SUPPORT DOCUMENT

NCVER

Estimating the stock of skills in Australia: what data are needed?

Support document: literature review

John Stanwick
Michelle Hall
NCVER

This document was produced by the author(s) based on their research for the report *The stock of qualifications in Australia*, and is an added resource for further information. The report is available on NCVER's Portal: <https://www.ncver.edu.au>.

Publisher's note

This document should be attributed as Stanwick, J & Hall, M 2021, *Estimating the stock of skills in Australia: what data are needed?,* NCVER, Adelaide.

This work has been produced by NCVER on behalf of the Australian Government and state and territory governments, with funding provided through the Australian Government Department of Education, Skills and Employment.

Published by NCVER, ABN 87 007 967 311

Level 5, 60 Light Square, Adelaide, SA 5000
PO Box 8288 Station Arcade, Adelaide SA 5000, Australia

Phone +61 8 8230 8400 **Email** ncver@ncver.edu.au

Web <https://www.ncver.edu.au> <https://www.lsay.edu.au>

Follow us: <https://twitter.com/ncver> <https://www.linkedin.com/company/ncver>

Contents

Tables and figures

Tables

Figures

Literature overview

Key points

- Indicator-based approaches are more useful than accounting approaches in the context of measuring skills supply and demand.
- Complementary measures of skills are more appropriate than single metrics for adequately describing human capital.
- Recent integrative frameworks provide promising avenues for sourcing information on skills supply and demand.
- Key challenges to measuring skills supply and demand include measuring actual skills, including those acquired outside formal learning, and accounting for skills depreciation.
- Gaps still exist in data sources for addressing all aspects of the skills supply and demand picture.

Our interest in measuring the stock of skills and qualifications in the economy is prompted by a number of valid reasons. Importantly, this information can provide indications of where skills gaps and skills mismatches exist, enabling action to maximise the utility of skills and match skills to jobs. In addition, the stock of skills and qualifications is an indicator of potential competitiveness (Eurostat 2016) and prosperity and wellbeing (OECD 2013). From the perspective of vocational education and training (VET)[1] the information can inform training needs to ultimately improve the match between supply and demand (Gasskov 2018).

This overview focuses on issues that need to be considered when measuring the stocks of skills and qualifications in an economy, from the twin perspectives of the supply of and the demand for skills. While information and data on skills and qualifications supply and demand are used to inform issues associated with skills mismatches and their measurement, this is not the focus of this review, except as it relates to the reasons for measuring skills supply and demand. The review also does not cover issues concerned with skills utilisation except incidentally.

Definitions and measurement of skills

Braham and Tobin (2020) noted that recent developments such as technological change have created gaps in information in the area of skills and skills requirements for jobs, advocating for a stronger and more illuminating informational architecture associated with skills, one involving greater clarity of definitions and better measurement of skills, as well as easily accessible data. They suggested that ‘good labour market information lies at the heart of solving the skills puzzle’ (p.vii). The need for timely and high-quality labour market information was reiterated by the Organisation for Economic Co-operation and Development (OECD 2017) in a discussion on developing skills for jobs indicators (see also OECD 2013). This issue is discussed further in the section on recent approaches and new initiatives.

OECD (2017) also noted that employers place more emphasis on skills than on education and referred to a survey conducted by the Canadian Labour Market Information Council, which found skill requirements to be the second most-wanted piece of information by Canadians, after wages. All this implies that there is a need for easily accessible information on skills and skill requirements.

1 Note however that this current review is applicable to qualifications and skills obtained from both VET and higher education, as well as elsewhere.

Among the challenges noted by Eurostat (2016) is 'improving skills intelligence and information for better career choices' (p. 7), meaning that good skills data are needed to inform policy on skills. In particular, Eurostat (2016, p.7) posed a fundamental policy question relating to the requirement for good information on skills:

> How well do systems responsible for skills development (i.e., education and training) function in providing required skills and addressing skills mismatches, thus ensuring good labour market and social outcomes?

Given this background, this review will examine the literature that considers ways of measuring skills and qualifications, from both supply- and demand-side perspectives. The review focuses on measurement and data rather than findings of studies per se.

We begin by looking at standard approaches, including standard accounting approaches to measuring human capital, but in particular indicator-based approaches. Newer initiatives, those that make use of newer technology and 'big data', are then examined. The paper then considers what this means for the measurement of supply and demand for skills and qualifications in Australia, including the available data sources, and where the gaps are.

In the context of our research, and acknowledging there is no real consensus on how 'skills' are defined, we apply the 2017 OECD definition (cited in Brunello & Wruuk 2019, p.4), which defines skills as referring to:

> both cognitive and non-cognitive abilities and to abilities that are specific to a particular job, occupation or sector (technical skills).

What do we know about ways of measuring skills?

Standard approaches

Human capital accounting approaches

Much of the economic analysis literature talks about the stocks and flows of 'human capital' for measuring human capital accumulation. While human capital approaches are not concerned with specific skills as such, they are still instructive in the context of what should be measured; that is, the stocks of skills and the sources of information for these measures.

Human capital for the purposes of this discussion can be defined as 'the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being' (OECD 2001, cited in Stroombergen, Rose & Nana 2002). This definition itself, with its various components, provides challenges for measurement, as has been noted by Boarini, d'Ercole and Liu (2012), and in addition makes a 'one size for all' measure impossible.

Income-based accounting approaches

Wei (2004, 2008) provides examples of studies that adopt the human capital approach, measuring human capital flows for Australia using a variation of what is known as the Jorgensen-Fraumeni approach.

This accounting approach measures human capital in terms of nominal lifetime earnings, discounted to present value, of all people in an economy (Fraumeni, Christian & Samuels 2020). Because it measures the change of stock over time, it is considered a flow approach. This type of approach is also referred to as the 'income-based approach' to measuring human capital (as opposed to the cost-based approach).

Wei (2004, 2008) confined his calculations to the working-age population and separated out and reported on-the-job training as an investment component of human capital formation (both key modifications to the Jorgensen-Fraumeni approach). This approach measures human capital in monetary terms rather than according to the specific skills an individual has, but nevertheless provides pointers on the sorts of considerations we should be thinking about when estimating the stock of skills.

In summary, the main elements Wei (2004, 2008) estimated for his papers are:

- *Post-school education*: this covers post-school formal qualifications.
- *Job experience, including on-the-job-learning*: some accounting frameworks do not specifically separate out job-based learning, but it is in fact an important source of human capital and should be considered in calculations (see also Boarini, d'Ercole & Liu 2012). Additionally, human capital can be increased through experience.
- *Depreciation of human capital formed by post-school qualifications and by on-the-job learning*: very simply, this is represents depreciation due to ageing of the education capital, although this not a linear process (for example, the need to account for/balance this with regular use of the education capital and working experience).
- *Other*: this covers new entrants to the labour market, migrants, emigrants and a re-valuation account.[2]

To this list could be added, although not explicitly covered by Wei (2004, 2008), other post-school education, including non-completed qualifications and sub-qualification courses (for example, skill sets and micro-credentials). Note also that school education is not included for estimates relating to changes in human capital for the working-age population, as it is not produced during the current accounting period.

These accounting approaches typically use proxies, such as highest level of educational attainment or years of education, to derive their estimates. As will be discussed later, these approaches have limitations, with other approaches to measuring skills available.

In his two papers Wei (2004, 2008) used Australian census data from the Australian Bureau of Statistics (ABS), which contains information on, among other items, the highest level of post-school education and income (from all sources). Using his income-accounting approach, Wei (2008) found a growth in human capital over the twenty years of census data used. More particularly, he found that education is an increasingly important driver of human capital growth, more so for women. At the same time, depreciation of human capital has increased through the ageing of the population since the 1990s, which slows the growth in human capital. Wei (2004) also found that the stock of human capital was depreciating quickly — more quickly than population growth was increasing — and so investment in education and training becomes key for human capital growth.

This sort of information is useful from a policy perspective, as it shows, for example, the importance of education in human capital growth. The ageing population also clearly has implications for policy.

Wei (2008, p.5) also mentioned challenges associated with measurement:

> To identify and measure these different forms of investment in human capital is surprisingly difficult … data on various aspects of human capital investment are fragmented and difficult to aggregate over time (p.5).

---

2 Changes in real lifetime labour incomes from period to period (Wei 2008, p. 12)

Cost-based accounting approaches

Another (direct) monetary approach to human capital measurement is the cost-based approach. This approach enumerates human capital by looking at the stream of past investments undertaken by individuals, households, employers and government in formal education, although it can be extended to include expenditure on work-related and other adult training. Boarini, d'Ercole and Liu (2012) noted that this approach has been criticised on conceptual grounds for only considering the costs of production of human capital rather than examining both the demand and supply of human capital.

Having said this, Squicciarini, Marcolin and Horvat (2015) used a novel process within the expenditure approach to estimate cross-country investment in firm-level training. Utilising information in the OECD's Programme for the Assessment of Adult Competencies (PIAAC),[3] their approach importantly distinguishes between the three types of training in which workers engage: formal training, on-the-job training and informal training. This information is derived from individual-level information in PIAAC relating to training, together with data from other industry and country-level sources. Squicciarini, Marcolin and Horvat (2015) found evidence to demonstrate differences across countries in workers' engagement in the three forms of training. This type of analysis is important as it provides evidence on the extent to which the workforce engages in training and the types of training, and reinforces the point made by Wei (2008) on the importance of capturing job-related training as part of the investment in human capital formation.

Added to this can be the indirect or residual monetary approach. This will not be discussed further here, other than to note that it is the difference (residual) between a measure of a country's wealth (discounted value of future consumption flows) and the components of that wealth (produced capital and the market component of natural capital).

The main the aim of Boarini, d'Ercole and Liu's (2012) paper was to review international initiatives in the development of monetary measures of the stock of human capital to complement indicator-based measures of the quantity and quality of education. They noted that, in addition to monetary approaches, other approaches are adopted in measuring human capital. These indicator measures are more salient to this paper and are described below.

Indicators approaches

This section reviews indicator-based approaches to measuring skills supply and demand and subsequently considers the kinds of data available in the Australian context. We focus on the indicators-based approach here because we are more interested in stocks of actual qualifications and skills rather than monetary amounts.

With regard to measurement, Boarini, d'Ercole and Liu's (2012) review of cross-country initiatives found that, when it comes to physical indicators, most countries surveyed rely on conventional indicators of education, taken from the country's education statistics. Few countries reported developing their own indicators of the quality of education and skills.

Eurostat (2016), and to an extent Braham and Tobin (2020), provided a comprehensive discussion of the measurement of skills in terms of skills supply, skills demand, skills mismatch (the match between the qualifications and skills people have in a job as opposed to what the job requires) and skills development

3 PIAAC is discussed later as a source of information on skills but it is worth mentioning that Australia takes part in the PIAAC survey. The last round of PIAAC for Australia was administered in 2011/2012, with the next round being due to be administered in 2021/22.

(initial, continuing and work-based), although the last two are beyond the general purview of this review. Within these categories, they discussed direct and indirect measures, and also self-assessment of skills. These approaches will be discussed in turn.

Boarini, d'Ercole and Liu (2012) noted that a single measure is rarely adequate for measuring all of the skills and competences that go to make up human capital. By extension, it could be argued that complementary measures should be used, potentially involving multiple data sources. The types of indicator measures available are discussed below.

Indirect measures

Indirect measures, such as the highest level of education and occupation if employed, are most often used in measuring skills supply and demand (Eurostat 2016; Braham & Tobin 2020), as these data are readily available, reliable and timely. In particular, when standard classifications are used, data can be compared between countries and between years, consequently providing useful information on the supply of qualifications (proxy for skills) across occupations.

Many of the surveys used to assess these measures also give some level of detail on the field of education in which the qualification(s) were undertaken, which does add some extra information to the skills picture. Added to this could be supply-side information on new graduates and information on adults upgrading their skills (Gasskov 2018).

However, Braham and Tobin (2020) pointed out that these are not necessarily the best data for measuring skills supply as they do not provide information on actual skills. Furthermore, the information was related to full qualifications obtained (and usually the highest level), which excludes information on qualifications other than highest level, incomplete qualifications, sub-qualification courses (for example, skill sets and micro-credentials), work-related training courses and on-the-job training. These are very important sources for obtaining skills (see Wei 2008; Eurostat 2016). AlphaBeta (2019) predicted that in the future most new learning (to obtain skills), particularly post-initial qualification, will be short courses and on-the-job training focusing on skills requirements, so information on this type of learning will become increasingly important to gather. How these data are obtained is another matter.

Another issue with using qualification proxies is that it does not account for the quality and relevance of the skills obtained through the education. There can be variation across educational institutions and variation according to personal factors (Eurostat 2016).

Yet another issue relates to when the qualification was obtained. In his human capital accumulation discussion, Wei (2008) introduced the concept of skills depreciation. Does a qualification obtained 20 years ago have the same currency as one obtained two years ago? This again highlights the importance of obtaining information on work-related training or sub-qualification training in terms of keeping skills up to date.

Looking at the issue of occupational classifications in terms of demand for skills, while the Australian and New Zealand Standard Classification of Occupations (ANZSCO) is the 'best available' classification now, it does not provide a facility for capturing all skills for current jobs in the labour market. One of the issues is that jobs and occupations change constantly, particularly with new technology, whereas ANZSCO is a static classification, meaning that new jobs and occupations are not being identified. The National Skills Commission however has published a list of emerging occupations in Australia.[4] Using the Jobs and Education Infrastructure project (JEDI), the commission was able to identify emerging occupations by looking at emerging skills and job titles with increasing numbers and undertaking a comparison with jobs in other classifications (such as O*NET). In the United States, O*NET collects a variety of information from different sources, including surveys of workers and occupational experts, to update their classification for new and emerging jobs and occupations.[5] Further detail on JEDI and O*NET is provided later.

Self-report measures

Self-report measures of skills supply and demand can also be utilised. The advantage of this approach is that information on actual skills is provided (albeit self-reported). In terms of skills supply, data are available on self-reported ability to perform tasks. An example of this, mentioned by Eurostat (2016), includes self-reported information on digital skills in the European Community Survey on 'ICT Usage in Households and by Individuals', while an example of a survey that includes self-assessment of skills is the Cedefop's European Skills and Jobs Survey, which provides information on self-assessed skills in areas such as literacy, numeracy, digital skills and others.

The JRA, or Job Requirements Approach, is another self-report measure. This approach focuses on self-reported tasks that are carried out in the workplace and so provides some measure of skills intensity. Some of these data are available in PIAAC.

On the demand side, there are subjective assessments by employers of skills demand. The European Union's Continuing Vocational Training Survey (CVTS), for example, asks enterprises questions about future skills and the skills considered important (Wiseman & Parry 2017).

Employer surveys asking about skills and skills shortages more generally can be used as a self-report measure of skills demand. Braham and Tobin mentioned, by way of example, employer surveys, including the UK Department for Education's Employer Skills Survey and the European Centre for the Development of Vocational Training's European Employer Survey. The limitations associated with these mentioned by Braham and Tobin include that they may be subject to response bias and that not every country has a national employer survey.

Employer surveys in Australia include the Survey of Employer Use and Views of the VET system (SEUV)[6] funded by the Australian Government Department of Education, Skills and Employment. While this survey has questions about recruitment difficulties and the reasons why, there are no questions relating to specific skills. The survey is also limited, in that it is only applicable to VET sector-related qualifications and skills (including unaccredited training), and furthermore does not provide data by occupational level.

4 <https://www.nationalskillscommission.gov.au/complementary-methods>.
5 <https://www.onetcenter.org/dataUpdates.html>.
6 <https://www.ncver.edu.au/research-and-statistics/collections/employers-use-and-views-of-the-vet-system>.

Also funded by the same department is the Employer Satisfaction Survey for supervisors of graduates of the higher education sector.[7] This survey asks about overall satisfaction with graduates but also satisfaction about their skills, including foundation, adaptive, collaborative, technical and employability skills. While the survey gives a breakdown of findings by broad level of industry and occupation, it cannot provide information at the fine level of occupation (due to the sample size).

The Survey of Employers' Recruitment Experiences in Australia collects information on employers' demand for skills and labour, with reference to their recent recruitment experiences and future recruitment intentions (Australian Department of Employment, Skills, Small & Family Business 2018). There are also a number of surveys that lack Australia-wide coverage such as the Victorian Department of Education and Training's Victorian Employer Skills Survey, last conducted in 2018. This survey asks employers in Victoria about skills, recruitment, and training needs.[8]

The inherent drawback with self-report measures is that they can be subject to bias from both the individuals and employers.

Direct measures

More direct measures of skills supply and demand can take different forms, which have been summarised by Braham and Tobin (2020, p.12) and Eurostat (2016).

A direct measure of demand mentioned by Eurostat (2016) is job-vacancy data. In Australia, a vacancy report, based on internet vacancies and prepared by the National Skills Commission (NSC), is available on the Australian Government's Labour Market Information Portal (LMIP).[9] Gasskov (2018) noted that (hard to fill) vacancies can be interpreted as skill shortages where there is a lack of qualified applicants rather than low pay or poor working conditions.

While these job-vacancy data represent useful information, they can be at a fairly broad level and furthermore not provide information on specific skills (Braham & Tobin 2020; Eurostat 2016). There have been more recent developments in collecting job-vacancy data from search engines and the like and these are discussed later.

Another direct measure of skills demand are data on the newly employed or new graduates entering the workforce. This measure could be compared with those already in employment (split by occupation) as a measure of demand. This information is available through the European Labour Force survey but may not be available in all countries' labour surveys (Eurostat 2016). However, the survey does not provide information on actual skills.

A direct measure of skills supply is skills testing, including psychometric tests, of which there are different classes. The OECD carries out some of these to measure aptitude, including PIAAC (mentioned above) and the Programme for International Student Assessment (PISA), which measures the literacy of 15-year-old students in the areas of reading, mathematics and science. This test is conducted every three years. While there are drawbacks to these surveys, such as cost and timeliness and that they only measure certain general skills (Boarini, d'Ercole & Liu 2012) rather than the specific ability to perform a task, they do provide some direct information on skills to complement other more indirect approaches. CEDEFOP (2013) noted that PIAAC focuses on the cognitive and workplace skills required for successful participation in an economy and, importantly, the results can be split by sector and occupation.

---

7 <https://www.qilt.edu.au/qilt-surveys/employer-satisfaction>.

8 <https://www.education.vic.gov.au/training/providers/market/Pages/employersurvey.aspx>.

9 See <https://lmip.gov.au/>. In addition, the LMIP also provides information on employment projections (by industry, occupation and region), information from the Survey of Employers' Recruitment Experiences (last done in 2018) and information on workforce shortages.

Personality-profiling tests represent another class of psychometric tests, one of the more famous examples of these being the Myers Briggs Type indicator. However, these tests also have limitations, such as social desirability bias (providing the answer the applicant thinks the employer wants). Importantly, the link between the personality types derived from these tests and skills is not well defined (Braham & Tobin 2020).

Finally, direct tests to measure skills can be given, such as may happen for job applicants; however, these tests are idiosyncratic and so not generalisable or comparable with other tests.

Table 1 summarises the approaches to skills measurement discussed above, together with the advantages and disadvantages of each type of measure.

Table 1 Indicator based approaches to skills measurement

	Example measures	Advantages	Limitations
Skills supply			
Indirect	Educational attainment, in particular highest level and field of non-school qualification	Data readily available, reliable and regular	No actual skill information; only information on full qualifications, not other forms of obtaining skills.
Direct	Test scores through direct skills assessment	Provides information on actual skills	Cost, timeliness, potential narrowness of skills covered.
Self-report	Self-reported ability to perform tasks Self-assessment of skills	Provides information on actual skills	Reports/assessments can be exaggerated/biased; may be small in scope.
Skills demand			
Indirect	Employment by occupation by qualification	Often readily available; reliable; relatively regular	No actual skills information; full qualification information only; does not capture all new and emerging jobs.
	Job-vacancy data survey	Provides some information on demand	Information can be at a fairly broad level; may not have actual skills information.
Direct	Job vacancies	Can be interpreted as skills shortages	Makes assumptions about reasons for vacancies
	New entrants to labour force	Information on new people available for labour market potentially by qualification and occupation	May not provide information on actual skills.
Self-report	Employer surveys	Can provide some information on skill needs; some surveys are conducted regularly or semi-regularly	Possible response bias; may be conducted only intermittently; may not directly address skills needs.

Sources: Summarised from Braham & Tobin (2020); Eurostat (2016).

More recent approaches and new initiatives

This section examines some relatively recent frameworks and initiatives, which may help to shed some light on aspects of the measurement of skill supply and demand. It looks at the data sources used and, where relevant, how they are integrated into the frameworks. While these approaches are not directly measuring the stock of skills, they do point towards instruments and frameworks that have the potential to assist in this endeavour.

Siekmann and Fowler (2017) noted that 'good practice' frameworks used for occupational skills analysis rely on more than just an analysis of qualifications and occupations; they use the actual discrete skills required in the workplace. Further to this, they noted that policy associated with skills, including skills imbalances and future skills demand, needs to be underpinned by accurate and timely information on skills. This requires a diversity of data sources.

Skills framework-based

United States O*NET

O*NET (Occupational Information Network), developed in the United States, is one of the most advanced of this kind of information source (Siekmann & Fowler 2017). O*NET provides detailed information on actual skills; it also gives the relative importance of those skills and their relevance to occupations, along with an organising framework for those skills to enable robust comparisons to be made.

O*NET contains standardised descriptors for each of the occupations on its database. To achieve this, O*NET has established a content model and the O*NET-SOC taxonomy.[10] The content model is a framework that provides information across six major domains:

- worker characteristics: including abilities, occupational interests, work values and work styles
- worker requirements: skills, knowledge and education
- experience requirements: experience and training, skills-entry requirement and licensing
- occupational requirements: generalised work activities, detailed work activities, organisational context and work context
- workforce characteristics: labour market information and occupational outlook
- occupation–specific information: tasks and tools and technology.[11]

The O*NET-SOC taxonomy defines occupations and is based on the Standard Occupational Classification. The taxonomy currently includes data on 923 occupations (and 93 occupations with titles only).[12] To add descriptors for each occupation based on the content model, O*NET has a data collection program, involving regular surveys of workers and occupational experts. It also collects online vacancy data for technical or tool-related skills (Siekmann & Fowler 2017). In addition, O*NET captures information on new and emerging occupations; for example, new occupations such as blockchain engineers and digital forensics analysts were added for its 2019 occupation list.

The data in O*NET is useful in exercises looking at skills supply and demand by linking it to, for example, occupationally based labour market data and online job advertisement data (discussed later). This enables quantification of the supply of and demand for actual skills.

As with all sources of information, O*NET has its drawbacks. Since O*NET is United States-based, there is potential for the skills profiles to be incorrectly mapped in other countries' contexts or for other countries to support occupations without an associated O*NET listing. Furthermore, the frequency of updates of skills information varies by category, for example, updates for skills based on tools and technology are updated more frequently than some other categories (Siekmann & Fowler 2017).

It is worth noting that O*NET is a key input into Australia's JEDI engine, which is discussed later.

---

10 <https://www.onetcenter.org/overview.html>.
11 <https://www.onetcenter.org/content.html>.
12 <https://www.onetcenter.org/taxonomy.html>.

The European Commission's ESCO

The European Skills, Competences, Qualifications and Occupations (ESCO) classification was launched in July 2017. A multilingual platform containing an assembly of skills information, it uses web-tagging technology (Siekmann & Fowler 2017).

The European Commission (2019) noted that ESCO was built from the ground up, utilising a variety of sources, including national occupation classifications from member states, classifications covering the European area, and international classifications (including the International Standard Classification of Occupations or ISCO). ESCO is published as linked open data, which means it can be used by developers as a building block in applications providing services such as job matching, career guidance and self-assessment tools to citizens.

The *ESCO Handbook* (European Commission 2019) provides information on the structure of ESCO, which essentially classifies, identifies and categorises skills, competencies, qualifications and occupations relevant to the European labour market and education and training (p.10). There are three 'pillars' to ESCO:

- occupations pillar, which attempts to describe all the occupations relevant to the European labour market
- skills pillar, which contains information on the knowledge, skills and competencies relevant to the European labour market
- qualifications pillar, which collects existing information on qualifications.

One of the great benefits of ESCO is that it links these three pillars by providing information on the skills required for working in a particular occupation and also for the skills gained from undertaking a particular qualification. It also provides information on the qualifications required by or requested for a particular occupation.

ESCO can be connected to other sources of skills intelligence (for example, online job advertisement data, occupational labour market data) by the use of a linked open data approach (Siekmann & Fowler 2017). It can therefore be used as a source in exercises for estimating skills supply and demand. As with all these approaches, ESCO also has some potential drawbacks: it is Eurocentric, meaning there may be difficulties in translating to contexts outside Europe (for example, the occupations may not easily translate to the Australian context).

In 2017 Siekmann and Fowler noted that a similar database could be created for Australia; since then the JEDI engine (described below) has been developed in Australia.

The OECD's Skills for jobs database

The OECD Skills for jobs database provides a ranking of hard-to-fill occupations (or, conversely, easy to fill), based on five main indicators:

- wage growth
- employment growth
- hours worked growth
- unemployment rate
- under-qualification growth (proportion of workers with qualifications below what is required for their job).

These labour market indicators are derived from large household labour market surveys. The five indicators are aggregated into an overall indicator of demand, using a weighting methodology (OECD 2017).

The premise of building this database was to measure skills imbalances in the labour market, such as a mismatch between labour market demand and labour supply (OECD 2017). The database covers information for European countries and South Africa.

Information contained in the O*NET database is used in the OECD database to map importance and the level of skills required for an occupation labour market information for that occupation. Three domains of competence are measured from O*NET — skills, knowledge and ability.

The database can provide information on labour market needs that have changed through technological progress and increased automation, finding, for example, that 'soft' skills such as leadership and adaptability are likely to be in shortage in some occupations, particularly those needing intensive cognitive skills (OECD 2017).

While this database does not measure the stock of skills in an economy per se, it does represent an important step in doing so by providing a mechanism to attach skills to occupations by various labour market indicators.

Australia

Australia has developed the Jobs and Education Data Infrastructure (JEDI), which brings together data on jobs, skills, units of study and qualifications from diverse sources, including O*NET, the Australian Taxation Office (ATO), student outcomes information, VET course information, student enrolment and graduate information,[13] and My Futures[14] data from Education Services Australia[15].

An important component of the JEDI project has been the development by the National Skills Commissioner of a data-driven Australian Skills Classification. This details the core competencies, specialised tasks and technology tools required by different occupations and enables exploration of connections and transferability both within and between jobs and qualifications (National Skills Commission 2021).

The development of more skills-based occupational classification was recommended by the OECD (2018), which highlighted that skill assessment and anticipation exercises in Australia at the time were focused on qualifications and occupations in demand, rather than on actual skills. A skills-based approach is seen as being more responsive to changes in demand due to technological progress and provides more specific information on where learning may be required for skills in demand; hence, undertaking training for a specific skill rather than retraining for an entire occupation.

One application of JEDI has been the development of a skills-matching methodology (Australian Department of Employment, Skills, Small and Family Business Future of Work Taskforce 2019), which was informed by a methodology developed by the World Economic Forum and Boston Consulting Group (2018). A key aspect of the skills-matching methodology is a similarity score calculated across occupations. JEDI has also been used to develop a Skills Match Tool on the Job Outlook Website.[16] This tool provides, for a

---

13 VET course information and VET student outcomes are available from the National Centre for Vocational Education research (NCVER), while student enrolment data and graduate information for the higher education sector are available from the Australian Department of Education, Skills and Employment.

14 <https://myfuture.edu.au/>.

15 See https://www.nationalskillscommission.gov.au/our-work/jobs-and-education-data-infrastructure-jedi (accessed April 2021) for further information on JEDI.

16 <https://joboutlook.gov.au/>.

given job, specific information on the skill needs required for that job, with comparisons to the skills required for a potential other job a person may wish to move to (based on O*NET). Hence, it provides information on potential skill gaps and therefore training needs.

While the Skills Match Tool is aimed at individuals, JEDI and the Australian Skills Classification can also be utilised to undertake macro-level skills supply and demand analyses of the entire labour market.

Other initiatives and recent study

Other more recent approaches have been identified as promising. Braham and Tobin (2020) discussed the use of digital approaches and the harvesting of big data in order to gain information on skills supply and demand. This includes mining self-reported skills data from anonymised job seeker profiles (skills supply) and employer job postings (skills demand). Platforms from which the data can be harvested include LinkedIn. Data are also available from forums that specialise in web and data scraping, such as Burning Glass Technologies (see, for example, Korbel 2018). Others include Vicinity Jobs Technologies, Magnet (which take data directly from job portals) and Adzuna (a job-search engine).

Considerable advantages to using these approaches have been identified, including access to timely and granular-level data. These techniques can also be cost-effective and an efficient way of linking skills to jobs.

These approaches also have limitations. Braham and Tobin (2020) noted that each of these organisations uses its own classification system, meaning that there is no one common skills classification used to organise the data. The skills that employers want, or the skills that job seekers have, can be exaggerated in job ads and job-seeker profiles. In addition, descriptors that are not actually skills can be identified and organised, or they are taken out of context. Furthermore, not all jobs are posted electronically, so it is not known how representative the data posted online are of the total job market, with an inherent bias a possibility. Evidence suggests that employers in some areas, such as information technology and health, are more likely to post jobs online than those in other areas. There are also some challenges in terms of data quality, such as classifying job information correctly and excluding duplicate postings.

In Australia, in addition to being an input into JEDI (see earlier), Burning Glass data are also used in the National Industry Insights Report[17] to provide information on employers' skill needs for various industry sectors. Despite the drawbacks and caveats associated with the Burning Glass data, as mentioned above, it is nevertheless an important source of information.

There has been a recent attempt in Australia to estimate the stock of skills of the workforce. AlphaBeta (2019) estimated the average amount of time that working-age Australians spend in school, tertiary education, other formal training and on-the-job training, using information obtained from various sources, including the census and other ABS data, as well as O*NET. The O*NET data were used to allocate skills, knowledge, abilities and work styles across occupations to an education level and a training source. This then allowed for a cumulative training profile for each occupation and, following this, an estimate of time for training for each skill in each occupation. In sum, AlphaBeta estimated an average 24 000 hours of education and training for working-aged Australians, which equates to a stock of education and training across the population of 300 billion hours. This was then extrapolated to the year 2040, with a calculation of 600 billion hours of education and training required to ensure that the workforce is fully equipped for future needs. Skills needed in the future were seen to be those that complement automation, with the fastest growing skills being those attached to people, such as adaptability, teamwork, creativity and integrity. Interestingly, most of the post-initial training is not

17 <https://nationalindustryinsights.aisc.net.au/>.

seen as being formal courses/qualifications at a tertiary institutions but rather on-the-job training and short courses. The AlphaBeta study is one approach to estimating skills in the economy (ultimately formulated in hours). This approach also utilises the skills data in O*NET.

Measuring stocks of skills in Australia

Considering the types of data we have available in Australia, particularly indicators-based data, but also skills classification-related information, we can arrive at a concept map for qualifications and skills supply and demand data for Australia (figure 1). The map shows the types of elements we need to think about in measuring skills supply and demand; associated with this are the possible data sources we have available for information on those elements.

Figure 1 Concept diagram

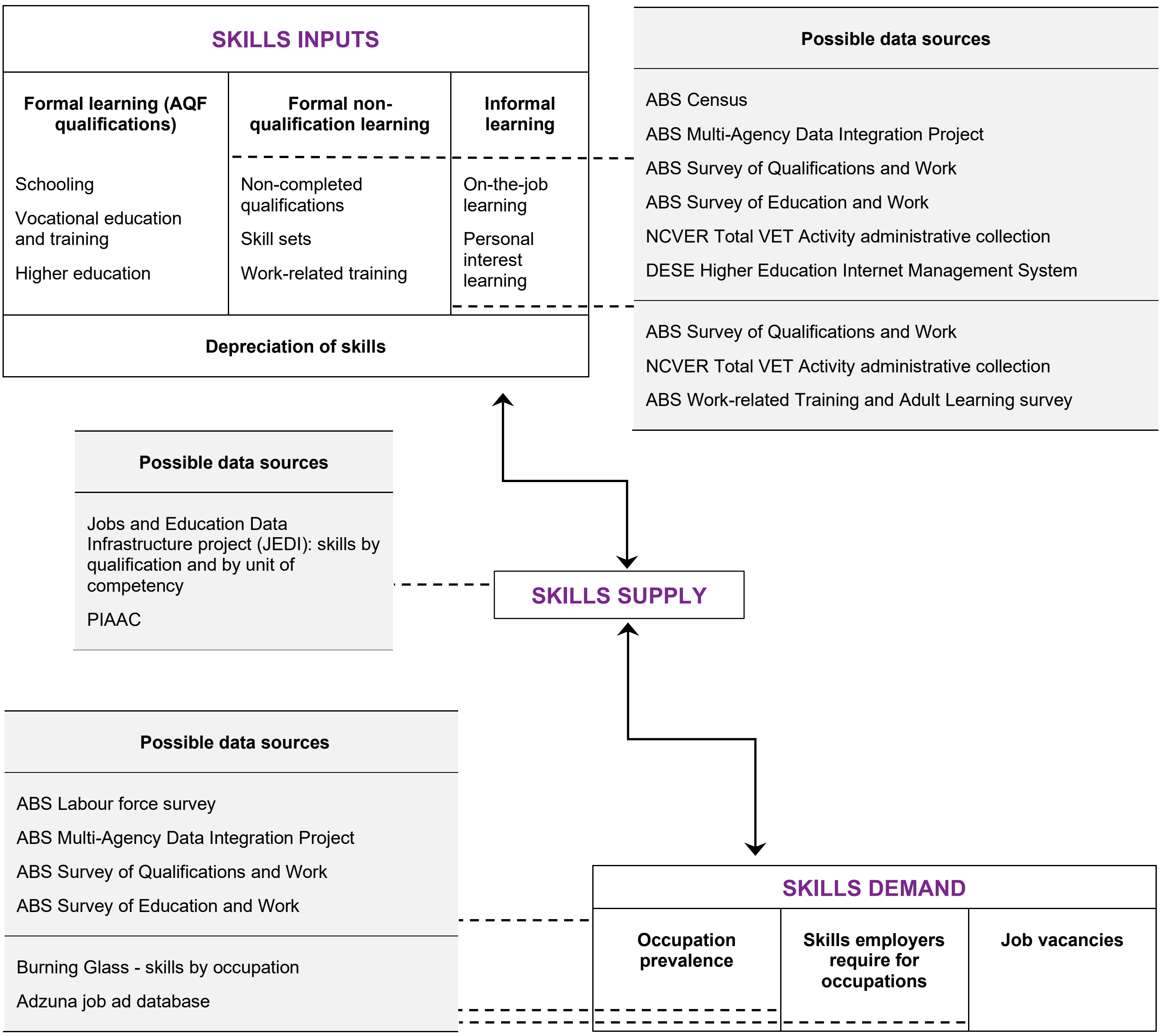

Table 2 provides a summary of the pros and cons associated with data sources shown in the concept map.

Table 2 Data sources available in Australia[1]

Data source	**Examples of pros and cons**
Australian Bureau of Statistics	
Census data	Contains population-wide data, so can drill down to detailed level of occupation, for example. Qualifications data are limited to highest level of education only. Conducted every five years so data may be slightly outdated. For example, the last census was in 2016 so the data dates to that time period.
Multi-Agency Data Information portal or MADIP (census, personal income tax, Higher Education Management System (HEIMS), TVA, skilled migration points data – see MADIP catalogue Microdata: Multi-Agency Data Integration Project, Australia (cat.no.1700.0)	Linked dataset including administrative data as well as ABS census data, thereby increasing the power of this information. Can potentially get detailed level of information for some variables. Not all data are up to date.
Survey of Education and Work	These surveys provide regular and reliable information on education and training activity, and labour force participation (by occupation and industry). As they comprise survey data with limited sample sizes, high standard errors become an issue when drilling into the data. In addition: The Qualifications and Work survey provides information on multiple qualifications obtained by an individual as well as relevance of the qualification to the job. The Work-related Training and Adult Learning survey provides some information on the important component of training outside qualifications.
Labour force data	
Survey of Qualifications and Work	
Work-related Training and Adult Learning survey	
Other Australian education and tax data	
Total VET activity (TVA)	Detailed administrative data on vocational education and training activity. Information only available for the last five or so years so limited in this sense.
Higher Education Management System	Detailed administrative data on higher education activity.
Alife (sample of data from Australian tax returns)	Alife provides information on income tax return data, including information on occupation of work (in addition to information on superannuation and student fees). Will be linked to TVA and HEIMS at via MADIP. Alife provides information to 2-digit ANZSCO level only, which may not be a sufficiently detailed level.
OECD survey data	
PIAAC	Provides some information on actual skills. Data are uniform and comparable across countries. Only a limited number of skills is surveyed. Data, in the case of Australia, are currently out of date.
Data (job classification and ad) engines	
Jobs and Education Data Infrastructure (JEDI)	Provides a skills-classification system with detailed skills information for qualifications and jobs. To be used to obtain stock of skills information it needs a linkage to detailed labour force information.
O*NET	
Adzuna	Provides information on skills needed for jobs (according to employer) according to a skills classification system. Data may be biased as only online postings are used and employers may exaggerate skills required).
Burning Glass	

1 The references for all the data sources mentioned in the table are contained in appendix A.

Gaps in and challenges with the data

While table 2 shows that there are data sources in Australia with the potential to provide some useful information in an attempt to measure skills supply and demand, there are still some areas where there are challenges. These include:

- information on the actual skills

- non-qualification-based training, including non-accredited training and qualification non-completion
- informal learning, including learning on the job
- accounting for skills depreciation.

These are discussed in turn.

Information on actual skills

As mentioned previously, Australia supports the JEDI data engine, containing the Australian Skills Classification, which can be linked to qualifications and occupations. This will be a very useful source for providing information on skills supply (through qualification and unit of competency information data) and skills demand (Job adverts from Burning Glass) in the future.

Most of the other information sources listed in table 2 do not provide information on specific skills. The exceptions are PIAAC, albeit on a limited range of skills, O*NET, and Adzuna and Burning Glass, both of which provide demand-side skills information.

Non-qualification-based training and informal learning

A significant challenge lies in obtaining data on the skills obtained outside qualifications, which is a significant component of all the skills held by people. A number of disparate sources provide information on parts of this puzzle, such as NCVER’s Total VET activity administrative collection, the Higher Education Internet Management System database and the ABS Work-Related Training and Adult Learning survey, but no comprehensive source is currently available. Further investigation would be required to determine how well these various sources of data could be brought together to paint a picture. Another way to approach this would be to employ an estimation procedure such as that undertaken by Alpha Beta (2019) or Wei (2008).

Skills depreciation

There is no obvious source of information on skills depreciation when estimates of stocks of skills are produced. In addition, a complicating factor is that any depreciation of skills obtained through qualifications can be topped up by work-related and other short-form training (for example, micro-credentials). The human capital approach explained in Wei (2004, 2008) may be one way to think about this challenge.

References

AlphaBeta 2019, *Future skills*, AlphaBeta, Sydney, viewed 22 January 2020, <https://www.alphabeta.com/wp-content/uploads/2019/01/google-skills-report.pdf>.

Australian Department of Employment, Skills, Small and Family Business 2018, Survey of employer recruitment experiences: 2018 data report, viewed 16 April 2021, < https://www.dese.gov.au/employment-research-and-statistics/resources/survey-employers-recruitment-experiences-data-report-2018>

Australian Department of Employment, Skills, Small and Family Business Future of Work Taskforce 2019, *Reskilling Australia: a data-driven approach*, Department of Employment, Skills, Small and Family Business, Canberra, viewed 16 March 2021, <https://docs.employment.gov.au/documents/reskilling-australia-data-driven-approach>.

Boarini, R, d'Ercole, MM & Liu, G 2012, *Approaches to measuring the stock of human capital: A review of country practices*, OECD Statistics working papers 2012/04, viewed 15 July 2020, <https://www.oecd-ilibrary.org/docserver/5k8zlm5bc3ns-en.pdf?expires=1596774588&id=id&accname=guest&checksum=C09B2FF32AA5B50DBE3424289D4FB9B1>.

Braham, E & Tobin, S 2020, *Solving the skills puzzle: The missing piece is good information*, Future Skills Centre, viewed 15 March 2020, <https://ppforum.ca/publications/solving-the-skills-puzzle/>.

Brunello, G & Wruuk, P 2019, *Skill shortages and skill mismatch in Europe: A review of the literature*, IZA Institute of Labour Economics, Discussion paper series, viewed 15 July 2020, <https://www.iza.org/publications/dp/12346/skill-shortages-and-skill-mismatch-in-europe-a-review-of-the-literature>.

CEDEFOP 2013, *Quantifying skill needs in Europe, occupational skills profiles: Methodology and application*, viewed 15 July 2020 <https://www.cedefop.europa.eu/en/publications-and-resources/publications/5530>.

European Commission 2019, *ESCO Handbook: European skills, competences, qualifications and occupations,* European Union, viewed 7 August 2020, <https://ec.europa.eu/esco/portal/documents>.

Eurostat 2016, *Statistical approaches to the measurement of skills*, viewed 15 July 2020, <https://ec.europa.eu/eurostat/documents/3888793/7753369/KS-TC-16-023-EN-N.pdf/438b69b5-2fcb-4923-b9e2-fa7b59906438>.

Fraumeni, B, Christian, C & Samuels, J 2020, *The accumulation of human and market capital in the United States: The long view, 1948—2013*, IZA Institute of Labor Economics, Discussion paper series, viewed July 2020, <https://www.iza.org/publications/dp/13239/the-accumulation-of-human-and-market-capital-in-the-united-states-the-long-view-19482013>.

Gasskov, V 2018, *Analysis of market demand for skilled workforce and its application to VET delivery planning*, viewed 20 July 2020, <https://www.ilo.org/wcmsp5/groups/public/---ed_emp/---ifp_skills/documents/genericdocument/wcms_628964.pdf>.

Korbel, P 2018, *Internet job postings, preliminary skills analysis,* Technical paper, NCVER, Adelaide.

National Skills Commission 2021, *Australian Skills Classification BETA release discussion paper*, Commonwealth of Australia, viewed 18 March 2021, <https://www.nationalskillscommission.gov.au/sites/default/files/2021-03/AUSTRALIAN%20SKILLS%20CLASSIFICATION%20BETA%20DISCUSSION%20PAPER.pdf>.

OECD (Organisation for Economic Co-operation and Development) 2013, *Indicators of skills for employment and productivity: A conceptual framework and approach for low income countries*, OECD and the World Bank in collaboration with ETF, ILO and UNESCO, viewed 11 August 2020, <https://www.cedefop.europa.eu/en/publications-and-resources/presentations/indicators-skills-employment-and-productivity-conceptual>.

——2017, *Getting skills right: Skills for jobs indicators,* viewed 15 July 2020, <https://www.oecd.org/employment/getting-skills-right-skills-for-jobs-indicators-9789264277878-en.htm>.

——2018, *Getting skills right, Australia*, viewed 15 July 2020, <https://www.oecd.org/australia/getting-skills-right-australia-9789264303539-en.htm>.

Siekmann, G & Fowler, C 2017, *Identifying work skills: international approaches*, NCVER, Adelaide.

Squicciarini, M, Marcolin, L & Horvat, P 2015, *Estimating cross-country investment in training: An experimental methodology using PIAAC data*, OECD science, technology and industry working papers, 2015/09, viewed 15 July 2020, <https://www.oecd-ilibrary.org/science-and-technology/estimating-cross-country-investment-in-training_5jrs3sftp8nw-en>.

Stroombergen. A, Rose, D & Nana, G 2002, *Review of the statistical measure of human capital*, Statistics New Zealand, Wellington.

Wei, H 2004, 'Measuring human capital formation for Australia: A lifetime labour income approach', 33rd Annual conference of economists, 27—30 September 2004, Sydney.

——2008, 'Measuring human capital flows for Australia: A lifetime labour income approach', cat.no. 1351.0.55.023, ABS, Canberra.

Wiseman, J & Parry, E 2017, *Continuing Vocational Training Survey: CVTS 5, main report no. 5,* DfE research report, no. DFE-RR754, Department for Education, Manchester, viewed 11 August 2020, <https://www.gov.uk/government/publications/continuing-vocational-training-survey>.

World Economic Forum & Boston Consulting Group 2018, *Towards a reskilling revolution: a future of jobs for all*, viewed 15 July 2020, < https://www.weforum.org/reports/towards-a-reskilling-revolution>.

Appendix A: Australian data source references

Australian Bureau of Statistics (ABS)

ABS 2016 Census products, <https://www.abs.gov.au/census>

ABS 2018 Microdata: Multi-Agency Data Integration Project, Australia, cat. no. 1700.0

ABS 2019 Education and work, Australia, cat. no. 6227.0

ABS 2016 Qualifications and work, Australia, cat. no. 4235.0

ABS 2017 Work-related training and adult learning, Australia 2016—2017, cat. no. 4234.0

ABS 2020 Labour force, Australia, cat. no. 6202.0 (various editions)

ABS 2020 Labour force Australia, detailed — electronic delivery (various editions), cat. no. 6291.0.055.001

ABS 2020 Labour force Australia, detailed, quarterly (various editions), cat. no. 6291.0.055.003

Administrative data

NCVER Total VET Activity (TVA), <https://www.ncver.edu.au/about-ncver/about-our-data>

Australian Department of Education, Skills and Employment, Higher Education Management System (HEIMS), <https://heimshelp.education.gov.au/resources/glossary/glossaryterm8642>

Australian Taxation Office and Sax Institute, Alife (sample of data from Australian tax returns), <https://alife-research.app/info/overview>

OECD data

OECD, Survey of Adult Skills (PIAAC), <https://www.oecd.org/skills/piaac/>

Data (job classification) engines

National Skills Commission, Jobs and Education Data Infrastructure (JEDI), <https://www.nationalskillscommission.gov.au/our-work/forecasting-skills-and-analysis#:~:text=JEDI%20is%20a%20flagship%20NSC,jobs%20that%20use%20similar%20skills>

Onetcenter, Occupational Information Network or O*NET, <https://www.onetcenter.org/overview.html>

Job ads

Adzuna, <https://www.adzuna.com.au/?gclid=EAIaIQobChMIopqKytOZ6wIVxAorCh25yQrXEAAYASAAEgLTTfD_BwE>

Burning Glass Technologies, <https://www.burning-glass.com/>