.4	Evolving journalism skills . . . . .	132
5.6	Conclusion . . . . .	133
5.7	Supplementary Materials . . . . .	135
5.7.1	Data Sources . . . . .	135
5.7.2	Skill Similarity . . . . .	138
5.7.3	Trend Analysis & Predictability . . . . .	140
5.7.4	Quantify Labour Demand Volatility . . . . .	140
5.7.5	Top Journalism Skills by Year . . . . .	141
<b>6</b>	<b>Paper 4 - Skill-driven Recommendations for Job Transition Pathways</b>	<b>143</b>
6.1	Introduction . . . . .	144
6.2	Materials and methods . . . . .	146
6.2.1	Datasets and ground-truth . . . . .	146
6.2.2	Measuring skill similarity . . . . .	147
6.2.3	Job Transitions Recommender System setup . . . . .	149
6.2.4	Constructing a leading indicator of AI adoption . . . . .	151
6.3	Results & Discussion . . . . .	152
6.3.1	Skill similarity results . . . . .	152
6.3.2	SKILLS SPACE results . . . . .	152
6.3.3	Validation of SKILLS SPACE distance . . . . .	154
6.3.4	Job Transitions Recommender System . . . . .	156
6.3.5	A leading indicator of AI adoption . . . . .	161
6.3.6	Limitations . . . . .	163
6.4	Conclusion . . . . .	165
6.5	Supplementary Materials . . . . .	167
6.5.1	Using a standardized occupation taxonomy – ANZSCO. . . . .	167
6.5.2	Model Features . . . . .	168
6.5.3	Validation . . . . .	168
6.5.4	Recommending Jobs & Skills . . . . .	175
6.5.5	AI Adoption . . . . .	175
6.5.6	Skill Count Distribution . . . . .	176
6.5.7	Posting Frequency of AI Seed Skills . . . . .	178
6.5.8	Advantages of Skill Similarity over Posting Frequency . . . . .	179
<b>7</b>	<b>Discussion &amp; Conclusion</b>	<b>181</b>
7.1	Limitations and future research . . . . .	182

7.1.1 Skill shortages . . . . . 182

7.1.2 Job transitions . . . . . 184

7.1.3 AI adoption . . . . . 185

7.1.4 A final note . . . . . 186

**Bibliography** **187**



## LIST OF FIGURES

FIGURE	Page
2.1 Monthly unemployment and underemployment rates in Australia from 1978 to 2020 for the (a) total Australian workforce and (b) youth workforce aged 15-24 years from the ABS [33]. . . . .	11
2.2 (a) Full-time (FT) and part-time (PT) monthly employment levels (000's) by gender in Australia (b) monthly employment to population ratio by gender in Australia. . . . .	13
2.3 Employment change by industry over 20 years from to May 2018 (000's). . . .	14
2.4 Australian (a) employment by skill type as a percentage of total employment and (b) employment by skill level as a percentage of total employment. . . . .	15
2.5 Australian unemployment and labour market participation in 2017 by educational attainment. . . . .	16
2.6 The number of persons (000's) who ceased a job during the last three months because they were retrenched or were self-employed whose business closed down. The stacked bar charts further indicate the current employment status of persons retrenched as 'employed', 'unemployed', and 'not in labour force' (NILF). The orange line highlights the retrenchment rate as a percentage of the total workforce. . . . .	22
2.7 A basic illustration of a feed-forward neural network architecture used for DL.	37
2.8 Examples of occupations according to the 'Task Model' put forward by Autor et al. [47]. . . . .	42
2.9 Comparison of labour automation risk by study as shown by Bruckner et al. [84]. . . . .	43
2.10 Distribution of labour force by agriculture, manufacturing, and services in the US from 1840-2010 [156]. . . . .	47
3.1 Defining DSA Categories adopted from Markow et al and Blake [70, 227] . . .	67

## LIST OF FIGURES

---

3.2	Labour demand variables for detecting skill shortages from job ads data: posting frequency (a) and its annual growth (b); median salary (Australian \$) (c); education level (years of formal education) (d); experience (years) (e) and job ad posting predictability in terms of SMAPE error scores (f). . . . .	69
3.3	Sliding window setup for evaluating job ads forecasting performance. . . . .	71
3.4	Trend lines of daily online job ad postings . . . . .	72
3.5	Top 10 DSA Skills for each year from 2012-2019 . . . . .	77
4.1	<b>Overview of Skills Shortage Dataset:</b> (a) Proportion of occupations represented in dataset by ANZSCO Major Group classes; (b) count of occupations grouped by the number of years <i>In Shortage</i> (the colors correspond to the same occupational categories observed in the Fig. 4.1(a) legend); (c) yearly distribution of occupations classified as <i>Not in Shortage</i> (light blue bars - 718 total) or <i>In Shortage</i> (dark blue bars - 206 total) and the yearly number of occupations whose shortage status has changed since the previous year (orange stars). . . . .	93
4.2	Top occupations most <i>In Shortage</i> at the ANZSCO 6-digit occupational level. . . . .	94
4.3	<b>Comparison of two methods to analyze underlying skill demands of occupations in shortage:</b> (a) posting frequency of skills in an occupation; (b) Revealed Comparative Advantage of skills in an occupation to normalize highly-common skills and uncover skills most relevant to an occupation. . . . .	95
4.4	<b>Skills Shortage prediction results:</b> (a) While the prediction results are highly auto-regressive, Labor Demand and Labor Supply features alone (and combined) perform almost as well for predicting occupational shortages; (b) Labor Demand and Labor Supply features perform better than other features at predicting shortage status changes of occupations. . . . .	96
4.5	Feature importance of Labor Demand (LD) and Labor Supply (LS) feature model. . . . .	99
4.6	Correlation analysis between modeled features. . . . .	106
5.1	Quarterly posting frequency of journalism job ads (see Sec. Section 5.3) and employment levels of ‘Journalists & Other Writers’ at the ANZSCO Unit level (000’s) from Jan 2012 to Mar 2020. . . . .	118

5.2	<b>Posting frequency for journalism jobs during the early stages of the COVID-19 crisis in Australia and its major cities:</b> (a) Weekly posting frequency volumes for journalists and all Australian job ads between April 2019 and March 2020. Both decreased as the early stages of the COVID-19 crisis hit; (b) Monthly posting frequency for journalists were down 63 per cent when comparing March 2019 to March 2020. This was significantly higher than all Australian job vacancies, which was down 37 per cent over the same period. . . . .	119
5.3	Journalist salaries ( <b>solid blue line</b> ) increased according to job ads data, but remained below market average levels ( <b>dashed blue line</b> ). However, according to ABS data, 'Journalists & Other Writers' (ANZSCO Unit level, <b>solid orange line</b> ) earned a growing wage premium above the market average ( <b>dashed orange line</b> ). . . . .	120
5.4	<b>Trend lines of posting frequency</b> for 'Journalists', 'Data Scientists', 'Data Analysts', and 'All Australian job ads'. Posting frequency for 'Journalists' trended downwards since 2016. . . . .	121
5.5	(a) Predictability comparison of temporal posting frequency highlighting the difficulties of predicting journalism job ads and their volatility. . . . .	121
5.6	<b>Journalist employment levels and salaries by Gender:</b> (a) Since 2015, the employment ratio of female-to-male journalists increased; (b) Wage inequality increased between males and females in the 'Journalists & Other Writers' Unit group. This was at the same time that the average age of journalists decreased for females and increasing for males since 2014. . . . .	122
5.7	<b>Location of journalists in Australia:</b> (a) Posting frequency for journalism jobs decreased in major Australian cities, in relative terms; (b) As of 2019, the majority of journalists in Australia were employed in New South Wales, Victoria, and Queensland, respectively. . . . .	123
5.8	(a) Years of Education demanded by employers from job ads were consistent with the market average; (b) Years of Experience required by employers consistently remained below the market average, according to job ads. However, this gap had closed since 2014. . . . .	124
5.9	Temporary positions represented the majority of journalism job ads in Australia. . . . .	125
5.10	The absolute posting frequency (a) and relative yearly rank (b) of three major journalism skills increased between 2012 and 2019. . . . .	126

5.11	<b>Skill and occupational similarity analyses: (a)</b> The changing similarity (or relative importance) of specific skills compared to the skill ‘Journalism’; <b>(b)</b> Eight occupations that had the highest similarity to the ‘Top Yearly Journalism Skills’.	128
6.2	<b>The SKILLS SPACE is statistically significant in representing job transitions. (A)</b> The x-axis shows the log-transformed SKILLS SPACE distance for a ‘True’ sample of actual transitions (shown in magenta color) and a ‘Random’ sample of simulated transitions (shown in gray color). Each Random transition is paired with an Actual transition: it shares the same ‘source’ occupation as the Actual transition but the ‘target’ occupation is randomly selected and is different to the Actual observation. The difference between the two populations is statistically significant (paired t-test, t-statistic = 4.514, p-value = $6.535 \times 10^{-6}$ , Cohen’s D effect size = 0.14). <b>(B)</b> We repeat the procedure 100 times: we generate 100 ‘Random’ populations, and we perform the statistical testing for each. The figure shows the histogram (density and rug plot) of the 100 obtained p-values, 87 of which are lower than 0.05.	155
6.3	Validation and the <i>Transitions Map</i> . Visualizes a subset of the <i>Transitions Map</i> , where 20 occupations and their pairwise transition probabilities can be observed. In this visualization, transitions occur from columns to rows, and dark blue depicts high transition probabilities, and white depicts low probabilities. While job transitions to the same occupation yield the highest probabilities (dark blue diagonal squares), it is clear that transitions are asymmetric. The dendrogram highlights how similar occupations cluster together, where there is a clear divide between services and manual labor occupations.	157
6.4	The prediction accuracy scores of the different classifier model feature configurations. The highest performance is achieved when ‘All Features’ are incorporated in the classifier models to predict occupational transitions (76%). Moreover, by incorporating all features, the standard deviation decreases (shown by the performance bars), which highlights the complementarity of the combined features and the ability to now account for the asymmetry between jobs.	158

6.5	Here, we demonstrate the <i>Job Transitions Recommender System</i> using the ‘Domestic Cleaner’ occupation as an example – an occupation classified as a ‘non-essential’ occupation and that has experienced significant declines during the beginning of the COVID-19 outbreak in Australia. (upper panel) The two-dimensional space of occupations (see Fig. 6.1) with ‘essential’ occupations in blue markers and ‘non-essential’ occupations in red markers. (lower panel) We first use the <i>Transitions Map</i> to calculate the occupations with the highest transition probabilities (other than itself). These are the nodes on the right side of the flow diagram in the bottom panel of the figure, where the link colors depict posting frequency percentage change from March-April 2019 to March-April 2020. The link widths represent the posting frequency volume of March-April 2020 to indicate labor demand. The top six occupations have all experienced significant declines during the COVID-19 period; however, the seventh recommendation, ‘Aged and Disabled Carers’, is experiencing significant labor demand growth. ‘Aged and Disabled Carers’ were also classified as an ‘essential’ occupation during COVID-19 in Australia. We select this as the target occupation and then make personalized skill recommendations. We argue that workers trying to transition to another occupation should invest time and resources into skill development when (1) the skills are of <b>high importance</b> and (2) there is a <b>high distance</b> to acquire the skill. Conversely, workers should <i>not</i> focus on skill development if (1) the skills are <b>low importance</b> or (2) there is a <b>low distance</b> to acquire the skill. . . . .	160
6.6	By applying SKILLS SPACE, we measure the yearly similarities between adaptive sets of AI skills against each of the 19 Australian industries from 2013-2019. As industry skill sets become more similar to AI skills, the colored area of the radar chart expands. All industries have increased their similarity levels to AI skills, albeit at different rates. We argue that higher levels of AI similarity indicate AI skills are becoming more important to firms within an industry and that the skills gap to acquiring AI skills is narrowed. Access to these skills accelerates the rate of firms adopting AI and making productive use of the technologies, which offers a leading indicator of AI adoption and potential labor disruptions within these industries. . . . .	162
6.7	(a) Statistical test against all occupational transitions and (b) against transitions where the worker changed occupations . . . . .	170
6.8	Network2 . . . . .	172



## LIST OF FIGURES

---

6.12 (a) Ablation test of classifier features and (b) feature importance analysis . .	174
6.13 Yearly skill similarities between AI skills and Australian Industry (ANZSIC Division) skill sets from 2012-2019. . . . .	176
6.14 Empirical Cumulative Distribution Function of skill counts within job ads for 2018. . . . .	177
6.15 Yearly posting frequency of the five AI seed skills used to build a dynamic list of yearly AI skills. . . . .	178
6.16 The percentage of vacancies in Australia that contain these five AI seed skills.	179

## LIST OF TABLES

1	Papers and contributions by co-authors. . . . .	x
	<b>TABLE</b>	<b>Page</b>
3.1	Selected DSA Occupations and their job ad counts. . . . .	67
3.2	Top DSA Skills Growth . . . . .	78
3.3	Selected 150 Data Science and Analytics skills. . . . .	80
4.1	Summary of constructed features and their explanation. . . . .	105
5.1	Random sample of journalism job ad titles . . . . .	137
5.2	Top journalism skills calculated by skill similarity methodology in <i>Skill Similarity</i> . . . . .	141
6.1	Summary of constructed features and their explanation. . . . .	169

