



Australian Government
Department of Employment,
Skills, Small and Family Business

Reskilling Australia

A data-driven approach



Terms of use and disclaimer

Reskilling Australia: A data-driven approach (**Report**) presents information and data that was compiled by the Commonwealth of Australia (**Commonwealth**) in collaboration with The Boston Consulting Group and Burning Glass Technologies.

Legal disclaimer in respect of data and information

The Commonwealth has taken reasonable steps to ensure the data and information included in the Report is accurate. However, the Commonwealth:

- (a) makes no representation or warranty, as to the accuracy, or fitness for purpose of any data or information included in the Report; and
- (b) does not accept legal liability for any error in any data or information in the Report or for any reliance upon any data or information included in the Report.

Use, modification and distribution of data and information

If you use, reproduce or distribute any data or information in the Report, this must be explicitly acknowledged and the Report must be cited. Where reasonably practicable, a URL or hyperlink to the Report should be included where this is cited. If any data or information included in the Report is altered, the nature and extent of this alteration must be explained.

Users who make the data or information in this Report available to other users through any type of distribution or download environment agree to make reasonable efforts to communicate and promote compliance by their end users with these terms.

You must not use any data or information included in this Report for commercial gain or profit.

ISBN

978-1-76051-754-0 [PDF]

978-1-76051-755-7 [DOCX]



With the exception of the Commonwealth Coat of Arms, the Department's logo, any material protected by a trade mark and where otherwise noted all material presented in this document is provided under a Creative Commons Attribution 3.0 Australia (<http://creativecommons.org/licenses/by/3.0/au/>) licence.

The details of the relevant licence conditions are available on the Creative Commons website (accessible using the links provided) as is the full legal code for the CC BY 3.0 AU licence (<http://creativecommons.org/licenses/by/3.0/au/legalcode>).

The document must be attributed as the *Reskilling Australia - A data driven approach*.

FOREWORD

Work and workplaces in Australia are changing due to new technology, globalisation, changing demography and consumer preferences. Growth in the service industry is driving job creation, with high-skilled and knowledge-based jobs growing rapidly. Jobs requiring a mix of creative and technical skills are also growing. These trends have altered, or likely soon will alter, the tasks and skills required for every job in the workforce.

The Future of Work Taskforce, established in the Department of Employment, Skills, Small and Family Business identified that moving towards a skills-based approach to labour market analysis could help Australia respond to this changing demand for skills. On a practical level, we identified the need to answer questions including:

- How can job seekers and workers make a quicker and smoother job transition as tasks and skills requirements change?
- How can employers improve their workforce planning to get the required skills?
- Can educational institutions monitor the skills market so course offerings can be adjusted quickly if required?
- How can policy makers guide people from declining sectors into areas of growing employment demand, and target welfare interventions to support job seekers better?

To answer these questions, we are exploring how analysis of large datasets using machine learning and other techniques can offer insights to improve labour market transitions.

This has involved adapting for Australia the approach in the January 2018 report, *Towards a Reskilling Revolution: A Future of Jobs for All*, issued by the World Economic Forum (WEF) and collaborating with Boston Consulting Group and Burning Glass Technologies.

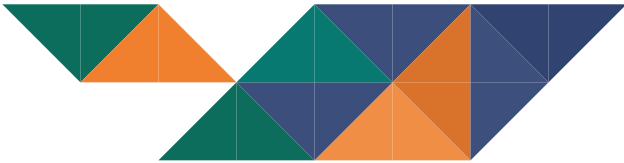
This report summarises our work to-date developing the first Australian model to map transferability between occupations in the changing labour market of the future.

July 2019

ACKNOWLEDGEMENTS

Reskilling Australia: A data driven approach published by the Department of Employment, Skills, Small and Family Business, validated by Boston Consulting Group and using proprietary data provided for this report by Burning Glass Technologies.

The Department would also like to acknowledge the work of Mohammad Ali Raza, Giang Nguyen, Ian De Oliveira and Regan Lu.



CONTENTS

FOREWORD	4	4. NEXT STEPS	13
Acknowledgements	4	Tools to help stakeholders make informed decisions about careers	13
1. INTRODUCTION	6	A data infrastructure that keeps up with a dynamic labour market	13
2. MAPPING JOB TRANSITIONS	6	5. REFERENCES	14
An ideal job transition is both viable and desirable	6	6. APPENDIX	14
Alternative big data enables an Australian model of occupation transferability	7	Viable and desirable job transition pathways	14
O*Net	7	Adapting data sources for job viability scores	14
Burning Glass Technologies data	7	Adapting O*Net to Australian occupation classification	14
Measuring job similarity	9	Burning Glass Technologies data	15
Incentivising workers in declining jobs to make earlier transitions	9	Computing similarity scores	15
Target jobs should grow in the future	10	Education and Experience job similarity score from Burning Glass Technologies	15
Target jobs should pay more	10	Job Transition scores	16
Making user recommendations	10	Assessing realistic leaps in education or experience	18
3. ECONOMY-WIDE RESKILLING OPPORTUNITIES	11	Job desirability through Australian projections and salary data	18
Most declining workers have transition options	11	Jobs growth forecast	18
The results are robust to wage desirability assumptions	12	Wage continuity (or decrease)	20
		Economy-wide reskilling opportunities (Leadership lens)	20

1. INTRODUCTION

The Future of Work Taskforce adapted the World Economic Forum (WEF) approach in the January 2018 report *Towards a Reskilling Revolution: A Future of Jobs for All*. Our adaptation addresses the need for better labour market modelling, and uses more granular skills information from alternative big data sources, to inform Australian workers facing career transition decisions.

This follows the 2018 Organisation for Economic Co-operation (OECD) report, *Getting Skills Right: Australia*, which recommends using new data techniques to facilitate better career transitions by identifying skills with a high degree of transferability between jobs (OECD, 2018).

2. MAPPING JOB TRANSITIONS

The approach used by the original WEF study was designed to systematically map realistic job transition opportunities for workers facing declining job prospects.

Job transitions uncovered by this modelling could be presented to individuals through a 'user lens', to display skill-based recommendations to support workers transiting from declining to growing jobs.

An ideal job transition is both viable and desirable

From the perspective of an individual job seeker or worker, practical transitions need to be viable and desirable.

A **viable** job transition involves moving from one job to another that is highly similar in terms of required knowledge, skills, abilities, work activities, education levels and experience. This does not cover all aspects of what makes jobs similar, such as industry and work culture. While it is possible to incorporate some of these aspects, the model intends to enable mobility across different workplaces and industries, therefore additional aspects are not explicitly included in the model.

A **desirable** transition for a job seeker or worker would result in higher wages in a field of work that is expanding rather than declining. The Department of Employment, Skills, Small and Family Business publishes five-year employment projections annually, which identify declining and growing job sectors.

Figure 1. Viable and desirable job transitions



Alternative big data enables an Australian model of occupation transferability

We used the same data sources as the original WEF study to measure job similarity (or job viability). This included the United States Bureau of Labour Statistics' Occupational Information Network (O*NET) database and Burning Glass Technologies Australian job advertisement data. Each source has strengths and limitations (as detailed in Table 1), and combining the two datasets produced a more robust evidence base than using one data source in isolation.

By using both of these datasets together, our study provides one of the first models of occupational transferability between each of the Australian 4-digit ANZSCO occupations (Australian and New Zealand Standard Classification of Occupation).

O*Net

O*Net is a rich database containing information on all United States occupations through annual surveys of United States workers since 2000. To measure job similarity, we analysed domains including skills, knowledge, abilities, education and experience of workers and work activities by occupation.

Due to the comprehensive and granular nature of O*Net data, it has been widely used in future of work studies. However, because it is tailored to the United States market, the data does not necessarily reflect the Australian context.

Burning Glass Technologies data

Burning Glass Technologies is a big data labour market analysis aggregator. It contains information derived from some 2.6 million online job postings in Australia during our analysis period of 2016–17.

Burning Glass Technologies scrapes job advertisements from 3,000 websites in Australia and uses Natural Language Processing to tag relevant information in the advertisements. It has a large skills taxonomy, with more than 16,000 skills including emerging skills such as 'data analytics' and 'block chain'. We used skills, education and experience requirements from this data.

Using Burning Glass Technologies data offset the limitations of O*Net by providing some Australian context: its tagger recognises vocational education and training (VET) qualifications and Australian degree systems, the occupations are coded to ANZSCO, and the skills requirements reflect local Australian demand.

Table 1. Strengths and limitations of O*Net and Burning Glass Technologies for modelling Australian viable transitions

O*Net	Burning Glass Technologies
<p>Dimensions used:</p> <ul style="list-style-type: none"> - Skills - Knowledge - Abilities - Work activities - Education and Experience 	<p>Dimensions used:</p> <ul style="list-style-type: none"> - Baseline skills - Software skills - Specialised skills - Education levels - Experience requirements
<p>Strengths:</p> <ul style="list-style-type: none"> - Standardised classification of skills, knowledge, abilities and work activities. - Comprehensive for most occupations in the labour market (in the United States). - Consistent taxonomy over time allows for longitudinal analysis. - Information is derived from a representative sample of those working in the occupation. 	<p>Strengths:</p> <ul style="list-style-type: none"> - Occupations are coded to ANZSCO - Education requirements are coded to Australian degree systems (such as VET, Bachelor degree or above) - Dynamic and large skills taxonomy capturing nuances in reskilling requirements (e.g. emerging skills such as 'data analytics' and 'wire-framing'). - Information is derived from advertisements that describe what employers are looking for locally.
<p>Limitations:</p> <ul style="list-style-type: none"> - Occupational information is not tailored to the Australian context, especially in education and experience requirements of the occupation. - Australian occupations do not align one-to-one with United States occupations, introducing errors (e.g. Australian occupations of 'Hotel Managers' and 'Camping Ground Managers' both map to the same United States occupation of 'Lodging Managers'). 	<p>Limitations:</p> <ul style="list-style-type: none"> - Job advertisements data are not from a representative sample and are typically biased toward professional (white collar), urban jobs. - Errors from omission are possible if employers do not list skills inherent in the role. - The number of job advertisements are low (less than 100 job postings) for about 30 of the 353 occupations, making job similarity scores somewhat unreliable.

Measuring job similarity

Viable transitions are highly similar in their skills, education and experience requirements. Following the method in the original WEF study, we aggregated each of the domains contributing to a job-fit category (see Table 2) into a single index of similarity, or a 'similarity score'.

To compute the similarity score between pairs of jobs, we used the cosine similarity method. This method is one of the fundamental distance measures used by many unsupervised machine learning algorithms, particularly in text mining. We computed the similarity scores for each pair of the 353 ANZSCO occupations (jobs) analysed for our study, resulting in numeric values between 0 and 1.

Job pairs with a similarity score of 1 are a perfect fit, and those with a score of 0 have a remote or imperfect fit. High similarity scores are considered to be at least 0.9 or higher, medium similarity scores are between 0.8 and 0.9, and low similarity scores are below 0.8. These boundaries are slightly lower than the original WEF study, as we used a broader occupational grouping of 353 occupations (jobs) compared with the WEF study's 958 occupations (jobs).

Any job pair with a similarity score of 0.8 or above is considered a viable transition.

Table 2. Examples of high, medium and low job fit similarity jobs

Starting job	'Job-fit' category	Similarity score	Target job
Secretaries	High	0.96	General Clerks
	Medium	0.83	Call or Contact Centre Workers
	Low	0.77	General Managers
Product Assemblers	High	0.9	Insulation and Home Improvement Installers
	Medium	0.82	Train and Tram Drivers
	Low	0.78	Air Transport Professionals
Accounting Clerks	High	0.87	Purchasing and Supply Logistics Clerks
	Medium	0.82	Tourism and Travel Advisers
	Low	0.78	Social Workers
Checkout Operators and Office Cashiers	High	0.89	Waiter
	Medium	0.83	Retail Supervisors
	Low	0.75	Security Officers and Guards

The similarity scores provide a useful tool for identifying viable job transitions. However, because similarity scores are based on a composite index, the original WEF study introduced additional filters so the job-fit indicated by the aggregated similarity score remains realistic. That is, the viability of a job transition was also constrained by realistic leaps of education and experience.

Our study used Australian Bureau of Statistics (ABS) Skill levels to constrain transitions to a move of one skill level from the starting job, similar to the original WEF study. The ABS Skill levels range from 1 (which may require tertiary qualifications or five years of work experience) to 5 (which requires minimal education and work experience).

Incentivising workers in declining jobs to make earlier transitions

We also wanted to explore what drives workers in declining jobs to decide to move jobs before the decision becomes imminent. Two driving factors incentivising a worker to move jobs are if the target job is growing and if it pays more than their current job.

Target jobs should grow in the future

Unlike the original WEF study, which used 10-year employment projections for the United States, our study used the Department of Employment, Skills, Small and Family Business' five-year projections, because projecting out to 10 years introduces greater uncertainty. While five-year projections may not provide a long-term reskilling strategy, it is sufficiently long to help workers reskill and find roles in growing jobs.

Target jobs should pay more

Sustainable job pathways involve transitioning to new jobs that pay more. Under a 'skills arbitrage' philosophy, the pay differential a worker gains from moving careers must be worth at least the cost of the upskilling required to make the transition (Burning Glass Technologies, 2018).

While the original WEF study used the average salary reported in job advertisements, we primarily used the ABS' *Survey of Employee Earnings and Hours* median hourly earnings. This is because it is comprehensive for all occupations, and less likely to be subject to representativeness bias.

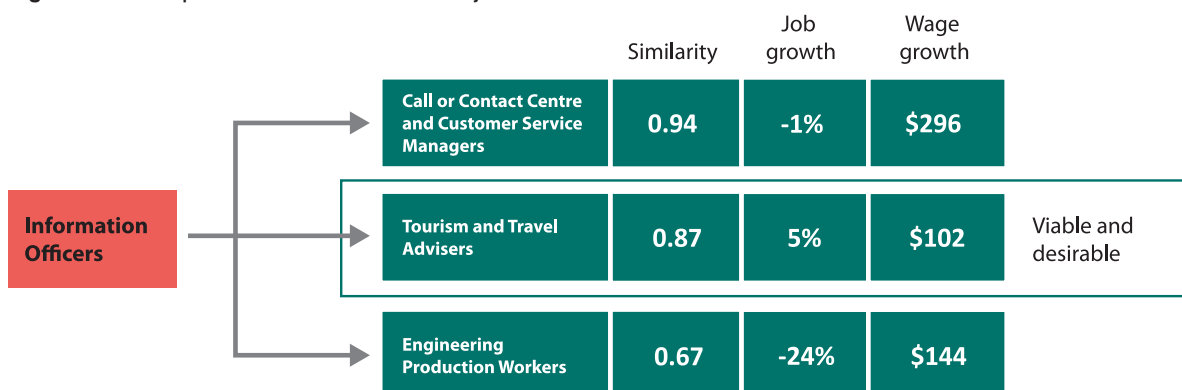
Making user recommendations

The concepts of viable and desirable job transitions provide a useful framework to recommend career pathways for job seekers and workers. Using the similarity scores generated from the two data sources as well as employment projections, we can define career pathways for those in declining jobs to transition into growing jobs.

These pathways include intuitive transitions, such as Secretaries to General Clerks, and ICT Sales Professionals to ICT Managers. However, the approach can also suggest transitions that may not necessarily be apparent, such as Personal Assistants to Conference and Event Organisers. This is highly relevant in the context of research that found results were significantly better when other factors such as skills transferability were taken into account to display jobs rather than relying solely on a job seeker's search criteria. When job seekers considered a broader set of jobs, there was a 50 per cent increase in their job interview rate. This effect was even more pronounced for job seekers who would have otherwise searched 'narrowly' (Belot et al., 2015).

Example pathways shown in Figure 2 are for Information Officers which is a declining occupation. While Information Officers are highly similar to Call or Contact Centre and Customer Service Managers, these are also declining jobs (hence, not a desirable pathway). Information Officers have a medium job-fit to Tourism and Travel Advisers, and based on their job attributes this occupation is growing in the future and pays substantially more, on average. This is therefore both a viable and desirable option for Information Officers to reskill for and transition into.

Figure 2. Example of viable and desirable job transitions



As can be seen from Figure 2, transitions from Information Officers to Tourism and Travel Advisers is viable because the two occupations are closely similar (with a similarity score of 0.87). It is also a desirable transition because the target occupation (Tourism and Travel Advisers) is projected to grow by 5 per cent to 2023, and there is a gain of \$102 per week from this transition.

3. ECONOMY-WIDE RESKILLING OPPORTUNITIES

The original WEF study incorporated a 'leadership lens', which is intended as a practical planning tool for government and business decision makers. This lens uses linear programming to optimise the outcomes for all individuals in declining jobs, and provides an economy-wide simulation of ideal pathways.

Like the original WEF study, which used official projections to operationalise the model. We used the 2018 Department of Jobs and Small Business' five-year projections forecasting employment growth by occupation over a five-year period to May 2023. These projections suggest 81 occupations (jobs) are declining in Australia. Linear programming is used to maximise viable transitions for all those in declining jobs into the remaining growing jobs with capacity in 2023.

The model is idealised, in the sense that it does not take into account labour market entrants or leavers that might affect the analysis. However, the purpose of the exercise is to suggest, at a global scale, the result of good fit or optimal transitions, including identifying those occupations that may face transitional challenges.

Most declining workers have transition options

Figure A2 in the Appendix shows the transition possibilities aggregated by occupation groups. Many in declining jobs find opportunities within their own occupation groups. However, the results suggest most of the viable and desirable opportunities are outside the declining jobs' original occupation groups.

One occupation group where most ideal transitions are within the same group is the Administration and Human Resources group. While this is the occupation group with the most declining jobs there are also a number of growing occupations in this group, such as General Clerks.

In Manufacturing, the second most declining occupation group, most transition options are out of this group and into similar construction-related roles, which are growing and higher paying. These include movements from roles such as Engineering Production Workers to Concreters and Structural Steel Construction Workers, and from Print Finishers and Screen Printers to Painting Trades Workers.

This exercise revealed that most people have a viable and desirable transition option, including non-traditional moves that could help individuals transition into a job more quickly. The results also show many occupation groups where there is excess capacity, requiring a substantial number of future entrants. These include health and community services, hospitality, and education and training.

Similar to the original WEF study, about 3 per cent of those in declining occupations we analysed do not have transition opportunities that are very similar and higher paying. These include Printers, Aquaculture Farmers, Plastics and Rubber Factory workers, and Metal Engineering Process workers. This indicates that people in these occupations may have to go through additional reskilling to ensure they have viable opportunities in the future.

The results are robust to wage desirability assumptions

As Table 3 shows, our baseline model (Model (1)) ensures there are no transitions to lower paid jobs. This model identifies transition opportunities for 96.4 per cent of those in declining jobs. Like the original WEF study, we relaxed the assumptions that people would only transition for a higher salary. Under this 'No-wage restrictions' assumption, Model (2) shows that only a slightly higher proportion of people will find a transition (97.3 per cent), while a substantially lower proportion will gain a higher salary from the transition. This means that relaxing wage restriction would have no material impact on the total number of workers being able to find viable and desirable transitions.

Where there are multiple declining occupations that could transition to a growing occupation with capacity, our baseline model ranks the occupation with higher similarity score higher. This ensures the most viable transitions are simulated. In contrast, the original WEF model (Model (3)) assumed capacity in a growing job is filled by a joint determination of how viable the job is, as well as how much of a salary rise it offers for the person in a declining job. This implicitly assumes a trade-off between viability of transitions and higher salary. While this is consistent with the 'skills arbitrage' philosophy, we cannot substantiate that an additional dollar is worth the same as an additional similarity point. Nevertheless, our modelling does suggest a similar total quantity of workers would find a viable and desirable transition under both these specifications.

Table 3. Proportion of workers who find a job-fit transition by different wage assumptions

Outcomes	With stable wage requirement: Model (1)	With no wage restrictions: Model (2)	Original WEF model (with wage restriction): Model (3)
Job transition under 'good-fit'	87,371 (96.4%)	88,153 (97.3%)	87,371 (96.4%)
Unable transition under 'good-fit' conditions	3,224 (3.6%)	2,442 (2.7%)	3,224 (3.6%)
Share of workers needing to move to new jobs who are female	48.1%	48.1%	48.1%
Share of job transitions that involve a change in occupation group	69%	56%	56%
Share of job transitions with stable or increasing wages	100%	49%	100%
For those increasing, average weekly wage increase	\$224	\$296	\$496
Share of job transitions with reduction in wages	-	51%	-
For those decreasing, average weekly wage decrease	-	\$201	-

4. NEXT STEPS

Our demonstration that the WEF approach can be adapted in Australia offers opportunities to improve labour market information and future job transitions across regional labour markets, occupations and industries.

More broadly, this success also indicates the power of alternative big data and machine learning techniques to provide evidence and insights valuable to stakeholders across the public, private, academic and community sectors that ultimately support improved outcomes for individuals.

Tools to help stakeholders make informed decisions about careers

The user lens described above will support the development of a Skills Match Tool on the Job Outlook career information portal managed by the Department of Employment, Skills, Small and Family Business. The tool's development is in line with calls for better labour market information with more sophisticated skills information. In addition to the user lens, the tool will identify the specific skills a job seeker or worker needs to upskill, and provide education or training recommendations to address any skills gap.

A data infrastructure that keeps up with a dynamic labour market

Our Australian model of job transferability is not only useful for the user lens for job seekers and workers. Integrating conventional labour market data, granular survey data on occupations and real time data, provides a valuable data infrastructure that is very useful to other cohorts in the community, such as employers and education providers.

The job viability model and occupational data from O*Net and real time job advertisement data can be useful to employers to identify and respond to their organisational skills gaps and enable them to conduct data-informed workforce planning.

Real time data can help education providers understand the trending skills in the labour market so they can better tailor their courses to meet skills demand. It may also be used to better personalise learning modules to make educational attainment more efficient for those who have gained some of the skills through work experience.

In addition, it can help policy makers by informing sophisticated and targeted policy interventions to those most in need.

To facilitate these goals, the Department of Employment, Skills, Small and Family Business intends to develop two prototypes. An employer prototype to help employers identify the skills they will need to plan job transitions, and a tertiary provider prototype that uses data about emerging skills to improve course design.

The Skills Match Tool and employer prototype are part of a broader Jobs and Education Data Infrastructure project led by the Department of Employment, Skills, Small and Family Business. This project aims to create a data engine, linking jobs and education data. The project is being developed in partnership with the Department of Education, the Department of Industry, Innovation and Science, and the Department of Infrastructure, Transport, Cities and Regional Development.

5. REFERENCES

1. Belot, Michele, Philipp Kircher, and Paul Muller (2015). Providing advice to job seekers at low cost: An experimental study on on-line advice.
2. Burning Glass Technologies (2017) The Secret of College ROI: Focus on Skills That Pay Off. Accessed on 29 March 2019 from <https://www.burning-glass.com/blog/college-roi/>.
3. Department of Jobs and Small Business (2018). Employment Outlook to May 2023. Accessed on 29 March 2019 from <http://lmip.gov.au/default.aspx?LMIP/GainInsights/EmploymentProjections>
4. OECD (2018) Getting Skills Right: Australia, Getting Skills Right, OECD Publishing.
5. World Economic Forum Boston Consulting Group (BCG). (2018). Towards a reskilling revolution: a future of jobs for all. World Economic Forum, Geneva, Switzerland.

6. APPENDIX

As described earlier, our study adapted for Australia the skills-based career recommendation tool described in the WEF 2018 report, Reskilling Revolution: A Future of Jobs for all. In this section, we discuss adaptation methods that contrast from the original study and present in more detail some findings of transition pathways from our study.

Viable and desirable job transition pathways

Adapting data sources for job viability scores

We used the same data sources as the original WEF study to measure job similarity (or job viability). This includes the United States Bureau of Labour Statistics' Occupational Information Network (O*NET) database and Burning Glass Technologies Australian job advertisement data.

Adapting O*Net to Australian occupation classification

The different codes for occupations presented a key challenge for adapting O*Net for use in the Australian context. O*Net codes occupations according to the Standard Occupational Classifications (SOC) used in the United States. In Australia, occupations are coded according to the Australia and New Zealand Standard Classification of Occupations (ANZSCO).

Additionally, in the United States occupation systems, each occupation maps to one of 23 Job families to visualise results in the original WEF study. Instead, we used 'Occupation Groups', which is an Australian adaptation of job families designed to group occupations based on broad categories of work (Department of Jobs and Small Business, 2017).

Burning Glass Technologies data

The Australian Burning Glass Technologies data on job advertisements contains data on approximately 2,750,000 jobs for 2016–17, the same sample period used in the original WEF study. Among the 353 occupations at 4-digit ANZSCO level, 30 occupations had less than 100 job postings. We excluded these occupations from our analysis.

Computing similarity scores

Table A1 describes the weightings for computing the similarity score. This is similar to the original WEF study, however, a key difference is that the similarity scores for each sub-domain were calculated separately and averaged to compute the domain similarity score. For example, we calculated a simple average of the similarity scores for knowledge, skills and abilities. This average score for the 'Knowledge, skills and abilities' domain then contributed to one-third of the similarity scores.

Table A1. Methodology—measuring job similarity

	Input	Domain	Number of features (Australia)	Type of information for scaling	Scaling	Weighting for similarity score
O*Net data	Knowledge, skills and abilities measure	Knowledge	33	Level	0–7	0.33
		Skills	35			
		Abilities	52			
	Work activities	41	Level	0–7	0.33	
	Education training and experience	43	Distribution	0–100	0.33	
BGT data	Skills measure (hybrid of skill clusters and skills used)	Baseline skills	495	% of job postings containing skill name	0–100	0.5
		Specialised skills	4,150			
		Software skills	100			
	Education and experience	Education	6	% of job postings containing experience/education	0–100	0.5
Experience		5				

Note: BGT = Burning Glass Technologies

Education and Experience job similarity score from Burning Glass Technologies

For the calculation of education similarity scores using Burning Glass Technologies data, we broke the educational domains down into categories described in Table A2. This considered the natural distribution of each category, and that of the non-tertiary qualifications 'CA/CPA' qualifications comprised half of all demand in Australia.

Table A2. Categories contributing to Education similarity scores

Category	Description
Postgraduate and above	Includes all jobs that require 'Master'(s) or a 'Doctor'(ate)
Graduate	Includes all jobs that require 'Bachelor' degrees, including 'Honours'
VET education	Includes all jobs that require a Certificate I–IV, Diploma and Advanced Diploma
Year 12 or lower	All jobs that require a 'Year 10/12' or a Senior School Certificate
CA/CPA	All jobs that require a 'Chartered Practising Accountant' or a 'Chartered Accountant' qualification
Other certificates	All remaining 'Required Degree' value labels

Similarly, we observed the data on the natural distribution of minimum years of experience employers look for in the job ads. For example, while it would be interesting to categorise an entry level job that requires 0–6 months of experience, less than 1 per cent of the data was categorised as such. Based on our analysis as well as intuitive reasoning, we coded experience requirements into five categories as described in Table A3.

Table A3. Experience categories construct for purpose of calculating similarity scores

Category	Description
<1 year	Less than 1 year of experience
1 – <2 years	1–2 years of experience
2 – < 3 years	2–3 years of experience
3 – < 5 years	3–4 years of experience
5 + years	5 or more years of experience required

Job Transition scores

When adapting the methodology to the Australian context, we observed that the indicative threshold for a 'good-fit' similarity score is slightly lower in the Australian context.

In the original WEF study, a similarity score of 0.85 or above represented a medium 'job-fit' category. However, our analysis of the distribution of the similarity scores indicated a more appropriate number in the Australian context as 0.8 or above. This considered the broader occupational groups we used (353 occupations versus 958 occupations used in original WEF study), and the comparative distribution of similarity scores in our study compared with the original WEF study.

We computed a total of 323 by 323 (or 104,329) similarity scores. Figure A1 shows these scores summarised (averaged) across each of the major occupation groups (ANZSCO 1-digit).

Figure A1. Summarised average similarity matrix across major occupation groups (ANZSCO 1-digit)

Major occupation group	Managers	Professionals	Technicians and Trades Workers	Community and Personal Service Workers	Clerical and Administrative Workers	Sales Workers	Machinery Operators and Drivers	Labourers
Managers	0.81	0.76	0.68	0.7	0.75	0.74	0.67	0.63
Professionals	0.76	0.76	0.66	0.68	0.72	0.71	0.64	0.6
Technicians and Trades Workers	0.68	0.66	0.77	0.7	0.7	0.7	0.75	0.73
Community and Personal Service Workers	0.7	0.68	0.7	0.77	0.75	0.75	0.72	0.72
Clerical and Administrative Workers	0.75	0.72	0.7	0.75	0.83	0.79	0.72	0.7
Sales Workers	0.74	0.71	0.7	0.75	0.79	0.83	0.73	0.72
Machinery Operators and Drivers	0.67	0.64	0.75	0.72	0.72	0.73	0.8	0.77
Labourers	0.63	0.6	0.73	0.72	0.7	0.72	0.77	0.78

Assessing realistic leaps in education or experience

The original WEF study asserts that prospective job movers are unlikely to be hired when their work experience and educational background are significantly divergent from the requirements of the new job. Therefore, the original WEF study used O*Net's 'job zones' to ascertain the expected level of education, experience and on-the-job training required to perform a job. Job zones are measured on a 1-to-5 scale, where occupations in job zone 1 require little or no preparation (e.g. dishwashers), and occupations in job zone 5 require extensive preparation (e.g. biologists).

By restricting job zone changes to no more than -1 or + 1, the analysis controls for unrealistic or unrewarding job moves. In addition to controlling for a good 'job-fit', the restriction also ensures consistency in the actual level of skills and knowledge used within any given occupation.

In the Australian context, the Australian Bureau of Statistics (ABS) also codes a similar measure called skill level. The skill level is coded to each ANZSCO 4-digit code and categorises each ANZSCO 4-digit occupation according to the level of education, experience and on-the-job training required. Skill level 1 represents a high skill level (where a bachelor degree or five years of relevant experience may be required). Skill level 5 represents the lowest skill level, (commensurate with a Certificate I, compulsory secondary education or a short on-the-job training) (ABS, 2005).

Job desirability through Australian projections and salary data

While a particular job transition may be viable (that is, a person transitioning into a viable job may realistically be able to perform the tasks with minimal training), some job transitions may not be desirable for a job seeker, as they may not be sustainable or seen as an attractive option.

The original WEF study described a viable job transition opportunity as a desirable job transition option if there was:

1. forecasted job growth: a job transition into an occupation with job numbers that are forecast not to decline
2. wage continuity (or wage increases): remuneration for tasks performed in the new job does not fall below a level that would allow the person to maintain their current standard of living.

To adapt the methodology to ensure job transitions are desirable, we used jobs growth forecasts and earnings information from Australian data.

Jobs growth forecast

The original WEF study used 10-year forecast of employment projected by the United States Bureau of Labour Statistics. The projections to 2026 indicated 1.4 million jobs are declining, against a projected growth of 12.4 million new jobs.

In the Australian context, the Department of Employment, Skills, Small and Family Business produces five-year projections. The most recent report provides the employment levels at May 2018 and projections for the five years to May 2023 (Department of Jobs and Small Business, 2018).

Our analysis by occupation groups indicated that the declining jobs are in Administration and Manufacturing occupation groups, although overall these occupation groups will have more jobs. Conversely, the projections suggest there will be less jobs in the Automotive occupation group in five years' time.

In most other occupation groups, jobs are projected to grow. Like the United States, the largest growth is projected in the health (and community services) industry, with a net increase of about 265,000 jobs. See Table A4 for details.

Table A4. Snapshot of projected Australian job changes 2018–2023

Occupation group	Gender breakdown in 2017 (%)		Employment		Change in employment 2018–2023		
	Male	Female	2018	2023	Increasing jobs	Declining jobs	Net change
Accounting, Banking and Financial Services	37	63	766,229	792,328	30,449	4,350	26,099
Administration and Human Resources	21	79	1,197,986	1,200,892	44,851	41,945	2,906
Advertising, Media and Public Relations	40	60	278,121	302,888	24,931	164	24,767
Agriculture, Animal and Horticulture	71	29	329,842	345,119	20,029	4,752	15,277
Arts and Entertainment	52	48	171,507	182,793	12,763	1,477	11,286
Automotive	97	3	165,580	163,592	414	2,402	-1,988
Construction, Architecture and Design	94	6	967,601	1,036,574	71,703	2,730	68,973
Education and Training	26	74	700,812	765,536	71,309	6,585	64,724
Electrical and Electronics	98	2	224,019	229,127	7,798	2,690	5,108
Engineers and Engineering Trades	96	4	383,757	400,462	20,802	4,097	16,705
Executive and General Management	64	36	218,061	237,672	20,641	1,030	19,611
Government, Defence and Protective Services	69	31	230,737	256,036	25,299	0	25,299
Health and Community Services	19	81	1,436,515	1,702,001	265,489	3	265,486
Hospitality, Food Services and Tourism	47	53	904,881	1,015,896	111,222	207	111,015
Information and Communication Technology (ICT)	81	19	416,089	472,785	59,509	2,813	56,696
Legal and Insurance	41	59	164,861	167,414	5,512	2,959	2,553
Manufacturing	71	29	419,321	423,818	14,248	9,751	4,497
Mining and Energy	92	8	67,041	67,742	1,244	543	701
Personal Services	37	63	420,865	450,656	30,436	645	29,791
Sales, Retail, Wholesale and Real Estate	46	54	1,567,761	1,601,268	34,681	1,174	33,507
Science	50	50	123,854	137,537	13,683	0	13,683
Sports and Recreation	62	38	88,466	103,162	14,696	0	14,696
Transport and Logistics	86	14	731,104	780,715	49,889	278	49,611
Total	51	49	11,975,010	12,836,013	951,598	90,595	861,003

Wage continuity (or decrease)

We used a number of business rules to ensure we could consistently compare earnings from each occupation.

The Australian Bureau of Statistics has two relevant wage data publications. Catalogue 6306.0 – Employee Earnings and Hours, Australia, May 2016 contains information of average employee earnings for each 4-digit ANZSCO code. The shortcoming with this data, however, is that average earnings may not necessarily allow comparisons between occupations that have varying levels of hours worked. For example, the average earnings for 'Models and sales demonstrators' was \$257 per week, which is significantly less than the median average. However, this is likely due to a high number of people working part-time.

The Department of Employment, Skills, Small and Family Business has also acquired data from another ABS publication, used for the job information portal, Job Outlook. Catalogue 6333.0 – Characteristics of Employment, Australia, August 2015 provides information on earnings by full-time and part-time workers. Full-time earnings provide a much more comparable means to assess differences in earnings between occupations. For example, 'Models and sales demonstrators' median earnings for full-time workers are reported as \$860 per week. As such, we used median full-time earnings from Catalogue 6333.0 (2015).

Catalogue 6333.0 does not have full-time earnings information for 38 of the 353 occupations included in our analysis. We used information from average earnings reported in Catalogue 6306.0 in the cases where average earnings were at least \$550 per week (27 occupations). For the remaining 11 occupations, we used the full-time earnings for the corresponding 3-digit ANZSCO code.

Economy-wide reskilling opportunities (Leadership lens)

The leadership lens perspective is an economy-wide simulation of the ideal pathways of viable and desirable job transitions that would maximise the resulting job-fit to target jobs. It ensures a stable and good quality future employment for workers whose current job is projected to decline.

The linear programming based optimisation algorithm is adapted for the Australian context to maximise job-fit transitions between starting and target jobs. As set out in the original WEF report, the optimisation conditions ensure that only good-fit transitions (0.8 similarity or above) that are realistic (skill level changes are less than 1) are made. It also ensures that the transitions are desirable, in that the salary of target jobs are at least those of starting jobs, and that the target jobs are themselves not projected to decline.

To adapt the methodology used in the original WEF study, as was done in the original WEF study we used the `Rglpk_Solve_LP()` function in R. This involved defining the Utility function and constraints specified in Table A5.

Table A5. Model set up

Utility function	Constraints
The sum of job transitions with each job transition, weighted by similarity score	There are no job transitions to jobs with lower wages
	There are only job transitions from jobs where projected employment in 2023 is lower than 2018
	There are no job transitions to jobs where expected employment in 2023 is lower than in 2018
	There are no job transitions with a similarity score of less than 0.8
	Only job transitions to jobs in one Skill Level lower, equal or one Skill Level higher are feasible
	Employment per job is smaller than or equal to projected future employment in 2023

As our model set up was slightly different to the original WEF study, we also conducted sensitivity analysis by first modifying the utility function by multiplying the similarity score by weighted wage increase, as per the original WEF study's specifications. In our second sensitivity test, we relaxed the first constraint and allowed job transitions to jobs with lower wages. The results, as shown in Table 3, indicate that the models perform similarly.

The results of our main model are visualised in Figure A2 and, as described in the report, reveal insights about the transition possibilities that can occur.

Table A6 also shows a more granular view of top transitions by occupation

Table A6. Top transitions projected by leadership lens model

Starting	Target	Transition opportunities
Secretaries	General Clerks	11281
Contract, Program and Project Administrators	Other Hospitality, Retail and Service Managers	5488
Personal Assistants	Conference and Event Organisers	5014
Contract, Program and Project Administrators	Other Specialist Managers	5012
Industrial, Mechanical and Production Engineers	Engineering Managers	2189
Bank Workers	Security Officers and Guards	2125
Motor Mechanics	Other Technicians and Trades Workers	1964
Engineering Production Systems Workers	Concreters	1910
Contract, Program and Project Administrators	Production Managers	1896
Insurance, Money Market and Statistical Clerks	Call or Contact Centre Workers	1728
Vocational Education Teachers	Health and Welfare Services Managers	1724
Training and Development Professionals	Occupational & Environmental Health Professionals	1611
Crane, Hoist and Lift Operators	Structural Steel Construction Workers	1586
Accounting Clerks	Credit and Loans Officers	1532
Vocational Education Teachers	School Principals	1517
Contract, Program and Project Administrators	Corporate Services Managers	1356
Inquiry Clerks	Tourism and Travel Advisers	1265
Electronics Trades Workers	Metal Fitters and Machinists	1259
Office Managers	Practice Managers	1246
Inquiry Clerks	Motor Vehicle and Vehicle Parts Salespersons	1225
Sewing Machinists	Building and Plumbing Labourers	1198
Engineering Production Systems Workers	Structural Steel Construction Workers	1196
Telecommunications Trades Workers	Fire and Emergency Workers	1186
Artistic Directors, Media Producers & Presenters	Advertising and Sales Managers	1139
Secretaries	Conveyancers and Legal Executives	1132
Vocational Education Teachers	Nurse Educators and Researchers	1117
General Managers	Chief Executives and Managing Directors	1030
Livestock Farm Workers	Other Farm, Forestry and Garden Workers	1027
Keyboard Operators	Transport and Despatch Clerks	1019
Mixed Crop and Livestock Farmers	Production Managers	1014

Source: Burning Glass Technologies

Figure A2. Linear programming—optimised job flows

Starting Occupation Groups	Accounting, Banking and Financial Services	Administration and Human Resources	Advertising, Media and Public Relations	Agriculture, Animal and Horticulture	Arts and Entertainment	Automotive	Construction, Architecture and Design	Education and Training	Electrical and Electronics	Engineers and Engineering Trades	Executive and General Management	Health and Community Services	Hospitality, Food Services and Tourism	Information and Communication Technology (ICT)	Legal and Insurance	Manufacturing	Mining and Energy	Personal Services	Sales, Retail, Wholesale and Real Estate	Transport and Logistics	Government, Defence and Protective Services	Science	Sports and Recreation	Viable job transition options found	Gross job destruction by 2023	Disrupted jobs without viable transition options
Accounting, Banking and Financial Services	1,532	0	0	0	0	0	0	0	0	0	0	450	0	0	243	0	0	0	0	0	2,125	0	0	4,350	4,350	0
Administration and Human Resources	1,415	13,922	0	0	0	0	416	0	0	0	5,012	1,246	11,803	1,168	1,896	0	0	0	2,362	2,477	228	0	0	41,945	41,945	0
Advertising, Media and Public Relations	0	0	0	0	0	0	164	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	164	164	0
Agriculture, Animal and Horticulture	0	0	0	1,027	0	0	11	0	0	0	0	0	0	0	1,076	0	0	584	0	0	107	0	0	2,805	4,752	1,947
Arts and Entertainment	0	0	1,139	0	0	0	0	337	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1,477	1,477	0
Automotive	0	0	0	0	0	0	339	0	52	1,964	0	0	0	0	0	0	0	0	0	47	0	0	0	2,402	2,402	0
Construction, Architecture and Design	0	0	0	0	0	0	2,333	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,730	2,730	0
Education and Training	0	0	0	0	0	0	0	1,517	0	0	0	4,452	0	0	0	0	0	315	0	301	0	0	0	6,585	6,585	0
Electrical and Electronics	0	0	0	0	0	0	0	0	692	1,998	0	0	0	0	0	0	0	0	0	0	0	0	0	2,690	2,690	0
Engineers and Engineering Trades	0	0	0	0	0	0	339	0	0	3,758	0	0	0	0	0	0	0	0	0	0	0	0	0	4,097	4,097	0
Executive and General Management	0	0	0	0	0	0	0	0	0	0	1,030	0	0	0	0	0	0	0	0	0	0	0	0	1,030	1,030	0
Health and Community Services	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	3	3	0
Hospitality, Food Services and Tourism	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	207	0	0	0	0	0	207	207	0
Information and Communication Technology (ICT)	0	0	0	0	0	0	0	0	0	378	0	0	0	186	0	0	0	0	0	572	1,186	0	0	2,322	2,813	491
Legal and Insurance	364	1,728	0	0	0	0	0	0	0	0	540	0	0	219	0	0	0	0	0	0	0	0	0	2,851	2,959	108
Manufacturing	0	139	0	224	352	0	6,143	0	0	982	0	0	0	0	1,110	0	0	0	3	263	352	0	0	9,568	9,751	183
Mining and Energy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	543	543	0
Personal Services	0	0	0	0	0	0	150	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	150	645	495
Sales, Retail, Wholesale and Real Estate	0	0	869	0	0	0	0	0	0	0	0	0	0	0	0	305	0	0	0	0	0	0	0	1,174	1,174	0
Transport and Logistics	0	0	0	0	0	0	278	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	278	278	0
Government, Defence and Protective Services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Science	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sports and Recreation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Optimal transitions to occupation groups by 2023	3,311	15,789	2,008	1,251	352	0	10,173	1,854	744	9,080	6,582	6,151	11,803	187	1,630	4,387	0	1,106	2,365	3,660	3,998	940	0	87,371	90,595	3,224
Gross job creation by 2023	30,449	44,851	24,931	20,029	12,763	414	71,703	71,309	7,798	20,802	20,641	265,489	111,222	59,509	5,512	14,248	1,244	30,436	34,681	49,889	25,299	13,683	14,696	87,371	90,595	3,224

