Australian Government

National Skills Commission

The state of Australia's skills 2021: now and into the future

Contents

Commissioner's foreword

Although COVID-19 appears likely to affect us for some time yet, Australia's labour market has emerged from the initial impacts of the pandemic in a robust fashion. The expected decline in the unemployment rate (as reflected in the 2021-22 Budget forecasts) points to a tightening in labour market conditions over the period ahead.

This means the focus must shift from the immediate task of getting the unemployed back to work to ensuring our education and skills system delivers the skills and knowledge that the economy is likely to need. It also means recognising what can, and what can't be forecast – especially as we look further and further into the future. And it means building resilience into our education and skills system – resilience to the inherent uncertainty involved in estimating the economy's future skills needs.

Although much of the focus of the National Skills Commission (NSC) has been on supporting reform of the VET system, this report takes as its subject the whole labour market. As a result, the term 'skills' should be read in its broadest possible meaning.

The state of Australia's skills 2021: now and into the future finds Australia has managed well the structural changes that have occurred in the labour market over the past few decades. The report offers a series of markers to help influence and inform the development of Australia's education and skills system over the years ahead.

The report does not offer a series of recommendations into what should, or should not, be taught across the education and skills system. Rather it examines the economy's current skills needs, those that are emerging, and the broader trends we can expect to see. The report also examines how well matched the broad supply and demand of skills across the economy is. Ultimately, better matching of supply and demand for skills will make it easier for Australians to get jobs and for businesses to get the workforce they need. This is one of the foundations of a strong, productive economy.

In this report the NSC seeks to help shape Australia's future workforce to deliver that strong, productive economy.

Adam Boyton
National Skills Commissioner

Executive summary

Executive summary

This report examines Australia's current, emerging and future workforce skills needs.

The report also examines how well matched the broad supply and demand of skills across the economy is. Better matching of supply and demand for skills makes it easier for Australians to get jobs. It also makes it easier for businesses to get the workforce they need. Both are the foundations of a strong, productive economy.

A fundamental innovation in the NSC's work – contained in this report – is the focus on skills, alongside the more traditional analysis of the changing mix of occupations. The NSC has applied this skills focus both to analysing the present state of the labour market and examining what lies ahead.

The Australian labour market has been transformed over the past 40 years

The shape of the Australian labour market has changed significantly over the past 40 years, with strong growth in higher skill level jobs, non-routine jobs and services. These changes have been reflected at both the occupation and industry level.

Alongside the changes in the types of jobs and the skills they require there have been a number of enduring structural changes. Female employment and participation have grown strongly and, in response to higher skills needs, young people are spending longer in education.

STEM skills (science, technology, engineering and maths) are an integral part of Australia's labour market, which have helped to facilitate the emergence of more complex, innovative work in many industries. Over the 20-year period to February 2020, before the impact of the COVID-19 pandemic on the labour market, employment in STEM occupations grew by 85.0%, or more than twice the rate of non-STEM occupations (which grew by 40.2%).

Some of these changes have been driven by automation, while greater use of technology has changed many jobs and encouraged growth in higher skilled jobs.

Overall, the labour market weathered well the impacts of these big picture forces and changes, and entered the COVID-19 pandemic with a relatively low unemployment rate following a number of years of solid employment growth.

The impact of the COVID-19 pandemic on the labour market

As the labour market started to recover from the impact of the COVID-19 pandemic and its restrictions late last year, the NSC released modelling that examined a number of potential recovery paths. The broad conclusion from this exercise was that while there will be lasting changes as a result of COVID-19, these may not be dramatic.

The two most enduring changes are likely to be changes in the way we do our jobs, known as task change, and the acceleration of changes that were already underway, such as increasing activity online and the ongoing need for post secondary qualifications.

Skills of workers in today's labour market

As well as taking an occupational based view of the labour market, this report also examines the skills embodied within occupations to enable us to form a picture of the portfolio of skills across the economy. This is done by combining occupational based analysis with the Australian Skills Classification (ASC) to link occupations to skills. Groups of skills can be clustered to form 29 skills cluster families.

Looking at the economy-wide skills portfolio, the most frequently occurring skills cluster family is business operations and financial activities. This includes skills such as maintaining inventory and stock, managing operational budgets, and negotiating purchases or contracts. Four-fifths (80%) of people required some skills from this skills cluster family for their occupation. This is followed by the communications and collaboration family (74%) – which includes skills clusters such as collaborating with stakeholders and dispute resolution – and human resources (66%), which includes supervising staff, training staff and recruitment. Although most people require some skills from the business operations and financial activities skills cluster family to do their jobs, only about 16% of time in the economy is spent on them. By contrast, although only around one-in-five workers have skills in the health and care cluster family, 9% of time in the economy is spent on these tasks, as they form a larger portion of the day for workers in this area.

Taking such an approach, we can form views about the intensity of skill use across the economy as well as how widely distributed a skill is.

This analysis also shows the gendered nature of the Australian workforce. Men are three times as likely as women to use skills from the construction family in their paid employment – including skills such as 'woodworking', 'earthworks' and 'crane operation'. Men are twice as likely to use skills from the vehicle operation family and from families often associated with manufacturing work such as 'work activities preparation' (preparing pieces for assembly, handling materials), 'production processes and machinery' (configuring equipment, developing technical designs), and 'quality control and inspections' (inspecting for damage and defects). Women are twice as likely as men to use skills from the health and care family and from the fashion, grooming and cosmetics family.

Labour market matching – a skills perspective

There appears to have been a slight deterioration in the ability of the labour market to match employers' demand for labour with the available supply of labour following the COVID-19 pandemic. In the context of changed consumer spending patterns, disruption to business models and supply chains and closed borders arising from the COVID-19 pandemic, this should not be surprising.

One analytical tool used by labour market economists to analyse trends and developments in labour market matching is the Beveridge Curve. The Beveridge Curve compares the unemployment rate (the number of people unemployed divided by the total labour force) to the vacancy rate (the number of job vacancies divided by the total labour force) and shows how this changes over time. A Beveridge Curve for Australia suggests that the observations over mid-2020 are consistent with a recessionary environment with a relatively high unemployment rate and few vacancies. More recent observations suggest a solid recovery in the labour market with a lower rate of unemployment and an increase in job vacancies. The position of the most recent observations relative to the origin suggests a more mixed ability of the labour market to match demand and supply.

In a similar vein, employer surveys show that in 2021 to date, 45% of recruiting employers reported having recruitment difficulty for their most recent vacancies, a slight increase on 2019 (42%) and broadly in line with 2018. Most starkly, recruitment difficulty has become more common outside capital cities following the pandemic, with rest-of-state recruitment difficulty exceeding that for capital cities in 2020 for the first time – a trend that has continued into 2021.

From the employee perspective, research shows a difference between the skills profile of unemployed and employed people. For many job seekers, the default option is often to seek work in the occupation they have most recently held. Unfortunately, the vacancy profile makes this challenging as there are differences between the skills profile of many unemployed people and jobs that are frequently advertised.

Labour market skills needs

The NSC's five-year industry employment outlook projects that the long-term structural shift in employment towards services industries will continue. Four services industries – 'health care and social assistance', 'accommodation and food services', 'professional, scientific and technical services' and 'education and training' – are expected to generate over three-fifths of the total projected employment growth. However, future employment growth is not just confined to these areas, with further increases projected across a range of industries.

The increasing importance of tertiary education and skills development beyond secondary school is highlighted by the five-year projections that show more than nine-in-ten new jobs are projected to require post-school qualifications. Employment in STEM occupations (using science, technology, engineering and maths skills) is projected by the NSC to grow by 12.9%, well above the average of all occupations (of 7.8%) and more than twice as fast as non-STEM occupations (6.2%).

From a skills perspective, occupations in high demand are more likely to be specialised and require higher level skills and formal qualifications. These include occupations such as registered nurse, software and application programmers and advertising and sales managers.

By combining the five-year employment projections with the ASC, the NSC produces five-year skills projections. Some of the most important and rapidly growing skills needs over coming years, identified by this analysis, can be summarised as the 'Four Cs': care, computing, cognitive and communication skills.

Turning back to an occupational lens and the present, there are pockets of shortages across most occupation groups. Generally, shortages are greatest among 'technicians and trades workers' occupations. Technicians and trades workers are employed in a wide range of occupations important to many different industries, and include electricians, carpenters, chefs, fitters and motor mechanics.

Emerging skills

Changes in technology are often thought to lead to the loss of jobs. But the biggest effect of advances in technology is on changes in the way existing jobs are done. Known as 'task change', this involves changes in the amount of time spent on existing tasks and the addition of new tasks.

The concept of task change is approached in this report through an examination of trending and emerging skills. Trending and emerging skills are affecting the way work is undertaken across many occupations. For example, infection control is trending in 45 occupations and emerging in 38 others, social media is trending in 47 occupations and emerging in 18, and enterprise resource planning is trending in 50 occupations and emerging in 14.

Data and digital skills are among the fastest growing emerging skills. Although Australia is doing well with respect to recognising the need for specific digital skills, further effort may be required to build base digital skills proficiency at all skill levels, not just the higher skill levels. There are also significant gains to individuals, and likely also the economy more broadly, from investing in those skills.

Skills and jobs of the future

Among the key skills that will be needed for jobs of the future are care, computing, cognitive and communication skills.

Although automation can replace labour in some jobs and tasks, it is also creating new tasks and demand for labour. For example, software and computers replaced labour in some white-collar jobs. They also create new tasks including programming, software and application development, and more specialist tasks within existing occupations. The NSC views computing as a key skill of the future, reflecting the job creation aspect of this mega trend.

The NSC's analysis also highlights the importance of core competencies or 'employability skills', with high proficiency in core competencies correlating with a decrease in the likelihood of automation. Within that group of core competencies, high proficiency in oral communication and writing are the least likely to be automated – a finding that sits behind the NSC's view that communication is a core skill of the future.

The combination of an ageing population and the lower ability to automate tasks and jobs in the cluster family of health and care suggests that 'care' is also likely to be a key skill needed in coming years.

One of the impacts of the pandemic on the labour market appears to have been an acceleration of long-term trends. One such trend is the shift in demand for labour away from routine tasks (repetitive physical labour that can be replicated by machines) towards non-routine (non-repetitive or non-codifiable) work. The greater difficulty in automating non-routine cognitive jobs and tasks (at high and lower skill levels) also suggests these types of jobs – 'cognitive' – will remain in high demand into the future.

Concluding comments

Throughout this report a key focus is on drawing out the big forces: a shift to higher skill jobs and an ongoing shift toward services, including care; the resilience of non-routine and cognitive jobs in the face of automation and artificial intelligence (AI); the opportunities and new jobs being created by technology; and an acknowledgment that many of those forces likely to shape the future have also shaped our recent past.

Encouragingly, the Australian labour market has, on the whole, managed the impacts of these big forces well over the past few decades and entered 2020 with a relatively low unemployment rate and a more highly skilled population than was the case decades earlier.

The recovery in the labour market following the initial impact of the COVID-19 pandemic is also another positive sign. Of course, that success in managing those initial impacts has also presented some current challenges – especially recruitment difficulty in regional areas.

Although past performance is no guarantee of future success, the ability of the Australian labour market to respond and reshape itself over the past few decades, as highlighted in this report, provides some grounds for optimism about our ability to do so into the future.

01

Introduction

Introduction

This report examines the current, emerging and future skills needs of the Australian labour market.

It also examines how well matched are the broad supply and demand of skills across the economy.

That said, there are always gaps between the skills employers need and those that workers possess.
The NSC's role is to help identify those gaps.

The report provides layers of intelligence from an industry, occupation and task lens on the skills needs of the economy, now and in the future.

The analysis starts with more traditional labour market insights and builds to provide new skills insights using innovative data science techniques. The result is a rich and complex blend of analysis that paves the way for better matching labour market demand and supply, and building the human capital needed for Australia's economic prosperity.

Labour market analysis has traditionally focused on occupations as the key unit of analysis. This remains an important and useful lens. But it doesn't tell us much about what lies within 'occupations'. It doesn't reveal the tasks employers need to be done. It doesn't reveal the skills workers use to achieve those tasks.

A fundamental innovation in the NSC's work is that it provides much more detailed understanding of the labour market than has been available until now. It puts a focus on skills, alongside the more traditional analysis of the changing mix of occupations.

The NSC applies this skills focus both to analysing the present state of the labour market and in forecasting what lies ahead. Better knowledge of skills gaps will help governments, trainers, educators, employers and workers find ways to bridge those gaps. This will help people get better jobs. They can better identify which jobs need the skills they have, and the training they could do to gain the skills that employers need.

The Australian Skills Classification (ASC) is one of the NSC's new analytical tools. It is the means by which a traditional occupation perspective on the labour market is expanded and deepened to bring a focus on skills. This chapter gives a detailed discussion of the ASC, then briefly outlines the other main analytical tools used by the NSC. Other tools and techniques are discussed in more detail later in the report.

The Australian Skills Classification in depth

The ASC provides the basis for turning an occupation based view of the economy into a skills based view – by mapping the way occupations are made up of skills. The ASC can be found on the NSC website (www.nationalskillscommission.gov.au).

Australian
Skills Classification

ASC skills profiles

The ASC includes skills profiles for some 600 occupations. A skills profile for an individual occupation comprises three main elements. These are:

- *core competencies* – which are common to all jobs. Currently there are different terms for core competencies, including 'employability skills', 'foundational skills' and 'transferable skills'. The ASC provides a consistent language and a way to compare the level of competency across occupations using a 10-point scale.
- *technology tools* – which are the technologies such as software or hardware required in an occupation. The ASC describes software and equipment types and provides specific packages or products as examples. Common technology tools, such as search engines and email, are featured across most occupations, and these are captured in the core competency of digital engagement. The remaining technology tools are highly specialised and occupation specific, such as computer aided design (CAD) software and carbon monoxide analysing equipment.
- *specialist tasks* – which are the work activities a person undertakes specific to a job. Specialist tasks change more frequently than core competencies and are useful for differentiating occupations.

The ASC views the skills composition of the labour market at several different levels. The 1,925 specialist tasks group into 279 skills clusters which in turn group into 29 skills cluster families.

Figure 1: Specialist tasks, skills clusters and skills cluster families

1,925
specialist tasks

279
skills clusters

29
skills cluster families

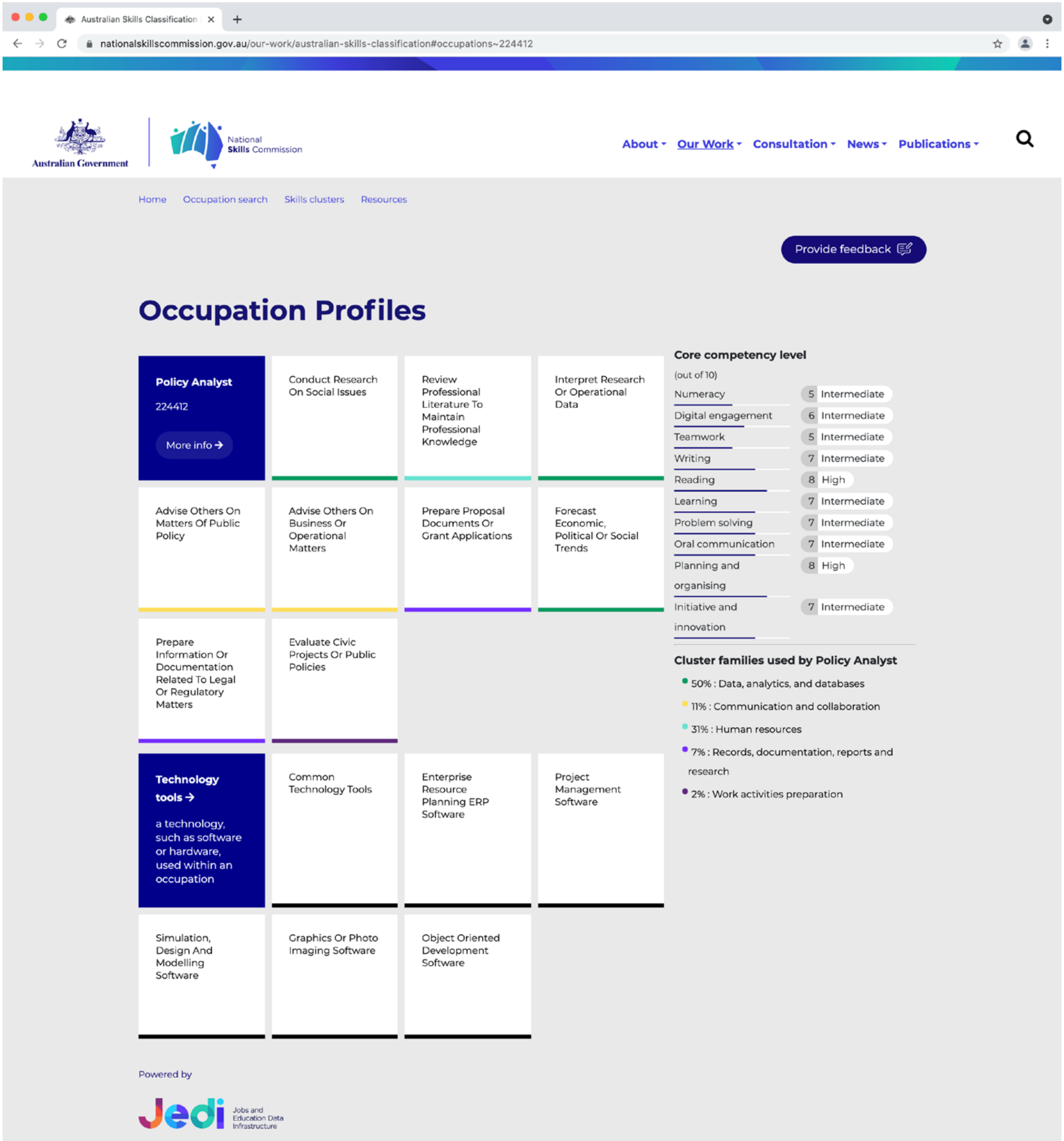
Source: NSC

Skills that are like one another are clustered together – if you can do one task in a skills cluster, you are likely to be able to do the others. This enables a more systematic way of thinking about transferable skills, and allows us to judge how well someone's skills, based on their past employment, might match current vacancies.

From an economy-wide perspective the ASC provides the basis to think not just about the range of jobs or occupations across the economy, but also the skills embedded in those jobs.

Figure 2 gives an example of the way the ASC can be used to identify the skills that lie beneath a 'policy analyst' occupation. The dominance of skills from the human resources and data, analytics and databases clusters are evident, along with the importance of the communication and collaboration cluster. The core competencies required for a policy analyst are towards the high end of the 10-point scale, particularly 'planning and organising' and 'reading'.

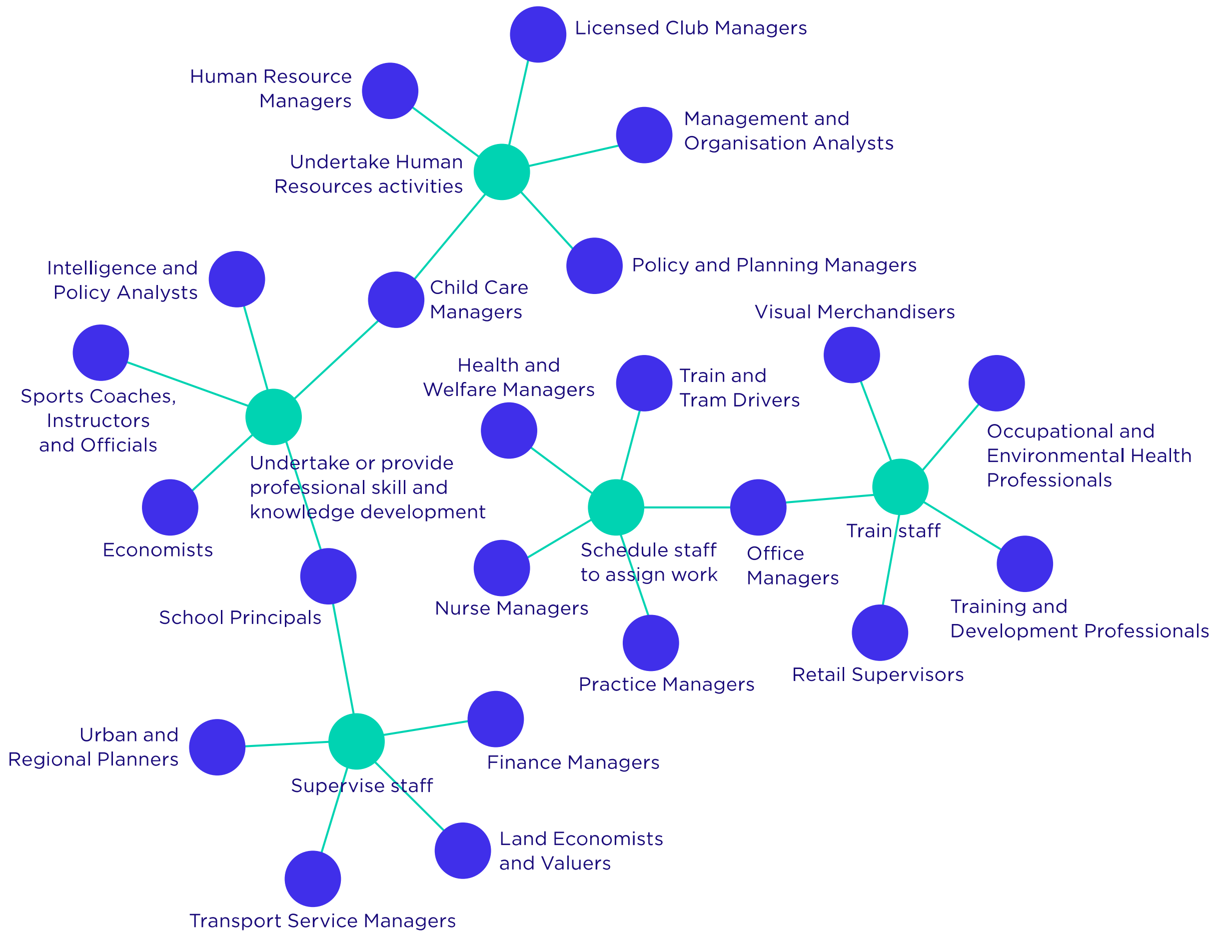
Figure 2: Skills profile of a policy analyst



Source: NSC

In addition to showing the skills profile of a single occupation, the ASC also shows the way occupations are made up of skills, and how one skill may be needed in many occupations. Figure 3 shows the top five skills clusters in the 'human resources' cluster family and the five occupations that use these skills intensively. For example, the 'schedule staff and assign work' skills cluster is used intensively in a range of occupations across different sectors such as train and tram drivers, health and welfare services managers, office managers and practice managers.

Figure 3: Requirement for human resources skills across occupations



Source: NSC

Different chapters in the report explore how the ASC can add depth to the current occupational labour market analysis. Chapter 4 explores the skills embodied in the labour market at different levels – from the skills composition of different cohorts to the broad portfolio of skills at an economy wide level. Chapter 6 takes the NSC five-year employment by occupation projections and turns them into skills-based projections.

Comparing the skills in the ASC to skills that are emerging or trending in more real-time data sources can highlight what are most likely to be the gaps between the skills the population has and those that will be needed in the future. This is important for identifying employment and training pathways that are likely to drive economic and productivity growth. There is further analysis of emerging and trending skills in Chapter 7.

The NSC's tools and techniques

The NSC has developed innovative tools and techniques for analysing the labour market. Along with an innovative approach to the links between skills and jobs, the NSC also undertakes more traditional analyses of the labour market.

The ASC has been described earlier. The other key tools are described below.

Skills Priority List

The Skills Priority List (SPL) outlines the occupations that are currently in shortage as well as their expected future demand. The focus of the SPL is on occupations rather than skills.

The SPL forms the backbone of the NSC's labour market advice, including on skilled migration, training funding and apprenticeship incentives.

Providing a single source of advice on occupations creates a direct line of input for stakeholders and ensures greater consistency and better targeting of resources across the various policy responses implemented by government.

Sources of data for the SPL include the NSC's Survey of Employers who have Recently Advertised (SERA). This survey, as the name suggests, collects quantitative and qualitative data from employers and recruiters who have recently advertised for certain occupations.

The SPL also draws on the NSC's five-year-employment projections covering industry, occupation and skill level. The employment projections are designed to provide a guide to the future direction of the labour market.

Chapter 6 has more information on the SPL and SERA and on the five-year employment projections.

Nowcasting generates monthly employment estimates by region

Nowcasting is an emerging technique used to identify current economic trends such as GDP, unemployment rates and consumer confidence, by the OECD (Organisation for Economic Co-operation and Development), the Reserve Bank of Australia, the Bank of England and the Federal Reserve Bank of New York.[1]

The NSC uses nowcasting to provide current estimates on employment by region and occupation. This is to ANZSCO 4-digit occupations and statistical areas level 4 (SA4) regions. Currently such data are only available every five years from Australian Bureau of Statistics (ABS) census collections. Nowcasting uses both traditional and real-time data as well as big data techniques to provide estimates in a timely manner.

Vocational Education and Training National Data Asset (VNDA)

The NSC is developing a Vocational Education and Training National Data Asset (VNDA), in conjunction with the ABS. The VNDA will provide a robust evidence base on the employment and further study outcomes from VET, by linking VET activity data with a range of outcomes-related data sets held by government.

The quality of data available through the VNDA will allow outcomes measures to be risk-adjusted, taking into account the diversity of students, courses and providers within the VET sector.

The first stage of the VNDA will identify the labour market outcomes achieved over time by workers with various qualifications, taking into account the nature of the student cohort. This could, for example, help inform students' views on courses of study they could take.

There is more detail on the VNDA in Chapter 5.

[1] See, for example, PC Higgins, 'GDP Now: a model for GDP "Nowcasting"', FRB Atlanta working paper 2014-7, 2014; D Moriwaki, 'Nowcasting unemployment rates with smartphone GPS data', *Lecture notes in computer science* volume 11889, 2020; H Choi and H Varian, 'Predicting the present with Google trends', *Economic record*, volume 88, Issue s1, 2012; OECD (Organisation for Economic Co-operation and Development), *Nowcasting trade in value added,* 2017; K Nguyen and G La Caga, Start spreading the news: news sentiment and economic activity in Australia, RBA Research Discussion Paper RDP 2020-08, 2020; G Kindberg-Hanlon and A Sokol, 'Gauging the globe: the Bank's approach to nowcasting world GDP', Bank of England, Quarterly Bulletin – 2018 Q3, 2018; Bok et al, 'Macroeconomic nowcasting and forecasting with big data', Staff reports, Federal Reserve Bank of New York, November 2017 Number 830.

Skills Tracker

Efforts to map the demand and supply of skills across the labour market have, to date, been limited by the absence of timely, granular data on the supply of skills in the economy. To bridge this gap the NSC, in partnership with the ABS, has developed a linked data set providing comprehensive data on skills supply.

Skills Tracker yields detailed information on the skills of the employed population. More importantly, it indicates the skills of the unemployed population, an Australian first. As new data sets are added, it will also indicate the flow of skills coming from tertiary education.

The outputs of Skills Tracker are combined with the ASC to provide information on skills profiles at the occupation level as well as on skill clusters at the economy-wide level.

There is more detail on Skills Tracker analysis in Chapter 4.

Emerging and trending skills

To identify how emerging and trending skills are changing jobs in the labour market, the NSC has analysed real-time data on job advertisements in Australia from Burning Glass Technologies. Because data and digital skills dominate the fastest growing emerging skills, the NSC has examined digital skills sought by employers from job advertisements in other countries such as Singapore and the United States. This provides a measure of how well Australia is faring in the international digital skills market.

There is more detail on emerging and trending skills in Chapter 7.

COVID-19 scenario modelling

The NSC has undertaken modelling to further help understand the nature of the jobs and skills recovery from COVID-19. The purpose of this modelling is to examine the impact on occupations, industries and skills as we move further through recovery. By examining a range of scenarios, we can see what might be common across different recovery paths and where the differences might lie.

02

The Australian labour market to 2020

The Australian labour market to 2020

The Australian labour market has been transformed over the past 40 years.

There has been strong growth in higher skill level jobs, non-routine jobs and services jobs, and growing use of automation. These changes have also been reflected at both the occupation and industry level.

Alongside the changes in the types of jobs and the skills they require there have been enduring structural changes. Female employment and participation have grown strongly; and in response to higher skills needs, young people are spending longer in education.

These structural changes have been influenced by broad social and institutional changes. Workplaces have become more flexible, parents have greater access to child care, gender roles are changing and fertility rates have fallen.

STEM skills (science, technology, engineering and maths) are an integral part of Australia's labour market, which have helped facilitate the emergence of more complex, innovative work in many industries. Over the 20 years to February 2020, before the impact of the COVID-19 pandemic on the labour market, employment in STEM occupations grew by 85.0%. This is more than twice as fast as non-STEM occupations (which grew 40.2%).

On the whole, the labour market has responded well to these changes and to the shock of the COVID-19 pandemic.

Even so, these changes have repercussions for traditionally disadvantaged cohorts such as youth and the long-term unemployed.

The first section of this chapter, on the changing shape of the workforce, takes a 40-year view, as many important changes are more apparent from this vantage point. It describes the historical performance of the labour market until early 2020, before the COVID-19 shock hit the labour market.

The chapter then reviews the changes in the skills mix and occupations mix of the Australian labour force over the past 20 years. Structural change has facilitated considerable evolution of the needs of industry, as well as those skills used by workers. These structural shifts, together with several large economic shocks, have also been the catalyst for the decline in the availability of a number of lower-skilled entry-level jobs. This has encouraged younger people to seek greater levels of education to improve their job prospects.

The effects of migration in this context are also significant, boosting labour force participation and increasing the diversity of the workforce.[2] In recent decades, net overseas migration has been a key driver of population growth and since 2005-06 has consistently contributed more to population growth than has natural increase. The composition of the migrant intake is also an important consideration, with the refocusing of Australia's migration program to target skilled migrants resulting in the permanent skilled intake being almost five times as large in 2020 as it was in 1996.[3] The rationale for this shift is that younger and more skilled migrants are best placed to make a positive economic contribution to Australia.[4]

The next section discusses changes in the shape of Australian industry. These changes have been more marked over the past 20 years, so the discussion of these trends begins in 2000. There are case studies of two industries: health care and social assistance, and manufacturing.

Automation has also affected the labour market over the past several decades and will continue to do so in the years ahead. Greater use of technology has changed many jobs and encouraged growth in higher skilled jobs. The chapter reviews the effects of increasing automation by looking at jobs according to their level of automatability.

[2] Treasury and Department of Home Affairs, *Shaping a nation*, 2018
[3] Centre for Population, *Population statement*, 2020
[4] Productivity Commission, *Migrant intake into Australia*, 2016

Short-term business cycles and long-term structural change in the labour market

Over recent decades there have been large fluctuations in the strength of the labour market as well as changes in its composition. Some of these changes have been short-lived while others have endured. The short-term changes arise mainly from the fluctuations in the business cycle, while the changes that endure are known as structural changes. The analytical challenge is to separate the two.

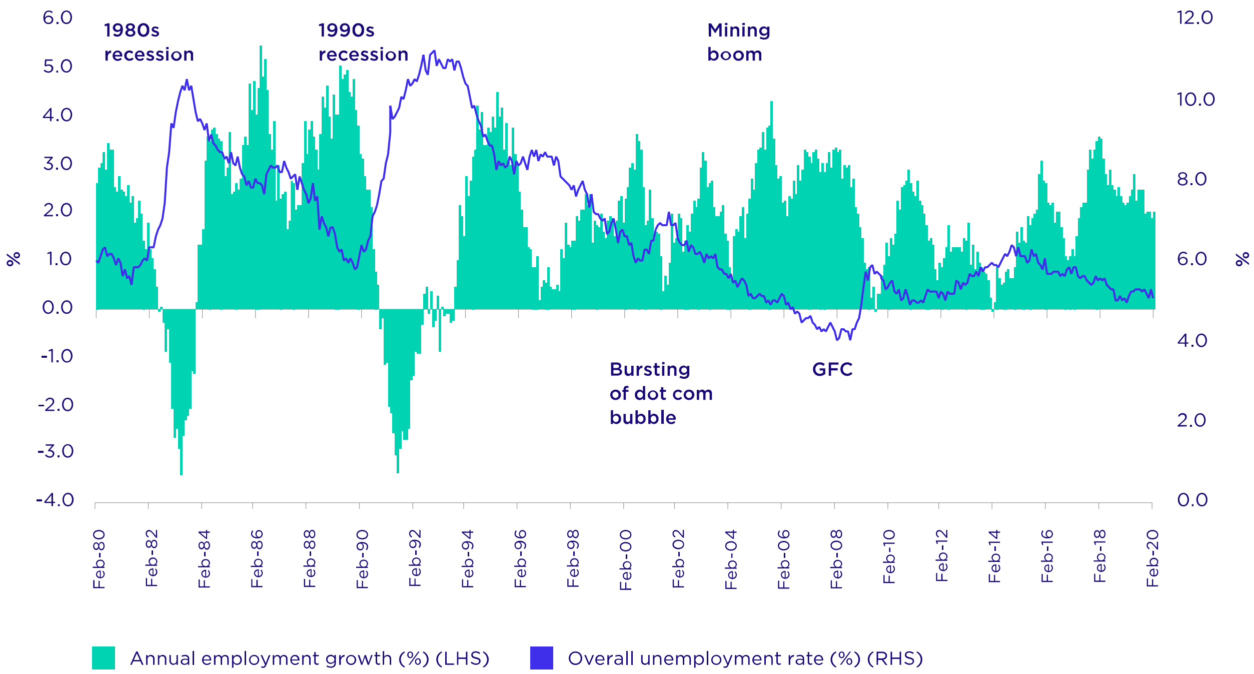
Structural change refers to long-term and persistent shifts in the composition of the labour market or economy. There are many different factors that can cause these shifts, such as the international economic environment, technological change and shifts in societal norms. Although commonly viewed as a shift in the composition of industries or occupations, structural change can also refer to other observable shifts in the labour market or economy, such as the continuing rise in female labour force participation or the increase in those aged 15 to 24 years who are remaining in education.

Increased global competition and advances in technology have led to considerable growth in occupations that require higher-level cognitive skills and that are not easily replicated by machines. These skills include social skills, emotional intelligence, creativity and advanced reasoning.

Although structural change in the labour market is an inevitable process as the economy grows and evolves, it is difficult to measure in real-time and considerably easier to observe retrospectively.

Over the last several decades, structural change in the economy, together with a number of economic shocks and associated movements in the business cycle, have resulted in some sizeable fluctuations in overall labour market activity. During economic downturns, the unemployment rate has tended to ratchet up quickly and the pace of employment growth has tended to slow. During periods of economic recovery, employment growth has strengthened but the unemployment rate has tended to decline slowly.

Figure 4: Unemployment rate and annual employment growth, February 1980 to February 2020



Source: ABS, *Labour force, Australia,* seasonally adjusted

For instance, as Figure 4 shows, between December 1989 and the peak of the 1990s recession in December 1992, employment fell sharply, at an annual average rate of 1.0%. Full-time employment also plummeted, at an annual average rate of 2.1%. As a result, the unemployment rate in Australia rose appreciably, from a pre-recession trough of 5.8% in December 1989, to a peak of 11.2% in December 1992.

After the low point of the 1990s recession the pace of employment growth recovered strongly, in line with the robust global recovery. Between December 1992 and August 2003 employment increased at an annual average pace of 2.0%. But even against this positive backdrop, it took well over a decade for the unemployment rate to return to its pre-recession rate of 5.8% in August 2003.

From 2003 the unprecedented impact of the mining boom on economic growth and labour market activity in Australia was clearly evident. The consequent flow-on effects on the labour market were also substantial, with the pace of employment growth averaging 2.5% over the five years to 2008, while the unemployment rate declined to a trough of just 4.0% in August 2008, prior to the onset of the global financial crisis (GFC) in September 2008.

The shock of the GFC also had a significant, albeit temporary, impact on economic and labour market conditions in Australia. The unemployment rate increased to a peak of 5.9% in June 2009, while employment growth was flat over the year to August 2009, compared with the robust growth of 3.3% over the year to February 2008, just prior to the GFC.

The Australian economy and labour market weathered the fallout from the GFC much better than most advanced economies, buoyed by strong demand from Asia for our resource commodities and the ongoing, positive impact of expansionary fiscal and monetary policies. In addition, Australian employers responded flexibly to the difficult economic circumstances during the global recession by reducing the average hours worked by their staff, rather than shedding employees, which mitigated the upward pressure on the unemployment rate, at least to some extent. This also meant that employers were able to swiftly reinstate employee hours when economic conditions recovered, which they did relatively quickly. Employment rose at an annual average rate of 2.0% over the two years to September 2011.

From 2011 to 2015, after the mining boom ended, global prices for bulk commodities fell sharply, which led to a substantial decline in export revenues and a significant fall in the terms of trade.[5] This had a significant impact on the Australian economy and labour market, with the pace of employment growth softening considerably and the unemployment rate rising, to a high of 6.4% in October 2014. Although labour market conditions were mixed between 2014 and 2016, the following period was, in the main, marked by reasonably strong labour market activity, with employment increasing at an annual average rate of 2.5% over the three years to February 2020, while the unemployment rate declined to 5.1% just prior to the onset of the COVID-19 pandemic.

[5] The bulk commodities referred to here consist of iron ore and coking coal, which are both used in steel production, and thermal coal, used in energy production.

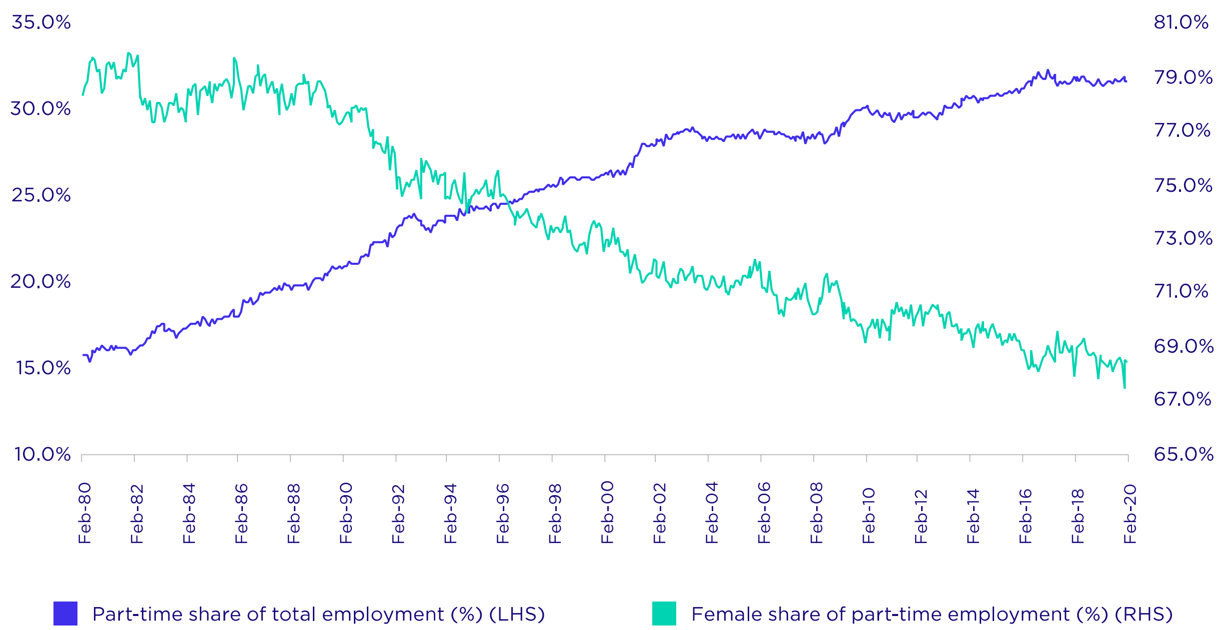
The rise in part-time employment

The part-time share of total employment rose significantly in Australia over the 40 years to February 2020, effectively doubling from just 15.7% of total employment in February 1980 to 31.8% (see Figure 5).[6]

After increasing relatively consistently throughout the 1980s and 1990s, the part-time employment share essentially plateaued during the mining boom, declining slightly, from 28.6% in September 2003 to 28.4% in September 2008 at the onset of the GFC. This was not surprising as mining is predominantly a full-time employing industry. Reflecting the strong rise in mining employment during this period, as well as the surge in construction employment associated with the labour-intensive construction phase of the mining boom, full-time jobs growth was robust, increasing at an annual average rate of 2.8%.

After the onset of the GFC towards the end of 2008, however, the part-time share of employment increased considerably, as employers initially chose to hoard labour and reduce the hours of their existing employees rather than lose staff. Since then, the part-time share of employment has generally been trending upwards.

Figure 5: Part-time share of total employment and female share of part-time employment, February 1980 to February 2020



Source: ABS, *Labour force, Australia,* seasonally adjusted

There are a number of demand, supply and institutional factors which can explain the rise in part-time employment in Australia over the past four decades. On the demand side, a greater requirement by employers for flexibility, as a result of increased competitive pressures and changes in technology, can explain the emergence of many new part-time jobs. Similarly, the significant growth in service industries and related occupations have also provided more part-time job opportunities.

On the supply side, young people are now remaining in education for longer and are combining study with a part-time or casual job. This is discussed in more detail in the section 'Trends in the youth labour market' later in the chapter.

There has also been a sharp increase in female participation in the labour market. Generally speaking, women are more likely to prefer part-time work than men because it enables them to combine work and family and caring responsibilities (see the section on 'Women' later in the chapter), with a greater proportion of hours spent undertaking caring responsibilities and household chores still being borne by women. In this regard, although the majority of

[6] A person is defined by the ABS as part-time employed if they usually work less than 35 hours a week, in all jobs.

part-time employment is still accounted for by females (68.4% in February 2020), this share has fallen, from 78.3% in February 1980. Men are also taking on more part-time jobs than they did several decades ago. In February 2020, 19.1% of male employment was comprised of part-time jobs, compared with just 5.4% in February 1980. Although a proportion of this may be involuntary, a portion may also be due to the fact that men are now more likely to take on home duties or caring responsibilities than they did decades ago.

Finally, as people are now living longer, there has also been a rise in mature-age participation, with older Australians more likely to work part-time and for much longer as they transition to retirement.

Although the impact of institutional forces on the growth of part-time work is more difficult to discern, one obvious factor to consider is the conditions of part-time work, which are likely to have influenced employers' and employees' decisions to pursue part-time work. A number of reforms to Australia's workplace relations laws (such as the *Fair Work Act 2009*) have increased the legal requirement for employers to provide flexible working arrangements, to cite one example.

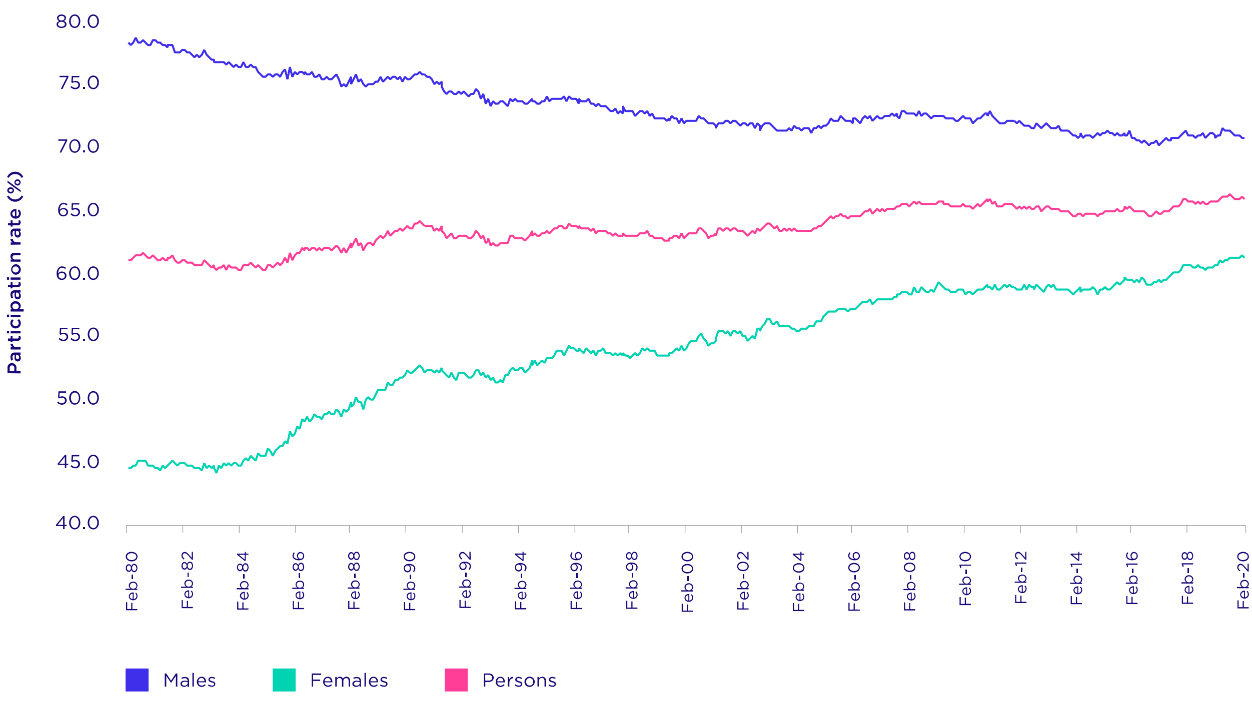
The substantial and sustained growth of part-time work in Australia, however, does suggest that the role of institutions has probably been subsidiary to the broader sweep of supply and demand forces noted above. Although institutions have undoubtedly had some impact on the growth of part-time work, it appears more likely that institutional change has in large measure responded to, and been driven by, changes in the structure of the workplace.

Trends in labour force participation by gender

Women

One of the most significant developments in the Australian labour market over the past 40 years has been the dramatic rise in female labour force participation. This sharp increase was particularly apparent in the 1980s and 1990s, but the upward trend continued over the 20 years to February 2020 (see Figure 6). The female participation rate rose from 44.4% in February 1980 to 54.0% in February 2000. In the 20 years since, it increased further, to 61.2% in February 2020.

Figure 6: Participation rates by gender, February 1980 to February 2020



Source: ABS, *Labour force, Australia,* seasonally adjusted

The rise in female labour force participation can be attributed to a range of factors. In particular, there has been a considerable shift since the 1970s and 1980s in social attitudes to women working, as well as changes in perceived gender roles, which have facilitated greater participation of women in the labour market across a range of occupations and in positions that were traditionally male-dominated.

Australia's fertility rate has also decreased significantly, from a peak of 3.55 births per woman in 1961, to 1.66 in 2019 (the latest data available from the Australian Bureau of Statistics, or ABS), which has meant that women are currently less likely to leave the labour force to have, and care for, children than they were in the 1960s. Although the fertility rate did temporarily rise, from 1.74 in 2001, to a recent peak of 2.02 in 2008, when the baby bonus and other non-means tested welfare measures were introduced, women with young children now have much greater access to formal child care than they did several decades ago. This, together with an increasing acceptance of women with children remaining in the labour force has also facilitated a rise in labour force participation of mothers with children. In this regard, the participation rate for mothers with children under 15 has risen significantly, from 57.2% in February 1991, to 73.3% in February 2020.[7]

The crude divorce rate (divorces per 1,000 Australian residents) rose considerably in the 1960s and 1970s and peaked at 4.6 per 1,000 in 1976, after the introduction of no-fault divorce. This trend also coincided with a rise in female labour force participation rates, as some single mothers with children had to enter the labour market for financial reasons after separating from their spouses. Many older women also returned to the labour market during this time after a long absence, often when their former spouse had previously been the main breadwinner.

[7] The earliest available data are for January 1991.

The emergence of more flexible working arrangements in Australia also coincided with an increase in female labour force participation. Most workers report that their workplace provides access to carers' leave and permanent part-time employment, while more than half of workers report that their workplace provides paid maternity leave (up from less than 40% in 2002) and around a third report that they can work from home, which is up from around 20% in 2002.[8] This is likely to have increased even further, due to the impact of the COVID-19 pandemic.

The structural change noted earlier has also been another key factor that has contributed to the rise in female labour force participation, with strong growth recorded over recent decades in service-based industries that have traditionally employed a high proportion of women, such as health care and social assistance, and education and training. Service-based industries are also more likely to offer part-time employment, which is attractive to people choosing to balance work with caring responsibilities.

The strong rise in the educational attainment level of women over the last 40 years, together with the recent strong growth in occupations which require degree-level qualifications, have also contributed to the significant increase in female labour force participation. Although the figures are not strictly comparable, ABS data from the *Education and work* survey show that the proportion of women with a bachelor degree or above has increased from just 4.2% in 1982 (when it was well below the 7.5% for men), to stand at 32.6% in 2019, above the 26.7% recorded for men.[9]

Interest rates can also have a significant impact on the female participation rate, as more women tend to participate in the labour force when interest rates are higher in order to help alleviate the greater debt servicing ratios that ensue, in part, because of the emergence of larger family mortgages. For example, the significant increase in home loan interest rates that occurred in the late 1980s, following the lifting of the mortgage interest rate ceiling in mid-1986, also coincided with a rise in female labour force participation over that period. Analysis by the Reserve Bank of Australia has found that higher levels of household debt increase labour force participation in Australia, particularly for women with young children.[10]

Men

The large rise in female labour force participation over the four decades to February 2020 has occurred in conjunction with a clear downward trend in the male labour force participation rate, from 78.2% in February 1980 (when the male-dominated manufacturing industry was the largest employing sector in Australia), to a low of 71.1% in August 2004. From that trough, the mining boom and the related strong economic growth provided solid support for the male labour force participation rate, which rose to 72.8% in January 2011. Since then, however, the male participation rate has fallen to 70.7% in February 2020.

The downward trend in male participation over the past several decades can be attributed to a range of factors, including an increase in the number of reported cases of ill health (own injury or illness, and disability), increased participation in education, structural change away from manufacturing and lower skilled entry-level jobs and, to some extent, the increasing role of males in unpaid domestic work such as home duties, child care and looking after ill people or those with disabilities.

Other factors that have contributed to the decline in the male participation rate include early retirement – due to the difficulties that some mature age men have encountered finding subsequent employment upon retrenchment in industries such as automotive manufacturing.

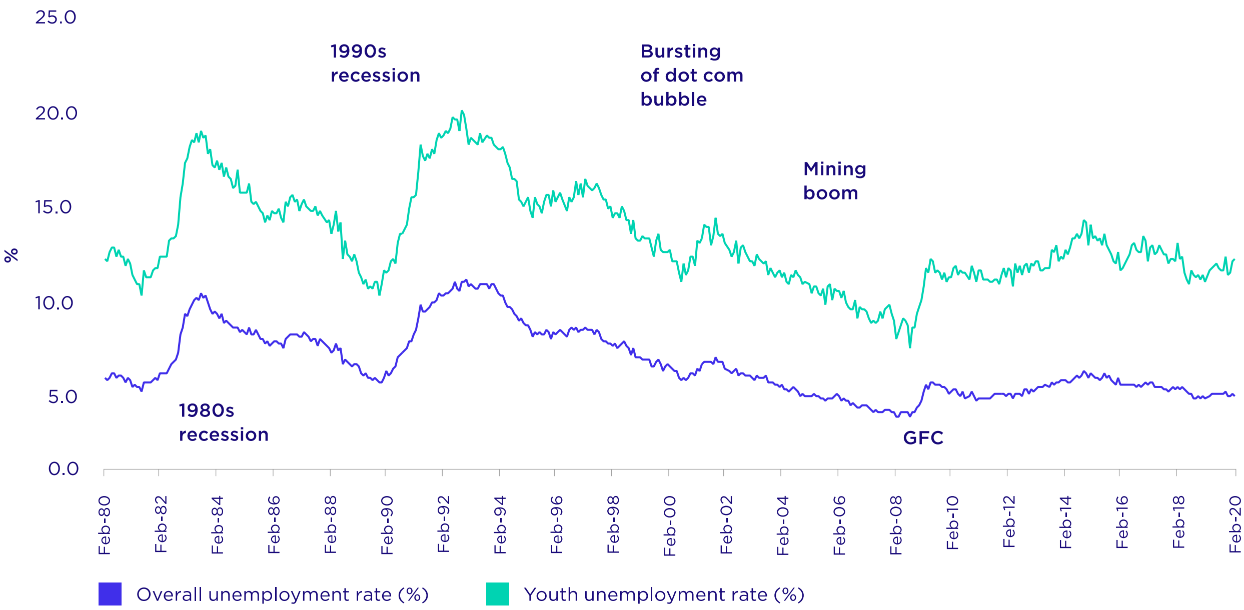
[8] Alexandra Heath, 'The evolving Australian labour market' [speech transcript], Reserve Bank of Australia, 2018. Figures are from have been sourced from *The Household, Income and Labour Dynamics in Australia* (HILDA) Survey, Release 16, Australian Data Archive, 2021.
[9] ABS, *Education and work, Australia*. 1982 data are for women and men aged 15-69 years; 2019 data are for women and men aged 15-64 years. Data are collected in May of each year. The 2019 data were the latest available prior to the onset of COVID-19.
[10] R Belkar, L Cockerell and R Edwards, *Labour Force Participation and Household Debt*, Reserve Bank of Australia 2007-05.

Trends in the youth labour market

Labour market conditions for young people have also been significantly affected by structural change in the economy over the past several decades and also tend to be disproportionately negatively affected by fluctuations in the business cycle. Young people are a traditionally disadvantaged cohort and are particularly vulnerable during periods of economic and labour market softness as they tend to have less education, skills and experience than their prime-age counterparts and are therefore the first to be retrenched by employers in times of economic difficulty.

The youth unemployment rate has been consistently above the overall unemployment rate for the past 40 years and stood at 12.2% in February 2020, more than double the rate recorded for all persons, of 5.1%. Figure 7 shows that the youth unemployment rate also tends to increase to a greater extent during economic downturns and remain elevated for longer, even as overall labour market conditions improve.

Figure 7: Youth (15-24 years) and overall unemployment rate, February 1980 to February 2020



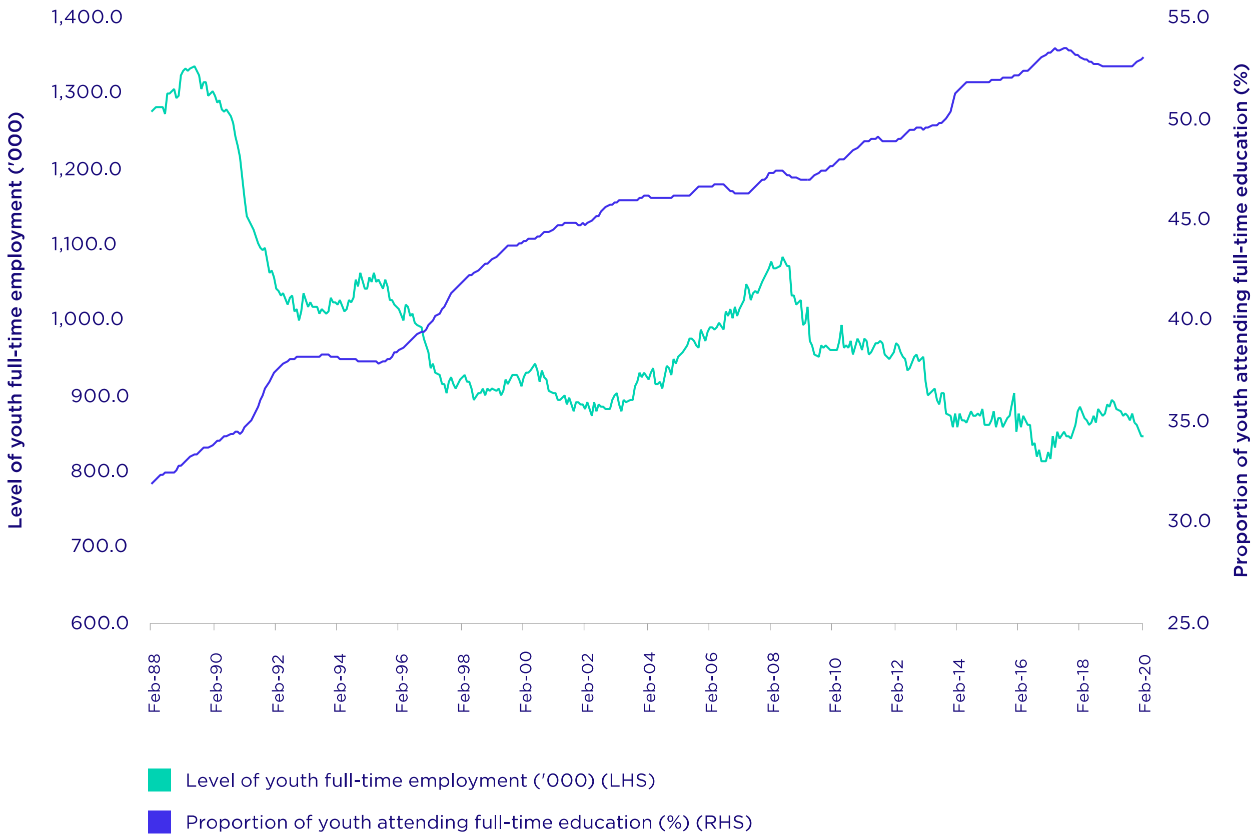
Source: ABS, *Labour force, Australia,* seasonally adjusted

Encouragingly, however, there has also been a considerable rise over several decades in the proportion of young people participating in full-time education, from 31.9% in February 1988, to 53.1% in February 2020 – see Figure 8.[11]
This is significant, given the strong link between higher educational attainment levels and a person's future employment prospects. In this regard, prior to the onset of COVID-19, the unemployment rate for persons aged 15 to 64 years with a bachelor degree or above stood at 2.9%, well below the 6.8% for persons whose highest level of educational attainment was Year 12 or equivalent.[12]

[11] Earliest available 12-month average data for February.
[12] ABS, Education and Work, May 2019.

Although the increase in participation in full-time education for young people continued throughout most of the 1980s, the disappearance of many entry-level jobs during the 1990s recession meant that there was an even greater incentive for young people to either remain in school for longer or enrol in further post-school study. In addition, the structural shift in the economy at that time and advances in technology also resulted in an increase in demand for more highly skilled labour. This became more evident throughout the 2000s.

Figure 8: Youth participation in full-time education and youth full-time employment, February 1988 to February 2020



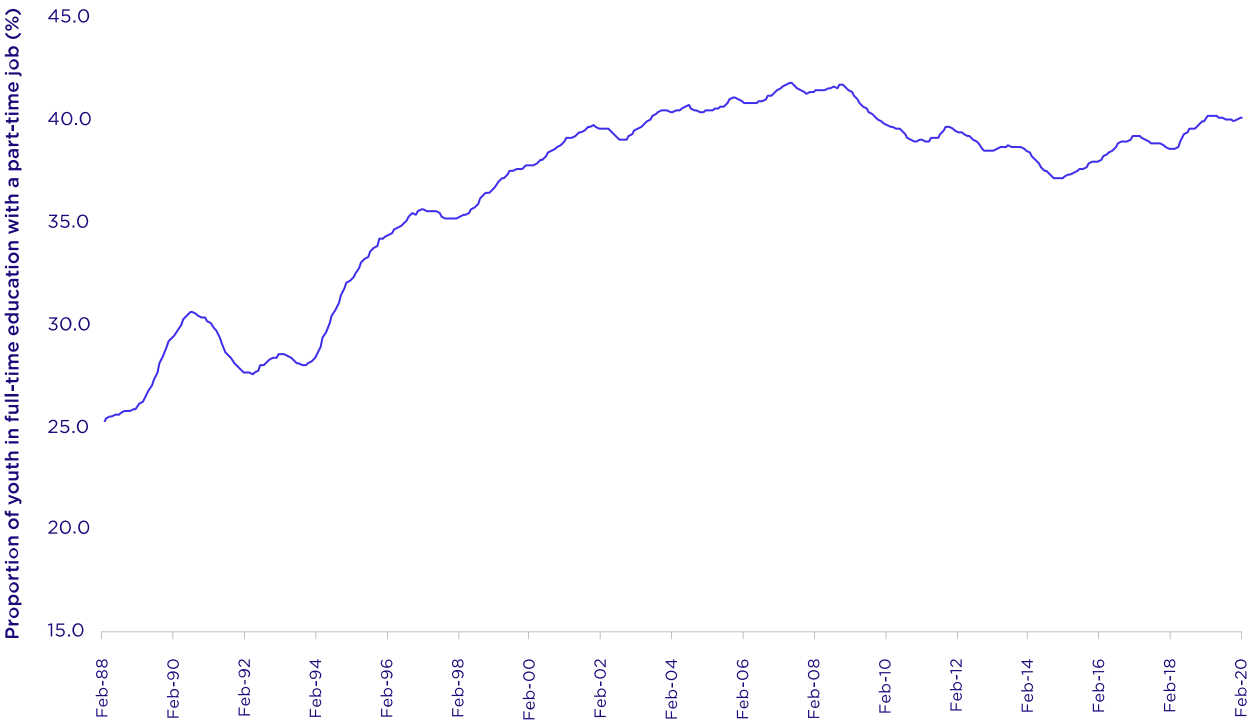
Source: ABS, *Labour force, Australia*. Full-time employment data are in seasonally adjusted terms, while the youth participation in full-time education data are 12-month averages of original estimates.

Figure 8 shows that the sharp rise in youth participation in full-time education, which began in the 1980s and rose again during the 1990s recession, was associated with a significant fall in youth full-time employment. Indeed, youth full-time employment fell by nearly 30%, from a high of 1,410,700 in June 1981 to 998,900 in November 1992 – the peak of the 1990s recession. Notwithstanding some occasional marginal improvements, youth full-time employment continued on a general downward trend until the mining boom in the early 2000s.

During the mining boom there was a period of strong and sustained economic growth, an increase in wages, particularly for low-skilled labour in the resource-rich states, and an overall rise in full-time employment. As a result, full-time employment for the youth cohort also increased, by 22.0%, from 879,100 in September 2001 to 1,072,700 in September 2008 at the onset of the GFC. From that point, full-time employment for young people deteriorated significantly and has failed to recover since. It fell by 225,800 (21.0%) between September 2008 and February 2020.

Another trend over recent decades has been the increased tendency for young people to combine full-time study with part-time work. The proportion of young people in full-time education with a part-time job has risen substantially, from 25.3% in February 1988, to 40.2% in February 2020 – see Figure 9.[13]

Figure 9: Proportion of youth in full-time education with a part-time job, February 1988 to February 2020



Source: ABS, *Labour force, Australia, detailed,* 12-month averages of original estimates

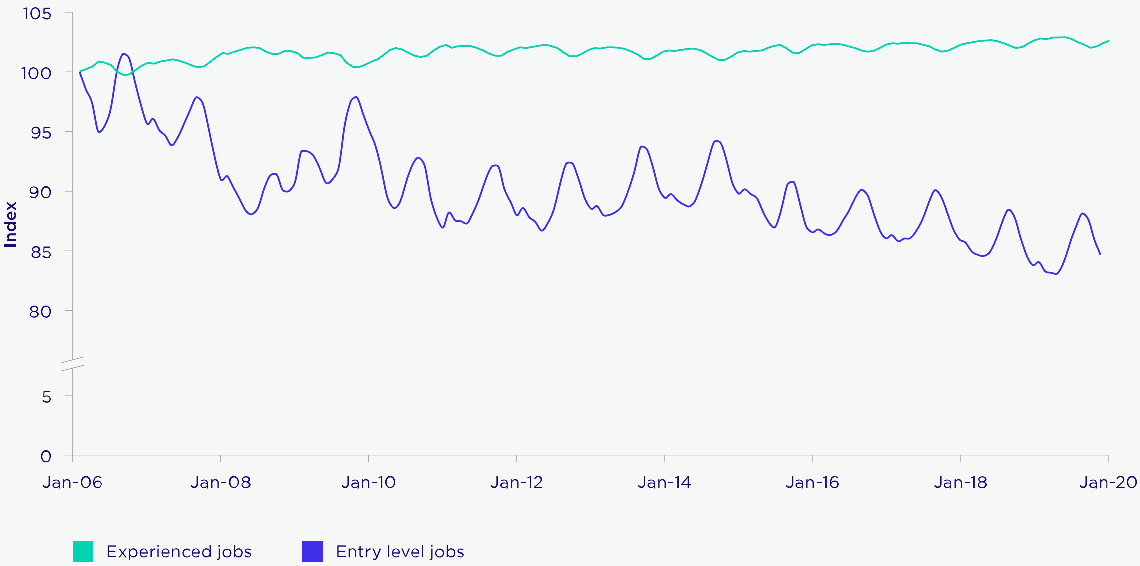
[13] February 1988 is the earliest available 12-month average data for February.

Trends in entry level jobs in Australia

Each year, approximately 300,000 young Australians aged between 15 and 24 years are in the process of transitioning into the full-time workforce. Making this transition successfully is critical to their future career opportunities, income and wellbeing.

To understand the availability of entry level jobs, economics consultancy AlphaBeta created for the NSC an entry level job advertisement index to show the change in the rate of entry level jobs advertised over time.[14] This index shows that the share of entry level jobs advertised decreased between March 2006 and January 2020, compared with the share of jobs advertised for more experienced workers, which increased (see Figure 10).[15] The decline in entry level jobs being advertised was driven by a reduction in job advertisements for the lowest skilled entry level jobs (defined as ANZSCO skill level 5, commensurate with secondary education attainment), which fell by 13%.

Figure 10: Jobs available to experienced and entry-level workers, 2006 to 2020



Sources: NSC, Internet Vacancy Index, ABS, Census (2006, 2011, 2016), ABS, *Labour force, Australia*

Note: The index is constructed to control for the hours worked by young people, fluctuation in overall job advertisements, and the changing composition of occupations that young workers take up.

[14] The proportion of young workers in occupations was calculated during 2008, before the global financial crisis, so the index does not capture the decline in the proportion of young people in jobs over time. AlphaBeta did not analyse if the number of young people working in each occupation is low or high, because if the Australian labour market is efficient the dominant reason would be that a young person isn't able to compete for a job in that occupation, or there is not enough financial incentive for a young person to work in that occupation, given their preferences.
[15] NSC research shows that, in recent years, employers have increasingly used online recruitment methods such as recruitment websites, job boards and social media to advertise vacancies compared with advertising in newspapers. Recruitment websites and online job boards generally have greater coverage for professional and managerial occupations, and as such they may not reflect the full range of entry level opportunities for job seekers.

Young workers have a higher employment share than average in accommodation and food services, retail trade, and arts and recreation services, which have been relatively steadily growing industries over the longer term, particularly before the COVID-19 pandemic. By contrast, older workers have a much larger employment share in faster growing industries such as health care and social assistance, mining, and professional and scientific services. The reasons that young people are entering steadily growing industries are varied. Some young people may choose to take up entry-level jobs in the retail trade industry, for example, because entry-level roles may serve as a stepping stone to other jobs in faster-growing industries and a valuable means of developing skills and accruing experience.

One explanation for the decline in lower skilled occupations employment could be their vulnerability to outsourcing, automation and technological change. For example, six of the ten largest declining occupations over the 30 years to February 2020 were lower skilled (skill levels 4 and 5 occupations). Of these lower skilled occupations, keyboard operators (down by 83,400 or 62.8%) recorded the largest fall in employment over the 30 years to February 2020. They appear to have been displaced by the widespread adoption of technology and software such as personal computing – see Figure 11.

Figure 11: Employment for keyboard operators

Source: ABS, *Labour force, Australia, detailed,* seasonally adjusted by NSC

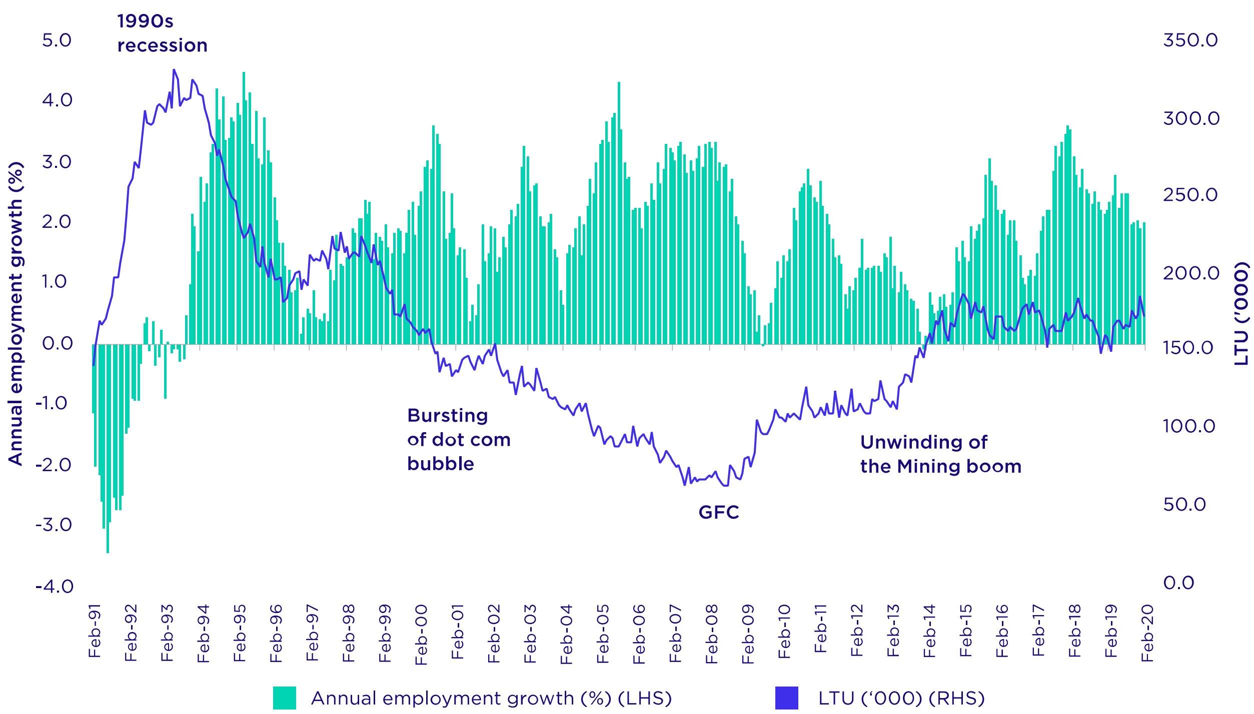
Although the share of employment at the lowest skill level fell over the 30 years to February 2020, against this trend there were some occupations at the lowest skill level that grew strongly. For example, employment for sales assistants (general) recorded the largest increase in employment of occupations at the lowest skill level over the period (up by 168,000 or 48.2%), followed by checkout operators and office cashiers (up by 99,400 or 152.6%), kitchenhands (up by 49,100 or 56.0%) and fast food cooks (up by 40,100 or 322.7%).

The long-term unemployed

Long-term unemployment (LTU) rises during periods of weak employment growth and tends to decline during periods of strong and sustained employment growth.[16] For example, LTU rose sharply during the 1990s recession, to a peak of 331,400 in May 1993 (as shown in Figure 12).

Aside from the rises recorded in the second half of the 1990s and when the dot com bubble burst in the early 2000s, LTU essentially trended downwards after the 1990s recession to reach a trough of 65,200 in June 2007. After the onset of the GFC in September 2008, LTU again rose sharply, by 51,100 (65.7%) in just two years, to stand at 128,900 in October 2010. The unwinding of the mining boom in 2012 led to a further rise in LTU and in February 2020 it stood at 173,400 – 95,600 (122.9%) above the level recorded in September 2008. Although employment increased by 1,081,500 (9.1%) over the four years to February 2020, long-term unemployment also rose, albeit marginally, by 300 (0.2%).

Figure 12: Long-term unemployment and annual employment growth, February 1991 to February 2020



Source: ABS, Labour force, Australia, and ABS, *Labour force, Australia,* detailed, seasonally adjusted

Note: Earliest available comparable LTU data for February is for 1991.

[16] LTU is defined as persons continuously unemployed for 52 weeks or more.

It is also important to consider the damaging impact of hysteresis, or the ratcheting up of LTU, which tends to fall at a much slower rate than overall unemployment. Aside from the obvious social consequences, this also results in a reduction in effective labour supply and the potential productive capacity of the Australian economy.

A high level of long-term unemployment is of concern, as people who have been unemployed for a significant length of time face greater difficulty, on average, finding subsequent work, due to skill depreciation, loss of motivation, screening out by employers and marginalisation from the labour market.

A longer duration of unemployment is also associated with a degrading of human capital and a 'scarring' effect, whereby the long-term unemployed believe their own re-employment prospects are poor.

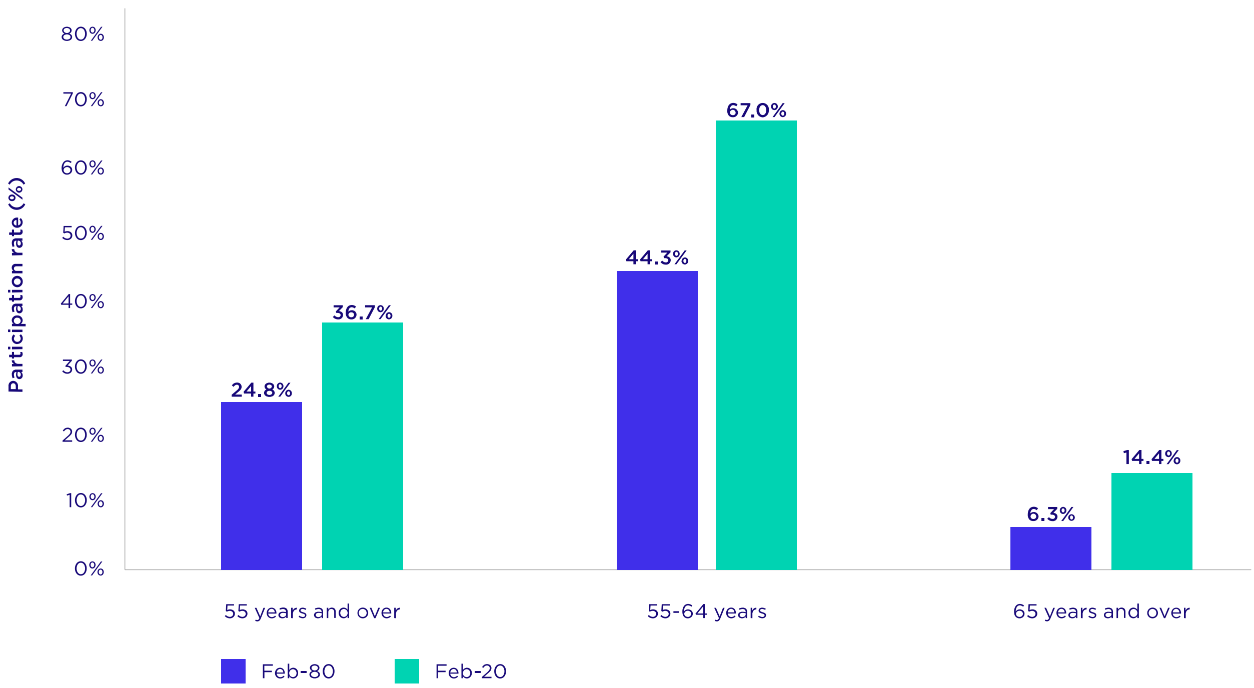
In addition, a sectoral shock (such as the decline in manufacturing jobs and move towards service industries) or technological change following a downturn can result in a greater mismatch between the job vacancies available and the skill level of unemployed persons who could fill them, resulting in fewer exits from LTU. This is because workers who were previously employed in shrinking industries may need to retrain to secure a job in a different industry or occupation – for example, automobile manufacturing workers seeking employment in the health, hospitality and retail sectors.

Mature age people

Another long-term trend and ongoing shift in the Australian labour market has been the increase in the share of older workers. The proportion of total employment accounted for by mature age persons (55 years and over) has increased significantly, from 10.5% in February 1980 to 19.4% in February 2020. This equates to a rise in mature age employment of 1,862,700, or an annual average growth rate of 3.4% over four decades to February 2020. The increase in mature age employment, however, must be viewed in the context of the ageing population, with workers 'taking their jobs with them' as they move into the older age cohort.

The participation rate for persons aged 55 years and over has also risen considerably over this period, from 24.8% in February 1980 to 36.7% in February 2020. Although the majority of this increase has been for persons aged 55 to 64 years, the participation rate for persons aged 65 years and over has also risen over the period, from 6.3% in February 1980, to 14.4% in February 2020, which has coincided with an increase in the average retirement age – see Figure 13. In addition, the rise in the Age Pension eligibility age, which has been slowly increasing (from 65 years, to 67 years on 1 July 2023), could continue to put upward pressure on the participation rate of persons aged 65 years and over.

Figure 13: Participation rates for older people, February 1980 to February 2020



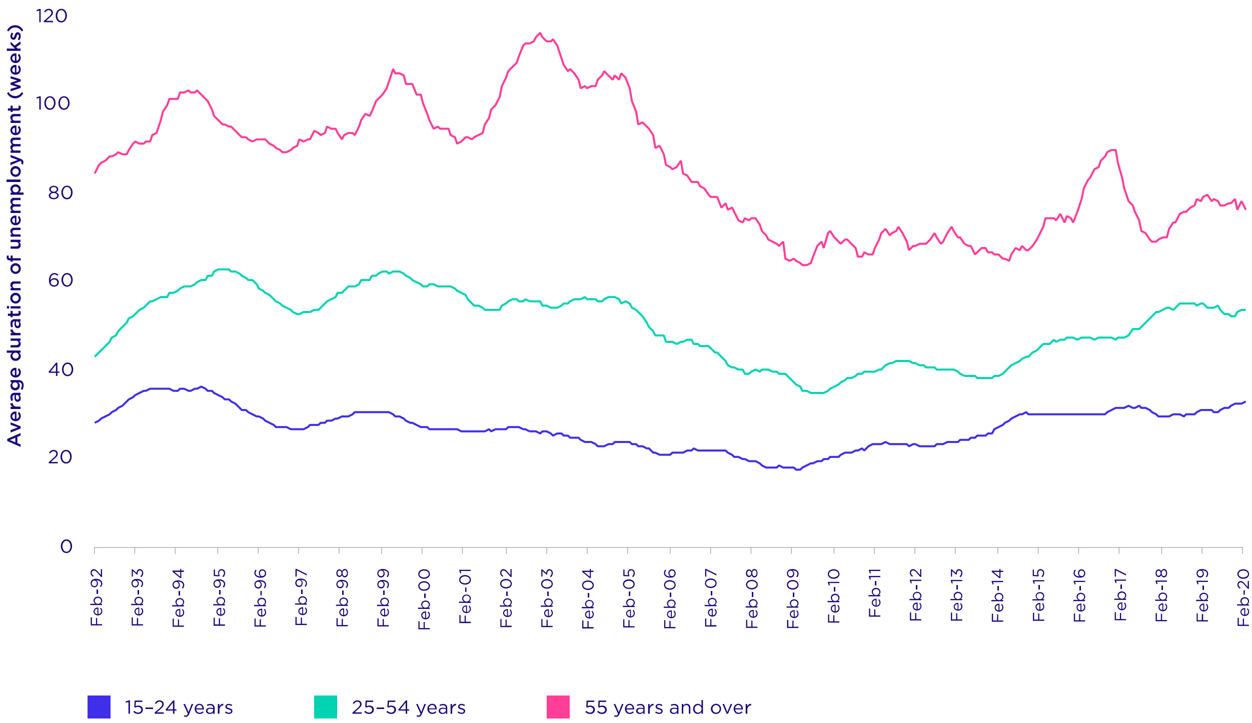
Sources: ABS, *Labour force, Australia,* seasonally adjusted and ABS, *Labour force, Australia, detailed,* three-month averages of original estimates

Other reasons for rising mature age participation include the increase in life expectancy and improved health outcomes, a rise in flexible working arrangements (with mature age people working part-time as they transition to retirement) and an increase in less physically demanding work (due to new technologies).

The mature age unemployment rate has also tended to move with the business cycle over the past four decades, although mature age persons have traditionally recorded a lower unemployment rate than their prime age counterparts. The mature age unemployment rate reached a peak of 10.6% in December 1993 after the 1990s recession, and was on a downward trajectory until it reached a trough of 2.0% in August 2008, prior to the GFC. After that, the mature age unemployment rate rose to 3.6% in February 2020.

Despite recording a lower unemployment rate than other age cohorts, older people continue to have far greater difficulty finding subsequent employment upon becoming unemployed, compared with their younger counterparts. In February 2020, mature age persons had an average duration of unemployment of 76 weeks, compared with 33 weeks for youth and 54 weeks for persons aged 25 to 54 years – see Figure 14.

Figure 14: Average duration of unemployment for mature age people, people aged 15 to 24 and people aged 25 to 54 years, February 1992 to February 2020



Source: ABS, *Labour force, Australia, detailed,* 12-month averages of original estimates

Note: Earliest available data for February in 12-month average terms is for 1992.

Industry analysis

By contrast with the large trends apparent in the labour market over the 40 years to February 2020, industry employment trends became more marked over the 20 years to February 2020. During the later period, trends such as the shift in employment away from manufacturing to service-based industries have become particularly pronounced.

This section focuses on pre-COVID-19 employment dynamics for the 20-year period to February 2020. For more analysis of structural change in the labour market, including the effects on industry, occupation and skill level of employment from COVID-19, see Chapter 3.

Over the 20 years, before the impact of COVID-19 on the labour market, employment increased strongly, up by 4,230,700 or 48.3%. Figure 15 shows that at an industry level, this growth was reflected in some key compositional changes to the structure of the labour market. For example, employment grew in 15 of the 19 broad industries as the labour market underwent a continuation of long-term structural change.

Figure 15: 20-year change in employment by industry, February 2000 to February 2020

Source: ABS, *Labour force Australia, detailed,* seasonally adjusted

The health care and social assistance industry recorded the strongest growth of any industry over the 20 years to February 2020, with employment rising by 977,400 (119.4%). The growth recorded over the period saw health care and social assistance move from Australia's third largest employing industry in February 2000 to the country's largest employing industry by February 2020. The share of total employment accounted for by health care and social assistance increased by 4.5 percentage points over that period.

Other labour-intensive service-based industries to record large growth in employment over the 20 years to February 2020 included:

- professional, scientific and technical services – up 601,500 or 106.2%
- education and training – up 506,700 or 81.9%
- construction – up 499,000 or 72.9%
- public administration and safety – up 353,700 or 75.1%.

By contrast, employment growth in production-based industries was weaker or declined. For example, manufacturing was the largest employing industry in Australia 20 years ago, accounting for 12.0% of total employment. Employment in manufacturing decreased by 132,600 (12.6%) over the 20 years to February 2020, while employment across all industries increased by 48.3%. As a result, manufacturing was Australia's seventh largest employing industry at February 2020, accounting for 7.1% of total employment. Despite the long term decline recorded in the industry, manufacturing remains a large employing industry within the Australian economy, with 922,800 workers at February 2020.

Table 1 shows that as well as manufacturing, three other industries recorded falls in employment over the 20 years to February 2020:

- agriculture, forestry and fishing – down 109,700 or 25.2%
- information media and telecommunications – down 5,500 or 2.5%
- wholesale trade – down 4,200 or 1.1%.

Table 1: 20-year change in employment by industry, February 2000 to February 2020

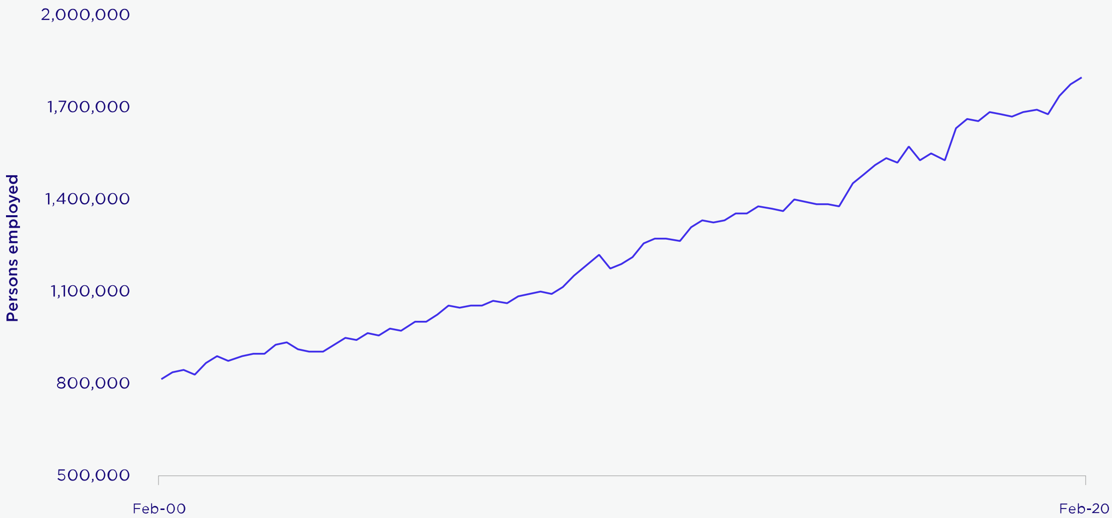
Industry	Employment Feb-2020	20-year change in employment		Change in total employment share (% pts) 20 years to Feb-2020
		(no.)	(%)	
Agriculture, Forestry and Fishing	324,900	-109,700	-25.2%	-2.5%
Mining	241,500	157,200	186.4%	0.9%
Manufacturing	922,800	-132,600	-12.6%	-4.9%
Electricity, Gas, Water and Waste Services	132,800	55,800	72.4%	0.1%
Construction	1,183,500	499,000	72.9%	1.3%
Wholesale Trade	390,600	-4,200	-1.1%	-1.5%
Retail Trade	1,244,400	251,700	25.4%	-1.7%
Accommodation and Food Services	937,300	339,700	56.9%	0.4%
Transport, Postal and Warehousing	648,300	212,600	48.8%	0.0%
Information Media and Telecommunications	216,400	-5,500	-2.5%	-0.9%
Financial and Insurance Services	466,800	130,400	38.8%	-0.2%
Rental, Hiring and Real Estate Services	219,800	83,100	60.8%	0.1%
Professional, Scientific and Technical Services	1,168,000	601,500	106.2%	2.5%
Administrative and Support Services	434,600	126,300	41.0%	-0.2%
Public Administration and Safety	824,600	353,700	75.1%	1.0%
Education and Training	1,125,100	506,700	81.9%	1.6%
Health Care and Social Assistance	1,795,800	977,400	119.4%	4.5%
Arts and Recreation Services	247,900	106,100	74.8%	0.3%
Other Services	489,200	81,200	19.9%	-0.9%
All Industries	**13,011,700**	**4,238,700**	**48.3%**	**N/A**

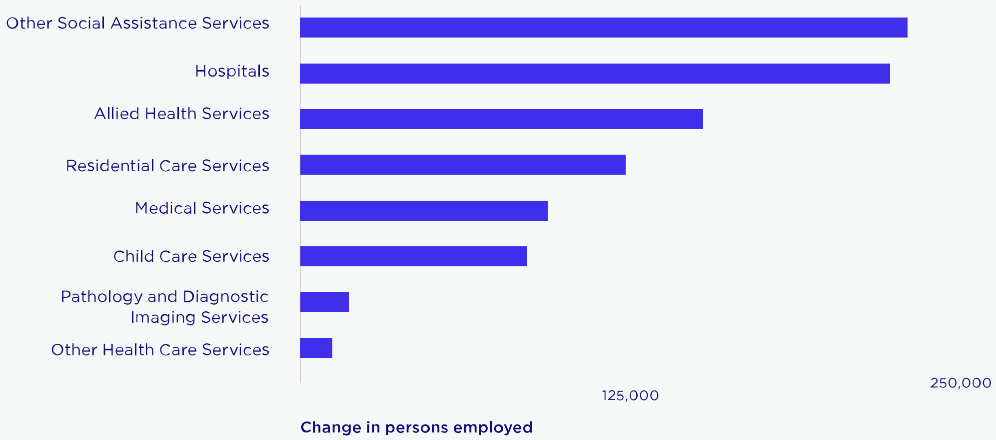
Source: ABS, *Labour force Australia, detailed,* seasonally adjusted

Health care and social assistance

All sectors (ANZSIC 3-digit industry groups) within the health care and social assistance industry increased in employment over the 20 years to February 2020. Employment growth in the industry is underpinned in the longer term by ongoing population growth and an ageing population, as well as more recently the roll out of the National Disability Insurance Scheme.

Figure 16: Health care and social assistance, 20-year employment growth and sector composition of growth, February 2000 to February 2020





Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC

Figure 16 shows that the largest sectoral increase in employment within the health care and social assistance industry over the 20 years to February 2020 was recorded in 'other social assistance services', with employment in the sector tripling over the period (up by 229,100 or 200.6%). The 'other social assistance services' sector includes employment in adoption services, youth welfare services, disabilities assistance services, welfare counselling, and aged care assistance services.

As Table 2 shows, other sectors that recorded strong employment growth over the 20 years to February 2020 included hospitals (up by 222,300 or 82.0%), allied health services (up by 151,700 or 156.7%), residential care services (up by 122,300 or 88.8%) and medical services (up by 93,300 or 102.5%).

As at February 2020, the hospitals sector was the largest employing sector in health care and social assistance (employing 493,300, or 28.1% of total employment in the industry), followed by 'other social assistance services' (employing 343,300 or 19.6%) and residential care services (employing 259,900 or 14.8%).

Table 2: Health care and social assistance, 20-year change in employment by sector

Sectors (ANZSIC 3-digit)	Employment Feb-2020	Share of Industry Employment Feb-2020	20-year change in employment	
			(no.)	(%)
Hospitals	493,300	28.1%	222,300	82.0%
Medical Services	184,200	10.5%	93,300	102.5%
Pathology and Diagnostic Imaging Services	48,800	2.8%	22,400	84.6%
Allied Health Services	248,500	14.2%	151,700	156.7%
Other Health Care Services	29,000	1.7%	14,400	98.6%
Residential Care Services	259,900	14.8%	122,300	88.8%
Child Care Services	146,100	8.3%	81,800	127.1%
Other Social Assistance Services	343,300	19.6%	229,100	200.6%

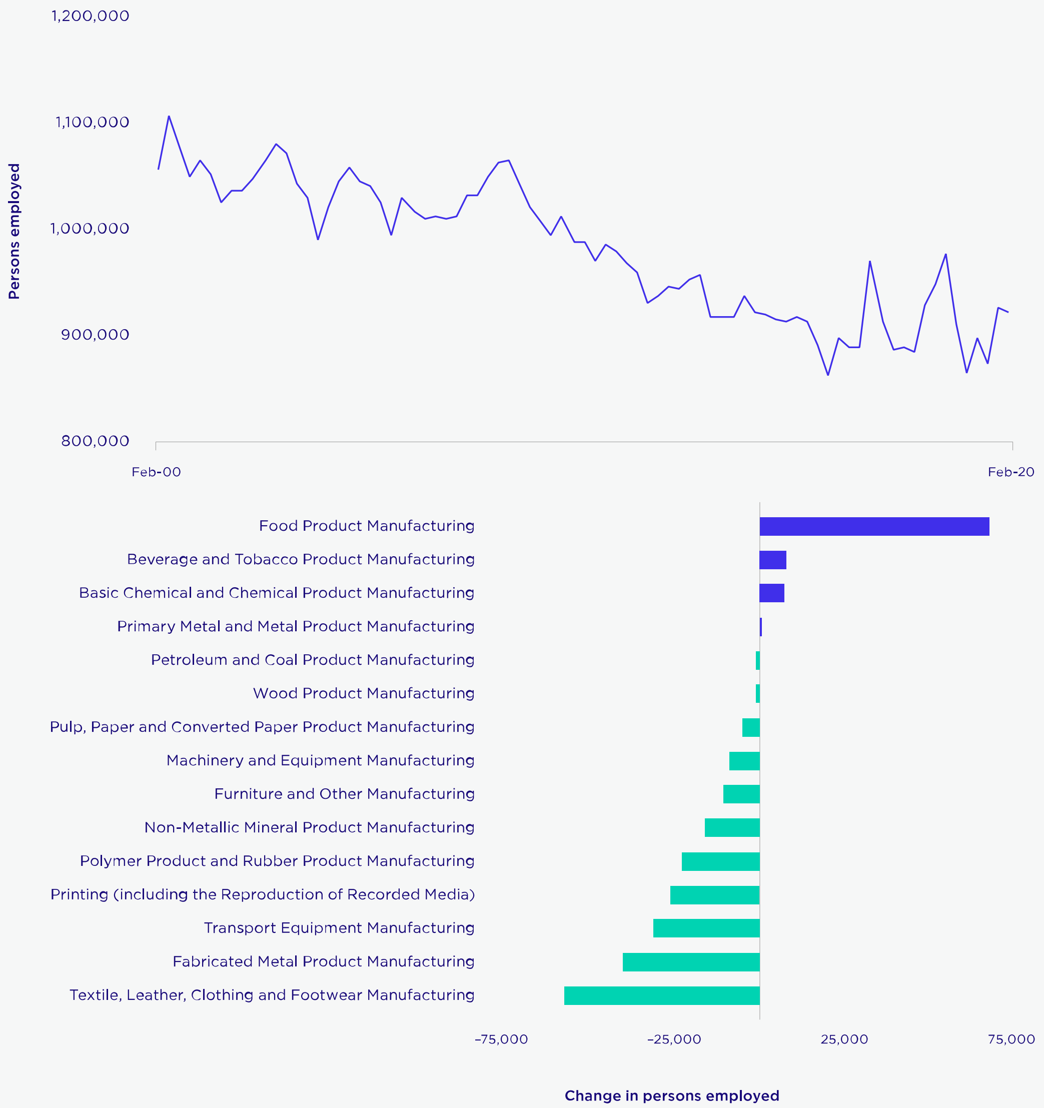
Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC

Manufacturing

Figure 17 shows that the majority (11 out of 15) sectors within the manufacturing industry recorded declining employment over the 20 years to February 2020.[17] Various factors have contributed to the trend of declining employment in such production-based industries, including strong global competition, offshore processing of natural resources and an increase in the capital intensity of production in the industry due to increased automation.

There has also been a change in the nature of manufacturing activity in Australia, with a recent focus on adding more value in pre-and post-manufacturing activity, such as research and development, design, sales and after-sales service.[18]

Figure 17: Manufacturing, 20-year employment growth and sector composition of growth, February 2000 to February 2020



Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC

[17] ANZSIC 2-digit group are described as 'sectors' for the manufacturing industry, differing from the 3-digit level of detail used to describe sectors for all other industries. This is due to the large number of ANZSIC 3-digit groups (55) contained in manufacturing industry.
[18] Advanced Manufacturing Growth Centre, *Sector competitiveness plan 2020*, 2020

A noteworthy exception to the trend of declining manufacturing employment in the Australian labour market is the food product manufacturing sector, which recorded strong employment growth over the 20 years (up by 66,600 or 39.0%). The beverage and tobacco product manufacturing (up by 7,400 or 31.9%) and basic chemical and chemical product manufacturing (6,800 or 14.0%) sectors also recorded employment growth.

As Table 3 shows, all other sectors within the manufacturing industry recorded declining employment, with over half (57.7%) of the gross decline in manufacturing employment accounted for by the three sectors with the largest declines:

- textile, leather, clothing and footwear manufacturing – down 57,100 or 64.4%
- fabricated metal product manufacturing – down 39,800 or 38.8%
- transport equipment manufacturing – down 30,900 or 32.9%.

Table 3: Manufacturing, 20-year change in employment by sector

Sectors (ANZSIC 3-digit)	Employment Feb-2020	Share of Industry Employment Feb-2020	20-year change in employment	
			(no.)	(%)
Food Product Manufacturing	237,400	25.9%	66,600	39.0%
Beverage and Tobacco Product Manufacturing	30,600	3.3%	7,400	31.9%
Textile, Leather, Clothing and Footwear Manufacturing	31,500	3.4%	-57,100	-64.4%
Wood Product Manufacturing	46,400	5.1%	-1,500	-3.2%
Pulp, Paper and Converted Paper Product Manufacturing	19,300	2.1%	-5,300	-21.4%
Printing (including the Reproduction of Recorded Media)	32,700	3.6%	-26,200	-44.5%
Petroleum and Coal Product Manufacturing	8,800	1.0%	-1,500	-14.8%
Basic Chemical and Chemical Product Manufacturing	55,500	6.1%	6,800	14.0%
Polymer Product and Rubber Product Manufacturing	30,800	3.4%	-22,900	-42.7%
Non-Metallic Mineral Product Manufacturing	34,200	3.7%	-16,400	-32.5%
Primary Metal and Metal Product Manufacturing	80,300	8.8%	350	0.4%
Fabricated Metal Product Manufacturing	62,700	6.9%	-39,800	-38.8%
Transport Equipment Manufacturing	63,000	6.9%	-30,900	-32.9%
Machinery and Equipment Manufacturing	112,200	12.3%	-9,100	-7.5%
Furniture and Other Manufacturing	70,400	7.7%	-10,700	-13.2%

Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC

Skill level analysis

Skill level is a concept used in the ABS's ANZSCO classification, which ranks occupations by their range of complexity of performed tasks. ANZSCO skill level is measured by the level or amount of formal education and training, the amount of previous experience in a related occupation, and the amount of on-the-job training required to competently perform the set of tasks required for that occupation.[19]

Analysing employment through a skill level lens is useful in assessing the composition of the labour market as it relates to further education and training. Skill level trends continue to emphasise the importance of further education and training to employment outcomes.

Employment increased across all skill level groups over the 20 years to February 2020. Figure 18 and Table 4 show that, alongside a shift towards a more service-based economy, the Australian labour force has also become much more highly skilled over the past two decades, with employment growth strongest in higher skilled occupations.

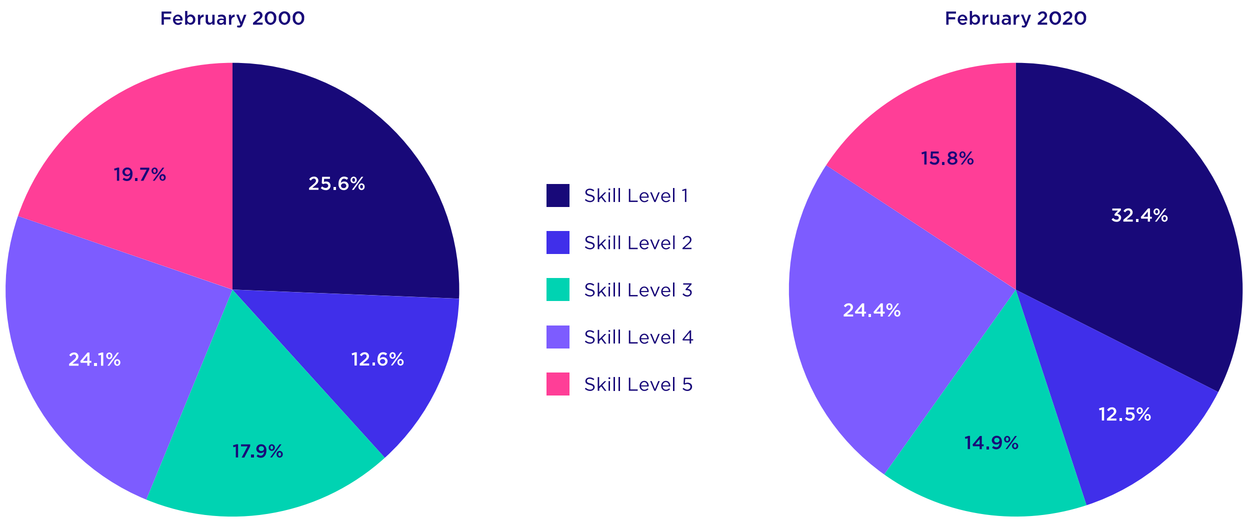
Skill level 1 occupations (the highest skill level group – usually requiring a bachelor degree or higher educational attainment level) accounted for 46.6% of total employment growth over the 20 years to February 2020. By contrast, skill level 5 occupations (the lowest skill level group – usually requiring only a certificate I or secondary education attainment level) accounted for the lowest share (7.5%) of employment growth over the period.

Over the 20 years to February 2020:

- the proportion of total employment accounted for by skill level 1 occupations (commensurate with a bachelor degree or higher educational attainment level) increased by 6.8 percentage points to stand at 32.4% of total employment
- the proportion of total employment accounted for by skill level 5 occupations (commensurate with a certificate I or secondary education attainment level) decreased by 4.0 percentage points to stand at 15.8% of total employment
- the proportion of total employment accounted for by skill level 2 (commensurate with an advanced diploma or diploma educational attainment level) and skill level 4 (commensurate with a certificate II or III educational attainment level) occupations remained relatively consistent, fluctuating less than 0.5 percentage points for both skill level groups. The share of total employment accounted for by these groups stands at 12.5% and 24.4% respectively.
- the proportion of total employment accounted for by skill level 3 (commensurate with a certificate IV or III educational attainment level) occupations decreased by 3.0 percentage points to stand at 14.9% of total employment.

[19] ABS, *ANZSCO – Australia and New Zealand standard classification of occupations*, 2013

Figure 18: Composition of employment by Skill Level Group, February 2000 to February 2020



Sources: ABS, *Labour force, Australia, detailed,* seasonally adjusted by NSC

Table 4: 20-year change in employment by Skill Level Groups

Skill Level Group	Employment Feb-2020	20-year change in employment (no.)	20-year change in employment (%)	Change in total employment share (% pts) 20-years to Feb-2020
Skill Level 1 - Bachelor degree or higher	4,217,700	1,971,400	87.8%	6.8%
Skill Level 2 - Advanced Diploma or Diploma	1,625,500	517,500	46.7%	-0.1%
Skill Level 3 - Certificate IV or III	1,936,700	365,600	23.3%	-3.0%
Skill Level 4 - Certificate II or III	3,169,900	1,061,600	50.3%	0.3%
Skill Level 5 - Certificate I or secondary education	2,048,100	318,700	18.4%	-4.0%

Sources: ABS, *Labour force, Australia, detailed,* seasonally adjusted by NSC

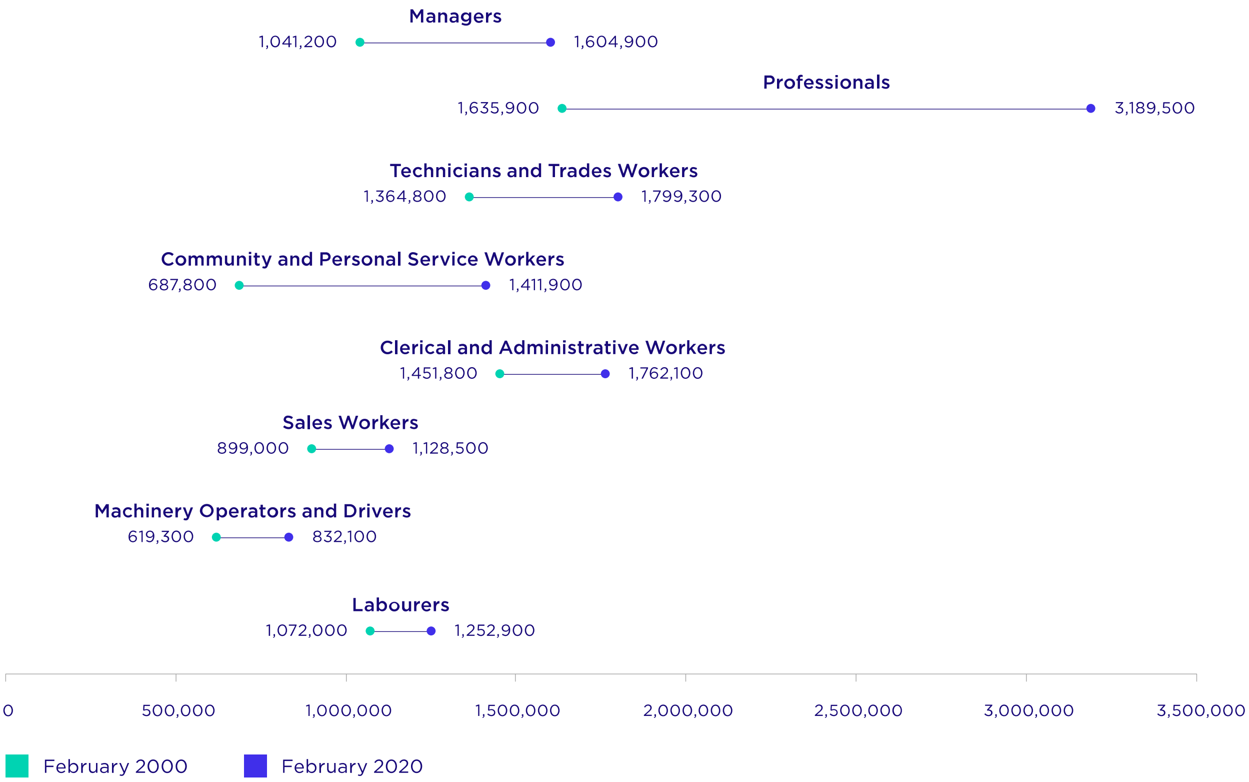
Occupation analysis

Occupations are categorised by ANZSCO using a combination of skill level and skill specialisation as criteria. This framework organises occupations into progressively larger groups across five hierarchical levels, with occupations being the smallest level (of which there are 1023), followed by unit group, minor group, sub-major group and major group (of which there are eight).[20]

As with skill level groups, employment increased across all major occupational groups over the 20 years to February 2020. However, as Figure 19 and Table 5 show, this growth was not evenly distributed, with professionals (up by 1,553,500 or 95.0%) and community and personal service workers (up by 724,100 or 105.3%) accounting for more than half (54.1%) of total employment growth over the period. Consequently, the share of total employment accounted for by professionals and community and personal service workers increased by 5.9 and 3.0 percentage points respectively.

Employment within the professionals and community personal service workers major occupational groups were on average less susceptible to automation compared with the average across all occupations. As at February 2000, the average automatability score for occupations within the professionals occupation group was 2.34, while the average automatability score was 2.44 for community and personal service workers. By comparison, the average automatability score across all occupations was 2.85 as at February 2000. For more on this topic see 'Trends in automatability' later in the chapter.

Figure 19: 20-year change in employment by occupation, February 2000 to February 2020



Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC

[20] ABS, *ANZSCO*, 2013

Table 5: 20-year change in employment by major occupational groups

Occupation	Employment Feb-2020	20-year change in employment (no.)	20-year change in employment (%)	Change in total employment share (% pts) 20-years to Feb-2020
Managers	1,604,900	563,700	54.1%	0.5%
Professionals	3,189,500	1,553,500	95.0%	5.9%
Technicians and Trades Workers	1,799,300	434,500	31.8%	-1.7%
Community and Personal Service Workers	1,411,900	724,100	105.3%	3.0%
Clerical and Administrative Workers	1,762,100	310,400	21.4%	-3.0%
Sales Workers	1,128,500	229,500	25.5%	-1.6%
Machinery Operators and Drivers	832,100	212,800	34.4%	-0.7%
Labourers	1,252,900	180,900	16.9%	-2.6%

Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC

Table 6 shows that at the detailed (ANZSCO 4-digit) occupation level, occupations such as registered nurses, accountants, software applications programmers, advertising and marketing professionals and management and organisation analysts were among the occupations driving the growth in the professionals major occupational group over the 20 years to February 2020.

Table 6: Professionals, largest growth detailed occupations, February 2000 to February 2020

Professionals (ANZSCO Group 2)					
Skill Level	ANZSCO Code	ANZSCO Title	Employment - February 2020	20-year change in employment (no.)	20-year change in employment (%)
1	2544	Registered Nurses	292,500	138,300	89.6%
1	2211	Accountants	179,000	64,800	56.7%
1	2613	Software and Applications Programmers	127,200	61,300	93.2%
1	2251	Advertising and Marketing Professionals	81,700	53,600	191.3%
1	2247	Management and Organisation Analysts	75,600	44,100	139.9%
1	2713	Solicitors	75,600	43,100	132.6%
1	2332	Civil Engineering Professionals	62,800	37,500	148.7%
1	2411	Early Childhood (Pre-primary School) Teachers	49,300	37,000	300.6%
1	2421	University Lecturers and Tutors	68,000	34,900	105.6%
1	2414	Secondary School Teachers	149,300	34,100	29.5%

Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC

Table 7 shows that the drivers of growth in the community and personal service workers major occupational group include:

- aged and disabled carers
- child carers
- nursing support and personal care workers
- education aides and waiters.

Table 7: Community and personal service workers, largest growth detailed occupations, February 2000 to February 2020

Community and Personal Service Workers (ANZSCO Group 4)					
Skill Level	ANZSCO Code	ANZSCO Title	Employment - February 2020	20-year change in employment (no.)	(%)
4	4231	Aged and Disabled Carers	225,300	156,300	226.4%
3	4211	Child Carers	131,400	66,000	101.1%
4	4233	Nursing Support and Personal Care Workers	99,000	62,900	174.4%
4	4221	Education Aides	107,500	60,700	129.4%
4	4315	Waiters	140,400	54,600	63.6%
4	4311	Bar Attendants and Baristas	106,400	45,500	74.7%
2	4117	Welfare Support Workers	67,200	40,900	155.2%
2	4116	Massage Therapists	30,600	24,900	436.8%
4	4521	Fitness Instructors	33,100	24,800	301.6%
3	4511	Beauty Therapists	39,600	24,400	161.8%

Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC.

The weakest employment growth over the 20 years to February 2020 was observed for the labourers and clerical and administrative workers major occupational groups. The share of total employment accounted for by these groups declined by 2.6 and 3.0 percentage points respectively over the period.

Occupations within the labourers and clerical and administrative workers major occupational groups were on average more susceptible to automation compared with the average across all occupations. As at February 2000, the average automatability scores for occupations within the labourers occupational group was 3.06, while the average occupation score for clerical and administrative workers was 3.29. By comparison, the average automatability score across all occupations was 2.85 as at February 2000. For more on this topic see 'Trends in automatability' later in the chapter.

Table 8 shows that within the labourers broad occupational group, 21 of the 44 detailed occupations recorded falls in employment over the period. The largest declines were recorded for crop farm workers, product assemblers and laundry workers.

Within the clerical and administrative workers broad occupational group, 11 of the 33 detailed occupations recorded falls in employment over the period. The largest declines were recorded for secretaries, keyboard operators and personal assistants (see table 9).

Table 8: Labourers, largest declining detailed occupations, February 2000 to February 2020

		Clerical and Administrative Workers (ANZSCO Group 5)			
Skill Level	ANZSCO Code	ANZSCO Title	Employment - February 2020	20-year change in employment	
				(no.)	(%)
2	5212	Secretaries	36,000	-96,100	-72.7%
4	5321	Keyboard Operators	49,400	-83,400	-62.8%
2	5211	Personal Assistants	49,100	-27,300	-35.7%
3	5512	Bookkeepers	88,600	-23,400	-20.9%
3	5521	Bank Workers	54,900	-22,300	-28.9%
5	5616	Switchboard Operators	2,000	-12,600	-86.2%
5	5614	Mail Sorters	8,900	-11,100	-55.6%
4	5511	Accounting Clerks	138,900	-10,000	-6.7%
5	5611	Betting Clerks	2,300	-2,700	-53.2%
4	5994	Human Resource Clerks	13,000	-1,000	-7.3%

Sources: ABS, *Labour force, Australia, detailed,* seasonally adjusted by NSC

Table 9: Clerical and administrative workers, largest declining detailed occupations, February 2000 to February 2020

Labourers (ANZSCO Group 8)					
Skill Level	ANZSCO Code	ANZSCO Title	Employment - February 2020	20-year change in employment (no.)	(%)
5	8412	Crop Farm Workers	23,400	-35,500	-60.2%
5	8322	Product Assemblers	27,200	-23,400	-46.3%
5	8115	Laundry Workers	12,000	-9,100	-43.1%
5	8415	Livestock Farm Workers	37,400	-8,900	-19.2%
5	8392	Plastics and Rubber Factory Workers	2,300	-7,100	-75.7%
4	8995	Printing Assistants and Table Workers	3,300	-4,600	-58.3%
5	8391	Metal Engineering Process Workers	9,600	-4,200	-30.3%
5	8416	Mixed Crop and Livestock Farm Workers	3,600	-3,700	-51.0%
5	8321	Packers	69,100	-3,600	-5.0%
5	8399	Other Factory Process Workers	11,300	-3,300	-22.7%

Sources: ABS, *Labour force, Australia, detailed,* seasonally adjusted by NSC

The previous section examined trends in specific broad occupational groupings. In this section we examine trends across 358 detailed occupations. Overall, employment increased in 265 of the 358 detailed occupations over the 20 years to February 2020. Increases were observed across all broad occupational groups and skill levels. Table 10 shows that the largest growth was recorded for general clerks, followed by:

- aged and disabled carers
- registered nurses
- advertising, public relations and sales managers
- sales assistants (general).

Employment fell in 91 of the remaining detailed occupations over the 20 years to February 2020 and two detailed occupations remained steady. Falls were observed across all broad occupational groups and skill levels over the period, with the largest falls recorded for secretaries, followed by:

- keyboard operators
- mixed crop and livestock farmers
- crop farm workers
- engineering production workers.

Table 10: Largest increasing and declining detailed occupations, February 2000 to February 2020

Skill Level	ANZSCO Code	ANZSCO Title	Employment - February 2020	20-year change in employment (no.)	20-year change in employment (%)
		Largest increasing detailed occupations			
4	5311	General Clerks	328,900	249,700	315.2%
4	4231	Aged and Disabled Carers	225,300	156,300	226.4%
1	2544	Registered Nurses	292,500	138,300	89.6%
1	1311	Advertising, Public Relations and Sales Managers	159,000	99,300	166.4%
5	6211	Sales Assistants (General)	516,800	95,600	22.7%
2	5111	Contract, Program and Project Administrators	122,400	80,500	192.0%
2	3513	Chefs	115,700	79,000	214.9%
2	5121	Office Managers	151,500	72,900	92.7%
3	4211	Child Carers	131,400	66,000	101.1%
1	1331	Construction Managers	115,600	65,500	130.4%
		Largest decreasing detailed occupations			
2	5212	Secretaries	36,000	-96,100	-72.7%
4	5321	Keyboard Operators	49,400	-83,400	-62.8%
1	1214	Mixed Crop and Livestock Farmers	32,600	-53,600	-62.2%
5	8412	Crop Farm Workers	23,400	-35,500	-60.2%
4	7123	Engineering Production Workers	15,400	-31,600	-67.3%
2	5211	Personal Assistants	49,100	-27,300	-35.7%
5	8322	Product Assemblers	27,200	-23,400	-46.3%
3	5512	Bookkeepers	88,600	-23,400	-20.9%
3	5521	Bank Workers	54,900	-22,300	-28.9%
1	1212	Crop Farmers	34,600	-20,800	-37.6%

Sources: ABS, *Labour force, Australia, detailed,* seasonally adjusted by NSC

STEM skills promote innovation

STEM skills (science, technology, engineering and maths) are an integral part of Australia's labour market and enable a range of complex, innovative types of work in many different industries. Digitisation and automation are shaping the composition of the labour market, and the need for workers in higher skill occupations will be greater in coming years. STEM skills are one part of this shift and are at the centre of the knowledge economy. The Department of Industry, Science, Energy and Resources reported in Australia's National Science Statement that businesses that innovate are twice as likely to use STEM skills, and 70% of Australian employers identify STEM-skilled employees as the most innovative.[21] People with STEM skills develop deep discipline knowledge in their respective fields, digital literacy, and the flexibility to pivot their careers to embrace new challenges – important for navigating the changing labour market and changing skills requirements for occupations.[22]

The National Skills Commission has identified 108 'STEM occupations' based on the ABS occupation classification, ANZSCO, at the four-digit level of detail. Latest available ABS *Labour force* survey data, for the February 2021 quarter, show that STEM occupations make up 21.9% of total employment, and over the 20 year period to February 2020, before the impact of COVID-19 on the labour market, employment in STEM occupations grew by 85.0%. This is more than twice as fast as non-STEM occupations (40.2% over the period).

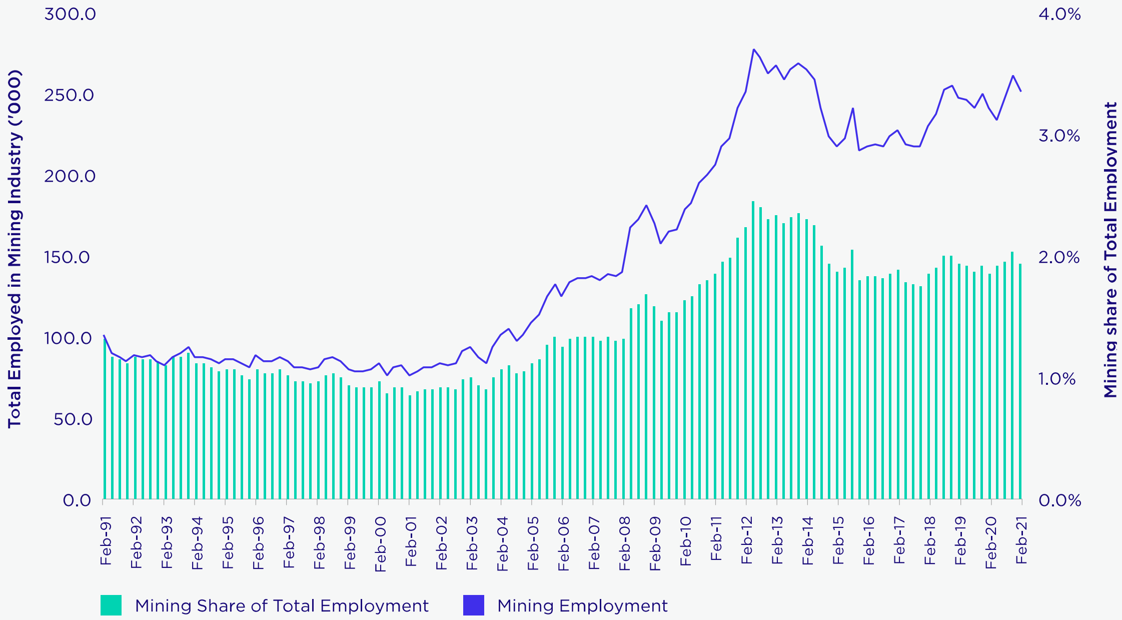
[21] Department of Industry, Science, Energy and Resources, *Australia's national science statement*, 2017.
[22] Office of the Chief Scientist, *Australia's STEM workforce*, 2020.

Temporary shock vs structural change: the mining boom and slowdown

For much of the 2000s, the Australian economy benefitted from increased global demand for resources, in particular strong demand for iron ore from China. This created a boom in mining employment, which rose by 190,100 (228.5%) over the 10 years to August 2012. By comparison, employment across all industries increased by 23.4% over the period.

Figure 20 shows that employment in the mining industry peaked in August 2012 during the mining boom. After the boom there was a slowdown in demand for resources and subsequently employment fell. Employment in the mining industry fell by 55,500 (20.3%) over the five years to August 2017. Although this fall in employment is often characterised as marking the end of the mining boom, employment in the industry has remained strong and at February 2020, prior to the onset of the COVID-19 pandemic, was at 86.8% of peak mining employment levels.

Figure 20: Mining employment over the 30 years to February 2021



Source: ABS, *Labour force, Australia, detailed,* seasonally adjusted

Retrospective analysis of the mining industry illustrates the difficulty in separating a temporary market shock from persistent structural change. Although mining employment fell over the five years to August 2017, since around 2016 the value of Australia's metalliferous ores and metal scrap exports have continued to rise, while the underlying factors which helped drive demand for resources, such as government infrastructure spending and demand for resource intensive technological goods, remain intact and continue to provide a tailwind for employment in the mining industry.

As a result, during the 2012 to 2017 period of softened resource demand it may have appeared that the level of employment in the mining industry was reverting to pre-mining boom levels. However, labour market data released from 2018 onwards have shown that the decline in mining employment over the five years to August 2017 was far smaller than the substantial increase in employment that occurred over the 10 years to August 2012. As at February 2020, the level of mining employment was 186.4% above the level recorded in February 2000. Moreover, the share of total employment in the mining industry nearly doubled from 1.0% to 1.9% over the 20 years to February 2020. It appears that mining employment will continue to remain at elevated levels as long as there is sufficient resource demand.

Trends in automatability over the past 20 years

Automation has also affected the labour market over the past several decades and will continue to do so in the years ahead. The development and use of technology has changed many jobs and encouraged growth in higher skilled jobs. Over the past 20 years, there has been a net increase in jobs that are less easily automated and this trend is likely to continue.

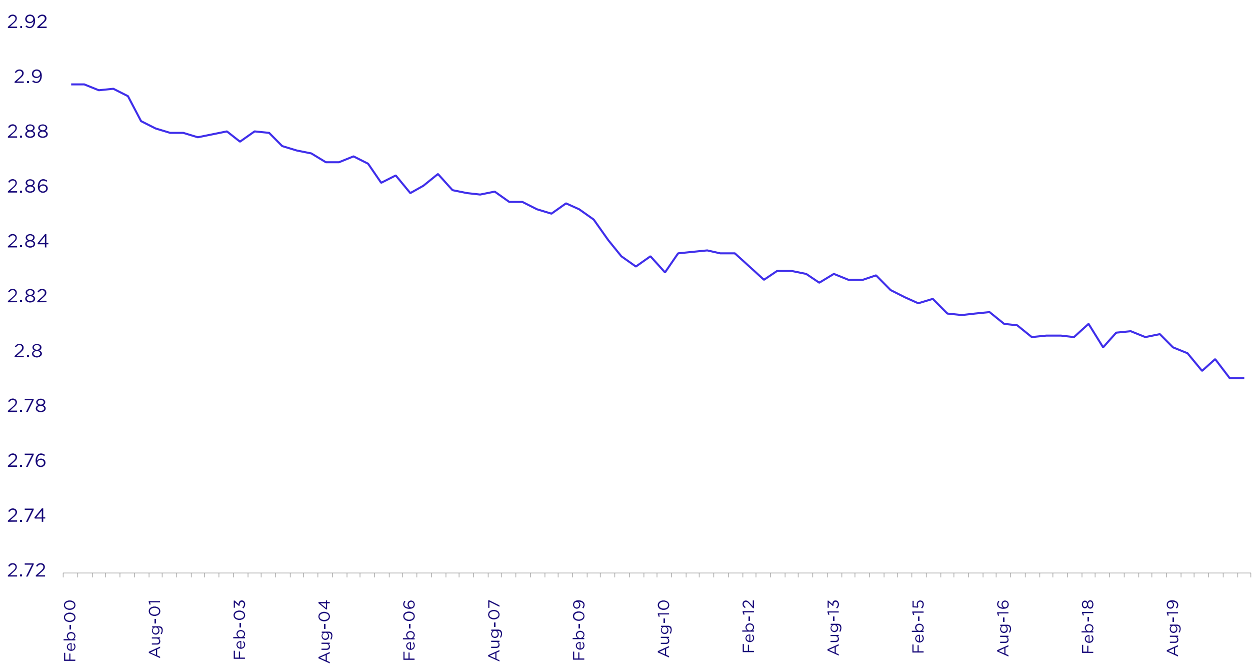
To observe the impact of automation on the labour market, the NSC estimated the average automatability of occupations based on research by Duckworth et al.[23] Using the Work Task Automatability model of the original study, a data set of predicted automatability of direct work activities was concorded to the specialist tasks of around 600 occupations in the ASC.

Based on this concordance, a weighted automatability score was derived for each of these occupations at the ANZSCO 4-digit or ANZSCO 6-digit level. The weighted automatability score is the weight of task automation by proportion of time spent on each task. The automatability score is rated from 1 to 4, with 1 being not at all automatable, and 4 being completely automatable. Further detail on the methodology can be found in Chapter 8 where the Work Task Automatability model is applied to outcomes from the scenario modelling exercises undertaken by the NSC.

Over the past 20 years, there has been a net increase in less automatable jobs. Figure 21 shows the gradual decline in the average weighted automatability score in the labour force with a weighted automatability score of 2.90 in February 2000 and 2.79 in February 2020, accounting for a difference in the score of 0.11over the 20-year period. The average weighted automatability score was derived by combining the weighted score of all occupations by the employment size of each occupation group at any given point in time, at each quarter over the past 20 years.[24]

The model to predict automatability assumes the specialist tasks for each occupation have been consistent over the past two decades. Therefore, the downward trend in the automatability of occupations is likely due to the net increase of occupations with lower weighted automatability scores.

Figure 21: Change in the average weighted automatability score in the labour force, 2000 to 2020



Source: NSC analysis using Duckworth et al.

Occupations with strong growth in employment are relatively less likely to be automated. Figure 22 shows the average weighted automatability score for each occupation group (y-axis) and the change in employment growth over the last 20 years (x-axis). The size of each bubble represents the current employment size of each occupation group as of February 2020.

[23] P Duckworth, L Graham and MA Osborne, 'Inferring work task automatability from AI expert evidence', [conference paper], AIES '19 (Artificial intelligence, ethics, and society), Honolulu, 2019.
[24] This differs from the 2.85 score cited in the 'Occupation analysis' section earlier in this chapter, as analysis in that section is limited to the ANZSCO 4-digit level of detail.

The 23 occupation groups are based on the NSC occupation matrix.[25] The average weighted automatability score for each occupation group was based on the weighted average of each occupation (at the ANZSCO 4/6 digit level) underlying each occupation group.

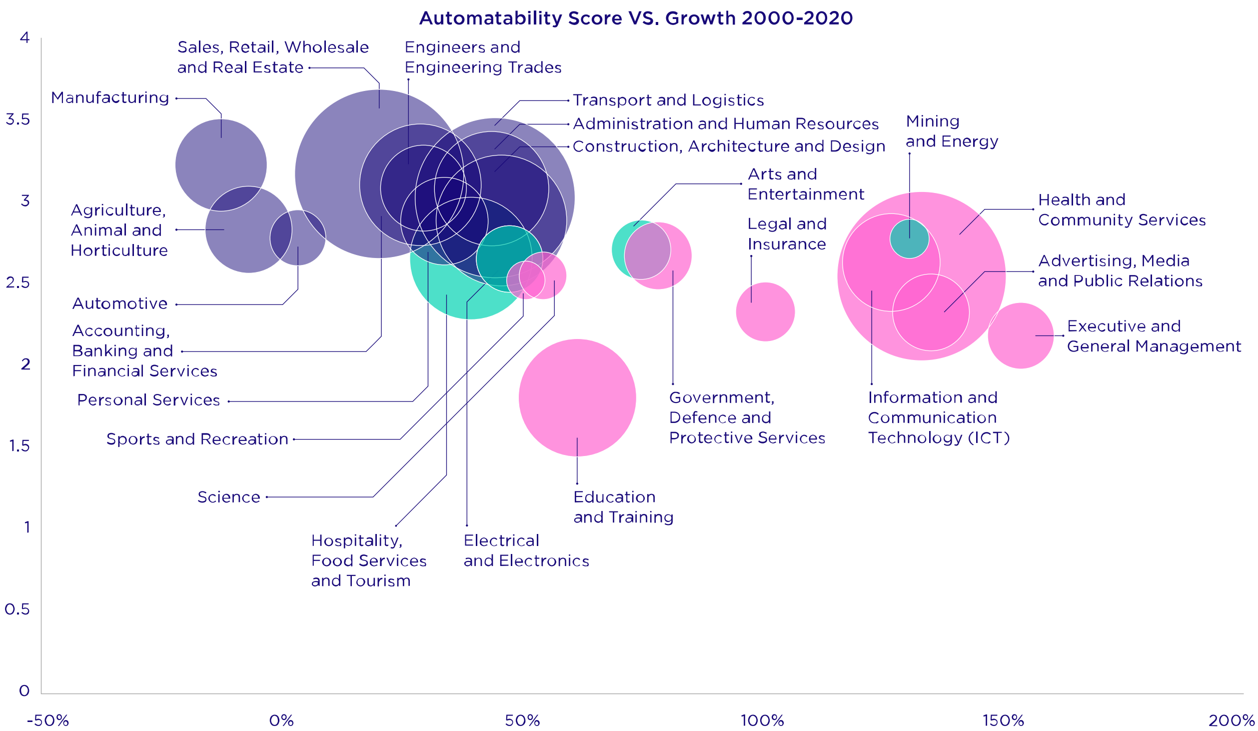
The median weighted automatability score across all occupation groups is 2.71 and the median employment growth over the past 20 years is 47%.

The purple bubbles each represent 10 occupation groups that have a weighted automatability score above the median and experienced employment growth below the median over the past 20 years. Manufacturing and agriculture and animal and horticulture have both declined in employment size (-13% and -7%, respectively) and have weighted average automatability scores above the median (3.22 and 2.83, respectively). These occupation groups also employ more than 450,000 and 400,000 workers respectively as at February 2020.

The pink bubbles each represent nine occupations with a weighted average automatability score below the median which experienced above the median employment growth. Executive and general management and health and community services have grown by 153% and 132% respectively over the past 20 years and have weighted average automatability scores of 2.18 and 2.55 respectively. These occupation groups employ more than 200,000 and 1.5 million workers respectively as at February 2020.

The green bubbles each represent four occupation groups with either a weighted average automatability score above the median and employment growth above the median or vice versa. As at February 2020, hospitality, food services and tourism employed almost 800,000 workers and had experienced 39% growth over the previous 20 years. The average weighted automatability score (2.65) for this group is below the median score across all occupation groups.

Figure 22: Weighted automatability score by employment growth for each occupation group, 2000 to 2020



Source: NSC analysis using Duckworth et al.

[25] The NSC Occupation Matrix differs from the more commonly used Australian and New Zealand Standard Classification of Occupations. Titles in the matrix have been grouped into broad categories based on field of work to assist users to better explore the labour market. More information on the occupation matrix can be found in Department of Jobs and Small Business, *Australian Jobs 2019*.

Table 11 includes the weighted automatability scores and employment growth for all 23 occupation groups. The five occupation groups that are the least likely to be automated have experienced an average growth of about 100% in the last 20 years. By comparison, the five occupation groups that are the most likely to be automated have only experienced an average growth of approximately 22% over the same period.

Table 11: Weighted automatability score by employment growth of occupations, 2000 to 2020

Occupation Group	Automatability	Growth
Education and Training	1.81	62%
Executive and General Management	2.18	154%
Advertising, Media and Public Relations	2.32	135%
Legal and Insurance	2.33	100%
Sports and Recreation	2.52	51%
Health and Community Services	2.55	133%
Science	2.55	54%
Information and Communication Technology (ICT)	2.63	127%
Electrical and Electronics	2.65	47%
Hospitality, Food Services and Tourism	2.65	39%
Government, Defence and Protective Services	2.67	78%
Arts and Entertainment	2.71	75%
Mining and Energy	2.77	131%
Automotive	2.78	3%
Agriculture, Animal and Horticulture	2.83	-7%
Personal Services	2.88	34%
Construction, Architecture and Design	2.89	46%
Administration and Human Resources	3.02	44%
Transport and Logistics	3.08	44%
Engineers and Engineering Trades	3.09	29%
Accounting, Banking and Financial Services	3.11	29%
Sales, Retail, Wholesale and Real Estate	3.17	20%
Manufacturing	3.23	-13%

Source: NSC analysis using Duckworth et al.

03

The imact of the COVID-19 pandemic on the labour market

The impact of the COVID-19 pandemic on the labour market

The COVID-19 pandemic initially had a significant, negative impact on the Australian labour market, with employment falling much more quickly and dramatically than in any previous recession. Since then the labour market has bounced back strongly, although the risk of ongoing outbreaks over the months ahead presents a degree of uncertainty.

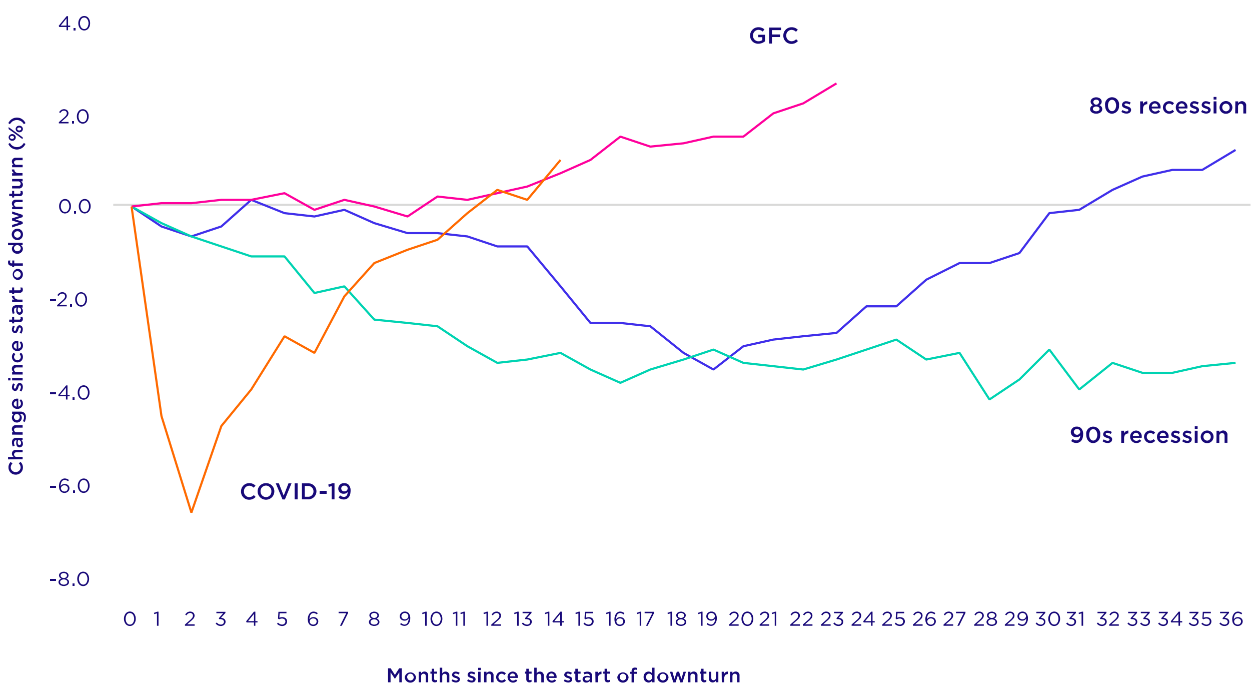
As the labour market started to recover from the impact of COVID-19 and related restrictions, late last year the NSC released modelling that examined a number of potential recovery paths. The broad conclusion from this exercise was that although there will be lasting changes as a result of COVID-19, these may not be dramatic. The broad distribution of occupations across the economy may not change all that much, although what might change is how we do our jobs. Issues relating to task change and trending and emerging skills are discussed more in Chapter 7.

When it comes to broader structural changes, it appears that the impact of COVID-19 has been to accelerate a number that were already underway, such as increasing activity online and the ongoing need for post secondary qualifications. The initial impact of the pandemic on the labour market and the subsequent recovery also highlighted the resilience in STEM related occupations.

The COVID-19 labour market shock and bounce back

Figure 23 reveals the initial negative impact of the COVID-19 pandemic. It shows that employment declined by 856,600 (or 6.6%) between March 2020, when Australia recorded its 100th case of COVID-19, and the trough in May 2020. The participation rate fell to 62.6% in May 2020 and the unemployment rate reached a peak of 7.4% in July 2020.

Figure 23: Change in employment since start of each downturn



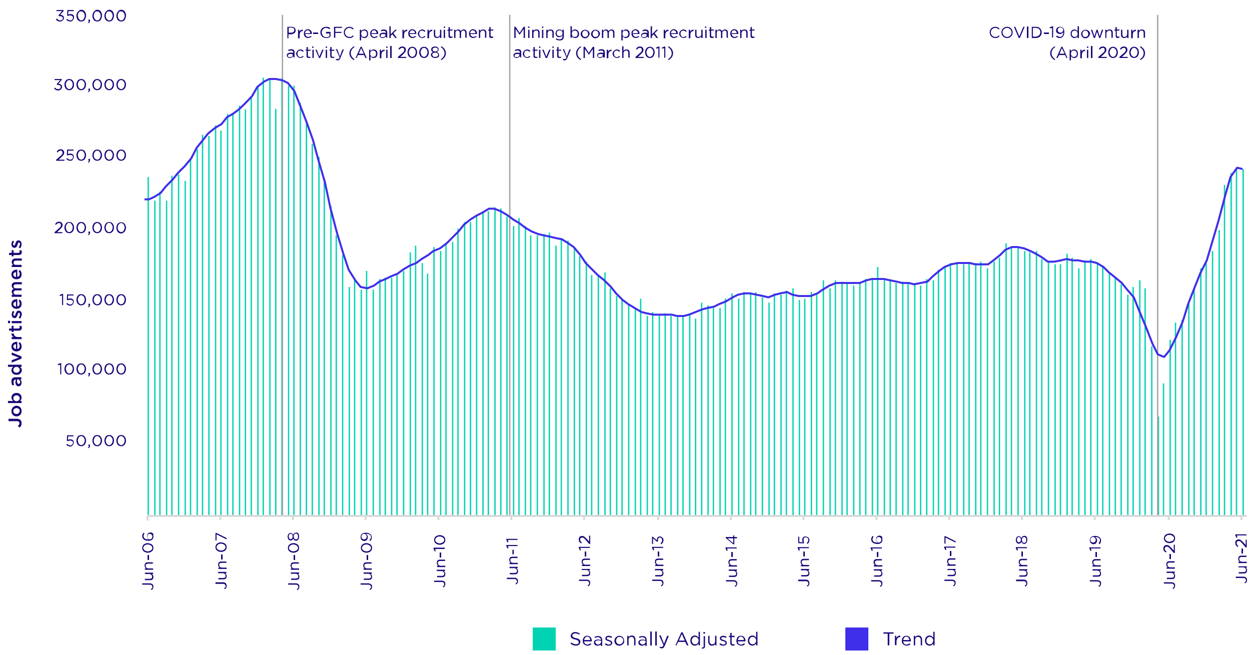
Source: ABS, *Labour force, Australia,* seasonally adjusted

In response to a sharp decline in coronavirus cases and an easing of restrictions in most jurisdictions, the Australian labour market rebounded strongly, with all of the jobs lost during the pandemic now recovered, to be 130,400 (or 1.0%) above the pre-COVID-19 level. Moreover, a record 13,125,100 Australians are in work, as at May 2021. Full-time employment has recovered particularly strongly since March 2020, up by 100,100 (or 1.1%), to a record high of 8,965,200 in May 2021, while part-time employment has also increased, by 30,300 (or 0.7%) to 4,160,000. Against a generally stronger backdrop, the unemployment rate has fallen to 5.1% in May 2021 and is now below the 5.3% recorded in March 2020.

The effective suppression of COVID-19 cases, coupled with the significant fiscal stimulus in the economy, has buoyed consumer and business confidence, with the number of people in the labour force increasing by 108,000 (or 0.8%) since March 2020. This has pushed the participation rate up, by 0.3 percentage points, to a near record high of 66.2% in May 2021, as strengthening conditions have encouraged more people to enter the labour force in search of work. That said, some uncertainty surrounds the labour market outlook, particularly in light of continuing outbreaks of COVID-19 and the associated reintroduction of restrictions in a number of jurisdictions.

Job advertisements have also continued to recover, after initially falling by 56.3% (or 89,900 job advertisements) between February 2020 and April 2020, in seasonally adjusted terms. Job advertisements increased by 4,500 (or 1.9%) in May 2021, continuing the month-on-month recovery in recruitment activity since April 2020 (the all-time low point in the IVI series). Job advertisements have now increased for 13 consecutive months and are 175,600 job advertisements (or 3.5 times) higher than that low point.

Figure 24: Internet Vacancy Index, January 2006 to May 2021



Source: NSC Internet Vacancy Index, trend and seasonally adjusted

Table 12 shows that job advertisements now exceed their pre-COVID-19 level (average level observed prior to the COVID-19 downturn) across all states and territories.[26] Of all jurisdictions, Western Australia recorded the strongest increase in recruitment activity compared with its pre-COVID-19 level (up by 68.9% or 11,100 job advertisements, followed by South Australia (68.6% or 5,200 job advertisements) and Tasmania (67.6% or 1,200 job advertisements).

[26] Pre-COVID-19 job advertisement levels are defined as the 12-month average in the seasonally adjusted IVI series to February 2020.

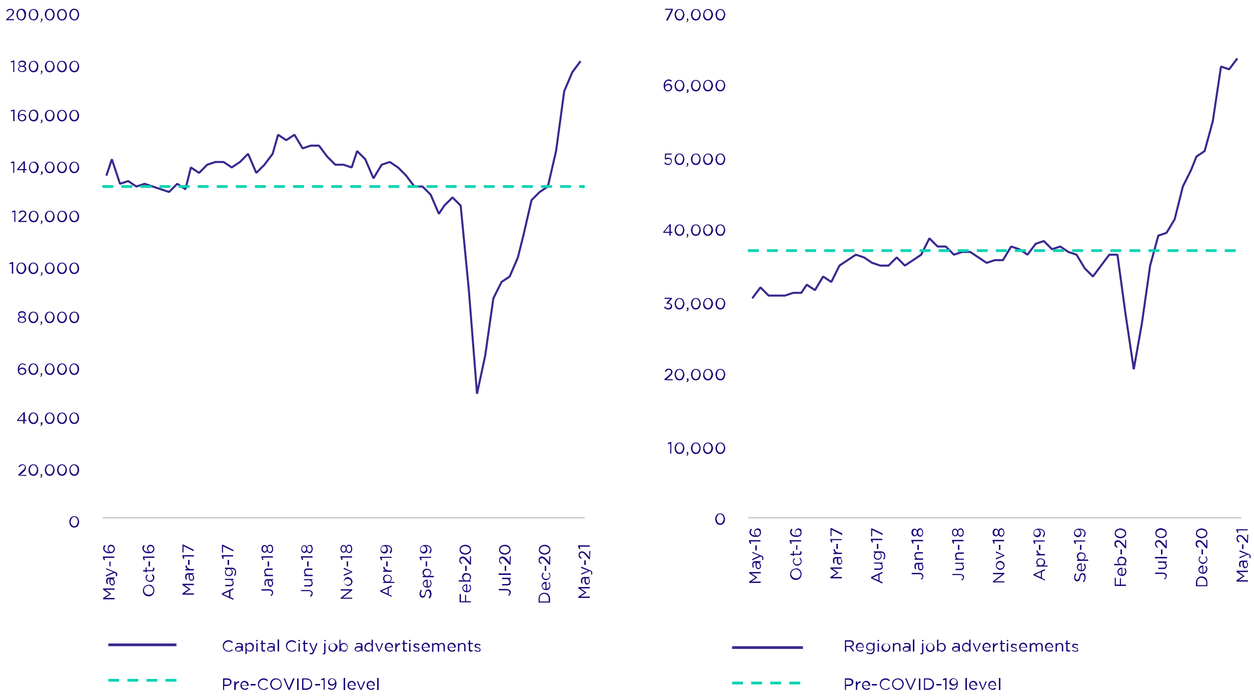
Table 12: Job advertisements by state and territory

State/Territory	Pre-COVID-19 change (%)	Pre-COVID-19 change (no.)	Number of job advertisements as at May 2021
New South Wales	36.9%	21,600	80,200
Victoria	41.9%	19,100	64,700
Queensland	56.2%	17,400	48,400
South Australia	68.6%	5,200	12,800
Western Australia	68.9%	11,100	27,300
Tasmania	67.6%	1,200	2,900
Northern Territory	66.0%	1,100	2,800
Australian Capital Territory	18.5%	1,100	6,900

Source: NSC, Internet Vacancy Index, seasonally adjusted

Figure 25 shows that although job advertisements have rebounded strongly in both capital city and rest-of-state areas, the impact of COVID-19 on job advertisements was initially more severe in capital cities than in rest-of-state areas. For example, job advertisements in capital cities fell by 60.2% between February 2020 and April 2020, while in rest-of-state areas they fell by 43.1% over the period. Recruitment activity has since recovered, with job advertisements in rest-of-state areas now 74.9% (or 27,200 job advertisements) higher than their pre-COVID-19 level and 38.1% (or 50,000 job advertisements) higher in capital cities. While the recovery in job advertisements has been stronger in rest-of-state areas than in capital cities, the vast majority (74.0%) of online job advertisements are still advertised in capital cities as at May 2021.

Figure 25: Capital city and regional recruitment activity, Internet Vacancy Index job advertisements, five years to May 2021



Source: NSC Internet Vacancy Index, seasonally adjusted

Note: Seasonally adjusted IVI estimates at the regional level of detail are not currently released publicly.

The NSC's Recruitment Experiences and Outlook Survey (REOS) shows that recruitment difficulty has become more common for employers in regional areas, while those in capital cities are now less likely to report difficulty in filling their vacancies than they did prior to the onset of COVID-19. The year 2020 was the first time that employers in rest-of-state areas more frequently reported having recruitment difficulty than those in capital cities and this has continued into 2021. To 30 April 2021, around half (51%) of recruiting employers in rest-of-state areas reported difficulty filling their vacancies compared with 41% of employers in capital cities.

Staffing expectations have also improved considerably since April 2020. For example, the proportion of employers expecting to increase staff numbers over the coming months increased sharply, from 3% in April 2020 to 21% in the four weeks to 16 October 2020. It has remained reasonably close to this level since, standing at 24% in the four weeks to 30 April 2021.

Although some uncertainty continues to surround the labour market outlook, particularly in the light of continuing outbreaks of COVID-19, the current, strong momentum in the jobs market, coupled with high levels of business confidence and a strengthening in job advertisements and hiring intentions, augur well for a continued expansion in employment in the period ahead.

Impact and recovery have varied widely across key cohorts and industries

Young people (15 to 24 years) have been particularly hard-hit by the pandemic, as they are overrepresented in industries that have been most severely affected by the impact of COVID-19. Indeed, youth employment is still 17,600 (or 0.9%) below its pre-pandemic level, which has been due, entirely, to a fall of 36,600 (or 4.3%) in youth full-time employment between March 2020 and May 2021.

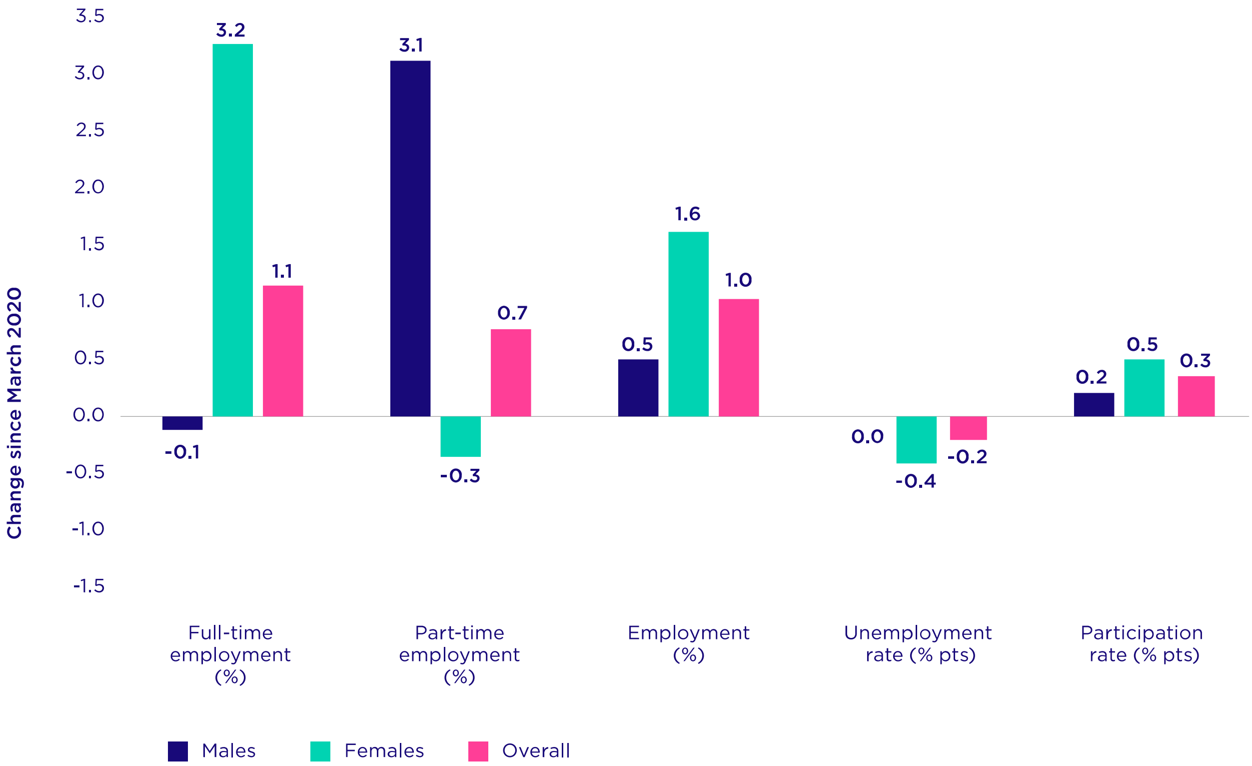
Moreover, the youth unemployment rate rose from 11.6% in March 2020 (at the onset of the pandemic), to a recent peak of 16.4% in July 2020. Despite the youth unemployment rate having fallen to 10.7% in May 2021, it remains more than double the rate recorded for all persons (of 5.1%).

The pandemic has also had a significant impact on the level of long-term unemployment (LTU) which has increased by 49,100 (or 28.1%) since March 2020, to stand at 223,500 in May 2021. An ongoing strong pace of employment growth will need to be sustained over the period ahead if inroads into LTU are to be achieved.

The negative impact of COVID-19 weighed most heavily on women in the initial stages of the pandemic, as they were more likely to be employed in the forward-facing industries most affected by lockdowns, but also because women were more likely to reduce their working hours to take on caring roles, particularly when there were school closures.

Over the course of 2020, however, and into 2021, the female cohort has recovered more strongly than males. Female employment has risen by 97,500 (or 1.6%) since March 2020, to stand at a record high of 6,255,000 in May 2021, compared with an increase of 32,900 (or 0.5%) for males (see Figure 26). The recovery in female jobs has been due entirely to a rise in female full-time employment (up by 107,100 or 3.2%), while part-time employment for women has fallen (by 9,700 or 0.3%). By contrast, full-time employment for males has fallen substantially since March 2020, down by 23,300 (or 0.4%), while part-time employment for men has actually risen by 7,100 (or 0.1%).

Figure 26: Change in key labour market indicators



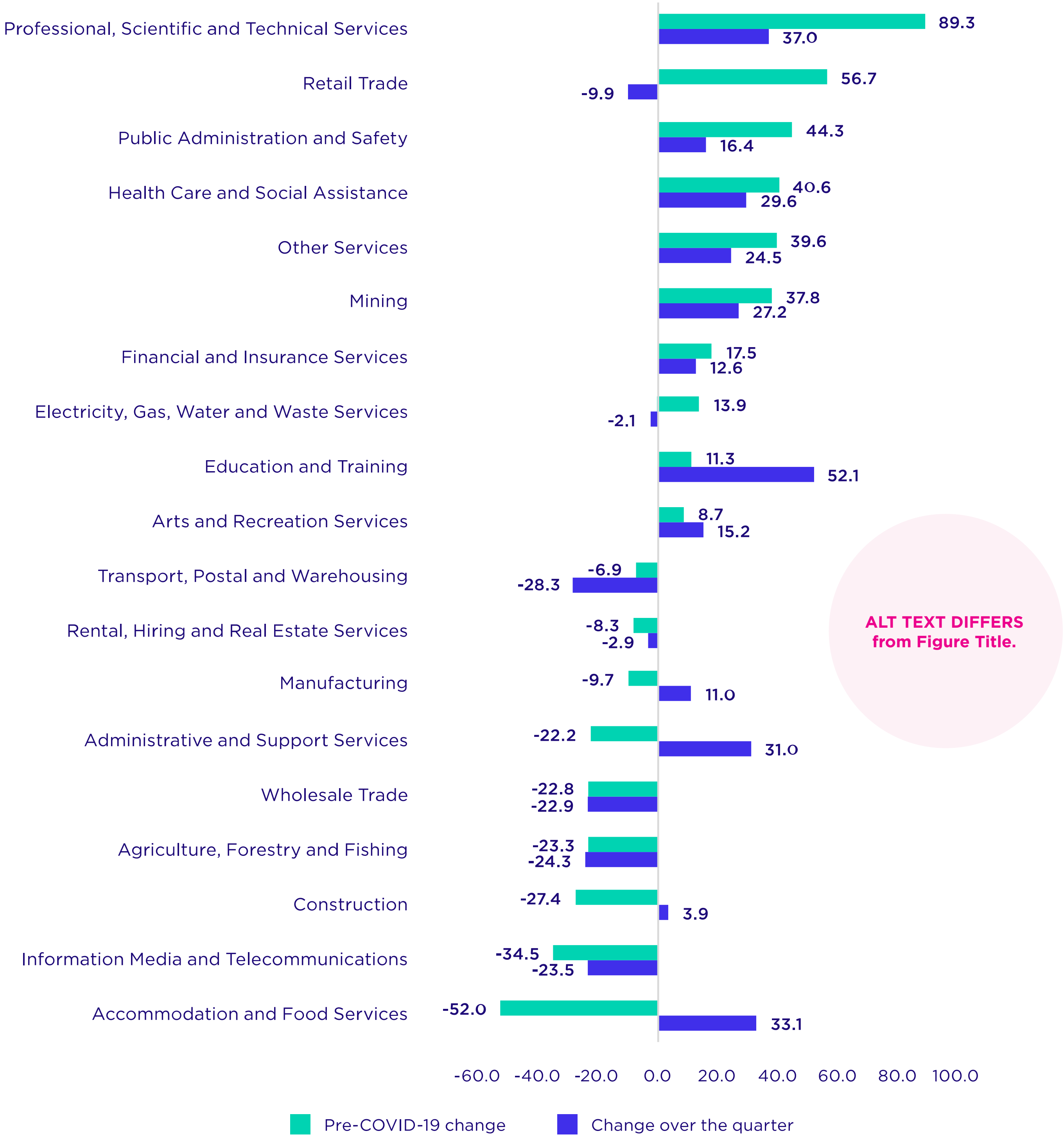
Source: ABS, *Labour force, Australia,* seasonally adjusted

Against a more positive backdrop, and reflecting the recovery in some female dominated industries, 73,500 women have entered the labour force since March 2020, pushing the participation rate up, by 0.5 percentage points over that period, to a near record high of 61.7% in May 2021. Over the same period, the male participation rate also rose, by 0.2 percentage points, to 70.9% in May 2021.

COVID-19 also had a significant impact on the Australian labour market at the industry level, with employment falling in 14 of the 19 main industries between February 2020 and May 2020 (the first quarter after the onset of COVID-19). That said, as Figure 27 shows, employment has since rebounded strongly across a number of sectors and now exceeds pre-COVID-19 levels in 10 of the 19 main industry groups (as at May 2021 – the most recent quarter of data available).

The professional, scientific and technical services industry recorded the largest increase in employment since February 2020 (up by 89,300 or 7.7%), followed by retail trade (up by 56,700 or 4.6%) and public administration (up by 44,300 or 2.3%). By contrast, the largest falls in employment were recorded in the accommodation and food services (down by 52,000 or 5.6%), information media and telecommunications (down by 34,500 or 16.2%), construction (down by 27,400 or 2.3%) and agriculture, forestry and fishing (down by 23,300 or 7.2%) industries.

Figure 27: Change in employment by industry, quarter and year to May 2021



Source: ABS, *Labour force, Australia, detailed,* seasonally adjusted

The COVID-19 pandemic – structural change or temporary shock?

A key question arising from the labour market slump caused by the COVID-19 pandemic and the surprisingly strong recovery is whether the effects of the pandemic were temporary or will be long-lasting. The early signs are that there will be both kinds of effects, but for the most part, the impact of the pandemic is more of a temporary shock than one that will bring permanent changes.

For example, accommodation and food services has been the industry most severely impacted by the COVID-19 shock and the economic restrictions that it brought, as Figure 28 shows. Employment in the industry fell significantly between February 2020 (pre-COVID-19) and May 2020 – the number of people employed fell 286,400 or 30.7%. But with the easing of restrictions, thanks to Australia's relatively low number of COVID-19 cases, employment in the industry has rebounded and now stands at around 94.4% of pre-COVID-19 levels.

There may be more permanent structural shifts in the industry, such as from changing attitudes towards travel, but it will take some time for these shifts to be reflected in employment data.

Figure 28: Change in employment in the accommodation and food services industry since COVID-19 pandemic began

Source: ABS, *Labour force, Australia, detailed*, seasonally adjusted

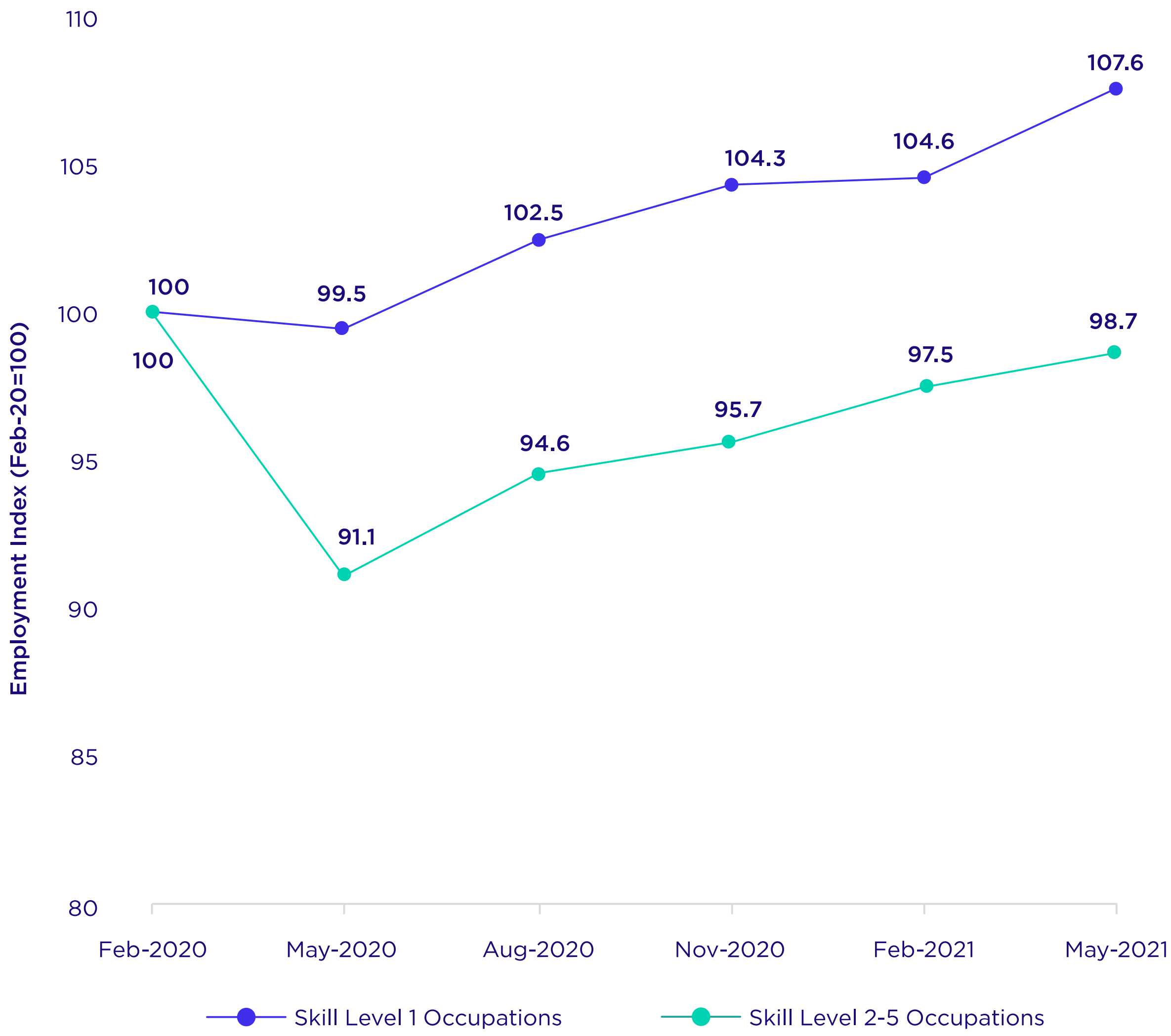
As for structural change, it is too early to say whether the COVID-19 pandemic has permanently shifted the underlying economic, social, technological, environmental or legal factors which influence the labour market.

The NSC's report, *The shape of Australia's post COVID-19 workforce,* showed that although there will undoubtedly be lasting changes as a result of COVID-19, these may not be dramatic. The broad distribution of occupations across the economy may not change that much. What might change is how we do those jobs. Also, where we do see structural change, these are more likely to be changes that were already underway, such as increasing activity online and the ongoing need for post-secondary qualifications.

That latter point becomes apparent when we examine employment trends by skill level of occupations. Skill level 1 and 3 occupations remain the only skill levels to have recorded an increase in employment since the February quarter 2020, covering the period since the onset of the COVID-19 restrictions. Employment in skill level 1 occupations rose by 319,400 (7.6%) between February 2020 and May 2021 followed by skill level 3 occupations (up by 14,400 or 0.7%). By comparison, employment in skill level 2, 4 and 5 occupations fell by 132,000 (1.9%) in total over the period. Moreover, the largest falls in employment between February 2020 and May 2021 were recorded in skill level 5 occupations (down by 61,300 or 3.0%) and skill level 4 occupations (down by 51,200 or 1.6%).

Figure 29 shows that the majority of the disparity between skill level 1 occupations and the other skill levels occurred in the early months of the COVID-19 pandemic. Employment for skill level 1 occupations fell by just 22,700 (0.5%) from the February quarter to the May quarter 2020, compared with a fall of 776,500 (8.9%) for skill level 2 to skill level 5 occupations combined.

Figure 29: Employment by skill level



Sources: ABS, *Labour force Australia, detailed,* seasonally adjusted by NSC

Note: The Employment Index base is February 2020.

In a similar vein, occupations using STEM skills (science, technology, engineering and maths) fell by just 1.5% during the height of the COVID-19 pandemic from February to May 2020, when economic activity was restricted. This is less than a third of the 6.9% decrease experienced in employment in non-STEM occupations.

The importance of post secondary education, the greater resilience to labour market shocks offered by higher level qualifications and the rapid growth in STEM related occupations were all trends apparent prior to the pandemic.

04

Skills of workers in today's labour market

Skills of workers in today's labour market

A better understanding of the skills embodied in the Australian labour market will help improve the ability to match the skills of workers with the jobs available. It will help maximise the strength of the post-COVID-19 recovery. To inform this goal, this chapter shows how outputs of a new linked data set, Skills Tracker, are combined with the Australian Skills Classification (ASC) to create the first economy-wide map of the skills clusters used by employed and unemployed workers in the labour market.

This innovative analysis shows the diversity of skills clusters used across the entire labour market. Among the more specialised skills clusters the difference in usage is more pronounced. For example, employed people more frequently use higher level cognitive skills such as data analytics and databases, teaching and education and human resources, and people looking for work are far more likely to have skills involving manual labour such as cleaning and maintenance, material transport, vehicle operation and food services.

The chapter shows the importance of the ASC's core competencies, with a similar proportion of employed and unemployed people having a high level of proficiency of 'teamwork' skills for their current occupation. Real-life insights into the role transferrable skills can play in improving labour market mobility also make it possible to identify occupations that may face a shortage of workers in the future (such as those with high turnover and limited similarity to other occupations).

Finally, the chapter examines the ways skilled migrants contribute to the Australian economy and supplement the supply of skilled workers available to businesses and industries. Skilled migrants tend to have high participation rates in the workforce. This means skilled migrants help stimulate economic growth and jobs growth.

Occupational composition of employed people

Skills Tracker enables employed people to be identified from single touch payroll data as at 24 February 2021, and enables their occupation to be inferred from 2018-19 income tax returns and 2016 Census data.[27]

The largest employing occupation identified in the analysis was sales assistants, employing 3.2% of people, followed by registered nurses (3.2%), general clerks (2.7%) and general managers (2.0%).[28]

The occupation distribution was quite different for young people getting their first footholds in the labour market. The largest employing occupation for people under the age of 22 was sales assistants (16.8%) followed by checkout operators (12.3%), fast food cooks (7.3%) and waiters (6.0%).

Regional differences were minimal. Similar patterns were observed in capital cities compared with the rest of the relevant state. All states closely mirrored the national occupational distribution, although the two territories were somewhat different. Reflecting its role as the home of the Australian Government, the largest employing occupation in the ACT was policy and planning managers (8.8%), an occupation that is not in the top ten elsewhere in Australia. The next highest employing occupation was contract, program and project administrators (8.5%). People in the ACT were also more likely to be working as software and applications programmers (2.4%, compared with 1.1% nationally). The NT had a comparatively greater share of people working in community and personal services occupations including welfare support workers (2.4%, compared with 1.0% nationally) and police (1.9%, compared with 0.7% nationally).

Occupations in Australia are highly gendered. More than 99% of the concreters, plasterers, air-conditioning and refrigeration mechanics and bricklayers and stonemasons in the NSC's analysis were male, and, more than 98% of the midwives, beauty therapists, secretaries and dental assistants were female. Of the 418 occupations we identified, 65% were highly dominated by one gender – that is, with more than 70% of people in the occupation having the dominant gender.

Skills composition of employed people

By taking the outputs of the occupational analysis described above and applying the ASC to this analysis, the skills composition of employed Australians can be determined. The occupations are mapped to the ASC to 'translate' occupations into skills.

The ASC sets out the skill requirements of occupations. As explained in Chapter 1, the 1,925 specialist tasks identified in the ASC group into 279 skills clusters, which in turn group into 29 skills cluster families. Figure 30 shows the number of employed Australians who use specialist tasks in the skills cluster families in their day-to-day work.

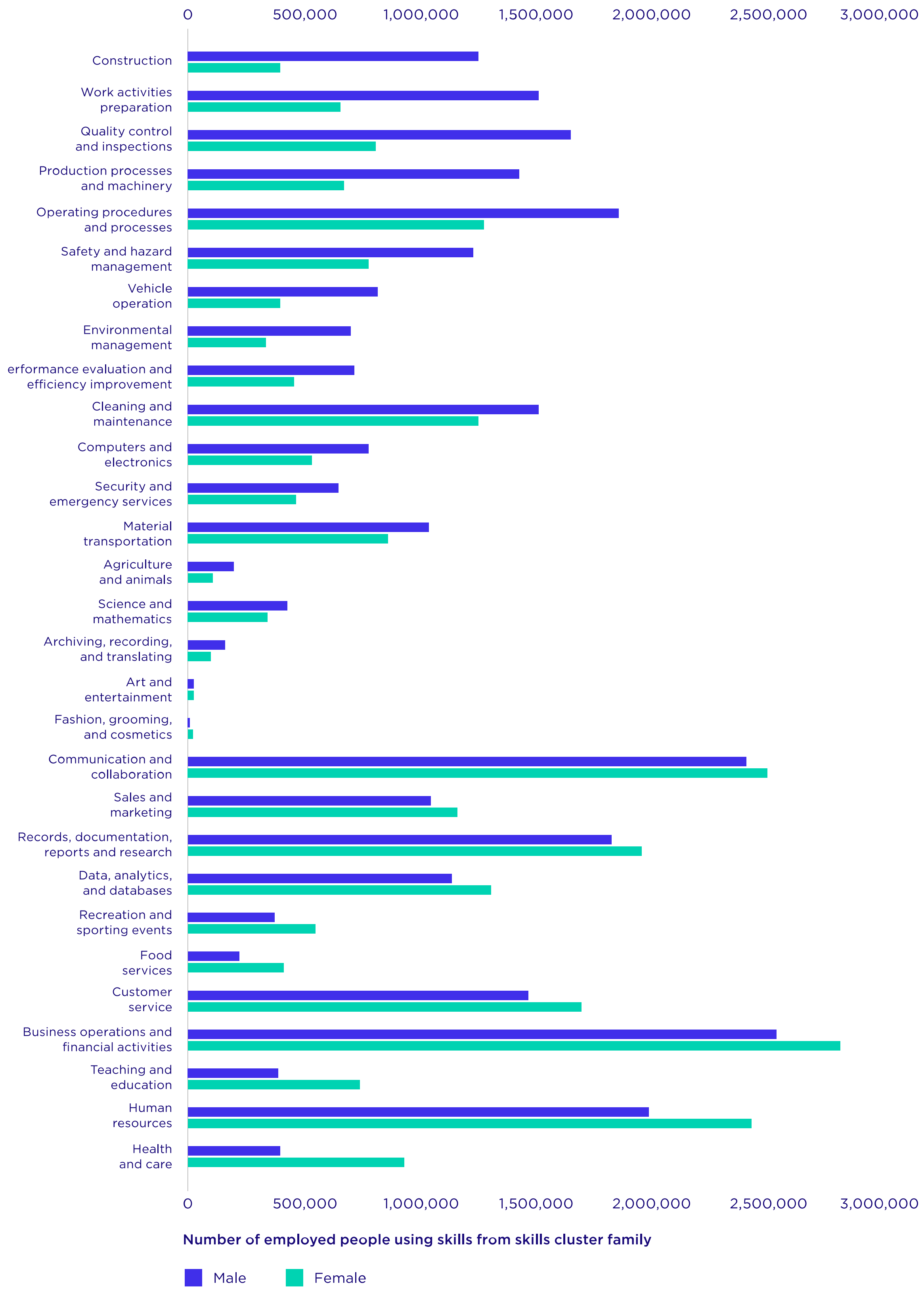
The most frequently occurring skills cluster family was business operations and financial activities. This includes skills clusters such as maintaining inventory and stock, managing operational budgets, and negotiating purchases or contracts. Four-fifths (80%) of people required some skills from this skills cluster family for their occupation. This was followed by the communications and collaboration family (74%) – which includes skills clusters such as collaborating with stakeholders and dispute resolution – and human resources (66%) – which includes supervising staff, training staff and recruitment.

The pronounced gender differences in occupations in Australia flow through into the distribution of skills. Figure 30 shows the number of employed Australians who use particular specialist tasks in the skills cluster families in their day-to-day work by gender.

[27] 24 February 2021 was the date of the latest available data at the time of writing which matched the period of the data on unemployed people from Department of Social Security data. Information on the occupations of employed Australians is available from a range of traditional data sources, including the Census and the ABS *Labour force* survey; however, for the analysis in this section, employed people were identified from single touch payroll data as at 24 February 2021. Their occupations were derived from 2018-19 income tax returns and 2016 Census data and converted into skills data using the Australian Skills Classification (ASC). This methodology was used because it provides more recent information on occupation than the Census, provides a larger sample of longitudinal occupation information and enables analysis consistent with the section on the skills of unemployed Australians later in the chapter. This methodology does not yet include people who are self-employed. Later this year the NSC will collect information on this group from the Business Longitudinal Analysis Data Environment (BLADE). The methodology also results in missing occupations for a further 12% of employed people in single touch payroll data, perhaps because they were too young to report an occupation at the last Census, were below the tax free threshold and had not submitted a tax return, or where responses were not clear.

[28] These figures are broadly comparable with those from the ABS *Labour force* survey, with some exceptions. For example, the NSC's analysis estimated a considerably higher share of the labour force for occupations such as general managers and general clerks. For comparison, the same occupational shares derived from the ABS Labour force survey in February 2021 are sales assistants (4.3%), registered nurses (2.2%), general clerks (2.8%) and general managers (0.4%). Our results vary from official statistics such as the ABS *Labour force* survey for a variety of reasons, including: single touch payroll excludes non-payroll employees, and the underlying income tax returns include self-reported occupations (people may classify themselves differently to the way they would be coded by ABS experts).

Figure 30: Distribution of skills cluster families by gender



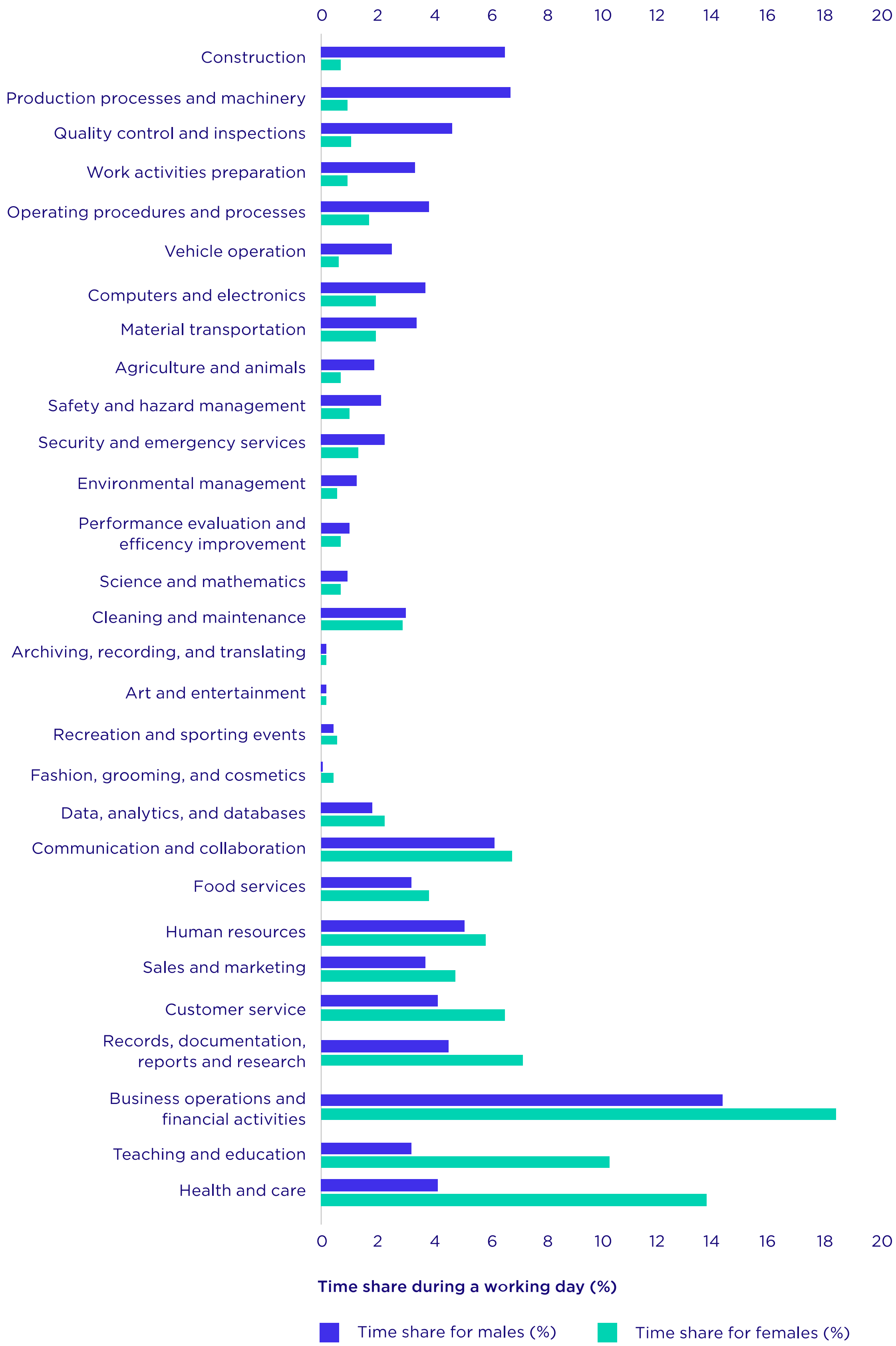
Sources: Skills Tracker, NSC analysis

Note: The figure is ordered by the difference between male and female. Clusters dominated by male employment are on the top and those dominated by female employment are on the bottom.

Men are three times as likely as women to use skills from the construction family in their paid employment – including skill clusters such as woodworking, earthworks and crane operation. Men are twice as likely to use skills from the vehicle operation family and from families often associated with manufacturing work such as 'work activities preparation' (preparing pieces for assembly, handling materials), 'production processes and machinery' (configuring equipment, developing technical designs), and 'quality control and inspections' (inspecting for damage and defects). Women are twice as likely as men to use skills from the health and care family and from the fashion, grooming and cosmetics family. Health and care is a broad skills cluster family which includes skill clusters ranging from 'caring for patients' to 'administering medications' to 'analysing medical research and data'. The fashion, grooming, and cosmetics family includes 'providing cosmetic advice' and 'designing jewellery or costumes'.

Data on the frequency of skills cluster families provide a useful way of looking at the breadth of skills across the employed population, but they don't necessarily capture the importance of a particular skill set. Some occupations might only require people to undertake some tasks sporadically. To assess this, the NSC has looked at the average amount of time spent on specialist tasks within different occupations. Figure 31 indicates that most Australians require some skills from the business operations and financial activities skills cluster family to do their jobs, but only about 16% of time in the economy is spent on them (14% of time for men and 18% for women). By contrast, although only around one-in-five workers have skills in the health and care cluster family, 9% of time in the economy is spent on these tasks, as they form a larger portion of the day for workers in this area. As discussed above, the gender difference in this family is striking, with 14% of women's time spent on these skills compared with only 4% of men's. Figure 31 shows the percentage of work hours that men and women spend on the different skills cluster families.

Figure 31: Time spent on skills cluster families by gender



Sources: Skills Tracker, NSC analysis

Note: The figure is ordered by the difference between male and female. Skills families dominated by male time share are on the top and those dominated by female time share are on the bottom.

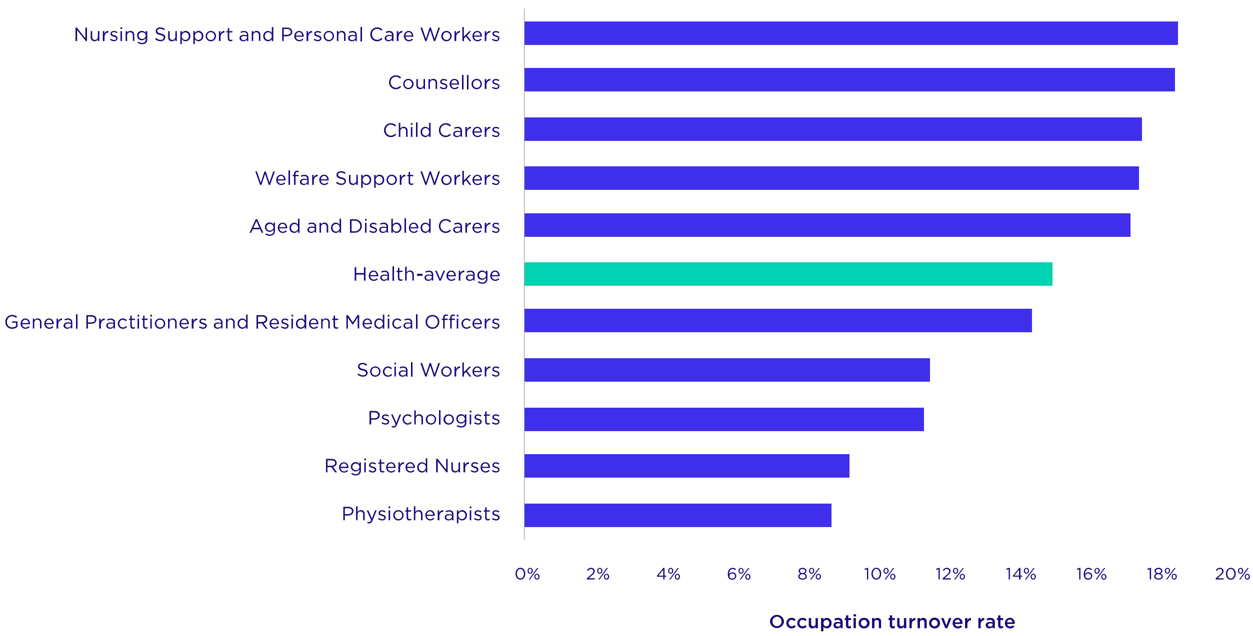
Movement between occupations and skills cluster families

Longitudinal data from Skills Tracker enables rich analysis of career pathways and mobility in the labour market. This includes how often people change occupations and the kinds of transitions they make. Our preliminary analysis considered occupational turnover – movement between occupations – from historical income tax record filings between 2017–18 and 2018–19. As additional data sets are added, this analysis will be extended to include more historical information.

The NSC identified people who had changed occupations, using two consecutive years of data. People working in the occupation automobile driver were the most likely to change, with 45% making a switch. This was followed by crop farm workers (45%) and aquaculture workers (42%) and telemarketers (41%). The occupations with the lowest turnover were police officers (7%), train and tram drivers (10%) and occupational therapists (10%). Overall, 22% of people left their occupation between 2017–18 and 2018–19.

Figure 32 shows an example of turnover in health care and social assistance sector occupations. Nursing support and personal care workers have one of the highest turnover rates of all occupations. This could be viewed as a concern. However, when you consider that the largest portion (26%) of people who left their nursing support and personal care roles went on to become registered nurses this is a positive result. A further 4% became enrolled and mothercraft nurses, showing a positive career pathway in the sector. A further 10% became aged and disabled carers. Just under half (48%) moved to other occupations in the health and care sector.

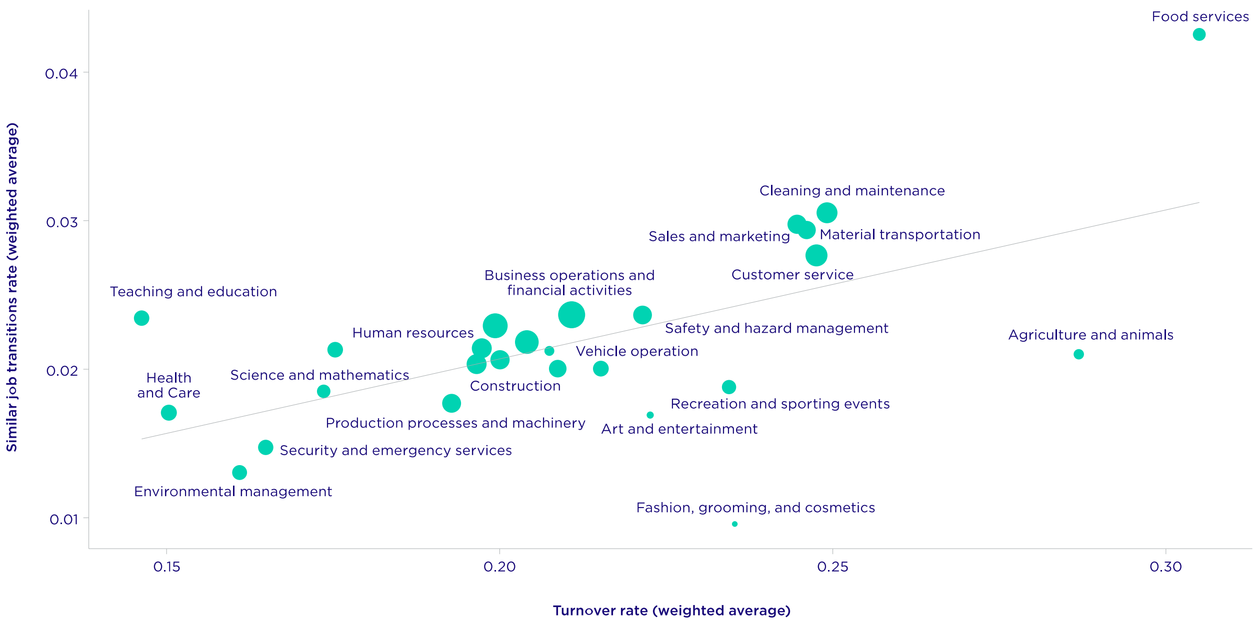
Figure 32: Turnover in health care and social assistance sector occupations



Sources: Skills Tracker, NSC analysis

A more sophisticated turnover analysis can be undertaken at the skills cluster level across the broader labour market. Figure 33 shows the turnover rate on the x-axis for people with skills from different skills cluster families against the extent they moved into similar roles. The higher the weighted average on the y-axis, the more similar the role they moved into. The diagonal line shows the average level of similarity. People with skills in skills cluster families above the line tend to move into occupations with above average similarity and people with skills in skills cluster families below the line tend to move into occupations with below average similarity.

Figure 33: Turnover and movement to similar occupations



Sources: *Skills Tracker*, NSC analysis

Note: The vertical axis shows how similar the job an individual transitioned into was to their previous job. The horizontal axis shows the degree of turnover. As an example, individuals with skills from the food services skills family had both high turnover and moved into jobs that were similar to their previous roles.

People with skills such as teaching, human resources and health care are more likely than average to transition into similar occupations and have lower turnover rates. These people are well placed in the current labour market.

This is in contrast with people with skills from the food services family, who are by far the most likely to change occupations. When they do so, they are most likely to move to other occupations which make heavy use of food services skills. Although this is not an issue in the current strong labour market for food services skills, it does show these people have a small number of alternative career options if the sector experiences substantial decline.

Occupations in the lower right of Figure 33 should be the focus of future analysis as their position shows a combination of high turnover with a lack of transition options utilising their current skills profile. For example, people with skills from the agriculture and animals family have high turnover rates and tend to move into less similar occupations.[29] People with skills from the fashion, grooming and cosmetics family have a slightly higher rate of turnover than average, and when they move, they tend to switch to quite different work. This kind of transition information could be useful in showing skills that are widely transferable and those that are not, providing additional intelligence for making decisions about investments in retraining, workplace planning initiatives and managing structural adjustment.

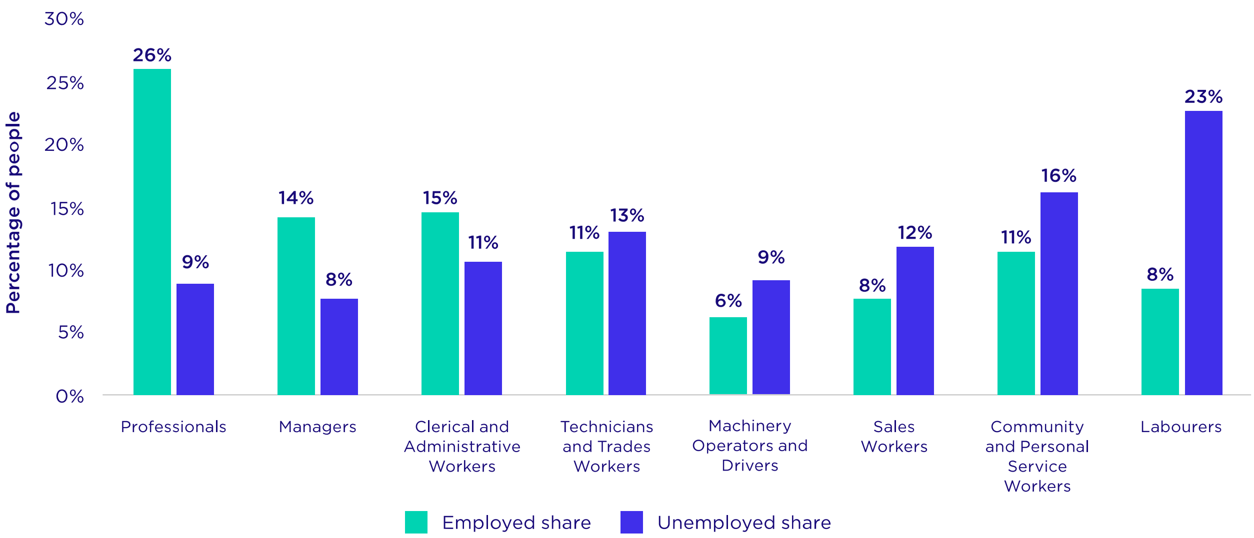
[29]Skills from the agriculture and animals skills cluster family are associated with a broad range of occupations across sectors, for example veterinarians, beekeepers and zookeepers. Figure 33 reflects turnovers across the whole skills cluster family.

Occupational and skills composition of the unemployed

In contrast to those employed, people looking for work are more likely to have skills involving manual labour such as cleaning and maintenance, material transport, vehicle operation and food services. It should be noted this data is limited to identifying the skills of people looking for work from their latest occupation recorded by the ATO or reported in the Census.

Over a fifth of the unemployed cohort had most recently worked as a labourer (22.7%) making it by far the most common occupational class.[30] By contrast, as Figure 34 shows, only 8.5% of employed people were working as labourers. Unemployed labourers were spread across five occupational types. The largest group was cleaners and laundry workers (5.4%), followed by other labourers – a broad category which includes shelf fillers, caretakers, vending machine attendants and rubbish collectors (4.7%) and factory process workers (4.3%).

Figure 34: Comparison of employed and unemployed by occupational class



Sources: Skills Tracker, NSC analysis

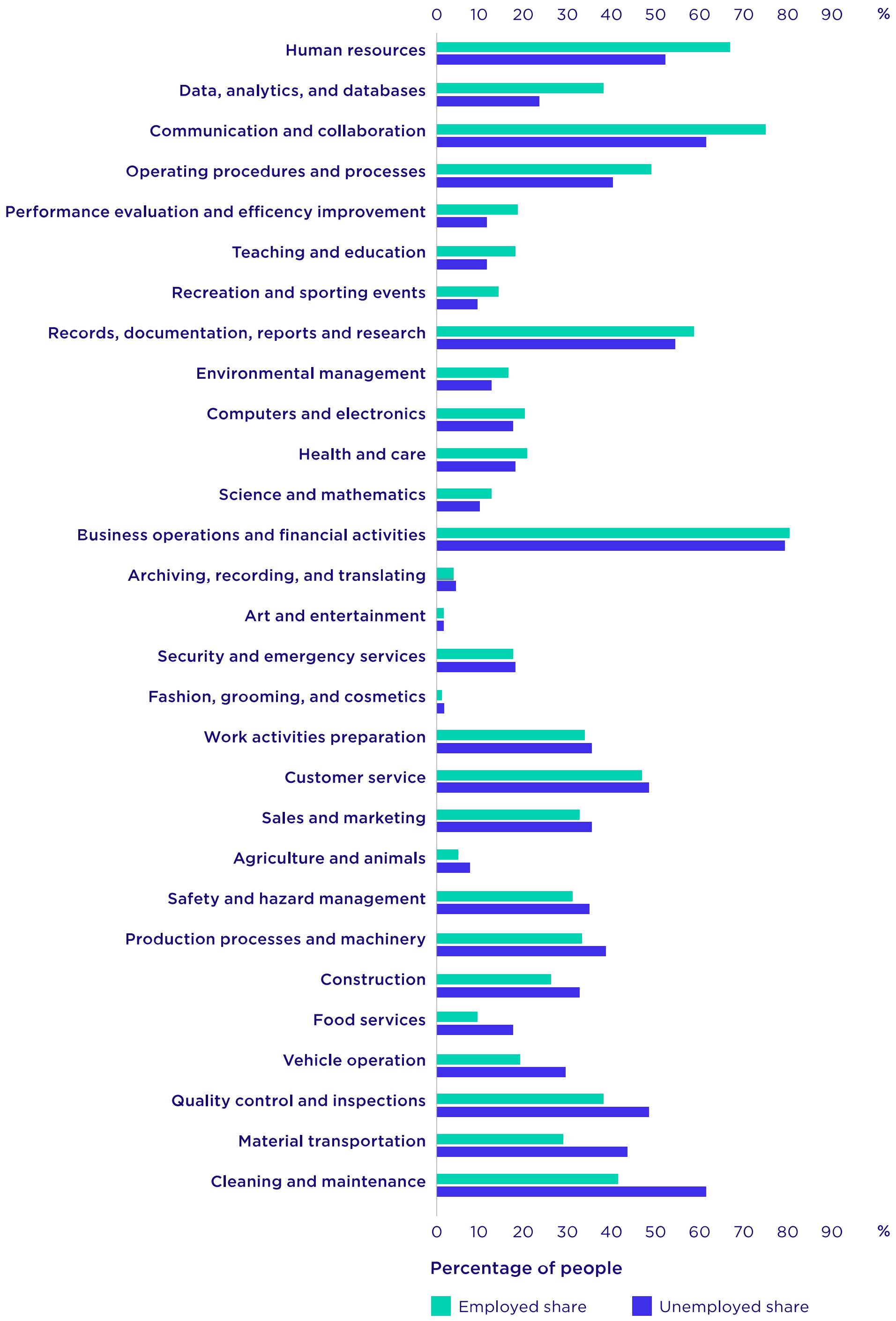
Note: The figure shows the distribution of the occupational class more highly dominated by the employed share on the left and those dominated by the unemployed share on the right.

[30]Labourers as defined by ANZSCO major group 8, labourers and associated minor groups.

Many of the unemployed had worked previously in occupations within hospitality and retail, which were disproportionately affected by the COVID-19 pandemic, but which are expected to return to pre-crisis levels of activity and employment. Such roles include bar attendants and baristas (1.9%), waiters (1.9%) as well as chefs (1.5%) and cooks (0.8%). These occupations are characterised by highly casual or part-time employment. Some of them are also currently seeing strong growth in, or high levels of, job vacancies.

The ASC enables us to compare the skills possessed by the employed with those of the unemployed. Figure 35 shows the most common cluster families held by each cohort.

Figure 35: Cluster families of employed and unemployed population



Sources: Skills Tracker, NSC analysis

Note: The figure is ordered by the difference between employed share and unemployed share. Skills families where employed people had a higher share than unemployed people are on the top and those where unemployed people had a higher share are on the bottom.

Many of the most common skills families, such as 'business operations and financial activities', 'communication and collaboration', and 'records, documentation, reports and research', are widely represented both among employed and unemployed people. This reflects the prevalence of these skills across a wide range of occupations.

Among the more specialised skills families there are more significant differences between employed and unemployed people. Unemployed people are far more likely to have skills in cleaning and maintenance (62% compared with 41% of employed people), material transportation (43% compared with 29%), vehicle operation (29% compared with 19%) and almost twice as likely to have skills in food services (17% compared with 9%). The over representation of food services skills may reflect the differential impact of COVID-19 on different sectors.

Employed people are significantly more likely to have skills in data, analytics and databases (38% compared with 23% of unemployed people), performance evaluation and efficiency improvement (19% compared with 12%), teaching and education (18% compared with 12%) and more likely to have skills in common cluster families such as human resources (67% compared with 52%) and communication and collaboration (75% compared with 61%). The skills of employed people are more likely to be associated with white collar occupations.

Figure 36 compares the amount of time employed people spend on specialist tasks within each skills cluster family with the amount of time unemployed people spent in their previous roles. For example, employed people across the economy spend 9% of their combined time on tasks in the health and care family; unemployed people only spent 5% of their combined time on them in their former occupations. Although a similar proportion of employed and unemployed people have skills in the health and care family, employed people are in occupations that use them more intensively.

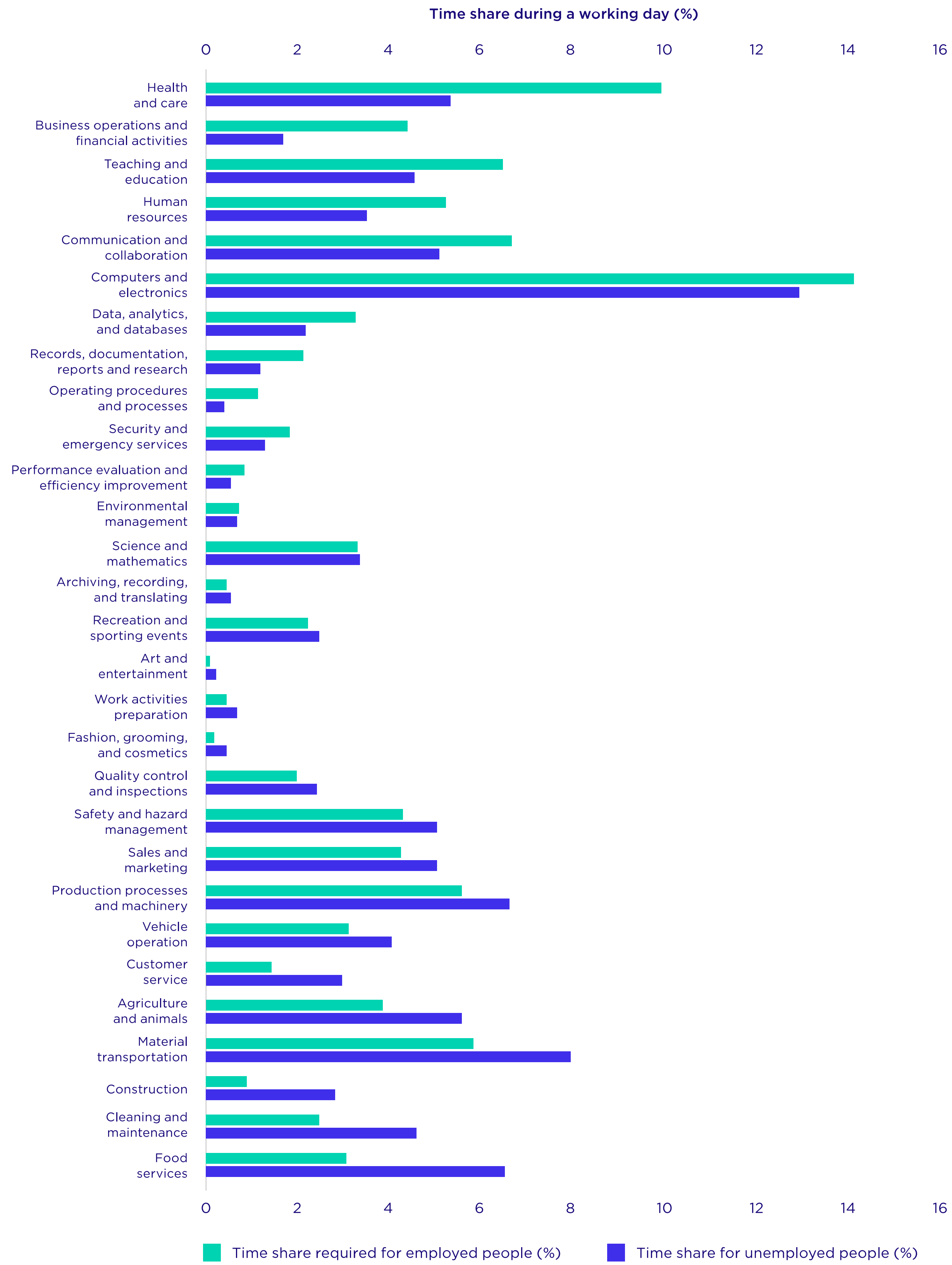
Similarly, skills in business operations and financial activities, teaching and education, and human resources take up a greater share of work time for employed people than they did for the previous occupations of the unemployed. Deepening skills in these families may be important for unemployed people wanting to re-skill to find new employment.

On the other hand, unemployed people are more likely to have worked in jobs that used skills intensively in the skills cluster families of food services, cleaning and maintenance, construction, material transportation and agriculture and animals families. Occupations that use these skills less intensively appear to provide better employment prospects than those that require them more intensively. Unemployed people with skills in these areas may benefit from broadening their skills in other areas. For example, although both aged and disabled carers and cafe workers perform specialist tasks in the food services family, these tasks make up a much lower proportion of the average aged and disabled carer's working day than the average cafe worker's (15% of time compared with 69%).

Drilling down to the next level of detail in the ASC – the 279 skills clusters – enables analysis of these differences at a more granular level. Employed people more frequently use skills clusters involving higher-level interpersonal and management skills, such as communicate and collaborate (50% of employed people compared with 39% of unemployed people), manage services, staff or activities (22% compared with 12%), train staff (35% compared with 25%), supervise staff (28% compared with 20%) and human resource activities (18% compared with 11%). Employed people are also more likely to perform tasks related to professional skill and knowledge development (35% compared with 25%) and managing operational budgets (19% compared with 8%). Employed people are more likely to have experience in relatively senior roles involving management skills than the unemployed, and more likely to be in roles requiring significant professional skill and knowledge.

By contrast, unemployed people are much more likely to have had experience with tasks relating to manufacturing and production processes such as procuring materials, supplies or stock (33% compared with 24% of employed people), inspecting, testing or maintaining equipment or systems (29% compared with 21%) and maintaining operational and production records (24% compared with 19%). Unemployed people are more likely to have experience in the direct production process, compared with employed people.

Figure 36: Skill intensity by skills cluster family for employed and unemployed people



Sources: Skills Tracker, NSC analysis

Note: The figure is ordered by the difference between time spent by employed and unemployed people, with skills cluster families where employed people had spent more time than unemployed people are on the top and those where unemployed people had spent more time than employed people are on the bottom.

Importance of core competencies

NSC research also highlights the importance of core competencies (otherwise known as employability skills or 'soft' skills) in the Australian labour market. Survey data indicate that employers place high importance on these skills.

The ASC identifies 10 core competencies which are required to a greater or lesser degree for all occupations. The core competencies are measured on a 10-point scale, with 1 indicating a lower level of competency and 10 representing an expert level. For example, for writing, a score of 1 represents a level of complexity roughly equivalent to being able to 'write name and address on a membership form, copying another document' and 10 'write a thesis on metaphor, syntax and grammar in nineteenth century novels'.

Most employed people (56%) are in occupations that require an 8+ score for the planning and organising competency, whereas less than a third (29%) of unemployed people needed the same competency level for their most recent occupation. Almost half (46%) of employed people worked in an occupation that has an 8+ score in initiative and innovation compared with about a quarter (26%) of unemployed people who worked in an occupation requiring a similar level of initiative and innovation. Other than teamwork, employed people are around twice as likely to be working in occupations with scores of 8+ compared with the most recent occupations of unemployed people.

Teamwork is the one core competency where a similar proportion of employed and unemployed people have a high level of proficiency. A wide range of occupations require significant teamwork skills, including some of the largest employing entry level occupations, such as sales assistant. As discussed in Chapter 7, demand for teamwork skills is increasing in many of these roles. Being able to work well in a team is more powerful when combined with other advanced core competencies.

Mapping an economy-wide skills profile

Figure 37 gives an indication of the breadth of skills available in the Australian economy and how they are related. It shows a network analysis of the skills which combines the outputs of the skills composition of both the employed and unemployed populations discussed earlier in this chapter.[31]

The size of each bubble represents the number of Australians with that skill; the connecting lines represent skills which are held by the same people. The colours of the bubbles indicate the skills cluster family to which they belong.

There are 279 skills clusters in the ASC; however, the figure displays only skills which are held by at least 20% of the labour force.

The figure shows that even though skills which are closely related are often part of the same skills cluster family, there are some broadly applicable skills which are required across sectors. These widely-used skills include having the ability to:

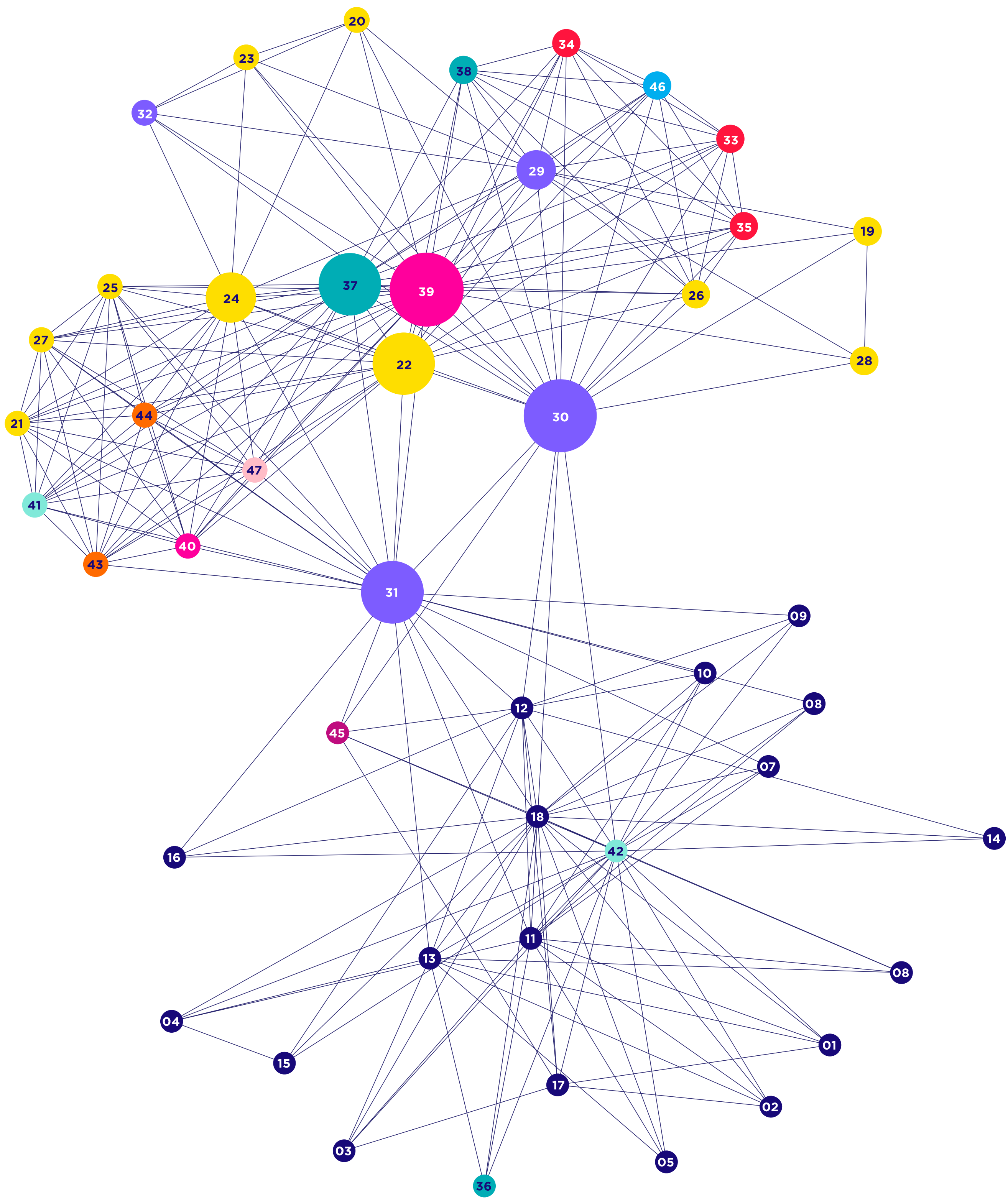
- train staff
- engage in professional knowledge development
- maintain inventory and stock
- provide customer service
- communicate and collaborate.

There are also skills from different families that are highly correlated. For example, there is a distinct group of health and care family skills in blue on the left-hand side of the figure. The figure shows that people with these skills also need other skills. They need to have a strong focus on the skills cluster 'undertake health, safety or hazard management and education activities', a skills cluster from the safety and hazard management family, and may also need to undertake biological research, a skills cluster from the science and mathematics family.

Skills from the business operations and financial activities family (in yellow) are less highly correlated with each other and are more likely to be used in combination with other skills such as sales and marketing (orange), records, documentation, reports and research (red) or human resources (purple).

[31] Network analyses are widely used in biology, ecology, epidemiology and to explain social networks, but are newer to economics. Network analyses diagrams show the relationships between different pieces of information; they are made up of a set of nodes connected by lines. The position of the nodes shows how closely related they are to each other (based on underlying raw data) and the lines show the links between them.

Figure 37: Current skills in Australia



Skills Family

- Health and care
- Business operations and financial
- Human resources
- Records, documentation, reports and research
- Communication and collaboration
- Customer service
- Safety and hazard management
- Sales and marketing
- Science and mathematics
- Data, analytics, and databases
- Cleaning and maintenance

Skills Cluster

01 Administer medications or immunisations
02 Administration of medical facility records and activities
03 Assist and support clients
04 Assist health care practitioners for medical procedures
05 Care for patients and clients
06 Collect, document and communicate medical information
07 Diagnose medical conditions and prescribe treatments
08 Direct medical or health care programs
09 Make, fit or support clients in the use of assistive devices
10 Manage health care operations
11 Monitor and evaluate patient treatment
12 Operate and maintain medical equipment
13 Perform medical tests and physical examinations of patients
14 Provide community health programs
15 Provide health care advice
16 Provide health care or administer medical treatment
17 Refer for health services or medical tests
18 Undertake community development activities
19 Conduct financial transactions or processes
20 Establish organisational policies or programs
21 Estimate costs of goods or services
22 Maintain inventory and stock
23 Manage services, staff or activities
24 Manage, monitor and undertake financial activities
25 Negotiate purchases or contracts
26 Perform administrative or clerical tasks
27 Procure materials, supplies, or stock
28 Verify and maintain financial records
29 Schedule staff or assign work
30 Train staff
31 Undertake or provide professional skill and knowledge development
32 Undertake recruitment activities
33 Distribute, write, edit or compile documents
34 Maintain records, documents or other files
35 Prepare or manage compliance documentation
36 Collaborate with health care professionals
37 Communicate and collaborate
38 Communicate with colleagues
39 Provide customer service and communicate information
40 Respond to customer queries
41 Inspect work environment to ensure safety and compliance
42 Undertake health, safety or hazard management and education activities
43 Conduct sales and marketing activities
44 Maintain sales and business transaction records
45 Undertake biological research
46 Verify accuracy of data or documents
47 Clean work areas or dispose of waste

Sources: Skills Tracker, NSC analysis

Note: This figure is a network analysis of skills clusters in the current labour market. The bubbles represent skills clusters from the ASC and their colours represent the skills cluster families. The figure includes skills which are held by at least 20 per cent of the labour force (people aged 22 and over who are employed or unemployed). Larger bubbles indicate skills that are held by more people. The connecting lines depict the relationship between skills clusters based on the occupations of people.

The contribution of migration to the Australian labour market

Skilled migrants make a significant contribution to the Australian economy and supplement the supply of skilled workers available to businesses and industries. Skilled migrants tend to have high participation rates in the workforce. This means skilled migrants help stimulate economic growth and jobs growth.[32]

Research and analysis has found that there are economic benefits from skilled migration arising from the transfer of skills to the resident Australian population. The importation of global talent may facilitate the adoption of new technologies, raise productivity and increase income per capita.[33]

The closure of Australia's international borders in March 2020 in response to the COVID-19 pandemic is therefore likely to have both short-term and longer-term impacts on the workforce and the economy.

Contribution of permanent skilled migration to the labour market

In recent years, the permanent migration program has been set at 160,000 places with about two thirds of the intake in the skill stream, which is designed to improve the productive capacity of the economy and fill skill shortages in the labour market.[34] This focus is consistent with data from the Continuous Survey of Australia's Migrants (CSAM) which shows positive employment outcomes for primary skill stream visa holders and, by extension, positive contributions to the Australian economy. Primary skill stream visa holders must satisfy specified qualification, work experience, English proficiency and age criteria. Secondary visa holders are accompanying dependents such as spouses and children.[35]

The most recent CSAM survey found that the employment outcomes for primary skill stream visa holders were strong at the six-month and 18-month stages of settlement. These findings have been consistent across all CSAM surveys (2013 to 2018). Recent CSAM surveys have found that:

- In aggregate terms, skilled migrants performed better than the resident population of both Australian-born workers and migrants, in terms of employment and participation rates.
- Employer-sponsored primary skilled permanent migrants reported high rates of employment (93.7%), participation (95.6%) and above average wages.
- Onshore independent primary skill stream migrants – those in Australia at the time of visa application – also reported high rates of employment (93.5%) and participation rates (97.4%).

Contribution of temporary skilled migration to the labour market

The employer-sponsored Temporary Skill Shortage (TSS) visa program supplements the skilled workforce needs of Australian businesses. Analysis of ABS Labour force data and Department of Home Affairs visa data shows that the longer-term national average reliance on temporary skilled migrants of 1.0% has been declining since the implementation of the April 2017 skilled visa reforms. This figure refers to the stock of primary visa holders as a percentage of the employed workforce.

Temporary visa holders are a major source of permanent skill stream migrants, accounting for some 80% of primary visas granted in 2019-20. This compares with an average of 65% for the preceding five years.[36]

The reduced intake of TSS and other temporary work visa holders following the closure of Australia's international borders in response to the COVID-19 pandemic is therefore likely to have longer-term impacts on both the skilled workforce and the population.

[32] Productivity Commission, *Economic impacts of migration and population growth*, 2006.
[33] Productivity Commission, *Migrant intake into Australia*, 2016.
[34] The Migration Program, for permanent migrants, comprises three key streams: skill, family, special eligibility and child. The planning levels for these streams are set by government as part of the annual Budget process. The planning level for the permanent Migration Program was set at 190,000 places for 2012-13 to 2018-19, and at 160,000 places for 2019-20 and 2020-21. The Migration Program was delivered at well below the planning level in 2017-18 (162,417 persons), 2018-19 (160,323 persons) and 2019-20 (140,366 persons – COVID-19 may have affected the June 2020 quarter).
[35] Department of Home Affairs, *Continuous survey of Australia's migrants*, 2018.
[36] Department of Home Affairs, *2019–20 Migration program report*, Table 1.2 skill stream outcome by location, applicant type and gender, 2010–11 to 2019–20, 2020.

Temporary work visas

The NSC analyses the labour market impact of temporary visa holders in Australia with a full or partial work right. These visa holders include temporary workers such as working holiday makers (often referred to as backpackers), international students, temporary graduates, New Zealand citizens and other temporary residents. Before the onset of COVID-19, the total number of temporary visa holders in Australia under these largely uncapped visa programs was often around or over 2 million.

The closure of Australia's international borders in March 2020 in response to the COVID-19 pandemic has resulted in a significant fall in temporary visa entrants. There were just over 1.5 million temporary visa holders with a work right in Australia at 31 December 2020, and the number fell to just over 1.3 million at 31 March 2021.

Contribution of skilled migration programs to the workforce needs of Australian business and industry

In 2018-19, before the COVID-19 pandemic, 42,100 employer-sponsored primary TSS visas were granted to directly meet the needs of Australian businesses. This fell to 28,400 visa grants in 2019-20 and to 11,200 visa grants for the six months to 31 December 2020.

Table 13 shows the top 15 occupations for primary visa grants under the TSS visa program for the five years to 2019-20.

Table 13: Top 15 occupations for employer-sponsored primary Temporary Skill Shortage visa grants, five years to 2019–20

	Occupation	(%)
1	Developer Programmer	4.5
2	ICT Business Analyst	3.9
3	Cook	3.9
4	Software Engineer	3.7
5	Resident Medical Officer	2.9
6	Chef	2.9
7	Cafe or Restaurant Manager	2.8
8	University Lecturer	2.7
9	Management Consultant	2.6
10	General Practitioner	2.3
11	Marketing Specialist	2.3
12	Analyst Programmer	1.9
13	Accountant (General)	1.9
14	Sales and Marketing Manager	1.6
15	Recruitment Consultant	1.5

Source: Department of Home Affairs, Temporary Work visas granted, BP0014, five years to 2019-20

In 2018-19, before the COVID-19 pandemic, the permanent skill stream contributed 49,100 primary visa grants, of which 20,200 were in the employer-sponsored categories that directly meet the needs of Australian businesses. This fell to 41,900 visa grants in 2019-20, of which 17,400 were in the employer-sponsored visa categories. Table 14 shows the top 15 occupations for permanent primary skill stream visa grants for the five years to 2019-20.

Table 14: Top 15 occupations for permanent primary skill stream visa grants, five years to 2019–20

	Occupation	(%)
1	Accountant (General)	7.0
2	Software Engineer	5.9
3	Cook	3.8
4	Registered Nurses nec	3.8
5	Developer Programmer	2.8
6	ICT Business Analyst	2.4
7	Computer Network and Systems Engineer	2.3
8	Cafe or Restaurant Manager	2.3
9	Civil Engineer	2.1
10	Mechanical Engineer	2.0
11	Chef	1.8
12	Marketing Specialist	1.6
13	Analyst Programmer	1.5
14	Engineering Technologist	1.4
15	External Auditor	1.4

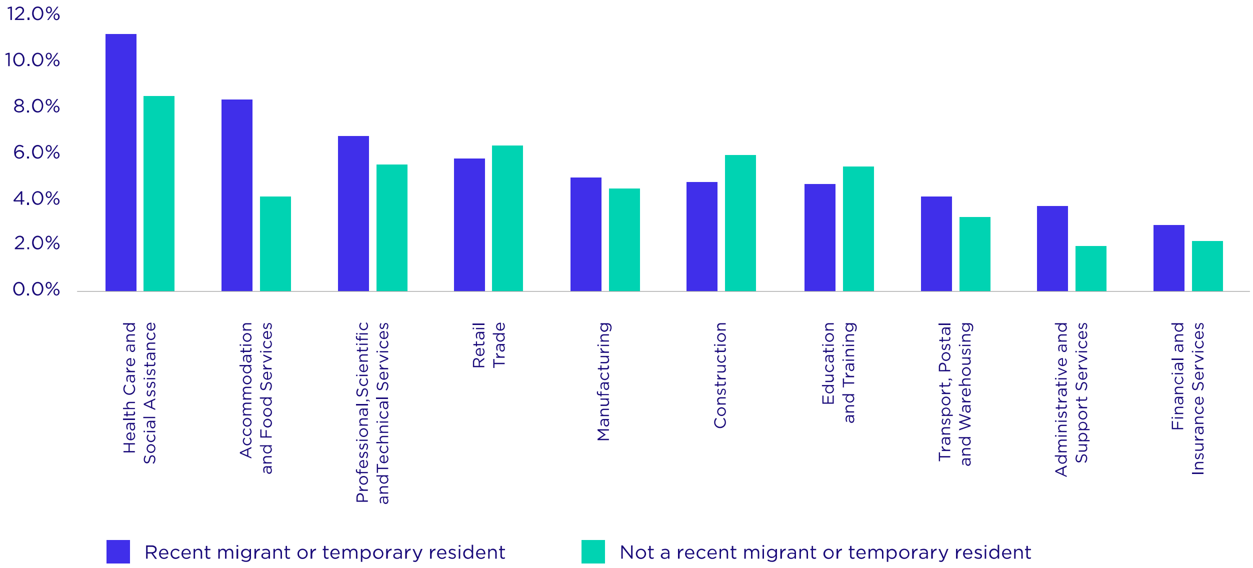
Source: Department of Home Affairs, Australian migration statistics, combined occupation tables, five years to 2019-20

Note: Permanent primary visa grants include data for subclass 186 Employer Nomination Scheme, subclass 187 Regional Sponsored Migration Scheme, subclass 189 Skilled Independent, subclass 489 Skilled Regional (Provisional), subclass 491 Skilled Work Regional (Provisional) and subclass 494 Skilled Employer Sponsored Regional (Provisional) visas.

Broader labour market impact of migrants and temporary visa holders

ABS data suggest that some industries are more likely than others to be affected by the closure of Australia's international borders in response to the COVID-19 pandemic. For example, the ABS's November 2019 *Characteristics of recent migrants* survey data show that industries such as health care and social assistance, accommodation and food services, and professional, scientific and technical services are more likely to be impacted.[37] Figure 38 shows that these three industries make up just over a quarter of those that migrants reported they worked in.

Figure 38: 10 main migrant employing industries



Source: ABS, *Characteristics of recent migrants,* November 2019

Note: 'Not a recent migrant or temporary resident' includes Australian born, long-term Australian citizens and permanent residents (who arrived before 2010) and New Zealand citizens who are long term residents of Australia. 'Recent migrants or temporary residents' includes recently arrived Australian citizens and permanent residents (who arrived in the 10 years to 2019) and temporary visa holders.

The percentages on the Y-axis are the percentage of each of the two categories across the industries (so that, if all industries were included in the figure, each series would sum to 100 per cent).

The *Characteristics of recent migrants* survey (CORMS) includes permanent and temporary residents who are not granted visas on the basis of their skills or human capital. This survey has a different occupational profile from that of the temporary and permanent skilled visa programs. Table 15 shows the CORMS survey ranking of the top 15 occupations for recent migrants, defined as those entering Australia in the 10 years to November 2019.

[37] Australian Bureau of Statistics (ABS) *Characteristics of recent migrants* survey, 2019.

Table 15: Top 15 occupations for migrants and temporary residents entering Australia in the 10 years to November 2019

	Occupation	(%)
1	Commercial Cleaners	2.5
2	Registered Nurses	2.4
3	Software and Applications Programmers	2.2
4	Sales Assistants (General)	2.1
5	Chefs	1.9
6	Aged and Disabled Carers	1.9
7	Kitchenhands	1.7
8	Child Carers	1.3
9	Packers*	1.2
10	Waiters*	1.1
11	Delivery Drivers*	1.1
12	Nursing Support and Personal Care Workers	1.1
13	Checkout Operators and Office Cashiers	1.0
14	Building and Plumbing Labourers	1.0
15	Accountants	1.0

Source: ABS, *Characteristics of recent migrants,* November 2019

Note: * Data for these occupation groups should be treated with caution as there is a relative standard error of more than 25%.

The ABS *Characteristics of recent migrants* survey defines migrants as people who came to Australia in the 10 years to November 2019 on permanent visas, including those who had become Australian citizens since arrival, and temporary visa holders with the intention to stay for one year or more.

05

Labour market matching – a skills perspective

Labour market matching – a skills perspective

A key purpose of the labour market is to match the skills required by employers with the skills and capabilities of current and potential employees. This chapter looks at the way the demand for labour from employers matches the supply of labour from workers.

The chapter outlines three perspectives on how well the labour market is matching demand with supply: the Beveridge Curve – a traditional indicator of labour market matching, employers' perspectives, and individuals' perspectives.

Employer surveys are revealing. In 2021, to April, 45% of recruiting employers reported having recruitment difficulty for their most recent vacancies, a slight increase on 2019 (42%) but significantly higher than 2016, when it was just 36%. Recruitment difficulty has become more common outside capital cities in recent years, with rest-of-state recruitment difficulty exceeding that for capital cities in 2020 for the first time.

From the job seeker perspective, the analysis shows there are differences between the last job held by a person seeking work and jobs that are frequently advertised.

The chapter also describes early work by the NSC to understand how well market matching is working in the vocational education and training (VET) sector, through the VET National Data Asset (VNDA). The data provided by the VNDA will allow information on the outcomes of training to be risk-adjusted, taking into account the diversity of students, courses and providers within the sector.

The economic theory of labour market matching

One of the most useful conceptual frameworks for understanding the dynamics of the labour market is search and matching theory. This framework describes a theory behind labour market search and matching, including the role of key participants such as firms and individuals. This approach is otherwise known as the Diamond, Mortensen and Pissarides model, named after three economists who won the Nobel prize in 2010 for their work leading the development of the framework.[38]

In the framework, firms produce products and services for customers. In order to deliver these products and services, the firms require certain tasks to be completed, which require a particular skill set to deliver. Together, these tasks and skills constitute a job, and collectively across the economy, firms' requirements for workers to complete these jobs constitute labour demand.

On the other side of the market, there are individuals who possess skills and capabilities. This may include skills developed through study or education or through previous work experience. These individuals also have preferences regarding the types of jobs they want to work in, and how they would like to participate in the labour market, for example, hours of work and job location. Together, these skills and preferences constitute available labour, or labour supply.

The labour market brings this labour supply together with labour demand from firms. Notably, both parties incur some costs in the matching process – for example, individuals have to spend time searching for a job, while firms incur advertising and recruitment costs including delayed productivity from on-the-job training. The labour market overall will be most efficient when there are good matches between workers' and firms' needs, and search costs are minimised.

Some degree of mismatch between demand and supply is unavoidable as labour market transitions can never be entirely seamless. It takes time for firms to advertise and recruit and similarly for individuals to search for, secure and be productive in a new job. Some mismatches are caused by imbalances between aggregate demand in the economy and aggregate supply. For example, during an economic downturn when business confidence is weak there is likely to be a surplus of labour supply relative to demand. This can come about through external shocks such as the global financial crisis and the COVID-19 pandemic. Structural imbalances are caused by the more persistent frictions in the labour market or entrenched obstacles that impede the efficient functioning of the labour market.

The factors influencing the mismatch between demand and supply are likely to be in play at any one point in time and can result in short, medium and longer-term matching inefficiencies. Although short-term mismatches may have minimal impacts on productivity and wealth, longer-term impacts caused by structural imbalances are of concern. Also, temporary shocks to the labour market can have persistent effects.

If potential workers (supply) are trained for a particular skill set or occupation but all the expanding firms (demand) require another skill set, then the matching process will be likely to be inefficient. As a consequence, the labour market will have simultaneously high unemployment and high vacancies. This has direct implications for the potential output of the economy as a whole. If there are persistent skill mismatches, overall economic output will be less than the potential output that could be produced given the overall labour supply. This shows how critical efficient labour market matching can be to an economy.

[38] The framework builds on earlier search models that explained how labour demand and supply adjust in the short run, extending these to account for changes in the matching process or the structural efficiency of the labour market once the adjustment has taken place. In other words, it accounts for situations where the labour market can be in a state of equilibrium but still have both unemployment and vacancies.

Three ways to assess labour market matching

The NSC has used three methods to gain a better understanding of the current degree of mismatch between labour market demand and supply. These are a traditional view using the Beveridge Curve, a perspective based on the NSC's surveys of employers and their recruitment difficulties, and a perspective from the employee through an analysis of the skills of the unemployed versus current job vacancies.

Together these different approaches create a picture of how well the labour market is matching supply with demand.

An economist's view – the Beveridge Curve

The Beveridge Curve compares the unemployment rate (the number of people unemployed divided by the total labour force) to the vacancy rate (the number of job vacancies divided by the total labour force) and shows how this changes over time.[39] The Beveridge Curve can be used to assess the current state of the labour market due to the economic cycle and is also a measure of the efficiency of labour market matching.

The NSC's Internet Vacancy Index (IVI) can be used to create a Beveridge Curve. The IVI provides a monthly measure of online job advertisements. The IVI dates back to 2006 and provides a high frequency measure to examine labour market matching in Australia. Using a monthly measure such as the IVI can be particularly valuable during periods of rapid change, such as those experienced since the onset of the COVID-19 pandemic. Figure 39 highlights the stark impact of the pandemic on the Australian labour market. The monthly data in particular help highlight the speed of the shock as well as the subsequent recovery.

[39] Labour demand, or the sum of employment and job vacancies, is sometimes used as the denominator for measuring the vacancy rate instead of using total labour force.

Specifically, the observations over mid-2020 are consistent with a recessionary environment with a relatively high unemployment rate and few vacancies. More recent observations suggest a solid recovery in the labour market with a lower rate of unemployment and an increase in job vacancies. The position of the most recent observations relative to the origin suggests a more 'mixed' labour market matching picture compared with before the pandemic, which should not be surprising in the context of changed consumer spending patterns, disruption to business models and supply chains, and closed borders. Chapter 4 has a discussion on the impact of migration on the labour market.

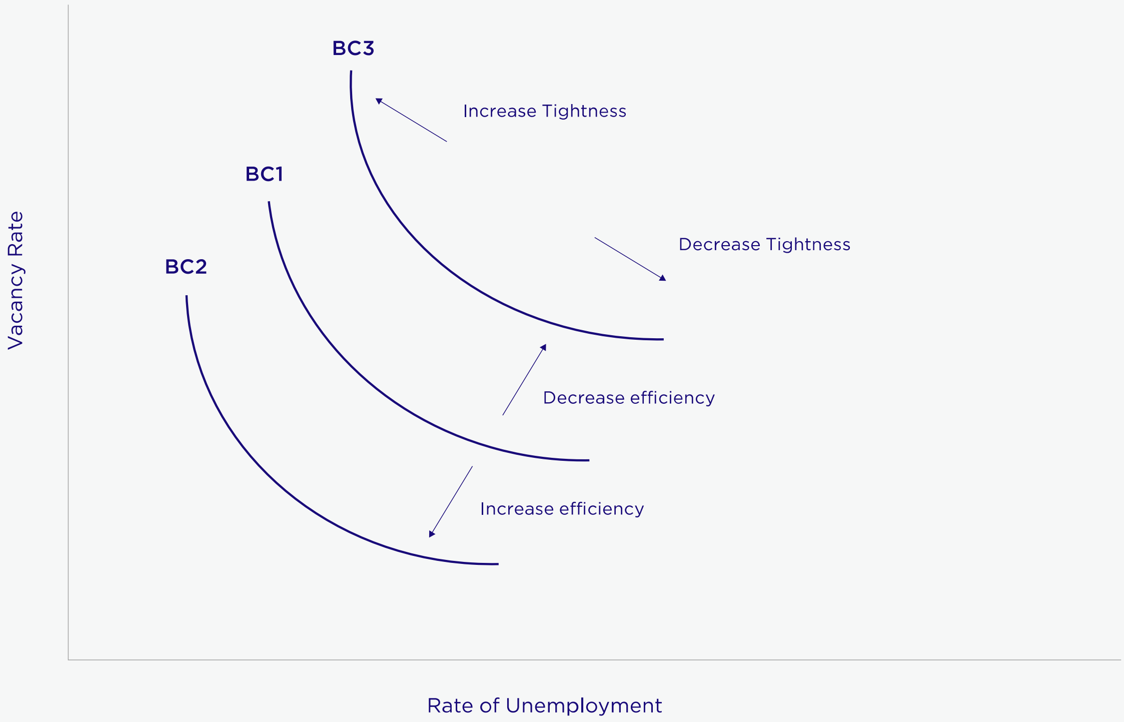
Figure 39: Beveridge Curve for Australia, 2006 to 2021, using NSC Internet Vacancy Index

Sources: ABS *Labour force, Australia,* seasonally adjusted and NSC Internet Vacancy Index, seasonally adjusted

The Beveridge Curve

The Beveridge Curve is named after Lord William Beveridge, who in 1944 looked at data on unemployment and the number of job vacancies and how they move over time. What makes the Beveridge Curve so useful is that it helps distinguish between cyclical and structural changes in the labour market matching process. Figure 40 shows how movements along the curve will generally reflect cyclical changes in labour market conditions. For example, when the economy strengthens the unemployment rate will fall while job vacancies will rise. When the economy weakens, the opposite is true. Firms lay off workers, so unemployment rises and the number of vacancies falls.

Figure 40: Beveridge Curves show labour market efficiency



Source: J Borland, Labour market snapshots, 78, 2021

As well as showing where we are in the economic cycle (boom or downturn), the Beveridge Curve also tells us something about the overall efficiency of the labour market. The closer the overall curve is to the origin, the more efficient the labour market is. If unemployment and vacancies are both low, this suggests that workers and vacancies are being efficiently matched. If the curve moves further away from the origin and unemployment and vacancies are both high, firms may be unable to find the workers they are looking for despite there being many unemployed people.

Employers' perspectives on labour market matching

Surveying employers on their day-to-day experience provides a practical way of understanding labour market matching and enables the NSC to gather insights directly from employers about their recent recruitment experiences. These recruitment processes occur at the intersection of labour supply and demand and provide valuable insights into how well the skills of the labour force are matching the needs of employers.

Employer surveys have advantages as a tool for measuring labour market matching:

- They gather information on a range of recruitment processes, including those where vacancies are not formally advertised. Such vacancies are not picked up in online vacancy measures such as the IVI.
- They can provide information on employers' experiences in undertaking recruitment. For example, they may be able to tell us if employers are receiving few applicants, or receiving applicants with insufficient skills, or whether there are external factors affecting their recruitment processes.
- They can be flexible, with questionnaires that can be adapted to gather information on the most pressing labour market issues.

One key measure of mismatch obtained from employer surveys is the extent to which, and frequency with which, employers find it difficult to fill their vacancies.

Recruitment difficulty generally occurs when employers are unable to find suitable applicants for their vacancies. It may result in vacancies taking a long time to fill, not being filled at all, or being filled with someone who is not a 'perfect fit' for the job.

Employers will more commonly have recruitment difficulty in a 'tight' labour market, that is a labour market in which there are relatively few job seekers (low unemployment) and a relatively high number of job vacancies.

Recruitment difficulty is not synonymous with skills shortages or the inability to fill vacant positions. NSC research on data from 2018-2019 shows that most employers were able to respond to their recruitment difficulty without their business being significantly affected.[40] Employers responded by increasing the hours of existing staff while they looked for new staff, hiring someone with less experience and training them, using labour hire to temporarily fill positions, or by readvertising the position.

Measuring recruitment difficulty – the Recruitment Experiences and Outlook Survey

The NSC measures and monitors different aspects of recruitment difficulty through its Recruitment Experiences and Outlook Survey (REOS). The current iteration of the survey began in August 2020 after a break in March 2020 from recruitment-themed questions due to the onset of the COVID-19 pandemic.[41]

Approximately 1,200 employers are surveyed each month, with updated data published weekly on the Labour Market Information Portal (www.lmip.gov.au). A report summarising key trends (the *Recruitment Insights Report*) is also published monthly.

Before 2020, the then Department of Employment, Skills, Small and Family Business conducted the Survey of Employers' Recruitment Experiences (SERE), a telephone-based employer survey with questions on recruitment difficulty similar to the REOS. Results from the SERE provide a nationally representative measure of the proportion of recruiting employers experiencing recruitment difficulty from 2016 to 2019.

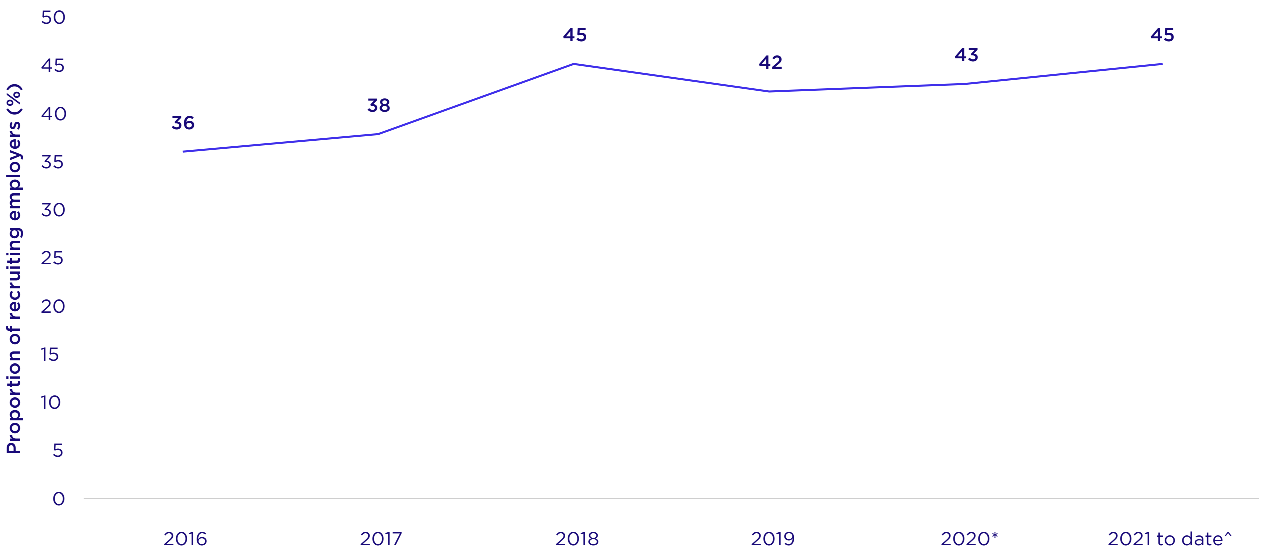
Together, the REOS and SERE provide insights into employers' recruitment experiences and a long time series of data on key trends and issues in the labour market from an employer perspective.

[40] Department of Employment, Skills, Small and Family Business, *Employer perspectives on recruitment difficulty – 2018 Data Report*, available from Employers' Recruitment Insights.
[41] Employers' Recruitment Insights, Labour Market Information Portal.

Trends in recruitment difficulty over the past five years

Results from REOS and SERE provide a measure of recruitment difficulty over the past five years.[42] Figure 41 shows that in 2021 up to 30 April, 45% of recruiting employers reported having recruitment difficulty for their most recent vacancies, a slight increase on 2019 (42%) and around the same level as in 2018.

Figure 41: Recruitment difficulty, 2016 to 2021



Sources: NSC, Recruitment Experiences and Outlook Survey, 2020 and 2021, and Survey of Employers' Recruitment Experiences, 2016 to 2019

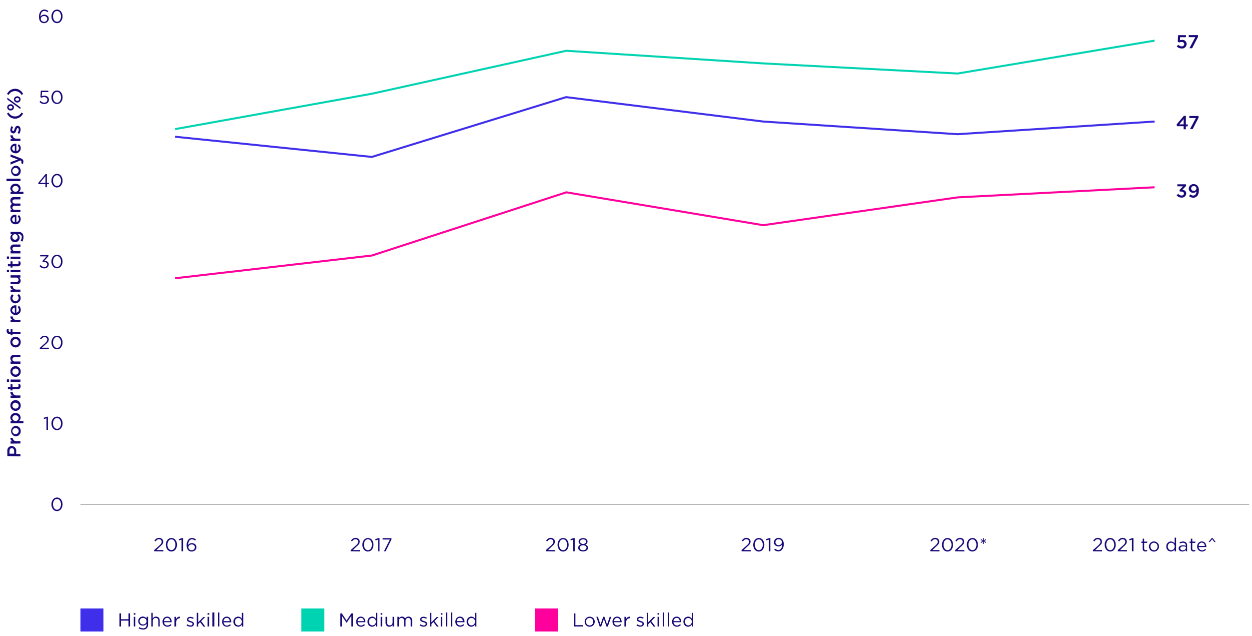
Note: *2020 data cover the period from 10 August 2020, when collection resumed, to 18 December 2020. As a result, they do not reflect recruitment conditions at the height of the restrictions imposed in response to the COVID-19 pandemic.

^'2021 to date' covers the period 11 January 2021 to 30 April 2021

Recruitment difficulty became more common for all skill level groups from 2016 to 2018, but since then there has generally been little change. Figure 42 shows that since 2019, before the pandemic, there have been slight increases in the incidence of recruitment difficulty for lower-skilled and medium-skilled occupations.[43]

[42] Data from 2016 to 2019 are based on results from the Survey of Employers' Recruitment Experiences (SERE). Due to changes in questions and survey timing from the SERE to the REOS, comparisons from 2019 to 2020 can be difficult to interpret and should be treated with caution. Both REOS and SERE are targeted towards employers with five or more employees and exclude many government organisations and employers in the agriculture, forestry and fishing industry.
[43] In this section of this report, lower skilled refers to occupations with an ANZSCO Skill Level of 4 or 5, medium skilled refers to an ANZSCO Skill Level of 3, and higher skilled refers to an ANZSCO Skill Level of 1 or 2.

Figure 42: Recruitment difficulty by skill level of the occupation being recruited for



Sources: NSC, Recruitment Experiences and Outlook Survey, 2020 and 2021, and Survey of Employers' Recruitment Experiences, 2016 to 2019

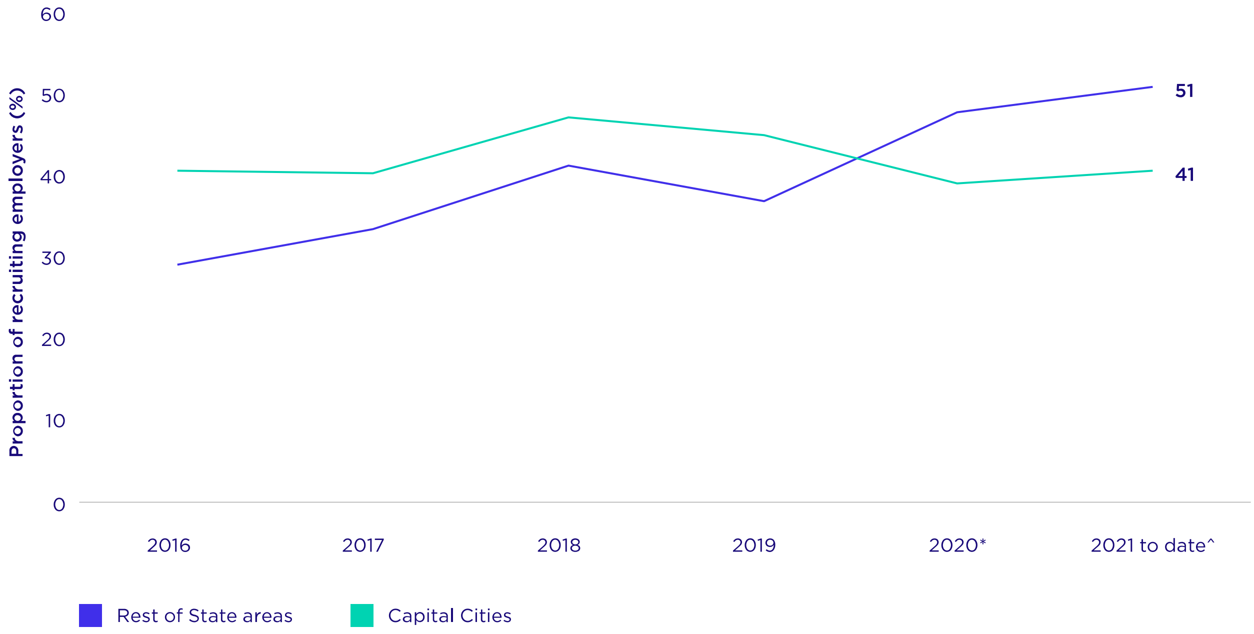
Notes: *2020 data cover the period from 10 August 2020 (when collection began again) to 18 December 2020. As a result, they do not reflect recruitment conditions at the height of the restrictions imposed in response to the COVID-19 pandemic.

^'2021 to date' covers the period 11 January 2021 to 30 April 2021

Recruitment difficulty has become more common in rest-of-state areas over recent years, with notable increases occurring from 2016 to 2018, and from 2019 to 2020. The first time recruitment difficulty in rest-of-state areas exceeded that recorded for capital cities was in 2020 – see Figure 43.[44]

[44] 'Capital cities' and 'rest-of-state areas' are defined according to the ABS's Australian Statistical Geography Standard (ASGS). Capital cities refer to 'greater capital cities' as defined in the ASGS, while rest-of-state areas refer to all other areas within each state or territory that are outside the greater capital cities.

Figure 43: Recruitment difficulty by region type



Sources: NSC, Recruitment Experiences and Outlook Survey, 2020 and 2021, and Survey of Employers' Recruitment Experiences, 2016 to 2019

Notes: *2020 data cover the period from 10 August 2020, when collection resumed, to 18 December 2020. As a result, they do not reflect recruitment conditions at the height of the restrictions imposed in response to the COVID-19 pandemic.

^'2021 to date' covers the period 11 January 2021 to 30 April 2021

Reasons for recruitment difficulty in 2020-21

Recruitment difficulty predominantly relates to employers being able to recruit the right people for the job.[45] Although a few employers reported reasons not related to applicants – such as struggling to find time to recruit – most employers who responded to the NSC's survey reported that their recruitment difficulty was due to difficulty attracting the right applicants. This has been the trend since the data began being collected in 2017.[46]

Figure 44 shows that from September 2020 to April 2021, the two most common reasons mentioned by employers were a lack of suitable applicants (mentioned by 39% of the employers who had difficulty) and a general lack of applicants (mentioned by 38% of employers who had difficulty).

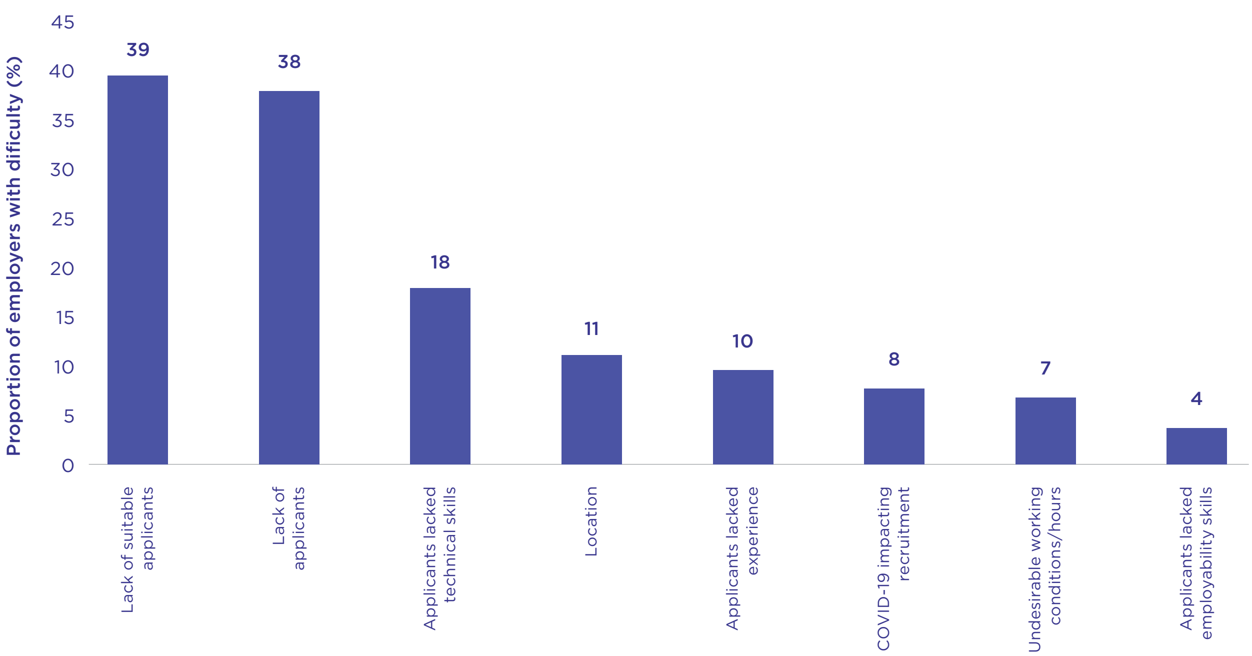
Employers who reported a general lack of applicants tended to receive fewer applicants per vacancy, with three quarters receiving at most five applicants per vacancy, despite most advertising their vacancies on the internet. A general lack of applicants was more commonly mentioned by employers in rest-of-state areas (43% of those with difficulty) compared with those in capital cities (33%).

Among employers who had difficulty, 18% reported applicants lacked the technical skills required for the job. Around half of these employers, despite reporting difficulty attracting qualified applicants, still received no more than five applicants per vacancy, demonstrating that many employers have little choice in hiring staff. Applicants lacking technical skills was more commonly mentioned by employers having difficulty recruiting for higher skilled (28%) and medium skilled (23%) occupations than for those having difficulty recruiting lower skilled occupations (11%).

Among the employers who had difficulty, 11% mentioned the location of their business or town as the reason. This was a particularly common reason for employers in rest-of-state areas (18%) and those recruiting professionals (22%).

'COVID-19 impacting recruitment' was cited as a reason for recruitment difficulty by 8% of employers from September 2020 to April 2021, although this proportion is changing as Australia's labour market recovery continues. The most recent data show that this proportion has declined to stand at less than 1% in the four weeks to 30 April 2021.

Figure 44: Reasons for recruitment difficulty, September 2020 to April 2021



Source: NSC, Recruitment Experiences and Outlook Survey, September 2020 to April 2021

[45] 'Reasons for recruitment difficulty' survey responses were collected from 21 September 2020 to 30 April 2021.
[46] 2020-21 data on 'reasons for recruitment difficulty' are not directly comparable with those from previous years because of changes in response categories.

Severity of recruitment difficulty in 2021

The NSC has recently researched in more detail the recruitment difficulty experienced by employers. The results will be released over the coming months although some early insights are available now.

Results from March and April 2021 show that employers recruiting for higher and medium skilled vacancies in rest-of-state areas not only have recruitment difficulty most frequently, but also experience a greater severity of difficulty. As Figure 45 shows, more than half of these recruiting employers had 'great difficulty' filling their most recent vacancies.

Figure 45: Severity of recruitment difficulty, by region and skill level of vacancy, March and April 2021

Source: NSC, Recruitment Experiences and Outlook Survey, March to April 2021

Changes in employers' recruitment processes and requirements

The NSC also recently collected information about whether, in response to difficulty recruiting, employers changed their recruitment processes or requirements.

In March and April 2021, about one-in-eight employers reporting recruitment difficulty changed their expectations or qualification requirements compared with earlier recruitment for the same occupation. This includes instances where employers were willing to hire applicants with experience even if they were not as qualified as the employer originally wanted, or had taken on people who demonstrated enthusiasm or a willingness to learn on the job.

Around one-in-five employers reporting recruitment difficulty changed the methods they used to try and fill their vacancies compared with earlier recruitment for the same occupation. There has been a trend towards internet-based recruitment over the past decade, with social media growing in importance as a means of advertising vacancies. However, research shows that employers are often flexible when trying to fill their vacancies. Some employers will test other methods, particularly word-of-mouth, without automatically using the same methods they previously used.

Individuals' perspectives on labour market matching

This section considers the difficulty of finding work from the perspective of the individual. It considers how hard it may be for an unemployed person to get a job based on their past occupation and current advertised vacancies, and what this looks like from a skills cluster perspective.

Data from the Australian Taxation Office indicate that when people change jobs, they most frequently change employers but remain in the same occupation. It is likely that, for many job seekers, the default option is to seek work in the occupation they have most recently held. Unfortunately, the vacancy profile can make this challenging. Figure 46 shows, at the national level, the most common previous occupations of unemployed people compared with the most frequently advertised vacancies.

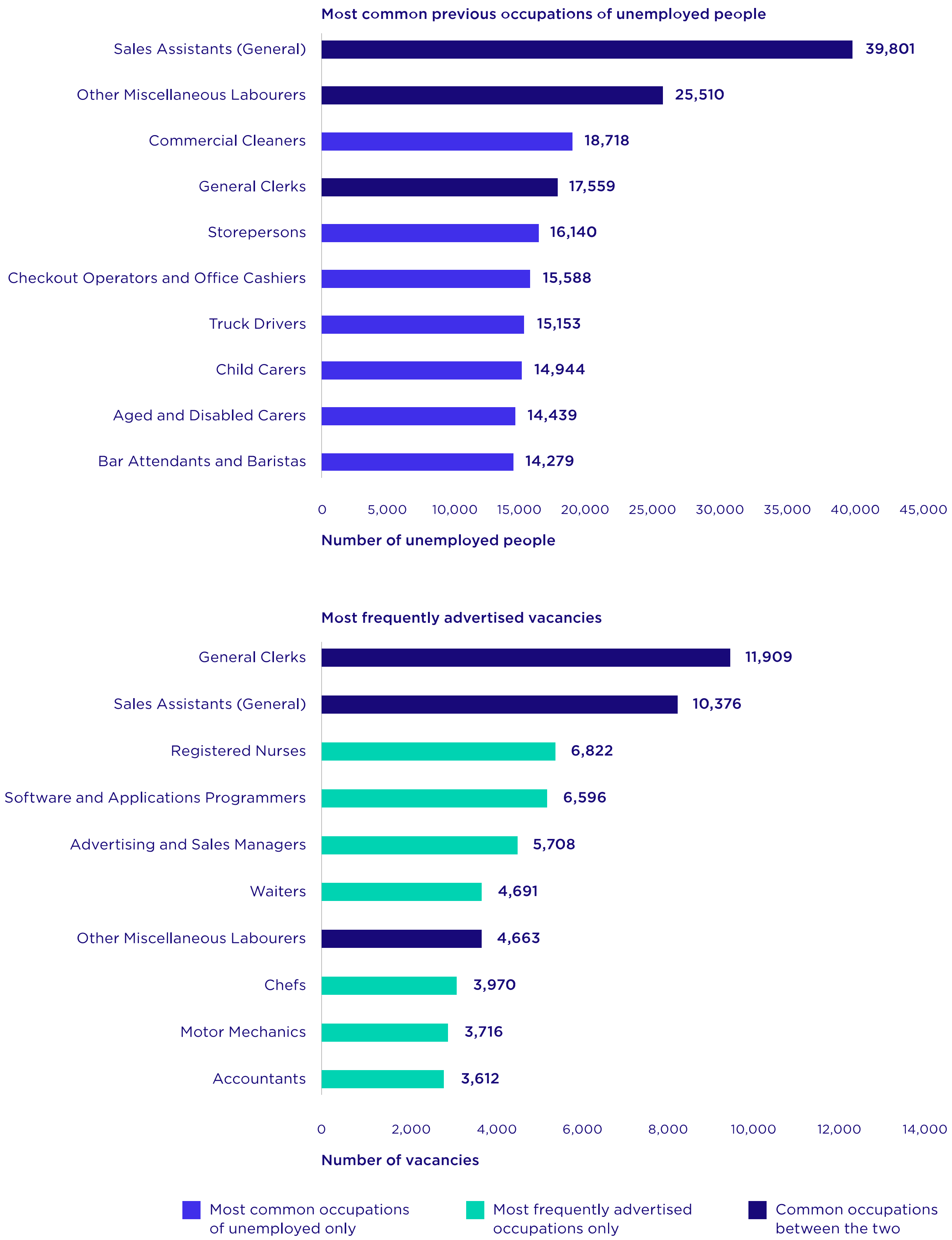
Occupations in high demand are more likely to be specialised and require higher level skills and formal qualifications. These include occupations such as 'registered nurse', 'software and applications programmers', and 'advertising and sales managers'.

Unemployed people tend to have experience in lower skilled or entry level jobs such as labourer, cleaner, storeperson or checkout operator. Even in occupations that make both the 'recent occupations of unemployed' and 'online jobs' lists in Figure 46, such as sales assistant and general clerk, the supply of unemployed workers outstrips the number of vacancies.

That said, caution should be taken when using internet vacancies as a measure of demand. Not all jobs are advertised on the internet and some are not advertised at all.[47] The NSC uses a range of inputs to measure skills shortages and surpluses; hence the charts in this section provide only one indication of the difficulties faced by unemployed people seeking jobs.

[47] This data is drawn from the NSC's Internet Vacancy Index (IVI), which is based on a count of online job advertisements newly lodged on SEEK, CareerOne and Australian JobSearch during the month. The IVI does not reflect the total number of job advertisements in the labour market as it does not include job advertisements still available from previous months, and jobs advertised through other online job boards, employer websites, word of mouth, in newspapers, and advertisements in shop windows.

Figure 46: Comparison of most recent occupations of unemployed people and online job listings, March 2021

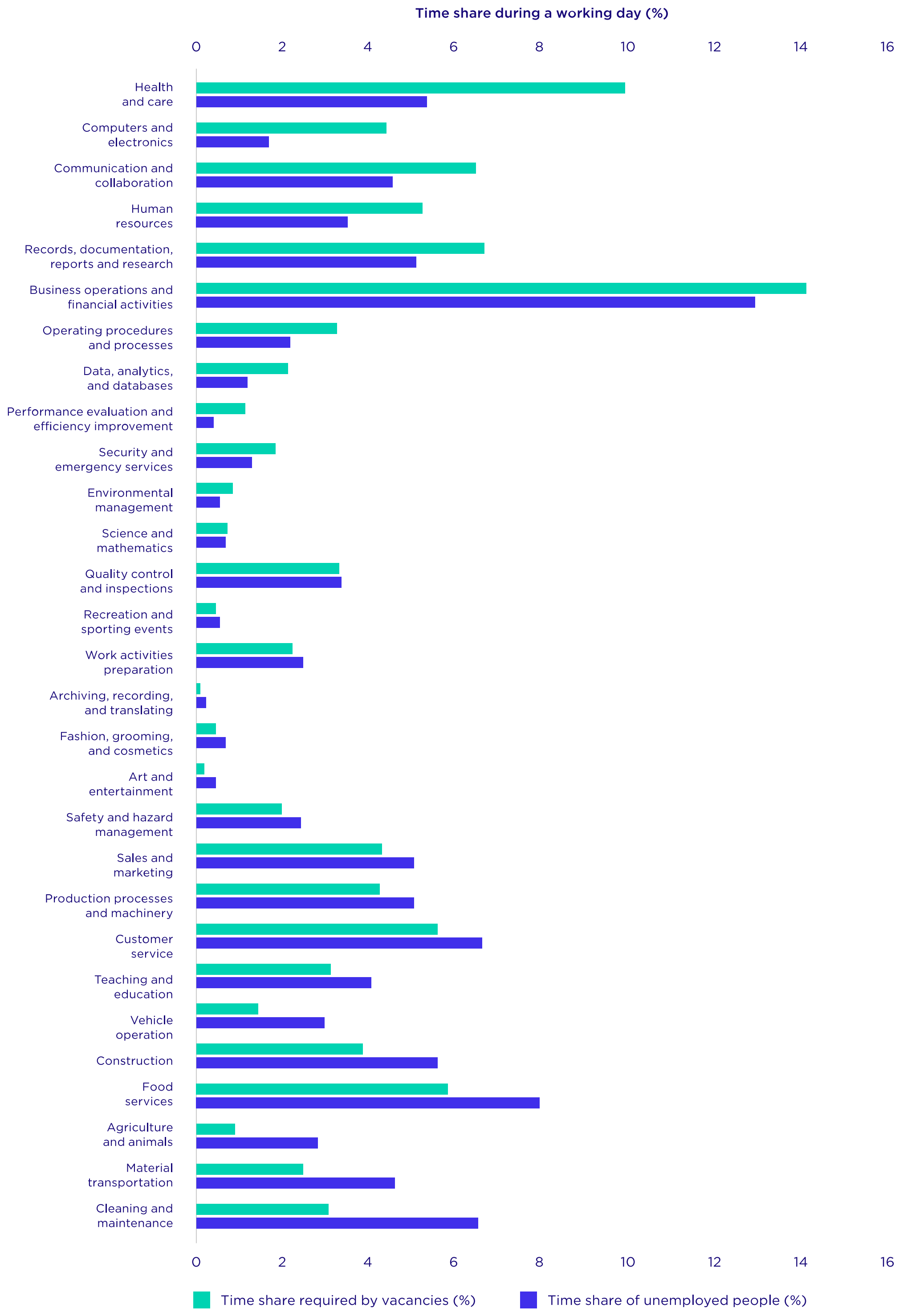


Sources: Skills Tracker, NSC Internet Vacancy Index, March 2021, seasonally adjusted, NSC analysis

Skills of unemployed Australians compared with current vacancies

Taking this analysis from the occupation to the skills cluster level shows there is a difference between the skills profile of the unemployed and the jobs that are frequently advertised. Figure 47 shows the average amount of time currently advertised roles require for a skills cluster family compared with that of unemployed people's previous occupations.

Figure 47: Skill intensity by skills cluster family for unemployed people and current vacancies



Sources: Skills Tracker, NSC Internet Vacancy Index, March 2021, NSC analysis

Note: The figure is ordered by the difference between skill intensity in vacancies and unemployed people, with families where vacancies required a higher skill intensity than skills held by unemployed people are on the top.

Vacancies for jobs requiring skills from the health and care family made much more intensive use of these skills than the occupations that unemployed people had come from. In total, vacancies required 10% of time to be spent on using these skills compared with 5% of time in the previous occupations of unemployed people. Vacancies also require a slightly higher proportion of time spent on health skills than is found in the employed population (9%) indicating that demand for health skills is increasing across the labour market. There is more discussion of this point in the section on 'Trending and emerging skills' in Chapter 7.

Drilling down into the health and care family reveals that the skills most in demand are related to management in the health sector, and high-level patient management. Skills in demand in management in the health sector include: 'managing health care operations', 'collecting, documenting and communicating medical information' and 'creating health care documentation'. Skills in demand in high level patient management include 'developing treatment plans' and 'monitoring and evaluating patient treatment'.

Few unemployed people have recently worked in occupations that have the required level of expertise in these areas. Unemployed people are more likely to have acquired skills from their previous occupation in direct patient care, such as 'assisting and supporting clients', 'caring for patients', and 'administering medical treatments'.

Work which involves significant use of skills from the health and care skills cluster family is heavily regulated and subject to accreditation and licensing requirements. Strategies to address shortages of specific skills, such as those mentioned above, would need to take these frameworks into account. However, the trend for vacancies to demand more technical, supervisory and strategic skills than are typical among some unemployed people is also reflected in other skills cluster families.

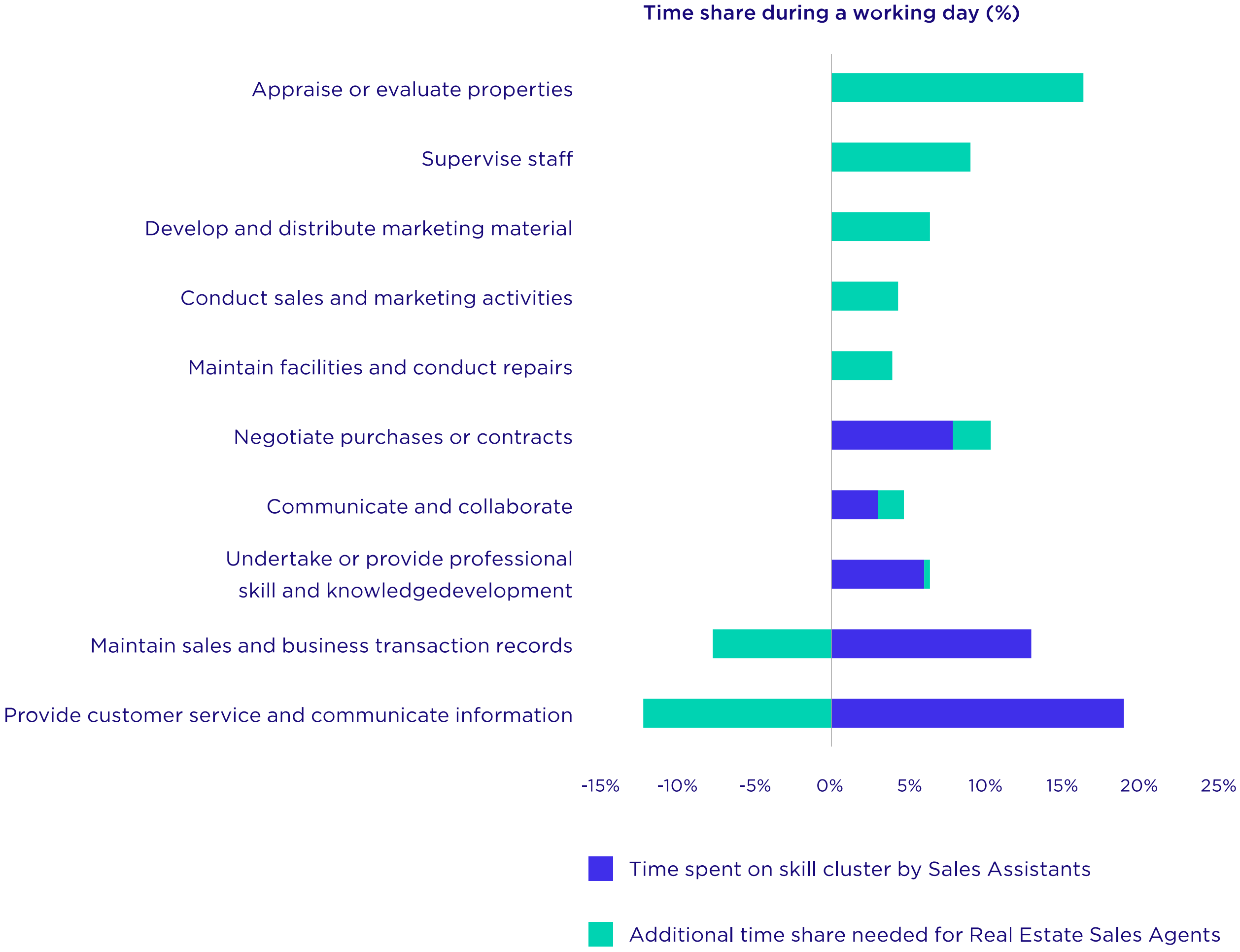
Although many unemployed people have skills from the business operations and financial activities family, they tend to be in more entry level clusters, such as 'conducting financial transactions', 'maintaining inventory', and 'estimating costs of goods or services'. Employers are more often seeking skills in management-related clusters, such as 'manage and monitor financial activities', 'managing services, staff or activities', and 'establishing organisational policies or programs'.

The usefulness of transitions in helping to address mismatches between individuals' skills and jobs

The Australian Skills Classification (ASC) expands the possibilities for job seekers by identifying skills which are transferable across occupations. For example, although the number of unemployed sales assistants appears to greatly outstrip the number of job openings in most states, many of the skills they are likely to have acquired in their last role could be applied to occupations such as 'beauty therapist', 'model and sales demonstrator', 'motor vehicle salesperson' and 'real estate sales agents'.

Figure 48 sets out the intensity of use for skills in common between 'sales assistant' and 'real estate sales agent'. Most sales assistants would already have more than enough experience in 'providing customer service and communicating information', as sales assistants typically spend 19% of their time using skills from this cluster, whereas real estate agents tend to spend about 7% of their time on them. In contrast, a sales assistant may need to extend their current skills in 'negotiating purchases or contracts', because this skills cluster takes up more of a 'real estate sales agent's' time than it does sales assistants (10% compared to 8%). In addition, sales assistants looking to move into real estate may need to build skills in 'appraising or evaluating properties', 'analysing market data and trends' and 'developing marketing material' which are not typically used in their current occupation. The number of real estate agents in Australia is projected by the NSC to grow by 8.5% over the next five years, and the move to such a job would bring the additional benefit of higher pay.

Figure 48: Transferable skills of sales assistants and real estate sales agents, percentage of transferable skill



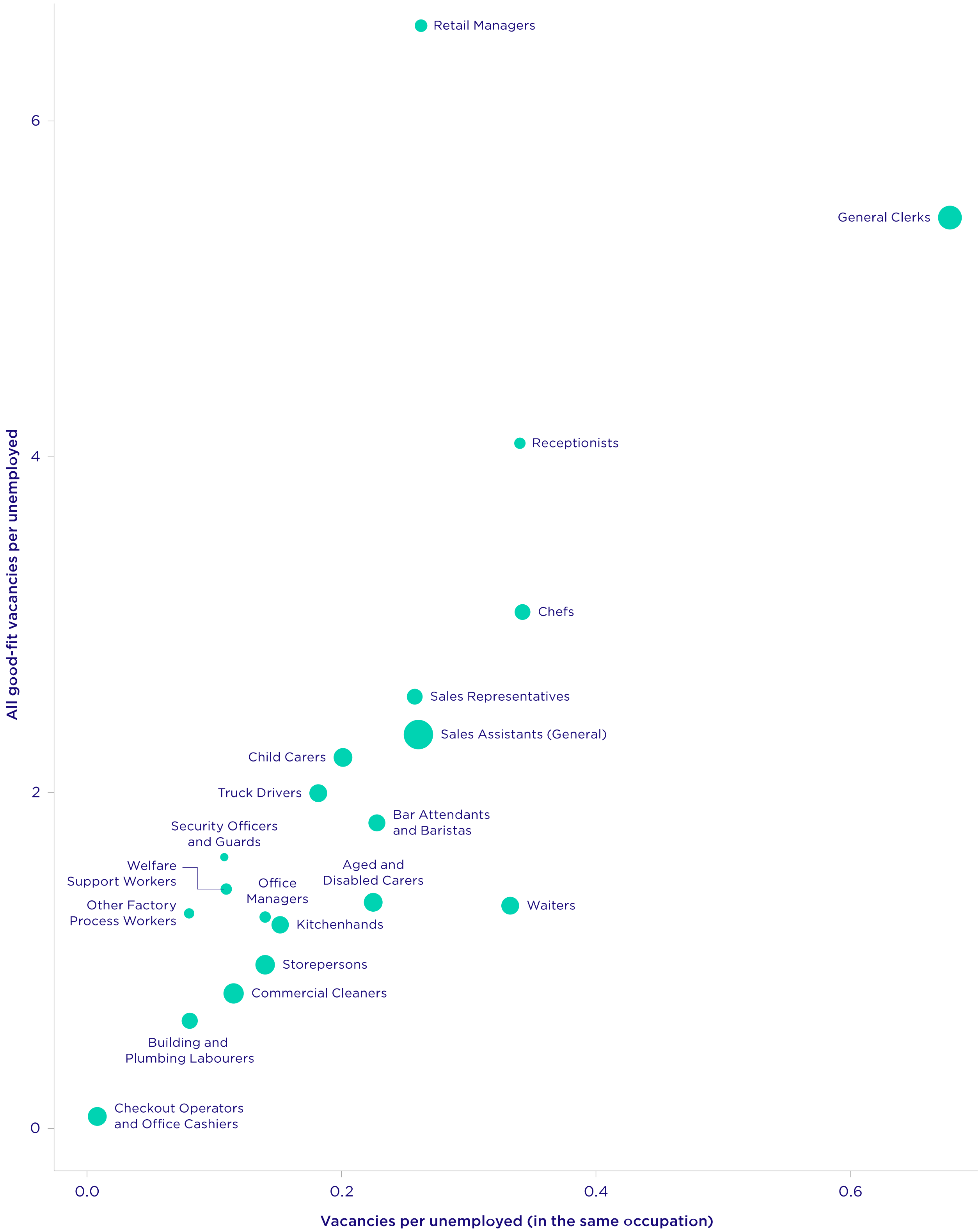
Source: NSC analysis, drawing on the ASC

Note: This figure includes top 10 skill clusters required by real estate sales agents, ordered by the additional time share needed for real estate sales agents.

Transition opportunities can also be mapped systematically across the labour market. Figure 49 shows the most common previous occupations of unemployed people, with the number of unemployed people in each category represented by the size of the bubble. The x-axis gives the number of current vacancies for the occupation and the y-axis shows the number of vacancies for similar occupations based on their underlying skills profile.

Unemployed retail managers face quite steep competition for roles in their own field, but many of their skills are transferable to other occupations with vacancies, making them relatively competitive in the overall labour market if they are prepared to consider other roles. General clerks both have a comfortable number of vacancies in their own field and many viable transition options. Checkout operators and office cashiers face the double disadvantage of few openings and a lack of skills that are transferable to occupations that are in higher demand.

Figure 49: Transition options for unemployed into wider labour market opportunities



Sources: Skills Tracker, NSC Internet Vacancy Index, seasonally adjusted, March 2021, NSC analysis

The VNDA offers insights into qualifications and training provider outcomes

The NSC is developing better ways to monitor the effectiveness of the vocational education and training (VET) sector to meet labour market needs.

The NSC is working in partnership with the Australian Bureau of Statistics (ABS) to create the VET National Data Asset (VNDA). This will allow us to assess the performance of the VET system with greater depth and accuracy. The VNDA will link Total VET Activity (TVA) data – showing who has participated in accredited training, whether they completed the course and their background characteristics – to the Multi-Agency Data Integration Project (MADIP).

To date, the ability to monitor the outcomes of VET courses in the labour market has been limited by the data available. The Australian VET system is fragmented and this introduces further difficulties. There are more than 1,200 nationally recognised qualifications and 600 accredited courses, delivered by more than 4,000 registered training organisations (RTOs). Each state and territory has responsibility for its own system of subsidised delivery, introducing a further source of variation. Until now, the primary data source for student outcomes was surveys, which are costly to administer and often have low response rates, potential response bias and reporting lags.

A robust assessment of the performance of the Australian VET system must overcome a number of challenges. The impacts of education and training can only be observed after training has ended, and sometimes years after. Disentangling the effects of the training from other factors, such as the student's aptitude, attitude, background characteristics and labour market experience as well as general community and economic effects, requires careful use of statistical techniques.

There are five outcomes of interest from this research. They have been chosen because they address the most pertinent areas of interest, and the required data for analysis appear to be already available. The outcomes of interest are:

- employment income
- employment status
- personal income tax payable
- social security payments received
- business income.

The NSC will develop a risk-adjusted methodology, based on stakeholder feedback, expert input, and the quality and usefulness of the data. It will be particularly important to ensure that the final assessment of qualification performance adequately focuses on the value add of the training. The methodology must also control for the range of student characteristics and local economic factors that have a large influence on individuals' labour market outcomes. In all cases the research is testing whether training in a course is a turning point in the private and public circumstances of the cohort.

06

Labour market skills need

Labour market skills needs

This chapter gives the NSC's industry, occupation and skills forecasts to 2025.

At present the labour market is buoyant, after a strong recovery from the worst effects of the COVID-19 pandemic. From the occupational lens, there are pockets of shortages across most occupation groups. Generally, shortages are greatest among 'technicians and trades workers' occupations. Technicians and trades workers are employed in a wide range of occupations important to many different industries, and include electricians, carpenters, chefs, fitters and motor mechanics.

The five year industry employment outlook projects that the long-term structural shift in employment towards services industries will continue. Four services industries – 'health care and social assistance', 'accommodation and food services', 'professional, scientific and technical services', and 'education and training' – are expected to generate over three-fifths of the total projected employment growth. However, future employment growth is not confined to these areas, with further increases projected across a range of industries.

Tertiary education and skills development beyond secondary school is increasingly important. Employment in STEM occupations (using science, technology, engineering and maths skills) is projected to grow more than twice as fast as non-STEM occupations.

By combining the five year employment projections with the Australian Skills Classification (ASC), the NSC has produced five year skills projections. Continuing the trend from the COVID-19 recovery, the food services cluster family is projected to experience the fastest growth. 'Computer and electronics' and 'performance evaluation and efficiency improvement' are the next fastest growing families. A large amount of time is projected to be spent on skills in the health and care family and the importance of communication and collaboration in a broad range of occupations comes through.

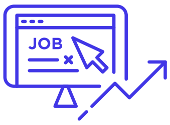
Some of the most important and rapidly growing skills needs over coming years, identified by this analysis, can be summarised as the 'Four Cs': care, computing, cognitive and communication skills.

The NSC has a suite of useful tools for analysing the skills needs of the economy now and in future. The commission uses well-established techniques for generating employment forecasts by industry and occupation. The newly-developed Australian Skills Classification (ASC) provides another dimension – projections of skills themselves.

The Skills Priority List (SPL) is another new NSC research program. The SPL outlines the occupations that are currently in shortage as well as their expected future demand. It will form the backbone of the NSC's labour market advice, including on skilled migration, training and employer incentives. The SPL is published on the NSC's website.

Among their key insights, these tools highlight the occupations and skills in demand now and likely to be in demand in the near future.

The employment recovery from a skills perspective



The NSC's Internet Vacancy Index (IVI) provides timely insights into occupation demand.[48] It is the most comprehensive count of online job advertisements newly lodged during a month and is the only source of data on recruitment activity available at the detailed occupation level over time.

Trends in internet job advertisements

The COVID-19 pandemic and associated restrictions saw internet job advertisements – measured by the IVI – fall to an all-time series low in April 2020. However, the latest IVI results at the time of writing, for May 2021, show that recruitment activity increased strongly after the downturn. Job advertisements have now reached a higher level than before the pandemic. The May 2021 IVI shows:

- There were 245,400 newly lodged job advertisements. This is the highest level of recruitment activity recorded by the series since October 2008.
- Recruitment activity increased for the 13th consecutive month and now stands 3.5 times higher than the April 2020 series low point.
- Job advertisements exceed levels observed before the COVID-19 downturn, up 46.0% or 77,300 job advertisements, compared with pre-COVID-19 levels.[49]

Recruitment has grown across all eight broad occupational groups

Recruitment activity has grown across all eight broad occupational groups over the period February 2020 to May 2021. Table 16 shows that the strongest gains, compared with pre-COVID-19 pandemic levels, have been for labourers (up by 102.7% or 10,000 job advertisements), followed by community and personal service workers (up by 75.8% or 11,100 job advertisements), machinery operators and drivers (up by 66.6% or 5,200 job advertisements), technicians and trades workers (up by 59.0% or 13,200 job advertisements), and sales workers (up by 52.0% or 6,600 job advertisements).

Table 16: Job advertisements by broad occupational group (1-digit ANZSCO) – Comparison to pre-COVID-19 levels

ANZSCO Title	Job advertisements – May 2021	Pre-COVID-19 comparison	
		Change (no.)	Change (%)
Managers	26,500	5,200	24.6%
Professionals	68,800	17,300	33.6%
Technicians and Trades Workers	35,500	13,200	59.0%
Community and Personal Service Workers	25,700	11,100	75.8%
Clerical and Administrative Workers	37,800	9,600	34.1%
Sales Workers	19,400	6,600	52.0%
Machinery Operators and Drivers	12,900	5,200	66.6%
Labourers	19,800	10,000	102.7%
All Occupations	245,400	77,300	46.0%

Source: NSC Internet Vacancy Index, seasonally adjusted

[48] The IVI can be used as an indicator of recruitment activity or demand but is not a complete measure as the IVI is not a count of all job vacancies in the Australian labour market.
[49] Pre-COVID-19 job advertisement levels are defined as the 12-month average in the seasonally adjusted IVI series to February 2020.

The IVI can be used to compare the levels of recruitment activity driven by recovery from the COVID-19 downturn to previous labour market shocks and developments. For example, in May 2021:

- Recruitment activity for community and personal service workers and technicians and trades workers stands at levels commensurate with all-time series highs.
- Recruitment activity for managers, professionals, machinery operators and drivers and labourers stands at the highest levels in more than 12 years but remains below peak recruitment activity levels recorded prior to the 2008 global financial crisis.
- Recruitment activity for clerical and administrative workers and sales workers is comparable with recruitment activity levels observed during the Mining boom (2011).

Job advertisements exceed pre-COVID-19 levels across all 48 detailed occupational groups

At the more detailed (ANZSCO 2-digit) level, job advertisements exceed levels observed before the COVID-19 downturn across all 48 detailed occupational groups.[50] The largest increases, compared with pre-COVID-19 levels, were for general-inquiry clerks, call centre workers and receptionists (up by 6,500 job advertisements), followed by hospitality workers (up by 5,700 job advertisements), sales assistants and salespersons (up by 5,000 job advertisements), medical practitioners and nurses (up by 4,200 job advertisements) and food trades workers (up 4,000 job advertisements).

[50] Some customised occupational groups are used in the IVI's analysis at the 2-digit level of detail.

Table 17: Job advertisements by detailed occupational group (2-digit ANZSCO) – top 10 largest growth compared with pre-COVID-19 levels

ANZSCO Title	Job advertisements – May 2021	Pre-COVID-19 comparison	
		Change (no.)	Change (%)
General-Inquiry Clerks, Call Centre Workers, and Receptionists	18,900	6,500	52.4%
Hospitality Workers	9,900	5,700	138.7%
Sales Assistants and Salespersons	12,400	5,000	68.4%
Medical Practitioners and Nurses	10,400	4,200	66.8%
Food Trades Workers	7,800	4,000	103.9%
Carers and Aides	10,200	3,600	54.3%
Drivers and Storepersons	6,800	3,400	97.7%
Automotive and Engineering Trades Workers	9,800	3,200	49.2%
Health Diagnostic and Therapy Professionals	7,200	2,800	62.1%
Other Labourers	6,500	2,700	71.0%

Source: NSC Internet Vacancy Index, seasonally adjusted

Recruitment activity has accelerated beyond previously observed levels for some occupational groups. For example, one combination of health-related occupations ('carers and aides', 'medical practitioners and nurses', 'health diagnostic and therapy professionals', and 'health and welfare support workers') surpassed record high job advertisement levels during late 2020 and early 2021. In May 2021 recruitment activity for these occupations remained at levels commensurate with record highs. In total, there were 30,500 advertisements for the positions in this combination of occupations during May 2021.

The IVI is one important source the NSC uses to understand current skills needs. When combined with other insights such as the skills of job seekers and where shortages may exist, it helps build our ability to improve the efficiency of matching in the labour market.

Occupation shortages

SERA data to date for 2020-21, up to April, show that employers are having a similar level of success filling their vacancies for skilled occupations as they did in 2019-20. Employers reported that the most common reason vacancies were unfilled was due to the lack of suitable applicants, often due to a lack of experience or relevant qualification. Employers advertising for professional occupations generally recruited with greater ease than those recruiting for technician and trade occupations. Those recruiting in regional areas also had more difficulty recruiting compared with employers in capital cities.

The NSC's Survey of Employers who have Recently Advertised (SERA) captures employers' views through a dedicated survey that asks a range of questions about their recruitment experience for an advertised vacancy, collecting both quantitative and qualitative data. The SERA is designed to assess occupational shortages and provides a direct measure of employer recruitment experiences. From June 2021 the SERA survey coverage was expanded from 80 occupations to around 250 occupations annually. Occupations selected for the SERA are typically skilled occupations which generally require at least three years of post-school education or training.

Examples of the quantitative data collected include the proportion of vacancies filled and the number of applicants, qualified applicants and suitable applicants.

Qualitative questions are asked, to identify key labour market issues, and include questions relating to reasons why vacancies are not filled, why applicants are considered unsuitable, and the impact of recruitment challenges on employers.

In 2020-21 to date (using data to April 2021), around 5,000 employers (representing almost 7,500 advertised vacancies) have been surveyed through the SERA, covering 80 skilled occupations.

SERA data from 2020-21 show that 61% of vacancies were filled, up slightly from 60% in 2019-20. (Note that the SERA was paused due to the COVID-19 pandemic from April 2020 to July 2020.) There was an average of 12.8 applicants per vacancy, of whom 2.9 were considered by employers to be suitable (compared with 14.1 and 2.5 respectively in 2019-20).

Vacancies most commonly remained unfilled because the employer did not receive any applicants they considered to be suitable. Applicants were most commonly regarded as unsuitable because they lacked the required experience or qualification. Other regularly cited reasons included 'poor application/interview or work history', and 'inadequate technical skills'.

The reasons why vacancies were unfilled are complex. Employers usually have very specific skills and experience requirements and, although they often attract qualified applicants, can be unwilling or unable to compromise those requirements. More than half of all qualified applicants were regarded as unsuitable. In addition, for some vacancies where employers attracted suitable candidates, vacancies were not filled for a range of reasons, most commonly because the suitable applicant accepted work elsewhere, or there was a lack of agreement on the terms and conditions of employment.

Employers advertising for professional occupations generally recruited with greater ease than those recruiting for technician and trade occupations. Of professional vacancies, 69% were filled, compared with 54% of technician and trade vacancies. Professional vacancies generally attracted more candidates, with an average of 15.3 applicants per vacancy, of whom 3.6 were suitable (compared with 10.7 and 2.3, respectively for technicians and trades).

Regional employers generally had more difficulty recruiting, filling 57% of their vacancies, compared with 63% in capital cities.

Five-year employment projections

Employment projections provide insights into future job opportunities that can support education policy, career decisions by job seekers and students, education provider course offerings, workforce planning and broader policy and program design. These insights are vital to answer the lingering questions on Australia's economic recovery from the impacts of the COVID-19 pandemic such as:

- How many jobs will return or be created?
- Where will the jobs be?
- What education, training and skill levels will be required?

The NSC's employment projections by industry, occupation and skill level help answer these questions. Although there is significant volatility in the Australian and global economies, the Australian labour market is recovering well from the impacts of COVID-19. This means it is appropriate to use traditional approaches to forecasting employment to provide data and insights about the performance of sectors and occupations in the labour market, albeit with a greater degree of uncertainty than usual because of the ongoing shifts occurring in the underlying data.

The NSC's industry and occupation employment projections are based on a well-established time series forecasting methodology that has been used within the Australian Government since 2013. The occupation projections are aggregated, applying the ABS concordance between occupations and skill levels, to provide employment projections by skill levels. To provide additional insights, the occupation projections have been mapped to the ASC to generate outlooks for specific skills.

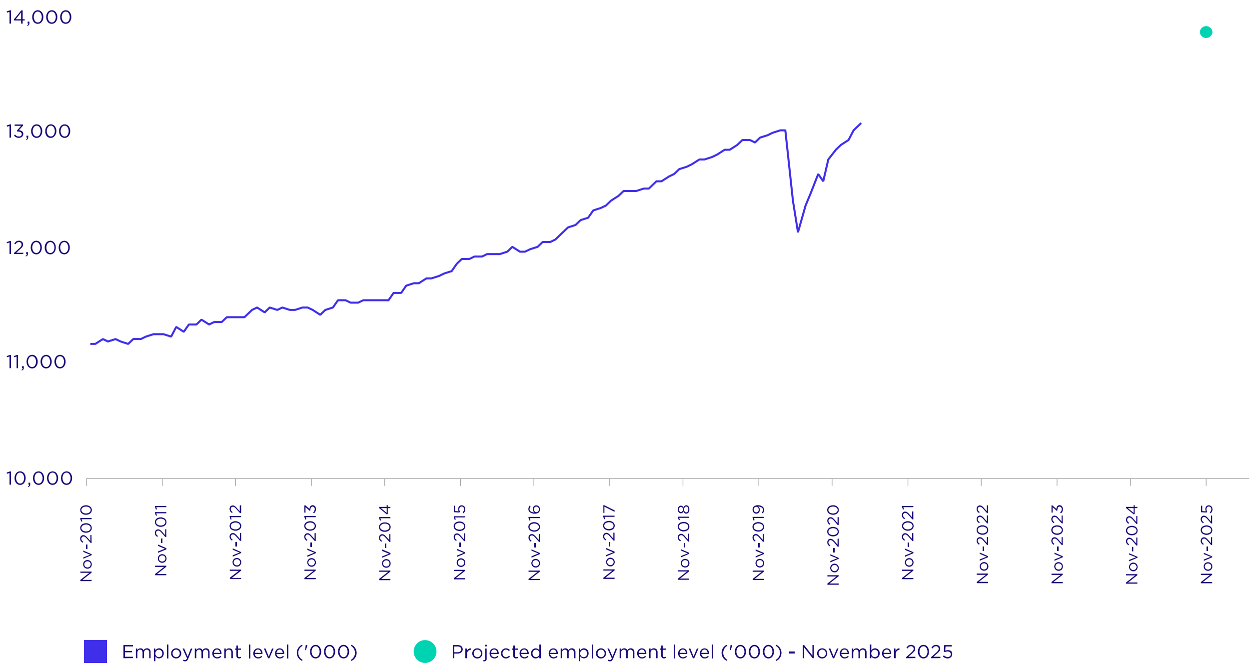
These employment projections are a part of the suite of analysis undertaken by the NSC to understand future workforce dynamics. The employment projections have been informed by computable general equilibrium modelling work the NSC undertook in 2020 and published in *The shape of Australia's post COVID-19 workforce*. That said, the nature of these exercises means that there are differences between them. The NSC believes that having a range of techniques assessing future skills trends is one way of mitigating the risks of error inherent in any single forecasting exercise.

The NSC's employment projections provide a foundation for many analyses within this report, and enable analysis to be undertaken with traditional and new data sources. The employment projections primarily use time series data taken from the ABS *Labour force* survey, which provides high quality estimates of employment from a large sample survey which has been run quarterly for almost 40 years. The projections are then derived from time series models applied to the *Labour force* survey data by combining forecasts from autoregressive integrated moving average (ARIMA) and exponential smoothing with damped trend (ESWDT) models, adjusted to take account of NSC research findings and expected industry and occupation developments.

The NSC's employment projections are based on forecast and projected total employment growth rates published in the 2020–21 *Mid-year economic and fiscal outlook* (MYEFO) and labour force employment data to November 2020.[51] Figure 50 shows that total employment is projected to increase by 991,600 (or 7.8%) over the five years to November 2025

[51]Applying to these data the forecast and projected employment growth rates from the 2021-22 Budget, published on 11 May 2021 results in no material difference to the future outlook for employment over a five-year period.

Figure 50: Employment level, past growth and projected growth to November 2025



Sources: ABS, *Labour force, Australia*, seasonally adjusted, and 2020-21 *Mid-year economic and fiscal outlook*

Five-year industry employment outlook

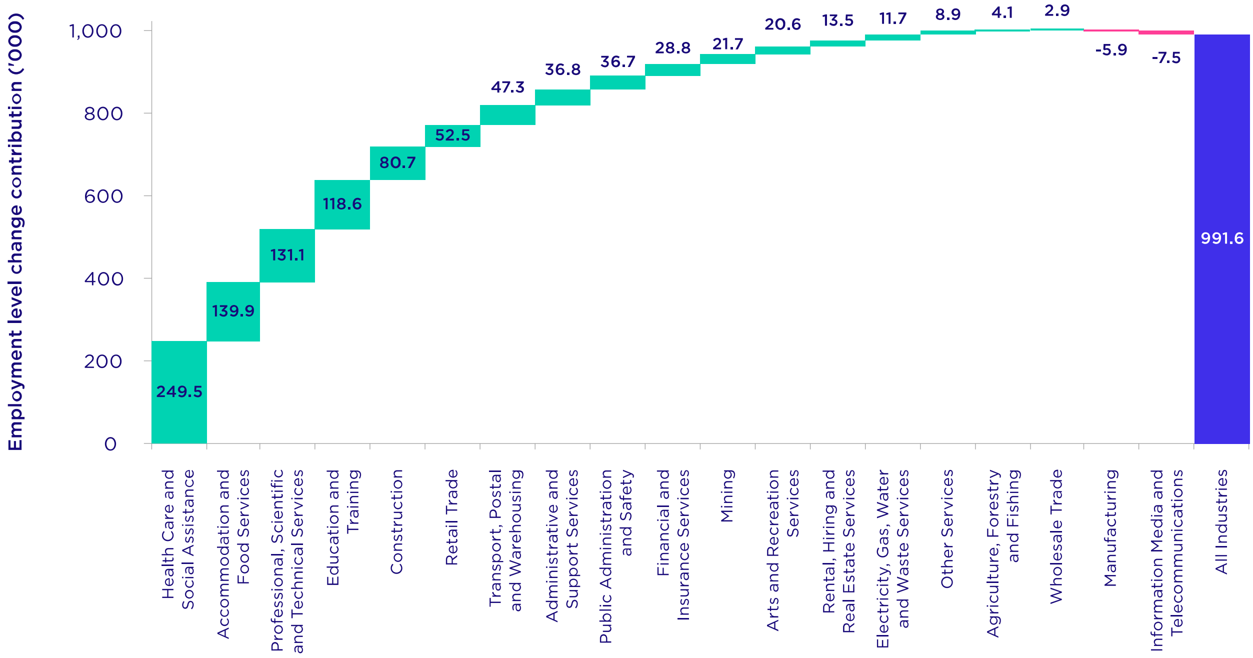
The NSC's five year employment outlook projects that the long-term structural shift in employment towards services industries will continue. Four services industries – 'health care and social assistance', 'accommodation and food services', 'professional, scientific and technical services' and 'education and training' – are expected to generate more than three-fifths (or 64.4%) of the total projected employment growth.

However, future employment growth is not just confined to these areas, with further increases projected across a range of industries. Employment in 17 of the 19 broad industries is expected to increase, reflecting a diverse and resilient labour market.

Figure 51 shows that health care and social assistance is projected to make the largest contribution to employment growth over the period (increasing by 249,500), followed by accommodation and food services (139,900), professional, scientific and technical services (131,100), and education and training (118,600).

Employment is projected to increase in 17 of the 19 broad industries over the five years to November 2025. Employment in 10 of these industries already exceeded pre-COVID-19 pandemic levels in November 2020 and is projected to exceed this level in a further five industries. Small declines in employment are projected for manufacturing (down 5,900) and information media and telecommunications (down 7,500).

Figure 51: Industry contribution to projected employment growth, five years to November 2025



Source: NSC, 2020 Employment Projections, five years to November 2025

Five-year occupation employment outlook

The continued long-term structural shift in employment towards services industries is reflected in the distribution of projected employment growth across occupations. The 'professionals' and the 'community and personal service workers' occupation groups combined are expected to account for 63.1% of the total growth in employment over the five years to November 2025.

The increasing importance of tertiary education and skills development beyond secondary school is highlighted by the data showing that more than nine-in-ten new jobs are projected to require post-school qualifications. Employment in STEM occupations (using science, technology, engineering and maths skills) is projected to grow by 12.9%, well above the average of all occupations (7.8%) and more than twice as fast as non-STEM occupations (6.2%).

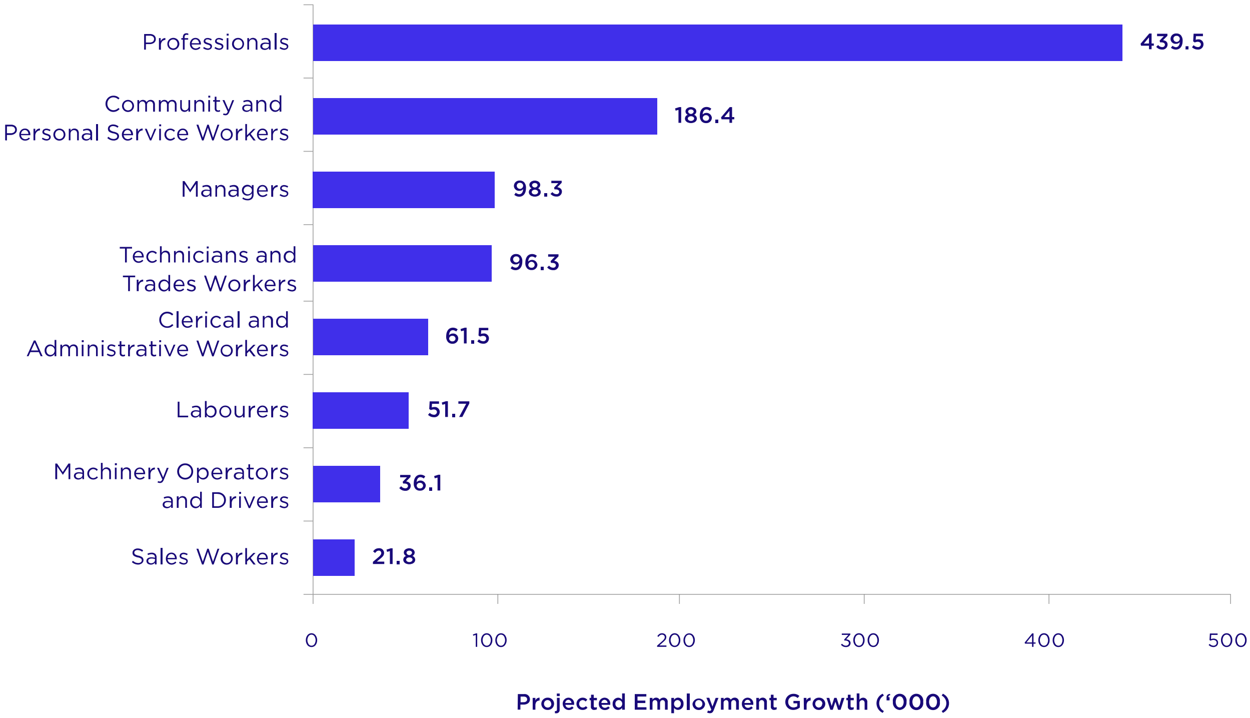
Employment is projected to increase across all eight of the broad occupational groups and all five of the skill levels over the five years to 2025.

As Figure 52 shows, very strong employment growth is projected to continue for professionals (up by 439,500 or 13.2%) and community and personal service workers (up by 186,400 or 14.6%), consistent with strong projected growth in the service industries that are leading employers of these occupational groups.

Together, these two occupational groups are expected to account for 63.1% of the total growth in employment over the next five years.

Below average employment growth (7.8%) is projected for all other broad occupation groups. Managers are projected to grow by 98,300 (6.1%), technicians and trades workers by 96,300 (5.4%), labourers by 51,700 (4.4%), machinery operators and drivers by 36,100 (4.4%) and clerical and administrative workers by 61,500 (3.5%), while the lowest rate of employment growth is projected for sales workers (21,800, or 2.0%).

Figure 52: Projected employment growth to November 2025, by major occupational group



Source: NSC, 2020 Employment Projections, five years to November 2025

As shown in Figure 53, projected employment growth in skill level 1 occupations (up by 523,100 or 11.8%) alone accounts for more than half (52.8%) of the projected total employment growth over the five years to November 2025.[52] While all skill level 1 occupations fall within the 'managers' and 'professionals' occupation groups, over four-fifths (82.8%) of employment growth in skill level 1 occupations is delivered by the 'professionals' occupation group.

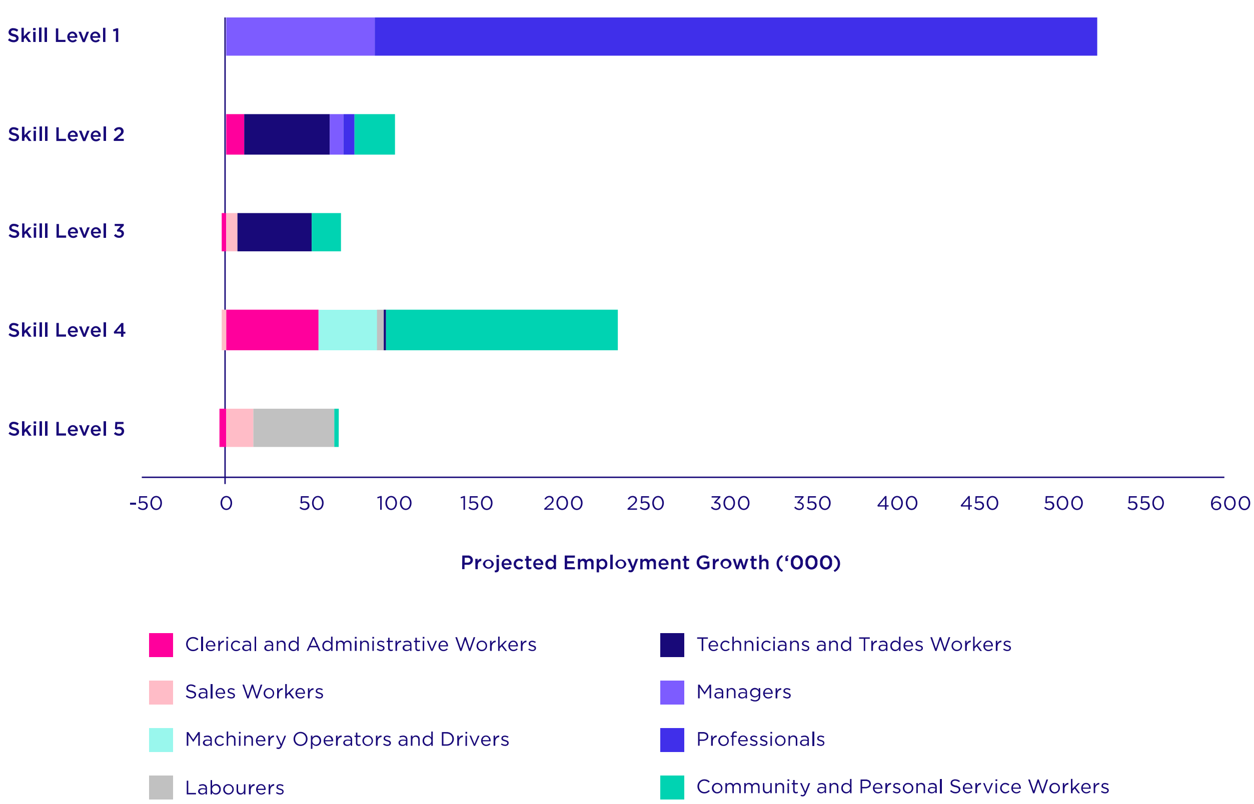
The importance of skills and training in the labour market is also evident, with projected employment growth for skill level 4 occupations (up by 233,400 or 7.7%) making the second largest contribution to total employment growth. Skill level 4 occupations are found in all broad occupation groups except 'managers' and 'professionals'. The community and personal service workers occupation group makes up almost two-thirds (59.8%) of employment growth in skill level 4 occupations.

Robust growth is projected for skill level 2 occupations (102,300 or 6.6%). Almost half of employment growth (49.6%) at this skill level is delivered by the technician and trade workers occupation group.

Subdued employment growth (67,900 or 3.6%) is projected for skill level 3 occupations, almost two-thirds (65.3%) of which is delivered by the technician and trade workers occupation group. The weakest employment growth is projected for skill level 5 occupations (64,600 or 3.3%), most of which (74.7%) is delivered by occupations from the labourers occupation group. At both these skill levels, employment growth is moderated by projected employment declines in clerical and administrative workers, resulting in negative contributions from this occupation group.

[52] Skill level 1 is commensurate with a bachelor degree or higher qualification; skill level 2 is commensurate with an advanced diploma or diploma; skill level 3 is commensurate with a Certificate IV or III (including at least 2 years on-the-job training); skill level 4 is commensurate with a certificate II or III; skill level 5 is commensurate with a certificate I or secondary education.

Figure 53: Projected employment growth to November 2025 for skill levels, by occupation



Source: NSC, 2020 Employment Projections, five years to November 2025

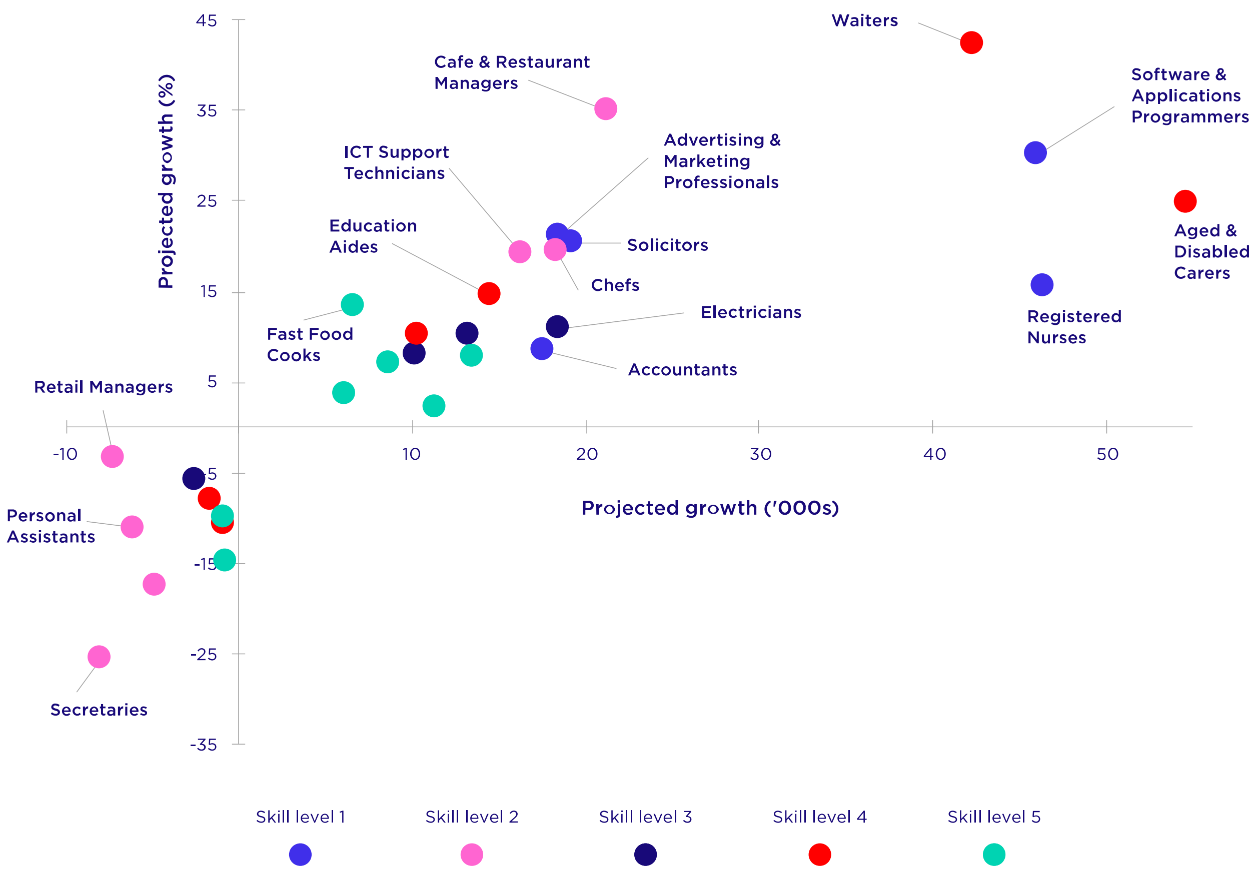
The two occupations projected to have the largest increases in employment – the skill level 4 occupation 'aged and disabled carers' (projected to grow by 54,700 or 24.7%) and the skill level 1 occupation 'registered nurses' (46,500 or 15.6%) – almost all work in the health care and social assistance industry. The majority of the skill level 3 occupation 'child carers' (13,300 or 10.2%) and the skill level 4 occupations 'welfare support workers' (11,000 or 17.7%) and 'social workers' (4,600 or 15.2%) also work mostly in the health care and social assistance industry. 'Registered nurses' are in the 'professionals' occupation group while the rest of these occupations belong to the 'community and personal service workers' occupation group.

Occupations largely employed in the accommodation and food services industry include waiters (projected to grow by 42,300 or 42.3%), cafe and restaurant managers (21,300 or 35.0%), chefs (18,300 or 19.4%) and bar attendants and baristas (10,300 or 10.2%). 'Waiters' and 'bar attendants and baristas' are skill level 4 occupations in the community and personal service workers occupation group. 'Cafe and restaurant managers' and 'chefs' are skill level 2 occupations in the managers and technicians and trade workers occupation groups respectively.

Almost all of the skill level 4 occupation education aides (projected to grow by 14,500 or 14.6%) and the skill level 1 occupation primary school teachers (11,000 or 6.5%) are employed in the education and training industry, along with most of the remaining child carers.

In addition, a number of skill level 5 occupations are projected to record strong employment growth over the period, including commercial cleaners (13,400 or 7.8%) – half of whom are employed in the administrative and support services industry, sales assistants (11,300 or 2.2%) – mostly employed in retail trade, and kitchenhands (8,700 or 6.9%) – mostly employed in accommodation and food services. The strong projected employment growth of such occupations, along with fast food cooks, checkout operators, and cashiers and handypersons, reflects the many opportunities available in skill level 5 occupations, providing career platforms for those seeking to enter the labour force.

Figure 54: Projected employment changes by occupation, group level, skill level and percentage growth



Source: NSC, 2020 Employment Projections, five years to November 2025

The occupations with the weakest projected employment growth, in the bottom left quadrant of Figure 54, face ongoing challenges, such as from globalisation and technological change.[53] Some of these occupations are from the clerical and administrative workers and skill level 2 groups, where work is routine and susceptible to automation. These include secretaries (projected to fall by 8,000 or 25.7%), retail managers (7,200 or 3.5%), personal assistants (6,000 or 11.3%) and call or contact centre and customer service managers (4,800 or 17.6%).

Within skill level 3, occupations projected to decline in employment include bank workers (projected to fall by 2,500 or 5.9%), plasterers (1,900 or 6.1%), telecommunications trades workers (1,100 or 4.6%) and printers (1,100 or 11.2%).

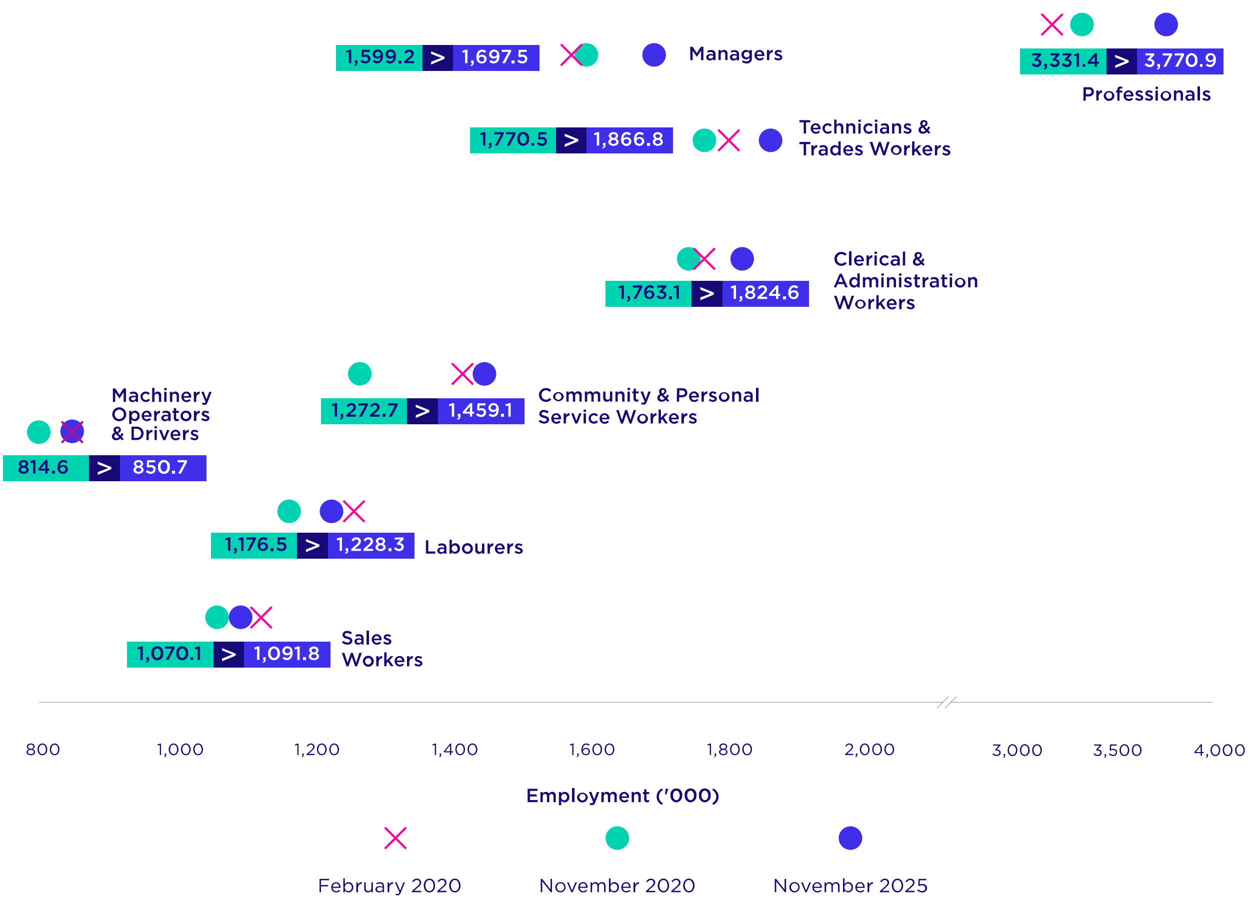
The impact of continuing structural change on manufacturing industry is expected to sustain the pre-existing trend of falling employment in occupations such as engineering production workers (projected to fall by 1,600 or 8.0%), plastics and rubber production machine operators (900 or 10.8%), timber and wood process workers (800 or 14.9%), metal engineering process workers (800 or 10.1%), clothing trades workers (800 or 7.7%), wood machinists and other wood trades workers (600 or 14.2%) and print finishers and screen printers (400 or 11.2%). These occupations range across skill levels 3, 4 and 5.

[53] For more on this topic see 'Trends in automatability' in Chapter 2.

The impact of COVID-19 on employment projections

In November 2020, employment remained below pre-COVID-19 levels for six of the eight major occupation groups, with only professionals and managers exceeding pre-COVID-19 levels. Figure 55 shows that over the five years to November 2025, employment is projected to exceed pre-COVID-19 levels for five of the eight major occupation groups, with machinery operators and drivers at about the same level and only 'sales workers' and 'labourers' remaining below pre-COVID-19 employment levels.

Figure 55: Employment levels by major occupation group, Pre-COVID-19, projection base, and projected



Sources: NSC, 2020 Employment Projections, five years to November 2025, and ABS, *Labour force, Australia, detailed,* seasonally adjusted by NSC

At a more detailed level, November 2020 employment exceeded pre-COVID-19 levels for 169 out of 358 occupations. Over the five years to November 2025, employment is projected to exceed pre-COVID-19 levels for 197 occupations, despite total employment being projected to exceed pre-COVID-19 levels by 854,300 (or 6.6%). This is because employment growth is concentrated in higher skilled occupations.

It is important to note that the employment projections are a point forecast for November 2025 and provide no data for employment in the intervening five-year period. That is, the recovery path of employment for occupations can only be implied by the NSC's employment projections. Low projected employment growth may indicate a slow recovery. However, it is entirely possible that employment will exceed pre-COVID-19 levels in the five-year period before settling at a lower point as longer-term trends unrelated to COVID-19 impact employment levels.

That said, the trends seen in the recovery from COVID-19 are having a large impact on projected employment growth by occupation. Of the 214 occupations that experienced decreases in employment over the May 2020 quarter (the quarter which saw the largest impact from COVID-19 and related restrictions), over two-thirds (70.1%) have employment projected to grow and nearly a third are projected to grow at a faster rate than the average across all occupations (7.8%). For example, waiters experienced the largest decline over the May 2020 quarter, declining by 73.7%, but employment for this occupation is projected to increase by 42.3% over the five years to November 2025 near to its pre-COVID-19 level.

In occupations projected to have employment fall the fastest over the five years, the impact of COVID-19 has compounded existing negative structural trends. Employment in these occupations has been subject to long-term declines as these occupations are particularly exposed to structural trends such as automation and globalisation. The fastest projected declines are for graphic pre-press trades workers (projected to decline by 30.2%), followed by secretaries (down by 25.7%), street vendors and related salespersons (down by 21.4%) and switchboard operators (down by 20.2%). Employment for each of these occupations has declined by 30% or more over the 10 years to February 2020 (pre-COVID-19).

Five-year skills employment outlook

By mapping the five year employment projections with the ASC to translate occupations into skills, the NSC has produced five year skills projections.

The skills cluster families in the ASC provide a helicopter view of demand for specific skills over the next five years. Although, on balance, demand for most skills is expected to grow, the NSC expects substantial divergence in growth rates across skills cluster families. Demand for some skills is expected to grow much faster than others, reflecting changes in the occupational composition of the labour force, broader transitions occurring in the economy and shifts to new ways of carrying out functions and tasks.

The findings explored below flow logically from the analysis undertaken in Chapter 4; they suggests there are skills currently important in the labour market that will be even more critical into the future. To add depth to the common reference of STEM occupations being important for the future, the fine-grained skills-based analysis undertaken in this report suggests a more nuanced selection of skills across different disciplines is needed for the future.

Some of the major skills needed for the future can be summarised as the 'Four Cs':

- *care,* the group of skills responding to demographic and health challenges
- *computing*, a group of specialised technical skills needed to respond to the digital world
- *cognitive abilities,* the group of advanced reasoning and higher order skills computers cannot replace
- *communication,* the group of skills needed to collaborate and engage within and across workplaces.

Figure 56 shows the projected growth in demand in both percentage terms and the number of additional hours per week expected to be spent on each skills cluster family across the workforce. The size of the bubbles represents the number of hours Australians currently spend on each family in a week.

The large bubble represented on the far right of the figure is the 'health and care' skills family. This family is expected the see the largest increase in hours worked, although the 'food services' cluster family is projected to experience the fastest growth (15.2%) over the five years to 2025 among the 29 skills cluster families. This family includes skills which are required for occupations in both food services and health and care related occupations. Many occupations using food services skills have been disproportionately affected by the COVID-19 pandemic, and some of the growth represents a recovery in these sectors.

'Computer and electronics' (15.0%) and 'performance evaluation and efficiency improvement' (14.7%) are the next fastest growing families. Skills in these families are associated with many professional occupations.

The 'business operations and financial activities' family currently makes up the largest amount of work time across the economy (74.4 million hours each week) and is expected to grow by 5.6% by 2025. This widely used family is associated with 224 different occupations. Many Australians use these skills as part of their day-to-day work but may not use them very intensively. The second largest amount of current work time is spent on skills in the 'health and care' family (39.6 million hours each week), but this family is projected to experience significantly higher growth (14.1%). Health and care skills are also more specialised; they are associated with 68 occupations. People with health and care skills tend to spend much of their time on them.

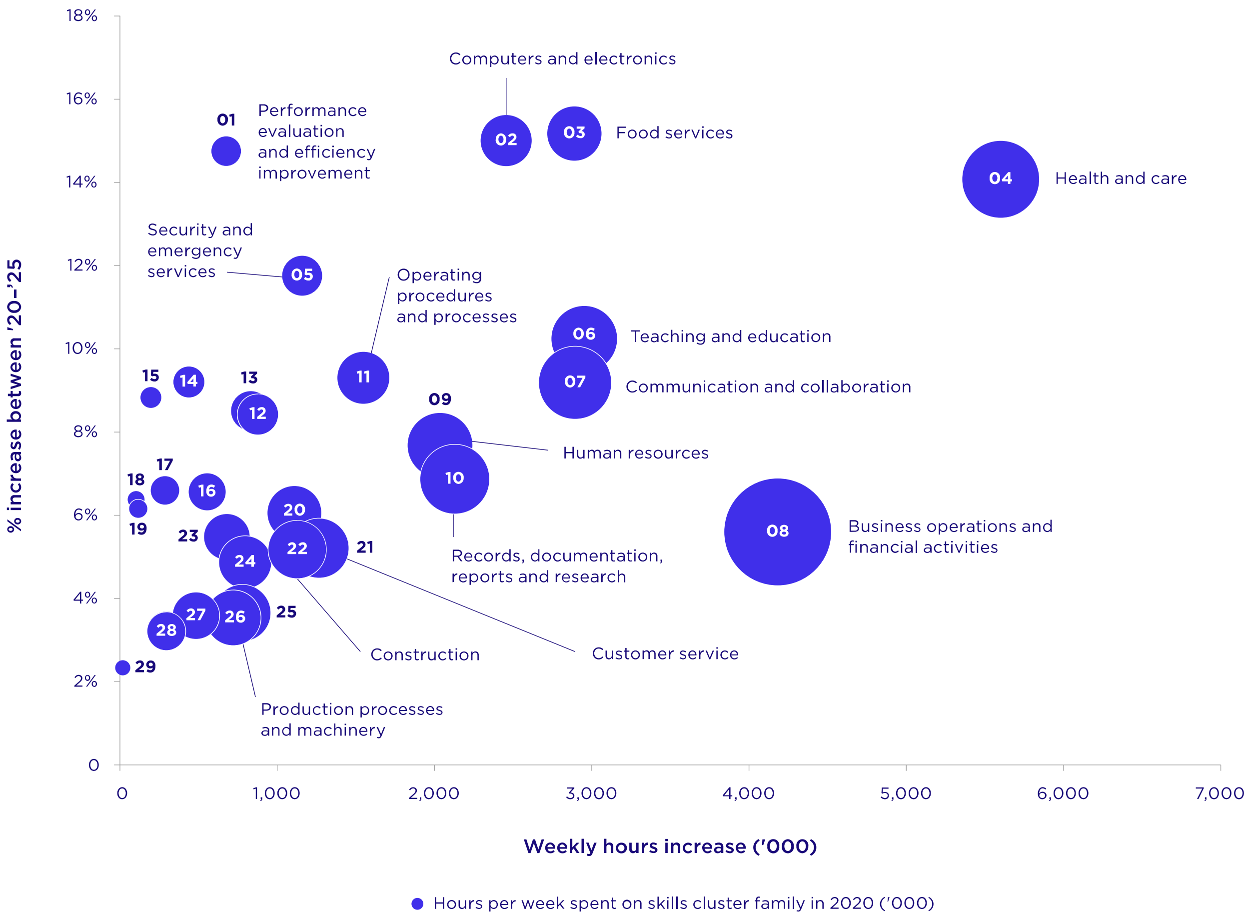
The 'teaching and education' and 'communication and collaboration' families are already a significant focus in today's workforce and are projected to continue to grow (at 10.2% and 9.2% respectively). On the other hand, the 'records, documentation, reports and research', 'human resources' and 'customer service' families take a similar amount of time today but are expected to grow more sedately (at 6.9%, 7.7% and 5.2% respectively).

Skills in the 'science and mathematics' skills cluster family are quite specific and while important, only make up a small proportion of many Australians' day-to-day work. For example, the 'operate and maintain laboratory or field equipment' skills cluster within this family is used by science technicians, life scientists, chemists and agricultural technicians but only makes up between 5% and 18% of their work. Broader STEM skills are spread across the ASC and contribute particularly to the growth in the 'data, analytics and databases', 'environmental management', 'computers and electronics' and 'health and care' families.

Several skills cluster families are of declining prominence in the labour market. These families, such as 'archiving, recording and translating', 'agriculture and animals' and 'material transportation', comprise a low share of workforce time. While growing in absolute terms, they are growing more slowly than the average skills family and will form a smaller share of the workforce's time in 2025 than they do currently.

Other skills cluster families are growing quickly from a relatively low base, such as 'performance evaluation and efficiency improvement', 'security and emergency services', 'environmental management', and 'data, analytics and databases'. While currently the skills in these families take up a lower share of the workforce's time than the average skills cluster family, these families are projected to grow at an above average rate and will be more prominent in 2025 than they are today.

Figure 56: Demand for skills by skills cluster family, projected growth



01	Performance evaluation and efficiency improvement	**11**	Operating procedures and processes	**22**	Construction
02	Computers and electronics	**12**	Safety and hazard management	**23**	Work activities preparation
03	Food services	**13**	Data, analytics, and databases	**24**	Quality control and inspections
04	Health and care	**14**	Environmental management	**25**	Sales and marketing
05	Security and emergency services	**15**	Recreation and sporting events	**26**	Production processes and machinery
06	Teaching and education	**16**	Vehicle operation	**27**	Material transportation
07	Communication and collaboration	**17**	Science and mathematics	**28**	Agriculture and animals
08	Business operations and financial activities	**18**	Art and entertainment	**29**	Archiving, recording, and translating
09	Human resources	**19**	Fashion, grooming, and cosmetics		
10	Records, documentation, reports and research	**20**	Cleaning and maintenance		
		21	Customer service		

Sources: NSC, 'Employment projections, five years to November 2025', ASC

Drilling into the next level of detail in the ASC, the skills clusters level, we see significant divergence in the growth rates of skills clusters within and across the skills cluster families. Figure 57 shows the 40 skills clusters that are projected to experience the most growth in hours. The 'undertake food services activities' skills cluster is expected to see the largest growth (1.3 million additional workforce hours per week by 2025, an increase of 20.8%). It is joined in the top 40 by two of the three other clusters from the food services family, reflecting the recovery from the COVID-19 pandemic.

Figure 57: Skills clusters with the largest growth over the next five years, level increase, total hours per week

Sources: NSC, Employment Projections, five years to November 2025, ASC

The second largest increase will be in the 'communicate and collaborate' cluster (1.2 million additional workforce hours, an increase of 9.7%) which includes liaison, relationship and information sharing skills. This skill set is associated with a wide range of occupations from senior executives to technical roles and customer facing positions and reflects the growing importance of collaboration across the workforce. While it is part of the 'customer service' skills cluster family, the third largest increase, the 'provide customer service and communicate information' skills cluster (1.1 million additional hours) also reflects this trend.

Six of the skills clusters with the largest growth are from the 'health and care' family, with the largest being 'provide health care or administer medical treatment' (713,000 additional hours) followed by 'assist and support clients' (569,000 additional hours), reflecting increasing demand in the care workforce.

A further five growing skills clusters are from the 'computer and electronics' family including 'ICT support, design and management' (587,000 additional hours), 'develop websites or software' (450,000 additional hours) and 'test computer or software performance' (417,000 additional hours), which was the fastest growing cluster, predicted to increase by 28% on current use levels. Skills in this cluster are used in 10 occupations, of which nine occupations are projected to grow more than 12% to 2025. Much of the growth is driven by ICT 'support and test engineers' (growing by 34%), 'computer network professionals' (30%), 'software and applications programmers' (30%), 'ICT business and systems analysts' (28%) and 'multimedia specialists and web developers' (25%).

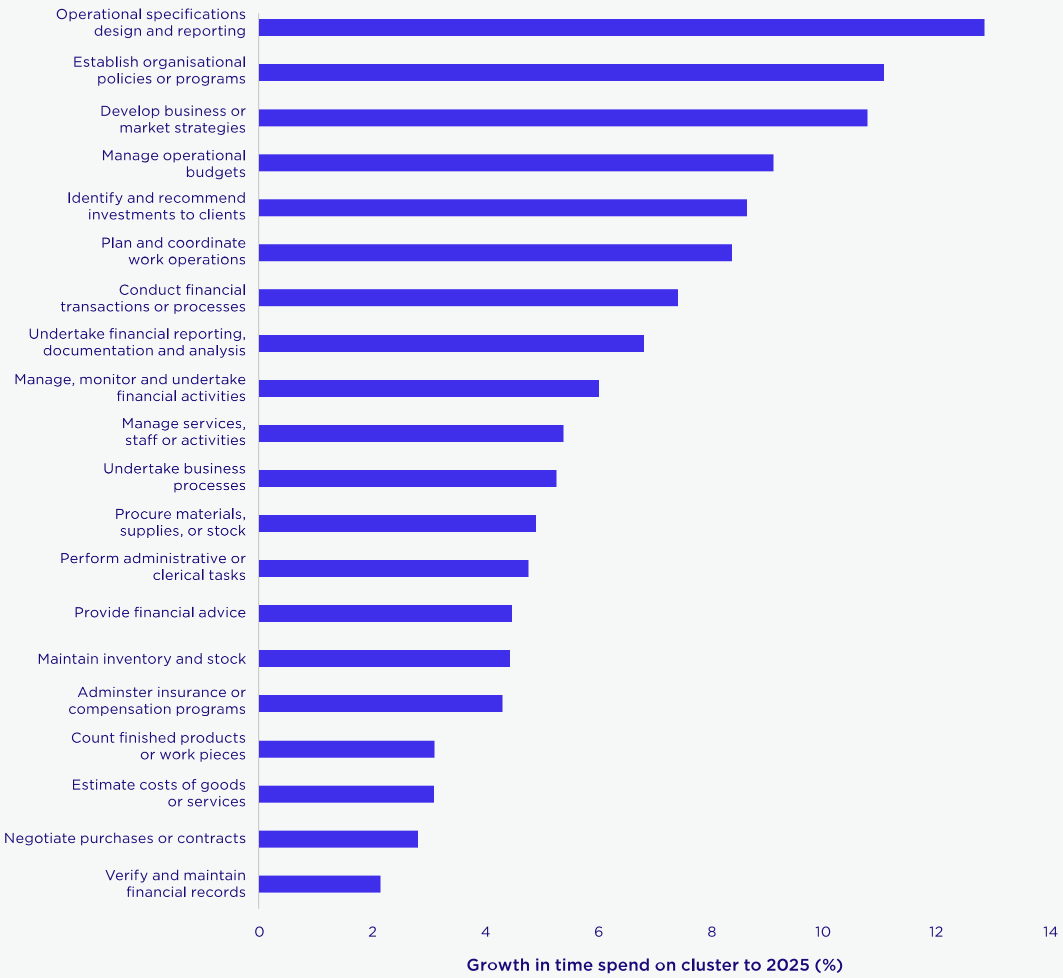
While the 'testing computer or software performance' skills cluster is strongly associated with IT occupations, the 'develop websites or software' cluster is required in a wider range of occupations across both the IT and non-IT sectors. This cluster includes the specialist task 'develop software or applications for scientific or technical use', a STEM skill which is required in the occupational category 'geologists, geophysicists and hydrogeologists' (projected growth of 15%) who spend about 5% of their time on this work. Another STEM related specialist task in the cluster is 'design computer modelling or simulation programs', which is required by 'actuaries, mathematicians and statisticians' (projected to grow by 7%), who spend about 2% of their time on it. The cluster also includes the specialist task 'create computer-generated graphics or animation', which is required in occupations like 'multimedia specialists and web developers' (growing by 25%), 'graphic and web designers, and illustrators' (13%), 'visual arts and crafts professionals' (11%) and 'film, television, radio and stage directors' (9%).

Case study: Business and operational skills

Many Australians use skills from the 'business operations and financial activities' skills cluster family in their day-to-day work, but demand for this family is projected to grow more slowly than average. However, this family is far from homogenous and significant growth is expected in some of its clusters. Figure 58 shows projected growth for skills clusters within the family.

Business and operational skills with the lowest projected growth, such as 'verify and maintain financial records' (projected to grow by 2%), 'estimate costs of goods or services' (3%) or 'count finished products or work pieces' (3%) are common to a range of clerical and process roles and are more routine and automatable. Conversely, skills requiring higher order strategic or planning skills such as 'establish organisational policies or programs' (11%) and 'operational specifications design and reporting' (13%) are projected to experience more significant growth. Chapter 8 discusses skills and automation in greater detail.

Figure 58: Projected growth in skills clusters in the 'business operations and financial activities' skills cluster family to 2025

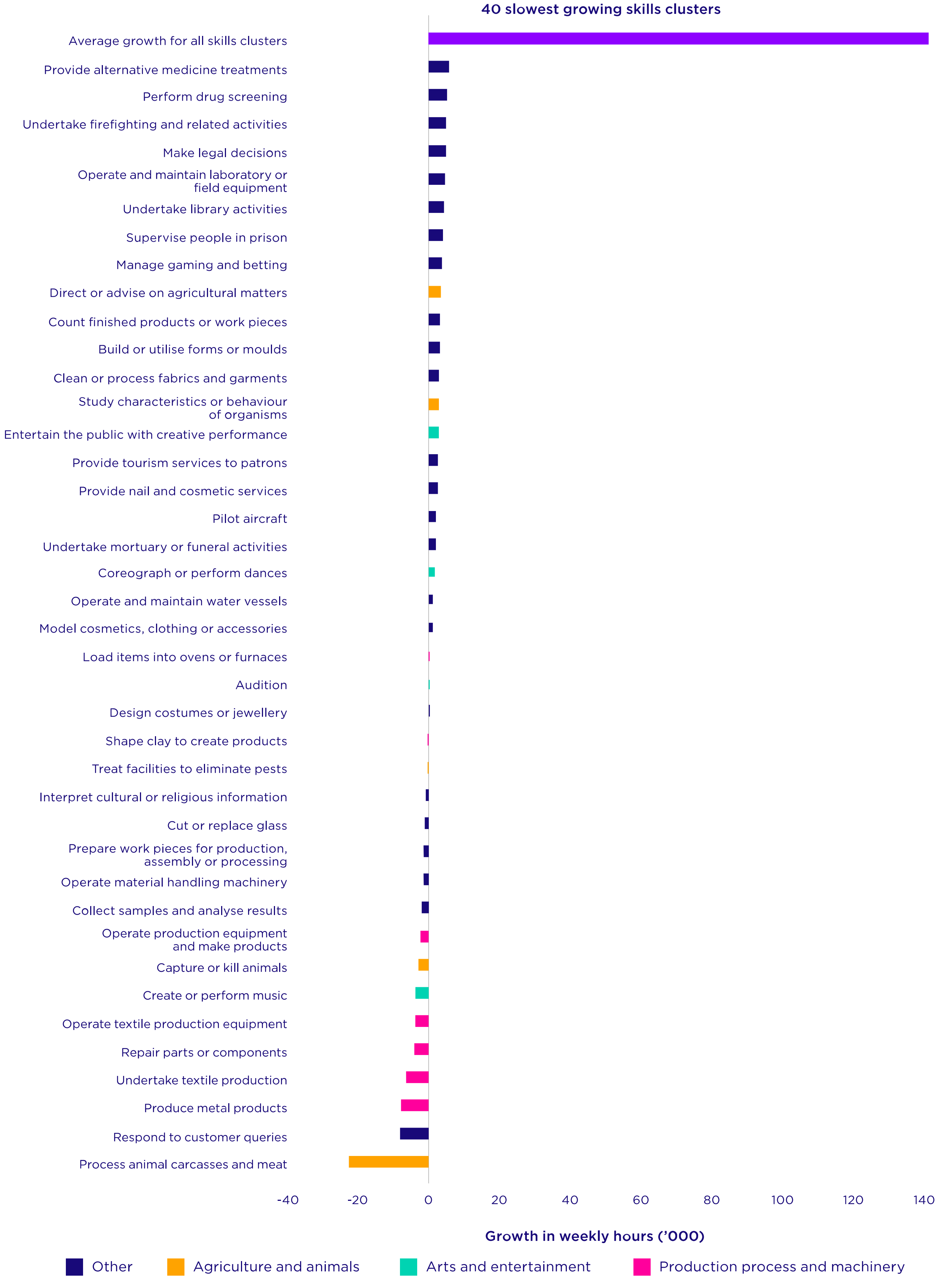


Sources: NSC, Employment projections, five years to November 2025, ASC

Of the 279 skills clusters, only 16 are projected to decline in absolute terms. Figure 59 shows the 40 skills clusters with the lowest projected growth.

The largest decline is projected for the 'process animal carcasses and meat skills' cluster (a reduction of 22,000 workforce hours per week by 2025, a decrease of 2.5%). A decline is also expected in the related skills cluster 'capture or kill animals' (-3,000 hours, or -1.2%). It is likely that these declines reflect automation in the meat processing industry.

Figure 59: Skills clusters with the lowest growth over the next five years, level increase or decrease, hours per week



Sources: NSC, Employment projections, five years to November 2025, ASC

Seven of the 16 declining skills clusters belong to the 'production, processes and machinery' family. This reflects a continued shift towards services and the automation of manual roles in the manufacturing industry, with the largest projected decline in the 'produce metal products' skills cluster (-8,000 hours per week or -8.3%). Declines are also expected in the 'undertake textile production' (-6,000 hours per week or -1.3%), 'repair parts or components' (-4,000 hours or -0.9%) and 'operate textile production equipment' (-4,000 hours or -1.1%) skills clusters.

Low or negative growth is expected in skills associated with labouring work such as 'operate material handling machinery' (-2,000 hours or -0.3%), 'cut or replace glass' (-1,000 hours or -1.5%) and 'build or utilise forms or moulds' (expected to grow by 3,000 hours per week or 0.5%). These skills and occupations are at risk of automation over the medium to long term. The issues arising from automation are discussed further in Chapter 8.

Some skills associated with routine clerical and customer service work, such as 'respond to customer queries' (-8,000 hours or -0.2%) or 'undertake library activities' (expected to grow by 4,000 hours or 1.5%) are expected to be in low demand.

Four skills clusters from the art and entertainment family are projected to have low growth. These include 'create or perform music', 'audition', 'choreograph or perform dances' and 'entertain the public with creative performance'. These skills are associated with music professionals occupations such as musician and singer which are expected to decline slightly.

Some niche skills clusters are also expected to experience lower growth because the skills are highly specialised. For example, the 'pilot aircraft' skills cluster, which is only used by air transport professionals, is projected to grow by 2,000 hours per week or 1.5%, matching the projected growth in this occupation, from 12,200 to 12,400 people. Similarly, 'interpret cultural or religious information', a skills cluster only used by 'ministers of religion', is expected to decline by 1,000 hours per week or 0.8%, matching the decline in employment in this occupation.

While the 'make legal decisions' cluster is expected to grow by 5,000 hours per week, this is actually an increase of 8.4%. This cluster is only associated with judicial and other legal professionals (such as judge and magistrates), accounting for the low hours across the labour market.

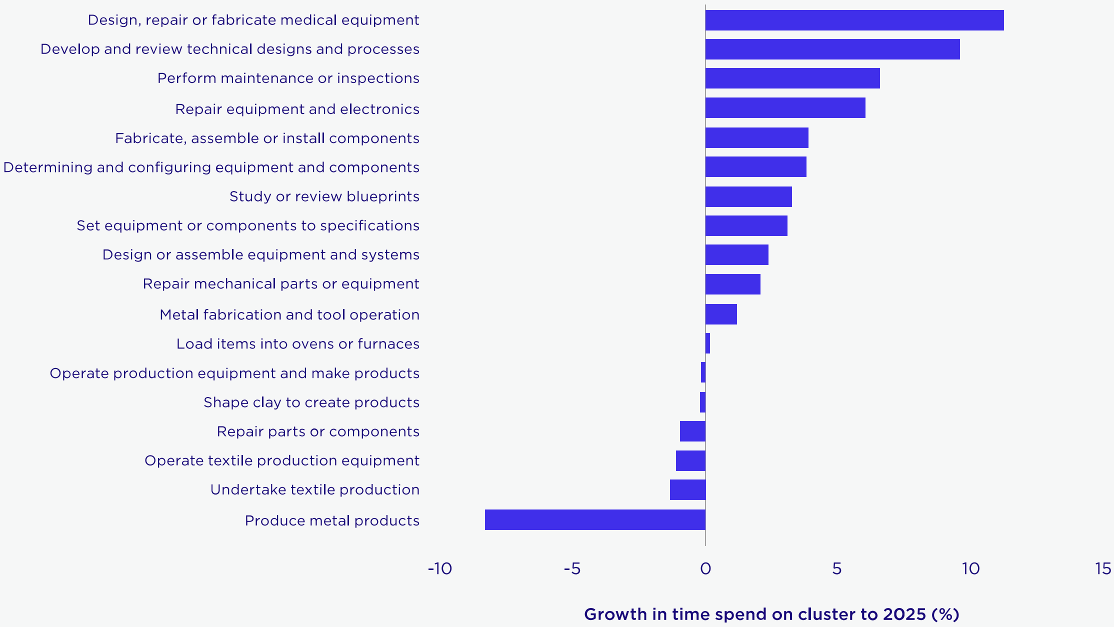
The 'provide tourism services to patrons' cluster, which is used by only four occupations, is expected to grow by 3,000 hours or 1.6% over the five years to 2025. Employment in the largest occupation using this skills cluster, 'gallery, museum and tour guides', is projected to remain at the same level over the next five years, while some of the smaller occupations using the skill will experience limited growth. Overall, this results in a low level of total growth for this skills cluster.

Common across many (but not all) of the more slowing growing skills clusters (including some that are expected to decline in coming years) is the non-cognitive and routine nature of those skills. By contrast, there is a tendency for non-routine cognitive skills and occupations to have stronger future growth prospects.

Case study: Production processes and machinery

Production processes and machinery skills are particularly relevant in the manufacturing industry. Although, as a whole, this family is expected to have low growth (3.5%), strong growth is expected for some skills clusters within it, as Figure 60 shows. These clusters are typically associated with advanced manufacturing and design and include 'designing, repairing or fabricating medical equipment' (11.2%), 'technical design and processes development' (9.6%), 'performing maintenance or inspections' (6.6%) and 'repairing equipment and electronics' (6.6%).

Figure 60: Projected growth in skills clusters in the 'production processes and machinery' skills cluster family to 2025



Sources: NSC, Employment projections, five years to November 2025, ASC

The Skills Priority List

The Skills Priority List (SPL) outlines the occupations that are currently in shortage or may be at risk of a future shortage. The focus of the SPL is on occupations rather than skills.

The SPL forms the backbone of the NSC's labour market advice, including on skilled migration, training and employer incentives. It is published on the NSC's website.

The SPL determines a Current Labour Market Rating for each occupation. Ratings are provided nationally and for each state and territory. Where there is evidence suggesting variation between metropolitan and regional areas this is reflected in the rating.

Each occupation is given an indicative Future Demand Rating of strong, moderate or soft to indicate the likely demand for the occupation over the coming five years. These ratings are available only at the national level.

Providing a single source of advice on occupations creates highly-specific information for stakeholders and ensures greater consistency and better targeting of resources across the various policy responses implemented by government.

The identification of occupational shortages and future demand is a crucial element in the development of timely and effective labour market policy. Historically, there is a range of labour market indicators that have been used in Australia and internationally to identify occupations, and sometimes the underlying skills, in short supply. However, it is difficult to cohesively combine these indicators into a single measure.

Occupations used in the SPL are:

- defined in the Australian and New Zealand Standard Classification of Occupations (ANZSCO) as skill level 1– 4 occupations at the six-digit level, excluding occupations 'not further defined' or 'not elsewhere classified'
- occupations with an open and contestable labour market.[54]

The SPL does not generate results on skill level 5 occupations because they have fewer barriers to entry and generally do not require significant post-school education and training.

Current Labour Market Rating

The Current Labour Market Rating of the SPL draws on evidence from several sources:

SPL Indicator Model – The NSC developed the SPL Indicator Model to help assess the current labour market for around 800 occupations at the ANZSCO six-digit level. It provides a valuable link to, and extension of, the targeted long-standing research on skill shortages: the Survey of Employers who have Recently Advertised (SERA).

Survey of Employers who have Recently Advertised (SERA) – The SERA employer survey undertaken by the NSC is unique. It provides an estimate of current skills shortages and can show whether there is adequate supply to meet demand.

Peak and representative body input – Formal consultation for the SPL involves a twice-yearly online survey and face-to-face or online engagement with representative bodies throughout the year. The survey captures information from stakeholders on recruitment challenges and skills needs across a wide range of occupations and industries.

Federal and state or territory government input – The NSC consults with government stakeholders on the development of the SPL. Many federal and state and territory government agencies conduct their own occupation and skills shortage research. Federal government agencies are consulted on the SPL occupations that are relevant to their portfolio – for example, the Department of Health is consulted on health-related occupations – and state or territory agencies are consulted on the SPL findings within their region. SPL findings are tested for verification and to seek any additional context or evidence that may not have been considered in the initial occupation assessment.

Other data and evidence – The availability of data varies from occupation to occupation and additional information is considered to provide accurate commentary and ratings. The following list is not exhaustive but outlines some of the additional sources which are considered in the assessment of occupations:

- studies, assessments and reports by federal government departments
- state and territory government occupation and industry findings
- relevant skills needs or workforce planning information from government departments or industry groups
- industry activity statistics, projections and reports
- media articles
- training activity or migration flows of significance to the occupation.

[54] 'Nfd' is used when a respondent has not provided adequate information for the response to be put into a category at the most detailed level, while 'Nec' allows occupations which do not fit into a suitable category in the classification to still be included. Defence force roles are an example of excluded occupations, as recruitment is mainly conducted internally. In some cases, stakeholder insight or external data may be available for closed labour markets, and in these cases an assessment of the occupation may be possible.

Future Demand Rating

Evidence informing the composition of the indicative Future Demand Rating for the SPL encompasses:

Five-year employment projections – Each year, the NSC produces employment projections by industry, occupation, skill level and regional areas for the following five years. These employment projections are designed to provide a guide to the future direction of the labour market and were discussed in more detail earlier in this section.

Replacement rates data – The NSC produces replacement rates by occupation at the national level, to provide an estimate of the total replacement demand resulting from flows of workers exiting a job irrespective of the inflows to employment over the same period.

In addition to the five-year employment projections and replacement rate data, other sources of reliable information on future demand may be used. These additional sources are considered in the final assessment of future demand and are similar in nature to those discussed earlier in respect to Current Labour Market Rating.

Final validation

Once all available sources of information have been considered, a determination is made regarding the Current Labour Market Rating and Future Demand Rating.

As noted previously, the SPL is published on the NSC's website.

07

Emerging skills

Emerging skills

Changes in technology are often thought to lead to the loss of jobs. But the biggest effect of advances in technology is on changes in the way existing jobs are done. Known as 'task change', this involves changes in the amount of time spent on existing tasks and the addition of new tasks.[55]

The concept of task change is approached in this chapter through an examination of trending and emerging skills, which are affecting the way work is undertaken across many occupations. For example, 'infection control' is trending in 45 occupations and emerging in 38 others, 'social media' is trending in 47 occupations and emerging in 18, while 'enterprise resource planning' is trending in 50 occupations and emerging in 14.

Trending and emerging skills exist across many occupations, highlighting the need for ongoing skills development for all Australians.

Data and digital skills are among the fastest growing emerging skills. The analysis in this chapter suggests that while Australia recognises well the need for specific digital skills, further effort may be required to build base digital skills proficiency at all skill levels, not just the higher skill levels.

The chapter also analyses the impact of the COVID-19 pandemic on demand for some skills and finds there has been some increase in demand for core competencies or 'employability skills' such as teamwork, planning and organising, and problem-solving skills. Particularly important during the pandemic were skills relating to resilience and flexibility and to managing tasks and staffing logistics outside more conventional and established working arrangements.

Emerging and trending skills in Australia

By understanding which skills are emerging and trending in the labour market, we can identify how jobs are changing and which new jobs are emerging. This ultimately provides an opportunity to better equip the workforce with skills that align to those emerging jobs, as well as developing new skills that are emerging within jobs.

What are trending and emerging skills?

Both emerging and trending skills are of growing importance, but because they have slightly different impacts on the labour market, they have been defined separately.

Trending skills are defined as those that have grown over the past five years. They are not necessarily new skills, but skills that are increasing in demand. For example, 'social media' skills are not new to the labour market, however over the past five years demand for them has grown in 47 occupations. For some occupations, this demand has grown more than ten times (for 'hotel or motel managers' and 'film and video editors') and in one case by more than 160 times (for 'child care centre managers').

Emerging skills are trending skills that are also new to particular occupations over the past five years. They are distinct from other trending skills because they have recently emerged in some occupations where they were not previously required. For example, 'infection control' skills are required by 38 new occupations compared with five years ago, and demand for these skills has grown by more than five times overall.

[55] See AlphaBeta, *Mapping Australian workforce change*, 2018.

Emerging and trending skills and the nature of work across roles

Emerging and trending skills analysis can give us close to real-time insights into how Australian jobs are evolving and changing. The fastest emerging skills across the economy are data and digital skills such as those in 'software orchestration/automation', 'artificial intelligence' and 'data analysis'. Demand is not limited to IT roles, with many conventional roles requiring these emerging skills.

NSC analysis of skills sought by employers from job advertisements and the roles that require them shows that emerging and trending skills in the wider labour market reflect the diversity of the occupations themselves. New skills will continue to be added to jobs, and core competencies such as teamwork skills and organising and planning will continue to be in increased demand across a range of occupations. Encouragingly, the analysis revealed the vocational education and training (VET) system is set up to deliver a range of emerging skills across the breadth of skill types or categories. The NSC will continue to monitor the demand for emerging and trending skills to inform how the VET system can better support the development of these skills.

Emerging and trending skills are affecting the way work is undertaken across many occupations. The skills spreading most quickly across the labour market are 'infection control' (trending in 45 of the 600 occupations currently represented in the Australian Skills Classification or ASC, and emerging in 38 others), 'data analysis' (trending in 61 occupations and emerging in 11 others), 'social media' (trending in 47 occupations and emerging in 18), 'enterprise resource planning' (trending in 50 occupations and emerging in 14), 'equipment repair and maintenance' (trending in 37 occupations and emerging in 20) and 'graphic and visual design software' (trending in 32 occupations and emerging in 14).

The Appendix shows the occupations where the 10 skills spreading most quickly across the labour market are either emerging or trending. The case studies below provide additional detail on several skills.

Identifying and analysing how skill needs within job roles are evolving and changing, and whether or not these skills needs persist, can bring new insights that inform the development of government responses, including short-term economic recovery measures and longer-term reform of the Australian education and training system.

Case study: infection control

In 2015, only 17 of the 600 occupations had at least 2% of job advertisements mentioning 'infection control' as a skill. These occupations were also largely health related – including operating theatre technicians, pathology collectors and sterilisation technicians.

By 2020, the number of ASC occupations with at least 2% of job advertisements mentioning 'infection control' skills had grown to 85 – and expanded beyond health-related roles to real estate representatives, amusement, fitness and sports managers, and locksmiths.

It is likely that this change is largely due to the COVID-19 pandemic and the new restrictions and regulations that were imposed on business. Regardless, it illustrates how access to immediate labour market information, including employer demand, can help drive an understanding of how jobs are changing in real time, and whether such trends may persist in future.

Case study: social media skills

Social media is a skill rising in importance – trending in 47 and emerging in 18 occupations. However, it is applied in different ways across these occupations. For managers and sales workers, social media has provided an alternative avenue for digital marketing. Community and personal service workers may use social media as a broad communication channel to keep stakeholders informed, and market research analysts use social media to collect data for campaigns.

Table 18 shows the top jobs for which social media skills are trending or emerging, and shows the growth (in percentage of job advertisements for these occupations requiring this skill) between 2015 and 2020. For some, the growth is significant – demand for these skills in child care centre managers grew from less than 1% of job advertisements in 2015 to just under 15% of job advertisements in 2020.

Table 18: Emerging and trending jobs for social media skills

	Top jobs	% of job ads requiring social media skills in 2015	% of job ads requiring social media skills in 2020	Growth
Managers Overall demand: 1.8%	Child Care Centre Manager	0.09	14.86	16,411%
	Hotel or Motel Manager	0.54	6.25	1,057%
	Public Relations Manager	1.28	3.24	153%
Professionals Overall demand: 1.9%	Graphic Designer	14.35	24.38	70%
	Film and Video Editor	1.83	21.9	1,097%
	Market Research Analyst	8.7	17.85	105%
Technicians & Trade Workers Overall demand: 0.2%	Camera Operator	4.15	17.56	323%
	Broadcast Transmitter Operator	3.19	10.45	228%
	Web Administrator	4.61	4.63	0%
Community & Personal Service Workers Overall demand: 0.4%	Fitness Instructor	0.7	1.91	173%
	Gallery or Museum Curator	5.16	8.64	67%
	Community Worker	1.72	2.06	20%
Clerical & Administrative Workers Overall demand: 1%	Library Assistant	1.49	4.08	174%
	Information Officer	0.85	1.54	81%
	Switchboard Operator	0	8	New
Sales Workers Overall demand: 1.5%	Street Vendors and related salesperson	4.93	9.5	93%
	Telemarketer	1.15	1.67	45%
	Real Estate Agent	0.9	1.19	32%

Sources: Burning Glass Technologies data, 2015-20, NSC analysis

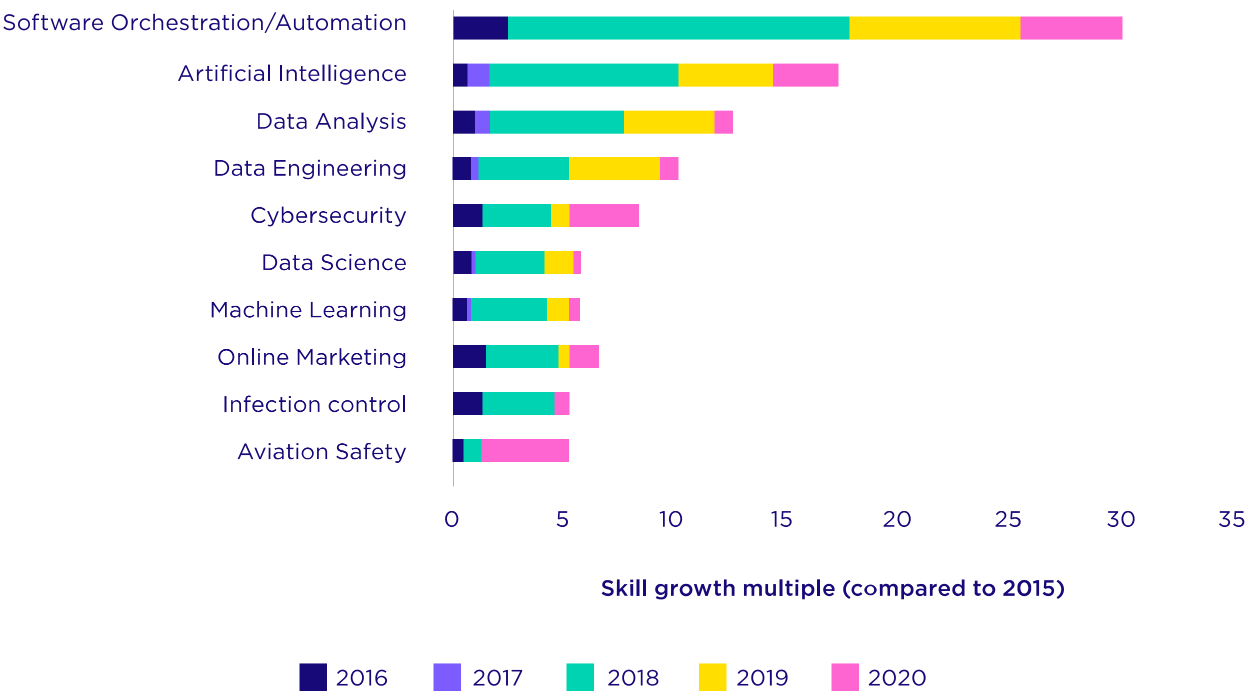
Other trending and emerging skills, such as 'equipment repair and maintenance', also feature in a diverse range of occupations in different contexts. Of the 37 occupations which have equipment and repair as trending or emerging skills, 32 relate specifically to preventative maintenance. This is trending in occupations such as 'ICT quality assurance engineers', 'business machine mechanics' and 'facilities administrators', and emerging in occupations including 'hotel service managers', 'agricultural and horticultural mobile plant operators' and 'wood machinists'. The rise in this skill is likely to be a result of technology-enabled predictive maintenance and its use in the workplace, and of the broader trend of workers increasingly requiring diagnostic repair skills within their roles.[56]

[56] Predictive maintenance is maintenance that monitors the performance and condition of equipment during normal operation to reduce the likelihood of failures.

Data and digital skills dominate the fastest growing emerging skills

The fastest growing emerging skills (in terms of percentage of all job listings which request them) are data and digital skills such as those in 'software orchestration/automation', 'artificial intelligence' and 'data analysis'.[57] For example, since 2015 demand for 'software orchestration/automation' has grown almost 30 times, as Figure 61 shows.

Figure 61: Cumulative growth multiple of the share of all skills, past five years compared with 2015

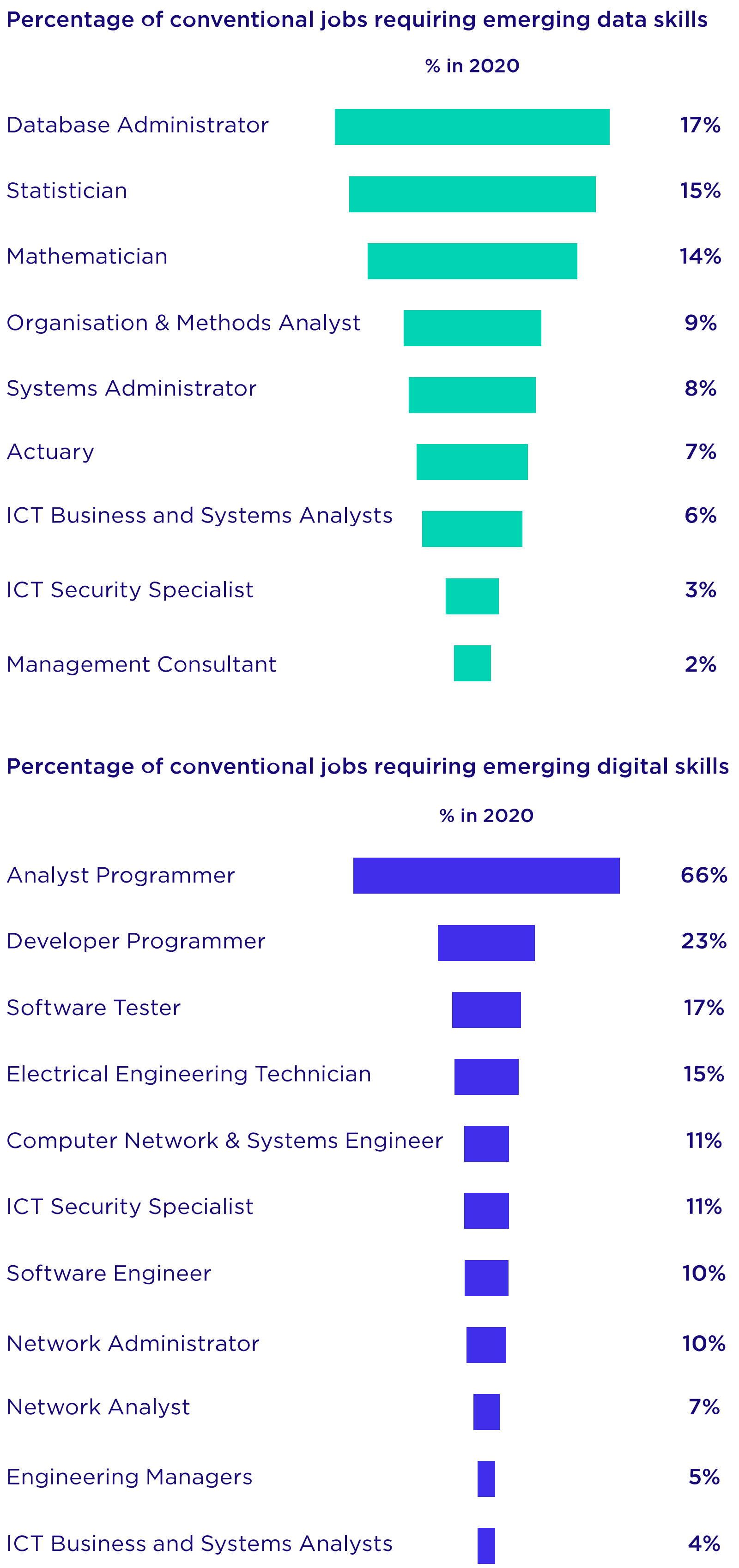


Sources: Burning Glass Technologies data, 2015-20, NSC analysis

Figure 62 shows the percentage of job advertisements for conventional jobs (which are jobs well-defined in the ANZSCO occupation classification) that require emerging data and digital skills. More than 66% of analyst programmer roles require emerging digital skills, demonstrating the pace at which the roles require individuals to keep pace with rapidly evolving technology. Demand for emerging data and digital skills is not limited to ICT roles; electrical engineering technicians, actuaries, and management consultants also among the top roles requiring skills in these areas.

[57] Software orchestration/automation refers to the automated configuration, management and coordination of computer systems, applications, and services, helping IT to more easily manage complex tasks and workflows.

Figure 62: Percentage of conventional jobs requiring data or digital skills



Sources: Burning Glass Technologies data, 2015-20, NSC analysis

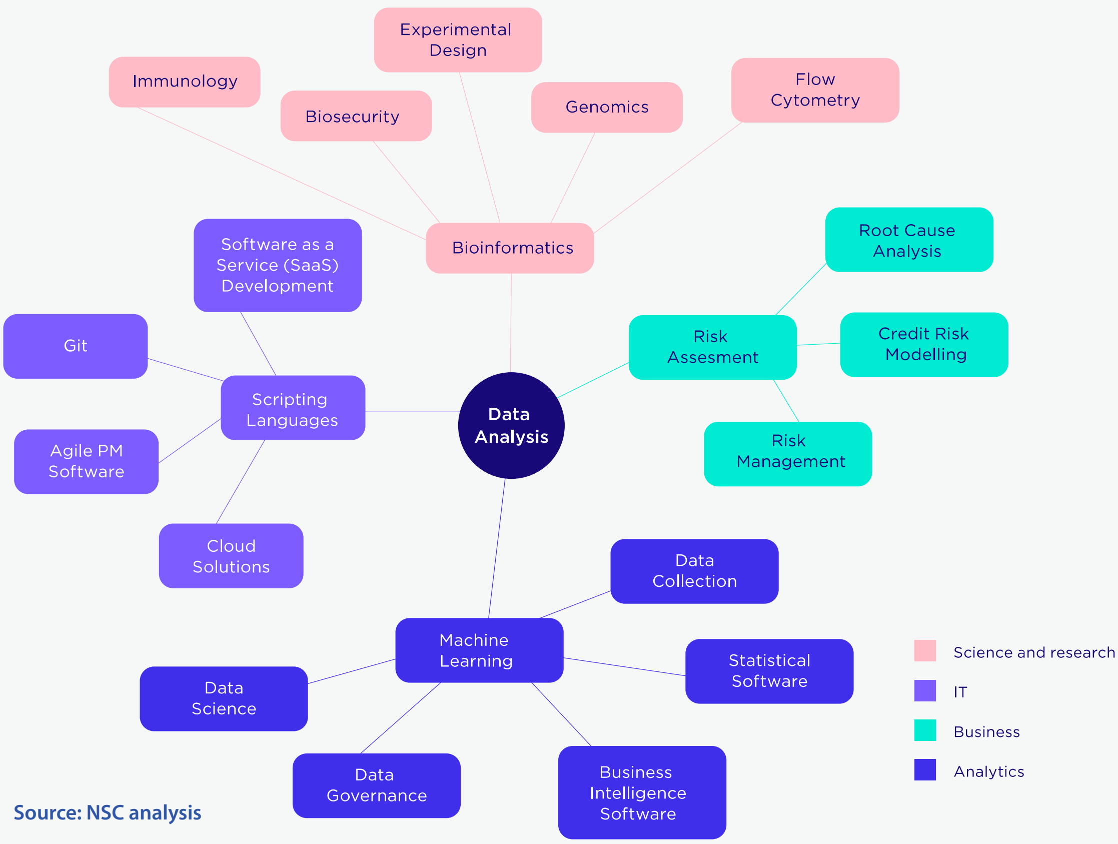
Case study: data analysis and job transitions

Demand for data analysis skills is growing fast, and trending in almost 70 job roles, or 12% of the 600 considered.

Data analysis skills are an example of a 'gateway skill'. Among the trending and emerging skills, gateway skills are those that play a unique role in enabling job transitions with other more specialised skills. They appear in many and diverse occupations and provide a point of transferability between them. To identify these skills, network analysis techniques can help understand when certain skills are requested along with other skills in particular occupations.

As shown in Figure 63, 'data analysis' skills are often requested in combination with IT, business, analytics, or science and research skills – including skills in 'scripting languages', 'root cause analysis', 'machine learning' and 'bioinformatics'.[58] A person in an analytic role who possesses 'data analysis' and 'machine learning' skills may be able to build on these with skills in 'scripting languages' to go on to work in an IT role, and further specialise by building skills in Software as a Service (Saas) development, Git, Agile PM software or Cloud Service to build their new IT career. Coupled with other information on the skills that underpin Australian occupations, including from the ASC, analysis of gateway skills will help us to better understand job transition pathways and how best to support and enable them.

Figure 63: Gateway skill map for data analysis skills



Source: NSC analysis

[58] Scripting languages are used to automate certain programming tasks, they are generally less code intensive than traditional languages, allowing for more compatibility and integrated coding. A common example is the facilitation of machine learning by Python. Root cause analysis (RCA) is a process or framework of problem-solving used for identifying and addressing underlying causes of system failures or incidents. RCA is evolving and is being increasingly applied in enterprise management and organisational settings. Bioinformatics is a subdiscipline of biology and computer science concerned with the acquisition, storage, analysis, and dissemination of biological data, most often DNA and amino acid sequences.

Emerging skills are driving jobs growth in emerging jobs

By analysing the highest growth job titles associated with trending skills, we can see how these skills may contribute to demand for emerging jobs. For example, demand for skills in 'big data', 'data architecture' and 'scripting languages' is driving demand for 'data engineers', 'data scientists' and 'data governance analysts'. Similarly, demand for skills in 'content development and management', 'front end development' and 'social media' is driving growth in demand for 'content writers', 'user interface designers' and 'social media managers'.[59]

Understanding which in-demand skills are linked to growing jobs can help inform more up-to-date labour market advice, programs and policies. It can also give closer to real-time insights into labour market trends.

For example, increases in demand for 'infection control', 'public health' and 'mental health management' skills in care occupations are unsurprising given the impacts of the current COVID-19 pandemic. The psychological impacts of prolonged business and social restriction have led to increased demand for 'mental health management' skills across occupations, but also have led to growth in demand for jobs such as 'school psychologist' and 'mental health clinician'.

Similarly, NSC analysis suggests that patient care and information management skills are rising in demand across supporting and enabling care occupations, as the medical and general practice system adapts to the demand of current conditions. This has led to increased demand for jobs such as 'allied health assistant', 'home care worker', 'health information officer' and 'clinical care coordinator'.

It is likely that demand for emerging jobs in the digital, data and online engagement sectors is driven both by the increasing uptake of technology overall, and a shift to online business models driven by the COVID-19 pandemic. The increasing need to collect, manage and safely store data and information online is leading to demand for skills in 'data management, architecture and analysis', 'cloud solutions' and 'scripting languages' in jobs such as 'data engineer' and 'cyber security analyst'. 'Content writers' and 'user interface designers' with skills in 'content development' as well as 'front end development' will help businesses find, reach, and keep customers engaged and help keep their businesses in operation.

Changing business practices are also driving growth in emerging jobs in the business and project management fields. 'Agile coaches' and 'product designers' are in demand for their 'product design' and 'software-as-a-service' skills.[60] 'Customer success managers' and 'risk managers' ensure the customer experience keeps customers engaged and helps keep in check the risks that come with implementing new business models and practices.

Emerging and trending skills in the wider labour market

Trending and emerging skills are affecting the way work is undertaken across many occupations in the labour market. New skills such as infection control, social media and data analysis are spreading quickly cross the labour market and core competencies such as teamwork will continue to be in increased demand across most occupations.

It is useful to consider how emerging and trending skills are affecting the labour market. Table 19 considers the top employing occupations in the Australian labour market, and the top trending skills for those jobs – including how they map to existing skills in the ASC.

The top trending skills across these occupations reflect the diversity of the occupations themselves – ranging from electrical control system design to safe chemical disposal. Combining this information with other data, such as from the ASC, will provide rich information on how the skills within jobs are changing, whether these trends are persisting, and how best people can be helped to develop the skills required by employers.

[59] The NSC report *Emerging occupations,* 2020, deliberately excluded alternative job titles. The work reported here will feed into the next *Emerging occupations* report, and this may involve an expansion of the original definitions and methodology. In *Emerging occupations,* 2020, NSC results were validated against ABS microdata. The new emerging occupations mentioned in this chapter have not gone through this process.

[60] Agile coaches train corporate teams on the agile methodology (an iterative approach to project management and software development). Also, they oversee the development of agile teams and guide them through project implementation processes.

Table 19: Top employing Australian occupations from each sector and their top trending skills

Largest occupation in sector (ANZSCO major code)	Top trending skills	Australian Skills Classification closest skills	Intensity 2015	Intensity 2020
Managers	Customer service enhancement	New	0.02%	1.15%
Retail manager	Loss control / prevention	Monitor work areas to provide security	0.17%	1.59%
	Retail operations	Establish operational policies	5.73%	7.69%
Professionals	Infection control	Treat acute illness or infections	1.46%	6.30%
Registered Nurse	Clinical leadership	Supervise patient care staff	3.80%	5.60%
	Community health care	Advise communities regarding health care	3.29%	4.20%
Technicians & Trade Workers	Electrical control systems design	New	0.55%	1.30%
Electricians	Enterprise Resource Planning (ERP)	Enterprise Resource Planning (ERP)	1.15%	2.10%
	Schematic diagram design	New	1.25%	1.60%
Community & Personal Service Workers	Cardiopulmonary Resuscitation (CPR)	Administer health care or medical treatments	6.27%	16.00%
Aged and Disabled Carer	Meal preparation	Prepare food	6.22%	9.20%
	Medical administration	Administer health care or medical treatments	1.16%	6.80%
Clerical & Administrative Workers	Social media	Social media and web publishing software	1.26%	1.36%
General Clerks				
Sales Workers	Payment processing	Process sales or transactions	1.12%	1.92%
Sales Assistant	Retail operations	New	1.03%	1.24%
Machinery Operators and Drivers	Commercial driving	Operate vehicles or moving equipment	0.06%	1.01%
Truck Drivers	Haulage transport	New	1.03%	1.24%
Labourers	Enterprise Resource Planning (ERP)	New	0.10%	1.40%
Commercial Cleaners	Safe chemical disposal	Dispose of rubbish or waste materials	0.17%	1.35%

Sources: Burning Glass Technologies data, 2015-20, NSC analysis

Note: 'Sector' is defined by the ANZSCO major groups (or one digit codes). There are eight in total, covering the whole labour market. This table gives information for the largest employing six digit occupation within each major group. For example, in the professionals major group the largest employing six digit occupation is registered nurse.

Demand for core competencies during the COVID-19 pandemic

During the COVID-19 pandemic, there has been an increase in demand for core competencies or 'employability skills' such as teamwork, planning and organising, and problem-solving skills.

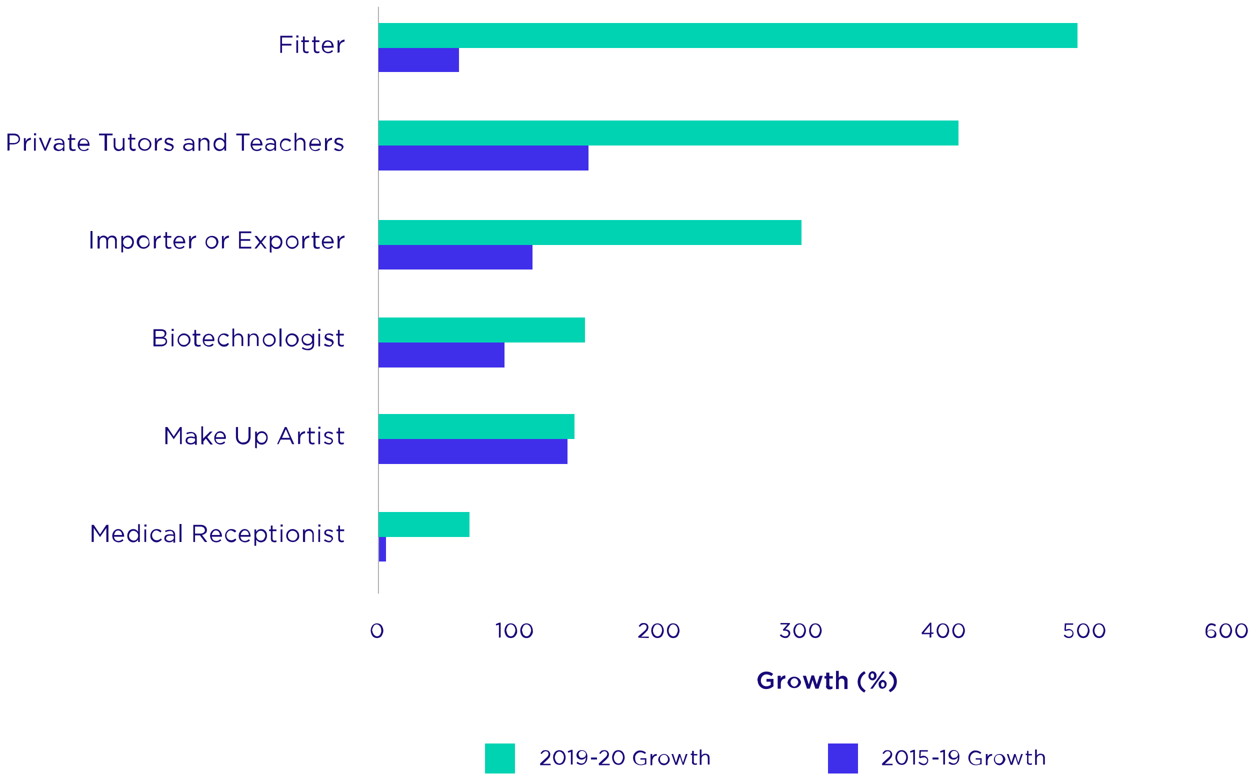
Core competencies are the basic building blocks common across most occupations and industries. They refer to a set of non-specialist skills gained in early life and schooling and provide a base to further develop skills and specialties. Popular terms for these include 'foundation skills', 'common skills', 'soft skills', 'core skills' and 'employability skills'.

These skills are important to employers. A 2019 survey conducted by the then Department of Employment, Skills, Small and Family Business found that 75% of employers considered employability skills to be as important as, if not more important than, technical skills.[61]

NSC analysis demonstrates that the importance of employability skills has not diminished, and can grow under pandemic conditions. Skills relating to resilience and flexibility (such as 'problem solving', 'learning', 'initiative and innovation') and to managing tasks and staffing logistics outside more conventional and established working arrangements ('oral communication', 'teamwork' and 'planning and organising') have proved critical in a rapidly changing labour market.

For example, Figure 64 shows that demand for 'planning and organising' skills for 'fitters' grew around 500% from 2019 to 2020, significantly more than the growth during the five years before. Similar patterns of growth can be seen for 'private tutors and teachers', and 'importer or exporter'.

Figure 64: Jobs with the most growth in planning and organising skills



Sources: Burning Glass Technologies data, 2015-20, NSC analysis

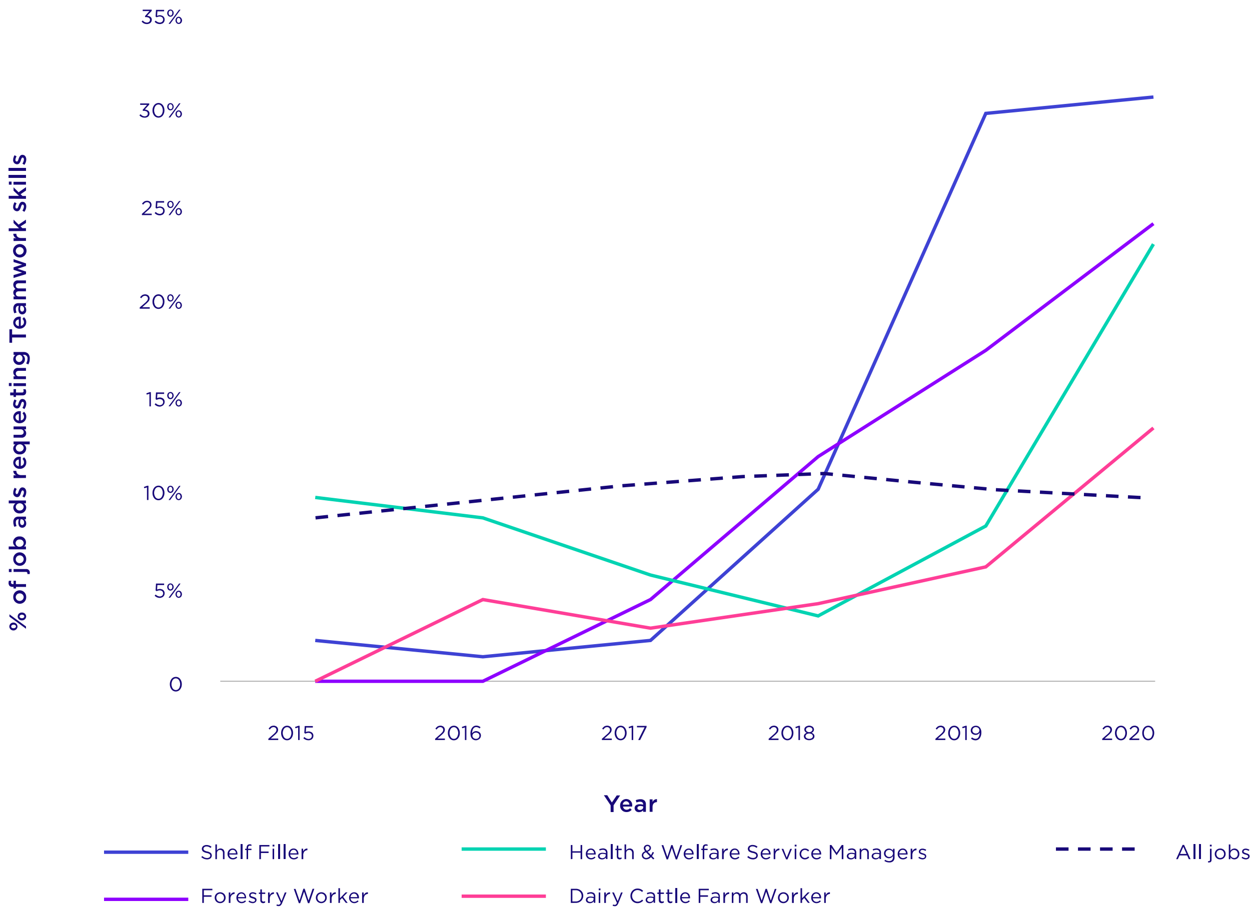
Figure 65 shows there has been an increase in demand for teamwork skills across a range of occupations. Advertisements requesting teamwork rose for many jobs, particularly in frontline and essential jobs over the pandemic.

This is likely to be due to the significant and often volatile surges in demand across the supply chain and health systems, indicating the importance of teamwork for reliable service delivery. Examples of this include jobs for shelf fillers, who were in high demand during the 2019-20 bushfire season and during the onset of the COVID-19 pandemic. Job listings explicitly requesting teamwork skills rose rapidly from a baseline of 5% in 2015 to 30% of shelf filler jobs by 2020.

This analysis demonstrates that core competencies remain relevant and in some cases are more in demand in times of economic change and uncertainty.

[61] NSC, Survey of Employers' Recruitment Experiences data report, 2019 data report

Figure 65: Percentage of job advertisements requesting teamwork skills, 2015 to 2020



Sources: Burning Glass Technologies data, 2015-20, NSC analysis

Emerging and trending skills and the VET system

It is important that Australians have access to quality training so they can develop emerging and trending skills. A responsive and dynamic vocational education and training (VET) system can help support the real needs of industry and equip individuals with skills that will help them succeed in the long term. An NSC analysis of existing qualifications, skill sets and units in the VET system found a number of these already provide training in relevant emerging and trending skills. Table 20 gives examples of the units, skills sets and qualifications or accredited courses delivering these skills across a range of emerging skills areas.

Table 20: Emerging skills in the VET system

Emerging areas	Example Units	Example Skill Sets	Example Courses
Data	BSBDAT501 Analyse data	ICTSS004004 Data Analysis	10917NAT Diploma of Data Science
	AHCWRK502 Collect and manage data	BSBSS00092 Manage Big Data	BSB50120 Diploma of Business (Digital Data)
Digital	ICTPRG446 Prepare software development review	ICTSS00405 Internet of Things Developer	ICT50220 – Diploma of Information Technology
	ICTCLD508 Manage infrastructure in cloud environments	ICTSS00099 – Cloud Design and Configuration	10621NAT Diploma of Cyber Security
Care	SHBBINF001 Maintain infection control standards	BSBSS000095 Cross Sector Infection Control	PUA42912 Certificate IV in Public Safety (Biosecurity Response Leadership)
	HLTAHW069 Develop health care policy	CHCSS00102 Mental health co-existing needs	CHC43315 Certificate IV in Mental Health
Agile PM	ICTICT530 Design use experience solutions		22446VIC Diploma of Product Design
	ICTICT529 Organise and lead agile projects		ICT40120 Certificate IV in Information Technology
Business	TLIX0009X Digital supply chain risk management practices	BSBSS00105 Human Resources Foundation	TLI50219 Diploma of Logistics
	SIRXCEG003 Build customer relationships and loyalty	SIRSS00027 People Management in Retail	BSB40120 Certificate IV in Business (Operations)
Online Engagement	SIRXMKT007 Developing a digital marketing plan	SIRSS00016 Ecommerce Management	BSB40820 Certificate IV in Marketing and Communication
	ICTWEB306 Develop web presence using social media		CAUA5075 Diploma of Graphic Design
Engineering and Trades	ERPBIM004 Order fulfilment and customer service with ERP systems	TLISS000099 Logistics Product Management	UEE41611 Certificate IV in Renewable Energy
	MEM09210A Create 3-D solid models using computer-aided design systems	MEASS00412 MTA065 Machine Aeronautical Product Component Parts Using NC/CNC Machining Centres	10287NAT Diploma of Environmental Management

Sources: Department of Education, Skills and Employment, data from www.training.gov.au, NSC analysis

Digital skills in Australia and internationally

Digital skills are increasingly important in today's economy. Growth in new technologies is changing the way businesses are run and the way tasks within jobs are undertaken. As discussed earlier, digital and data skills dominate the fastest growing emerging skills and can act as gateway for transitions between jobs.

The importance of digital skills is recognised by industry. In their 2019 skills forecasts, Australia's industry reference committees ranked a series of 12 generic skill categories, in priority order. 'Technology use and application' skills received an average ranking of fourth across all skills forecasts. Digital skills were also identified by around half of the industries that reported on priority skills.[62] The ASC has shown that almost all jobs require the use of at least one technology tool.

This section compares demand for digital skills between Australia and other countries. This can help us to develop an understanding of how the digital engagement of Australian industry compares internationally, where Australia's skills gaps might be, where skilled talent may be lost, and where industry growth opportunities and future skills demand may be.

Digital skills proficiency is important to the economy on multiple levels. It can ensure success for people in the labour market, enable transitions between jobs and open new opportunities for Australia to lead in the development of digital technologies into the future. The analysis in this section suggests that while Australia recognises the need for specific digital skills, further effort may be required to build base digital skills proficiency at all skill levels, not just the higher skill levels.

Defining digital skills – using a common taxonomy across countries

The ASC provides the common language to define skills in Australia. The term 'digital engagement' is used in the ASC to refer to the ability to identify and use technology (including hardware and software) confidently, creatively and critically. The ASC provides for all occupations a measure and description of the level of competency required for 'digital engagement' and a list of common technology tools that are likely to be used. The ASC also identifies 'technology tools' that are highly specialised and occupation-specific.

In this section, there are two skill types that align with the rationale behind the ASC of separating out digital skills required for most jobs and digital skills required for specific jobs.

Baseline digital skills – are digital literacy skills requested by employers for most jobs. They include skills in office suite software (word processing, spreadsheet, and presentation software), enterprise resource planning and project management software.

Specific digital skills – are digital skills required for more technical jobs, including skills in data analysis, digital design and computer networking.

The seven specific digital skill categories outlined in Figure 66 have been used to compare skills across international data.[63] To understand the spread of digital skills across the labour market, differences in demand for digital skills inside and outside the IT sector are considered. Finally, to get a better understanding of the digital skills driving change in the labour market, cutting edge skills are identified. These are defined as those with strong historical growth (of more than 150%) between 2013 and 2020.[64]

[62] 2019 Industry reference committee industry skills forecasts.

[63] This categorisation was developed by Burning Glass Technologies in a report for the UK Government Department for Digital, Culture, Media and Sport, *No longer optional: Employer demand for digital skills*, 2019.

[64] To overcome international classification differences, the NSC analysis uses the Burning Glass Technologies taxonomy, allowing a common definition of the IT or digital sector across all countries in our analysis.

Figure 66: Specific digital skill categories

Source: Burning Glass Technologies, 2021

The digital skills market in Australia, Canada, New Zealand, Singapore and the United States

Using big data techniques, this analysis tracks digital skills sought by employers from job advertisements, the roles that require them, and the salary benefit associated with them. This creates a picture of the international digital skills market. Comparing Australia's results with those from Canada, New Zealand, Singapore and the United States provides a measure of how Australia is faring in the international digital skills market. All these countries have similar economies but are at different stages of developing their IT sectors.

As shown in Figure 67, the proportion of Australian job advertisements requesting digital skills, both baseline and specific digital skills, remained relatively stable – between 26% and 33% over the period of the study. Australia had the second lowest overall observed demand for digital skills, with the downward trend from 2018 to 2020 in contrast to most other countries. Of the five countries, Singapore showed the strongest growth in demand, with a constant increase from 41% to 55%, with a noticeable upward trend from 2019.

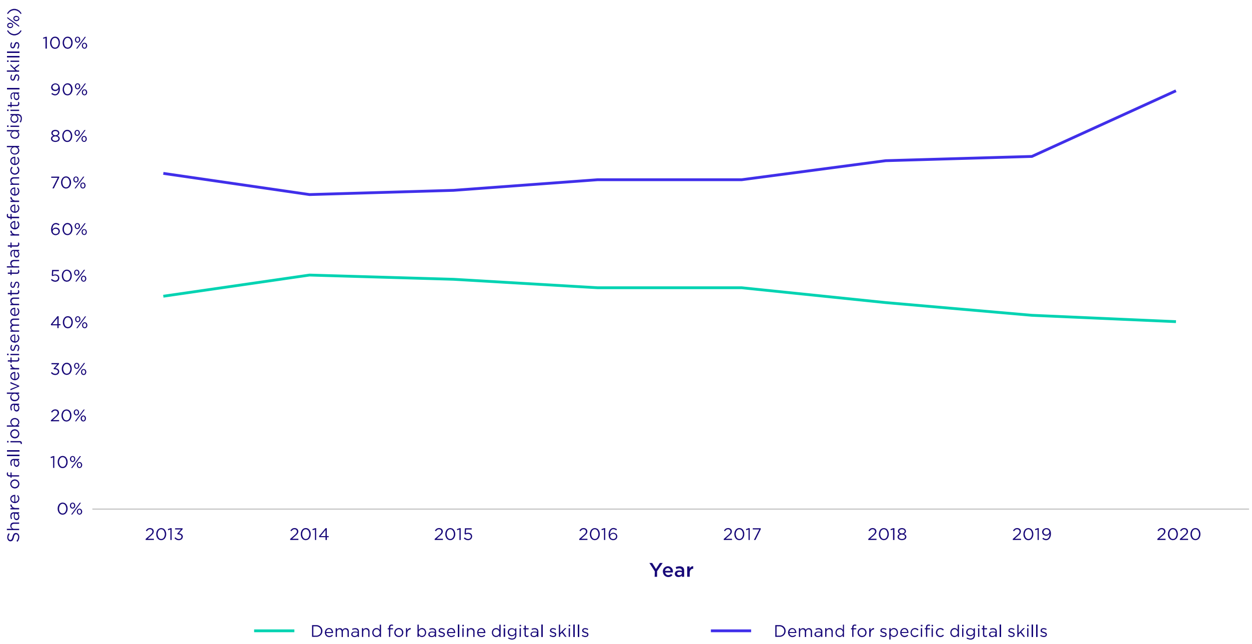
Figure 67: Demand for digital skills, 2013 to 2020

Sources: Burning Glass Technologies data, 2013 to 2020, NSC analysis

When Australian employers recruit for digital skills, they tend to be looking for technical skills. Figure 68 breaks job listings mentioning digital skills across the specific and baseline skill categories. While the demand for baseline skills flattens out and then decreases over time, the demand for specific digital skills slowly increases over time. This trend intensified in 2020.

It is difficult to know why the demand for baseline digital skills in Australia is the lowest among the five countries. On one hand it could mean Australian employers are slow to recognise the need for baseline skills for a range of occupations in the labour market. On the other, it is possible Australia's low figures for baseline digital skills reflect cultural differences in the type of information employers choose to include in job advertisements, rather than actual differences in demand. It may be that basic digital skills have become so ubiquitous they are now assumed job requirements and are often not explicitly stated. This is a limitation of web-scraped data that must be balanced against its richness and timeliness.

Figure 68: Demand for specific and baseline digital skills in Australia 2013 to 2020 as a percentage of job advertisements mentioning digital skills



Sources: Burning Glass Technologies data, 2013 to 2020, NSC analysis

In Australia the demand for specific digital skills (the share of job advertisements referencing these skills) is consistently high and comparable to other countries for each of the digital skill categories. Among job advertisement postings requiring digital skills, specific digital skills relating to software and programming have the highest demand across all five countries, ranging from 49% in Singapore to 37% in Canada. In Australia, the demand for software and programming is 46%, computer and networking support 17%, data analysis and digital design and marketing 15%.

Which jobs are driving demand?

When comparing demand for digital skills in IT sector occupations compared with non IT occupations, the trends are as expected. In the IT sector, the top three skills advertised are software development principles, SQL databases and programming and system design and implementation. These are the top three skills in all countries, although not necessarily in that order.

Looking outside of the IT sector, the top skills are unsurprisingly less technical. Here, office suite, enterprise resource planning and social media skills top the list of digital skills in demand.

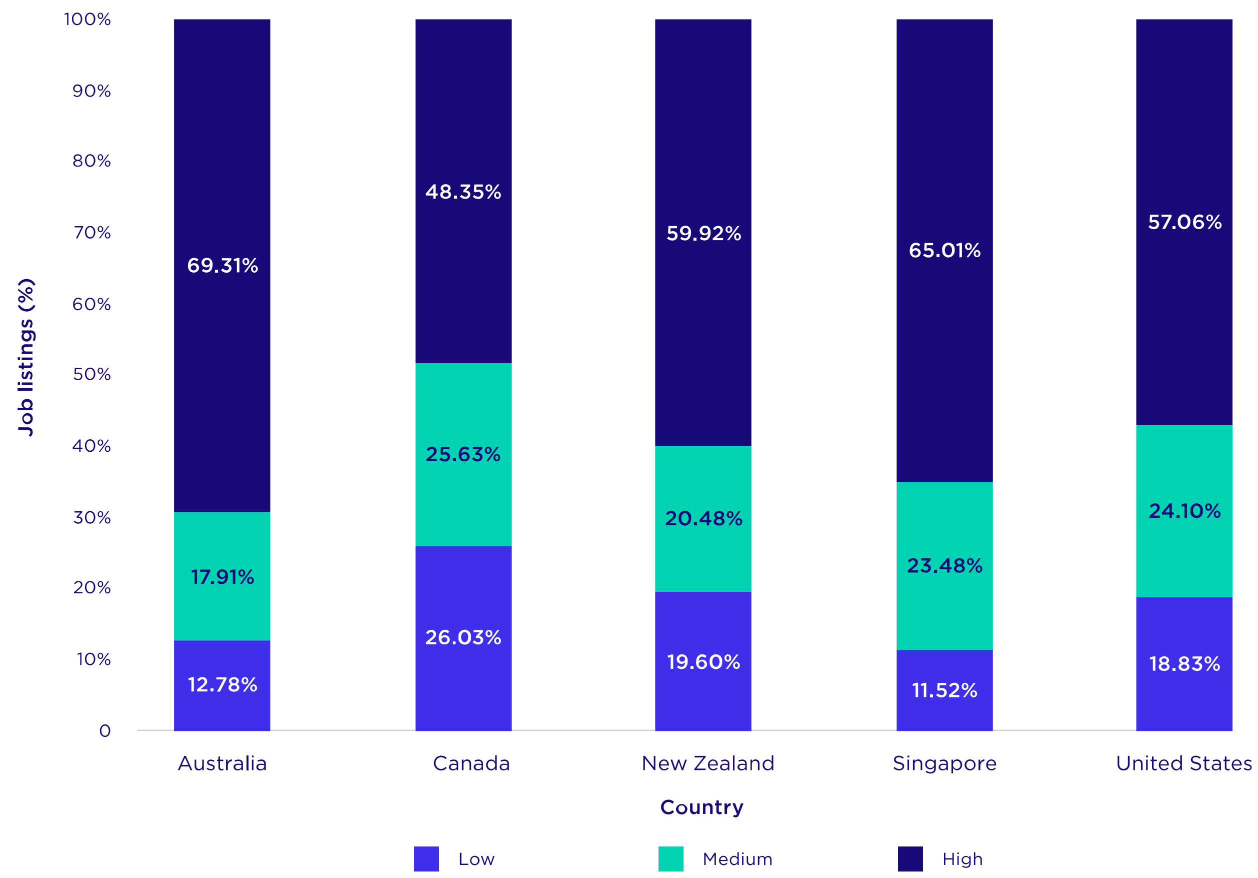
That is not to say that the suites of skills requested for each type of occupation are separate and distinct. There are digital skills that are commonly requested across sectors, including office suite, system design and implementation, and even, in some countries, software development principles.

In Australia, the highest proportion of job postings requesting digital skills is for software and application programmers and computer network professionals, comprising over 16% of all job ads. After these, many occupations outside the IT sector are represented – including sales, accountants, and consulting and marketing roles. As mentioned above, up until 2020, jobs in the non-IT sector have shown the most growth in demand for digital skills.

The findings were similar in other countries with both IT and non-IT sector occupations among the top occupations requesting digital skills. In other countries, IT sector occupations topping the list were software engineers and designers, software developers and web and multimedia developers. The top non-IT sector occupations that requested digital skills were sales, administrative, accounting, and consulting roles.

When looking at employer demand for digital skills based on skill level, the trends indicate most jobs requiring digital skills are highly skilled jobs, and this was true across the five countries.[65] Figure 69 shows Australia has the highest share of this category among the five countries at 69%. One possible explanation for this is Australia's higher recent growth in demand for specific digital skills and Australian businesses at the higher end of the labour market being more aware of the competitive advantage that could be gained from having more specialised technical IT skills. It may also be this trend reflects requirements within more highly skilled jobs to manage, manipulate and analyse more complex and larger volumes of data and information, which is increasingly done with digital tools.

Figure 69: Composition of jobs requiring digital skills, by job skill level



Sources: Burning Glass Technologies data, 2019, NSC analysis.

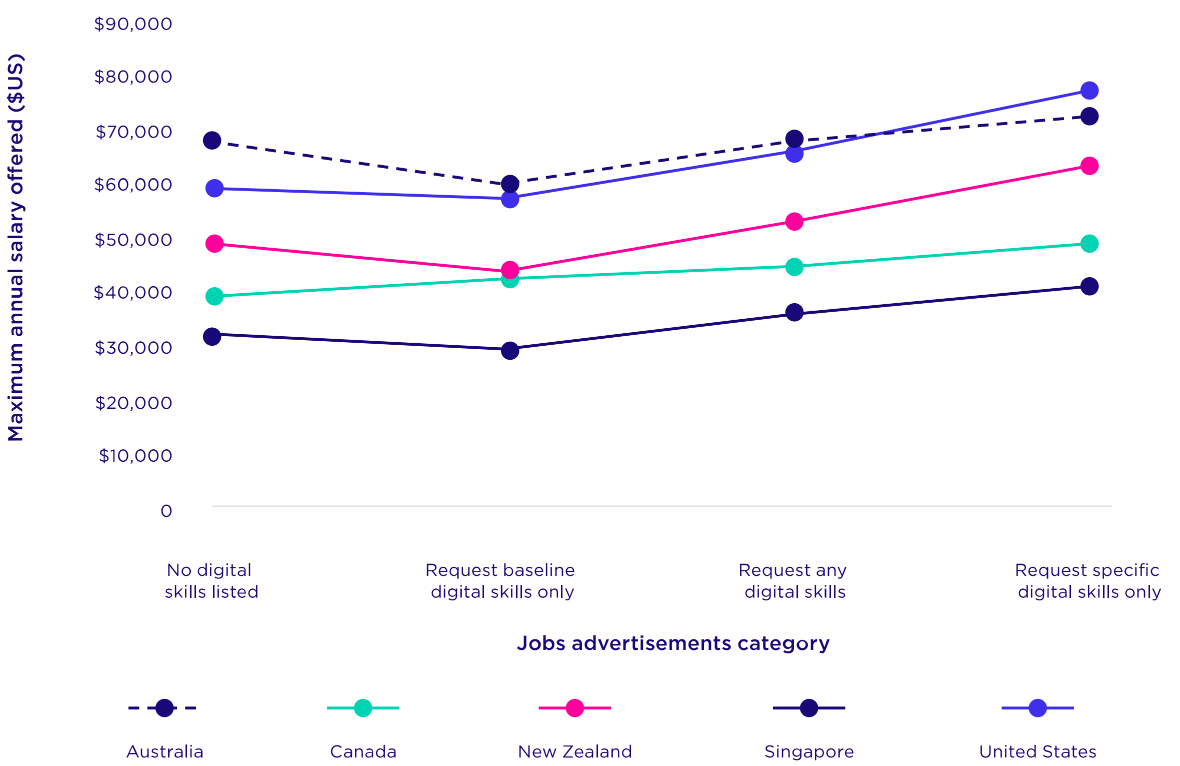
[65] Although Australia uses skill levels in the ANZSCO classification system, this was not available for all countries in the Burning Glass Technologies data set. Instead, we used the 'job zone' field from the US classification system, O*NET, as a proxy to allow us to compare across countries. O*NET defines 5 job zones, where 5 requires the highest qualification or experience and 1 requires almost no qualification or experience required. These were then categorised into high (4,5), medium (3) and low (1,2) categories of skilled occupations.

Specific digital skills provide scope for additional income

In most of the countries in this study, digital skills were associated with higher salaries when compared with jobs that required no digital skills.[66] As Figure 70 shows, in Canada and New Zealand, the requirement for digital skills is worth approximately $5,000 USD per annum, in Singapore it is around $3,500 USD and in the US it is worth almost an additional $7,000 USD per annum. Alongside the US, in the data set upon which this analysis is based, Australia has relatively high salaries, evident also in relation to digital skills. That said, the difference in Australia between jobs that do not require digital skills (an average salary in this data set of $67,000 USD per annum) and those that do (an average of $68,000 USD per annum) is minimal.

In all five countries there is also a bigger wage differential between jobs requiring only baseline digital skills, and those requiring specific digital skills from one of the six categories (listed in Figure 66). In Canada the difference is $7,000 USD per year, in Singapore $12,000 USD, in Australia more than $13,000 USD. The difference is the most in the US and New Zealand, where the requirement for specific digital skills is worth around $20,000 USD per year.

Figure 70: Maximum salary offered in job advertisements



Sources: Burning Glass Technologies data, 2019, NSC analysis

Note: Salaries are in US$

People considering their employment options often need to make complicated trade-offs between current possibilities, long term prospects and salary considerations. While the data analysis category is associated with the highest advertised salary of $99,579 USD per year on average across all five countries, its share of digital demand in the marketplace is 15% which makes it a relatively niche skill. By contrast, software and programming accounts for 46% of digital demand in the market, which suggests a skill of wider appeal, albeit with a slightly smaller income at $98,937 USD per year on average in the five countries.

The demand for specific digital skills increases and decreases faster than other skills in the labour market. This is driven by the pace of innovation in the IT sector and the increasing requirement for all businesses to adopt new technologies, update systems, and digitise.

To focus on this phenomenon, the NSC identified a group of cutting-edge skills which have grown by over 150% between 2013 and 2020. These skills are growing quickly, but from a low base. Table 21 compares the 10 fastest growing cutting-edge digital skills in Australia and the US. The results are quite similar in each country.

[66] Salary data is missing in many job advertisements, and results may not perfectly reflect salaries in the actual job market.

Table 21: Demand for cutting edge skills in Australia and the US

Australia	
Skill Name	**Growth over 2013 – 20 [%]**
Artificial Intelligence (AI)	4,412
IT Automation	3,817
Internet of Things (IoT)	3,645
Application Programming Interface (API)	780
Machine Learning (ML)	724
Natural Language Processing (NLP)	537
Distributed Computing	516
Data Visualisation	482
Software Development Methodologies	450
Big Data	384

United States	
Skill Name	**Growth over 2013 – 20 [%]**
IT Automation	3,597
Data Wrangling	2,250
Internet of Things (IoT)	1,350
Artificial Intelligence (AI)	999
Augmented Reality / Virtual Reality (AR/VR)	643
Device Management	459
Machine Learning (ML)	405
Data Visualisation	363
Tax Software	317
Software Development Technologies	288

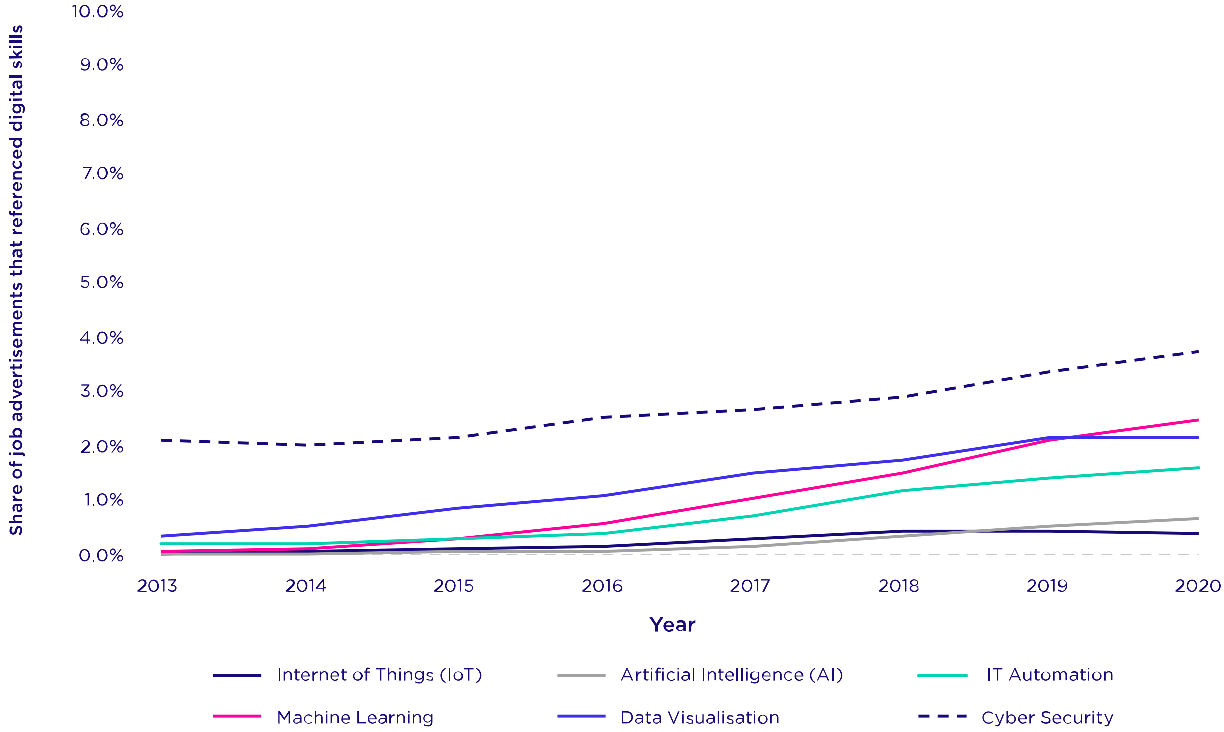
Sources: Burning Glass Technologies data, 2013 to 2020, NSC analysis

Despite considerable international consistency, time series analysis reveals some differences in the demand of cutting-edge skills across countries. Figures 71, 72 and 73 show a similar pattern of demand across Australia and the US for skills in data visualisation, IT automation, machine learning, artificial intelligence and the internet of things; but US job advertisements mention cyber security at twice the rate of those in Australia. The share of job advertisements demanding for cutting edge skills in Singapore outstrips those of the US and Australia, particularly for cyber security.

International differences also become apparent when looking at the interaction between cutting edge skills and specific occupations. For example, employers in Australia and New Zealand are more than three times more likely to seek data visualisation skills when recruiting actuaries (15% and 20% respectively) than those in Singapore, the US or Canada.

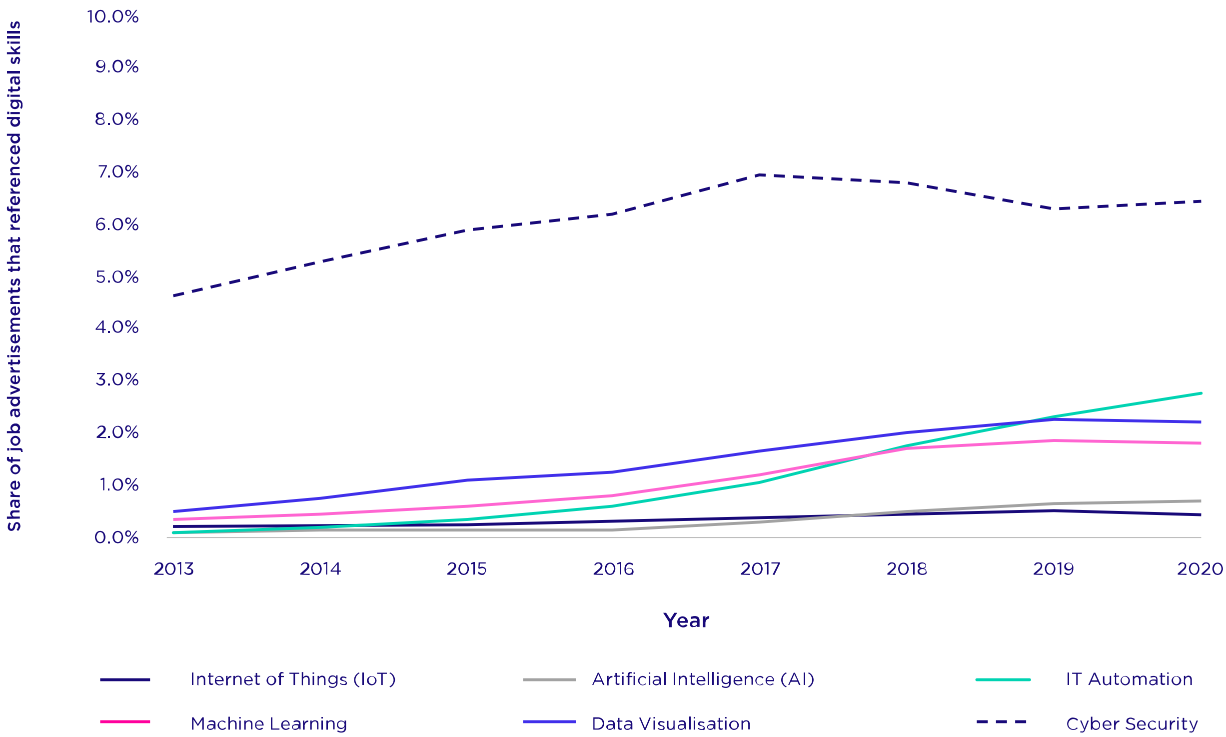
Examining skills that are emerging or growing rapidly in other economies can also provide a guide to potential developments in the Australian labour market.

Figure 71: Demand for cutting edge skills in Australia



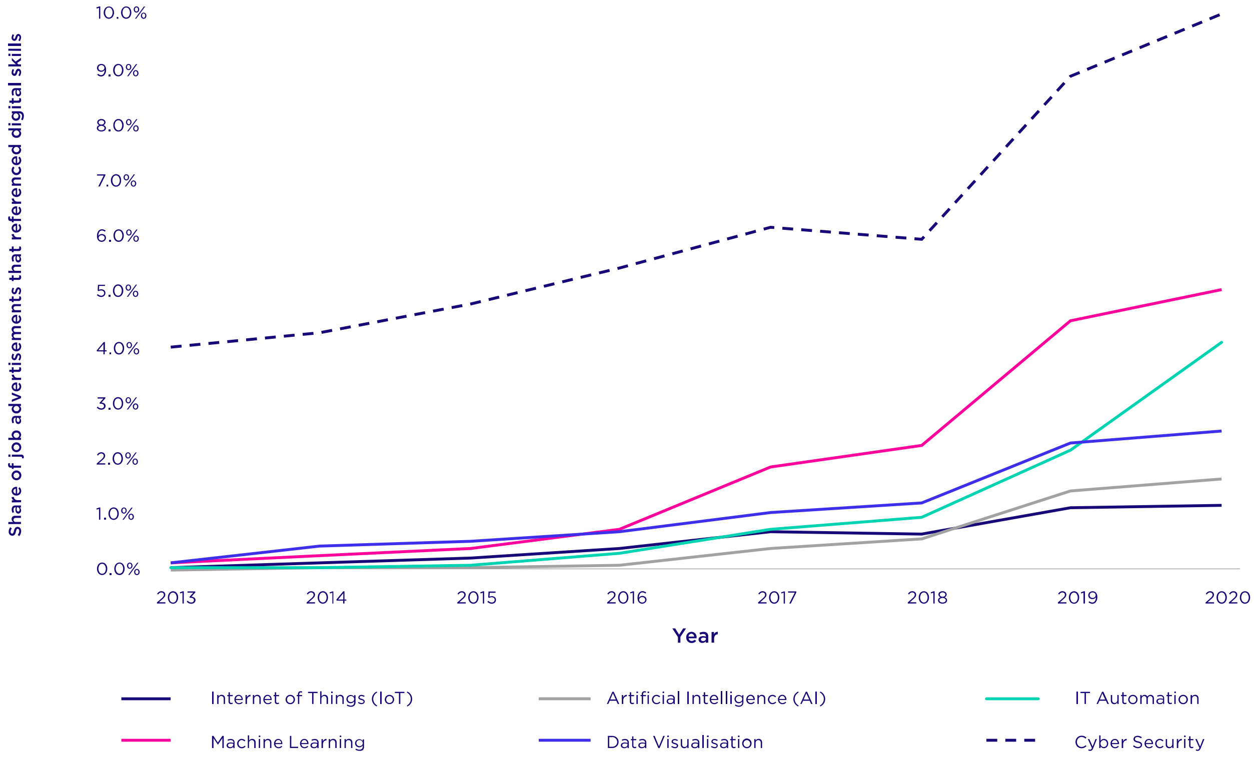
Sources: Burning Glass Technologies data, 2013 to 2020, NSC analysis

Figure 72: Demand for cutting edge skills in US



Sources: Burning Glass Technologies data, 2013 to 2020, NSC analysis

Figure 73: Demand for cutting edge skills in Singapore



Sources: Burning Glass Technologies International data, 2013 to 2020, NSC analysis

08

Skills and jobs of the future

Skills and jobs of the future

Among the key skills that will be needed for jobs of the future are care, computing, cognitive and communication skills.

There are many divergent views and research methodologies in the future of work debate. There are also a number of myths and misconceptions. Much of the debate centres around the single issue of how automation will threaten jobs in the future.

Automation has varying effects within occupations and industries. It can replace labour in some jobs and tasks humans used to perform as well as creating new tasks and demand for labour. For example, software and computers have replaced labour in some white-collar jobs. They also created new tasks including programming, software and application development, and more specialist tasks within existing occupations. The NSC views computing as a key skill of the future, reflecting the job creation aspect of this mega trend.

The combination of an ageing population and the lower ability to automate tasks and jobs in the cluster family of health and care suggests that 'care' is likely to be a key skill of the future.

One of the impacts of the pandemic on the labour market appears to have been an acceleration of long term trends. One such trend is the shift in demand for labour away from routine tasks (repetitive physical labour that can be replicated by machines) towards non-routine (non-repetitive or non-codifiable) work. The greater difficulty in automating non routine cognitive jobs and tasks (at high and lower skill levels) also suggests that cognitive jobs will remain in high demand into the future.

The analysis in this chapter also highlights the importance of core competencies or 'employability skills'. The analysis finds that high proficiency in core competencies correlates with a decrease in the likelihood of automation. Within that group of core competencies, oral communication and writing require high proficiency and are the least likely to be automated. This finding sits behind the NSC's view that communication is a core skill of the future.

Throughout this report a key focus has been on drawing out the big forces: a shift to higher skill jobs and an ongoing shift toward services, including care; the resilience of non-routine and cognitive jobs in the face of automation and Artificial Intelligence (AI); the opportunities and new jobs being created by technology; and an acknowledgment that many of those forces likely to shape the future have also shaped our recent past.

The future of work

How the world of work will evolve has fascinated economists, educators, workers, and planning and policy professionals for many decades – more so in recent years due to globalisation and the exponential growth of technological innovation. That said, there is a great difficulty in attempting to forecast the impact of such factors on individual workers and the labour market as a whole. Events such as the COVID-19 pandemic can also suddenly accelerate trends that have been reshaping the labour markets for decades.

Unsurprisingly, there are many views on the future of work, some of which are complementary and others that are divergent and conflicting.

There are two widely shared views about automation. One view held by researchers and economists is that policies will need to be put into place to address the challenge of labour shortages as technology and innovation creates a high demand for high-skilled workers. Another view is that advances in technology will gradually reduce the demand for low and medium skilled workers in jobs that are easily automated.

The underlying narrative of these views is similar – as the world becomes more dependent on technology and reliant on global supply chains there will be a net increase in the demand for more highly skilled workers to meet the challenges and opportunities of the future. Therefore, it is imperative that policies prepare the current and future workforce to make meaningful transitions to jobs that are in demand with the skills that are in-demand.

What will the future of work look like?

There are many divergent views and research methodologies in the future of work debate. There are also a number of myths and misconceptions. Much of the debate centres around the single issue of how automation will threaten jobs in the future – however this is not new. In 1921, The New York Times featured a book review entitled 'Man devoured by his machines', and in 1928 the same publication ran the headline 'March of the machine makes idle hands; farm employment less with increased output'.[67]

Narratives suggesting automation will wipe out large numbers of jobs were prevalent in the 1960s, 1980s and 2010s, each time suggesting the world was reaching a tipping point where machines would take over the majority of jobs.[68]
More recently, narratives in 2010 responded to concerns that even highly skilled knowledge-based jobs soon would be threatened by advancements in AI, robotics, software bots and autonomous vehicles.

Popular debates often cite Frey and Osborne's estimates as forecasting an impending employment apocalypse.
Their research published in 2013 estimated 47% of jobs could be exposed to automation from a technological capabilities point of view. They did this by analysing tasks, but then used a binary approach to determine whether an entire job would be replaced or not.[69]

Frey and Osborne's estimates have been contested, and other models have examined a greater breadth of variables and are more nuanced in describing task replacement rather than job replacement. For example, the OECD found that only 14% of jobs are exposed to automation while 'a further 32% of jobs have a risk between 50 and 70% pointing to the possibility of significant change in the way their jobs are carried out as a result of automation'.[70]

[67] New York Times, 'Man devoured by his machines', 1921; C Evans, 'March of the machine makes idle hands; farm employment less with increased output', New York Times, 1928.
[68] R J Schiller, *Narrative Economics*: *How stories go viral and drive major economic events,* Princeton University Press, Princeton and Oxford, 2019.
[69] CB Frey and MA Osborne, 'The Future of Employment: How Susceptible are Jobs to Computerisation?', *Technological Forecasting and Social Change,* 2017, 114:254-280
[70] L Nedelkoska and G Quintini, 'Automation, skills use and training', OECD Social, Employment and Migration Working Papers, 202, OECD Publishing, Paris, 2018,

Divergence in future of work models is substantial

The NSC has analysed the prominent future of work models across Australia, the United Kingdom, New Zealand and United States. Six of the models reviewed are described briefly in Figure 74. The figure highlights two main approaches used to predict the future of work. One approach assessed automation risk at the occupation level and the second assessed automation impacts at the job-task level.

The divergence between the occupational and task-based models is substantial – with variations of between 7% and 77% in the level of automation predicted for selected occupations. For nursing support, AlphaBeta predicts 30% of the job to be automated compared with 74% by Frey and Osborne. The difference between the models is not always in the same direction. AlphaBeta, with a task-based model, predicts 22% of secondary school teachers' roles will be automated compared with 1% across occupational based models.

Even within the task-based models developed in 2019 by the OECD and McKinsey & Company there is divergence, both in the framing of the high-level results and methodologies used.

Figure 74: Divergence in future of work models

10.6% of jobs in Australia are vulnerable to automation with a further 25% at risk of significant change

OECD (2019)

Between 25 to 46% of current work in Australia could be automated by 2030

McKinsey & Company (2019)

Failure to reskill could drive 2-4% jobless

AlphaBeta (2017)

9% of Australian workers at high risk of their jobs being automated

Borland & Coelli (2017)

35% of todays jobs in the UK are at high risk of automation

Deloitte (2015)

47% of US employment is in high risk of automation

Frey & Osborne (2013)

Source: NSC analysis

In summary, it is difficult to predict the future level of automation of the workforce. All models have inherent limitations in their methodologies and approaches. The Frey and Osborne model has gained much media attention without acknowledgement of the substantial variation in predictions from other models, especially task-based approaches, and the merits and drawbacks of each approach.

Analysis of comparative literature and future of work research

Narratives focusing on job losses often do not account for the net employment effects of automation. Implicitly, this focus on job destruction reflects the fallacy that there is only a fixed number of jobs, or a 'lump of labour', and that any job losses arising from automation cannot be offset by job creation. It is also easier to identify the jobs lost due to automation and the effects of global trade links. New jobs are less visible and can be spread out across different sectors.

The reality is that automation is not destroying human work. Neither is it always creating new jobs and tasks.[71] Automation has varying effects within occupations and industries. It can replace labour in some jobs and replace tasks humans used to perform as well as creating new tasks and demand for labour. For example, software and computers replaced labour in some white-collar jobs. They also created new tasks including programming, software and application development, and more specialist tasks within existing occupations related to administrative assistance.

When technology complements the work humans do, it can lift the productivity of workers, lower costs and increase demand for new products and services. New business models can increase multi-factor productivity, but realising these gains requires innovation and the right supply of skills, as well as other factors.[72]

We must also consider that the net number of jobs lost or gained is a deceptively simple metric to measuring the true impact of automation and new technologies on the labour market. For example, eliminating one million jobs and creating the same number of new jobs would appear to have a negligible impact. In practice, however, this causes huge economic disruption for the country and for workers – with flow-on effects to the economy as a whole.[73] A comprehensive understanding of the implications of automation and technology on the economy requires a deeper look at the broader effects of change, and the following sections seek to unpack these in greater detail.

Changing ways of working

An important goal of future of work research is to explore how the way we undertake our work will change. This includes increased access to flexible and remote working arrangements, facilitated by new technology, and the likelihood that workers may change jobs more regularly in future. There is also much debate about the rise of precarious working arrangements – about whether job polarisation will see 'middle jobs' decline in favour of both high and low skilled jobs, and whether the proportion of casual workers, gig workers, and underemployed workers will rise.

In 2018, Bankwest and Curtin University reported analysis from their index of precarious employment in Australia using data from the Household income and labour dynamics in Australia survey (HILDA). They found that between 2009 and 2018, precarious employment had increased for both men and women, but more rapidly for men. For both genders, the lowest levels of precariousness were for professionals and managers, and the highest were for labourers and machinery operators. There were differences between genders within occupations – for example female sales workers or community and personal services workers had significantly higher levels of precariousness then their male equivalents.[74] At an industry level, workers in 'public administration and safety', 'agriculture', and 'accommodation and food services' had the highest levels of precarious employment across all occupations. Among these, 'accommodation and food services' was the most precarious industry – with precariousness extending even to managers in the sector.[75] These trends are driven by multiple factors, which illustrates how future of work issues such as automation, globalisation and technological advancement cannot be considered in isolation. They arise in the context of other factors driving changes in the labour market. Other data, however, suggest that these concerns might be overdone. As an example, the extent of casualisation in the workforce has been little changed for the past 20 years according to data on employee leave entitlements produced by the ABS.

What is clearer is the rise in part-time employment. Part-time employment has become more common for both men and women over the 40 years to 2018, with part time employees growing to represent 31% of the workforce – double the level of around 15% in the late 1970s.[76] For men, the prevalence of part-time work arrangements has increased almost four-fold over this time, with the proportion of employed men working part-time growing from 5% to 18%. While the proportion of employed women working part-time has traditionally been larger than the proportion of men (about 50% of employed women in 2018), the reasons for working part-time are changing. The number of women citing caring responsibilities as the main reason for undertaking part-time work dropped to 30% in 2015 (from around 35% in 2002).[77]

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[71] D Acemoglu, 'Automation and New Tasks', 2019
[72] New Zealand Productivity Commission, *Technological change and the future of work,* 2020
[73] R Cassells, A Duncan, A Mavisakalyan, J Phillimore, R Seymour and Y Tarverdi, *Future of work in Australia: Preparing for tomorrow's world,* Bankwest Curtin Economics Centre, Focus on the States Series, 6(18), April 2018.
[74] R Cassells, *Future of Work,* 2018.
[75] R Cassells, *Future of Work,* 2018.
[76] R Cassells, *Future of Work,* 2018.
[77] R Cassells, *Future of Work,* 2018.

Much of the literature predicted increases to rates of working from home over the coming years, even prior to the COVID-19 pandemic. An increase in remote working arrangements put in place during the pandemic may persist, particularly as employers capitalise on potential benefits such as lower rent for smaller hybrid office spaces, and lower travel and meeting expenses. According to the World Economic Forum, in a report published in 2020, 84% of employers were aiming to further digitalise working processes. This included a significant expansion of remote work, with the potential to move 44% of their workforce to operate remotely.[78]

The future of work may increase access to work for some cohorts. For example, more flexible hours and alternative ways of working facilitated by technology can allow workers with mobility or accessibility requirements, or caring responsibilities, to undertake work at a place or time that accommodates their personal circumstances. In 2019, McKinsey & Company found that automation had the potential to boost workforce participation and create opportunities particularly for women with children, workers over the age of 65 and people with a disability.[79]

The opportunities for women stemming from the future of work and the need to support low skilled men has been highlighted in a range of recent literature. Bankwest and Curtin University analysis found that the rise in job insecurity in recent years has affected men more than women, and low-skilled females have had higher employment than low-skilled males for most of the last 15 years. Men have been working fewer hours and are more likely to be working in occupations where growth in hourly pay has stalled, and which are at high risk of technological disruption, while women currently dominate the fastest growing jobs.[80]

As the skills profile of the Australian labour market moves toward a greater proportion of higher skilled jobs, it will be important to ensure that workers, and lower-skilled men in particular, have access to education and reskilling opportunities to help them move into higher skilled, less automatable jobs.

The future of work is human

The literature also points to the growing importance of core competencies, or 'employability skills', to ensuring workers' continued success in the labour force. Core competencies are the basic building blocks common across most occupations and industries. They describe a set of non specialist skills, such as oral communication, teamwork and problem solving, gained in early life and schooling. They provide a base to further develop skills and specialties.

NSC analysis reveals that these skills are already highly valued by employers. A 2019 employer survey found that 75% of employers considered employability skills to be as, if not more, important than technical skills.[81] AlphaBeta analysis also found these kinds of skills to be the fastest growing in the labour market, and the World Economic Forum found that the top skills employers see as important in coming years include critical thinking, analysis and problem-solving skills and skills in self-management such as active learning, resilience, stress tolerance and flexibility.[82] In the future of work discourse these 'human' skills are regarded as being less automatable than manual skills, and occupations that heavily rely on these skills may be less susceptible to task change and obsolescence.[83] McKinsey & Company estimate that by 2030, workers will spend 43% more time on work interactions that require well developed social and emotional skills. Deloitte estimates that two-thirds of jobs will be soft-skill intensive in the same timeframe.[84]

[78] World Economic Forum, *The Future of Jobs Report 2020,* 2020.
[79] C Taylor, J Carrigan, H Noura, S Ungur, J van Halder and G Singh Dandona, *Australia's automation opportunity,* McKinsey & Company, 2019.
[80] R Cassells, *Future of Work,* 2018; Deloitte Australia, *The path to prosperity: Why the future of work is human,* 2019.
[81] NSC, *Survey of Employers' Recruitment Experiences, 2019 Data Report,* 2019
[82] AlphaBeta, *Future Skills,* 2020; World Economic Forum, *The Future of Jobs,* 2020.
[83] AlphaBeta, *Future Skills,* 2020; Deloitte Australia, *The path to prosperity,* 2019; C Taylor, *Australia's automation opportunity,* 2019.
[84] Deloitte Australia, *The path to prosperity,* 2019
Deloitte Australia (2019), *The path to prosperity*: Why the future of work is human.

Skills – the key to successful transitions

Across the literature, recommended responses to the future of work centre around the need for businesses to capitalise on technological advances to ensure their competitive success, and for workers to be prepared to reskill and retrain throughout their lives to meet changing skills demands.

AlphaBeta estimates that Australian workers will be likely to change jobs 2.4 times over the next two decades, but that even workers who stay in their jobs will need to frequently refresh their skills to navigate changes to their jobs. The tasks within Australian jobs are estimated to be changing by an average of 18% every decade, and Australians are predicted to spend 33% more time on education and training across their lifetime by 2040 – an additional 8,000 hours, or three hours per week until retirement.[85]

Workers must be prepared to reskill and retrain, businesses must be prepared to invest in workforce planning and learning and development, and policy makers and education providers must provide the necessary information and infrastructure to enable these investments.

Preparedness for the future of work

The literature concurs that skills and reskilling are key to success in the future of work, yet levels of preparedness and action in Australia are low. In 2019, Andrews and Friday published the results of a series of 34 executive conversations and over 2000 survey interviews with employers and workers across Australia's and New Zealand's largest organisations.[86]

Andrews and Friday broadly concluded that there is widespread complacency about the future of work among employers and employees alike. They found that 60% of workers have given little to no consideration to the impact of digital technology on their job, and 61% of employers believe they can rely on the market to deliver the digital capabilities they require – despite a number of these skills already being in undersupply.

Further, only 56% of employers surveyed reported that they understood the requisite skills to continue their business into the future, and 63% were still in the early stages of developing skills-forecasting and workforce-planning capabilities. In the absence of adequate long-term workforce planning, training tended to be for today's needs rather than future needs.

Andrews and Friday found that leaders were held back from proactively responding to technological change in the workforce by an inability to predict when and how digital technology would impact their work, and tended to invest more in automation than in reskilling their workers.

The future of work is now

Perhaps the biggest lesson about the future of work is that technological change is not looming over a distant and undefined horizon – the future of work is now. Globalisation, technological change and automation are already changing the way we work and the makeup of jobs, and are driving the creation of new jobs.

Occupations are already evolving to capture new opportunities in innovation – and this is affecting all job types and skill levels. For example, construction workers may have relied on operating physical tools and measurement techniques to plan and follow construction projects; however, more and more workers in these occupations are now relying on the use of drones, visualisation software and satellite imagery to plan and execute projects.[87] This also demonstrates how occupations that are considered medium-skilled are increasing their scope to include more high-skilled tasks due to the augmentation, increased safety, and productivity gains of technology.

[85] AlphaBeta, *The Automation Advantage,* 2017; AlphaBeta, *Future Skills,* 2020.
[86] J Andrews and C Friday, '*Stop talking about the future of work,*' EY, 2019.
[87] D Saccardo, The Impact of emerging technology on the value of construction projects, [unpublished paper], Bond University, 2020.

COVID-19 accelerated changes in the nature of work

The economic disruption of the COVID-19 pandemic was unlike that in previous Australian recessions, either in the distribution of its impacts or the speed of labour market recovery. The immediate disruption also had effects unlike some pre-COVID-19 ideas of what the future of work would look like. While the future of work was seen as a slow process of labour market change, the COVID-19 pandemic was a sudden shock. Previously, regions were more affected by longer term structural change among industries. However, the pandemic's economic and social restrictions hit capital cities harder than regions. Yet the longer-term effects are likely to be an acceleration of trends in the distribution of occupations that were evident before the pandemic, rather than an emergence of whole new trends.

Modes of delivering products and services changed

Digital adoption is likely to accelerate through changing consumption patterns and modes of delivery. E-commerce has expanded considerably across big and small business during the COVID-19 pandemic. In January 2021 the total value of online sales in Australia was more than $3 billion (seasonally adjusted) compared with more than $1.8 billion in January 2020.[88] This change in consumer demand is likely to be sustained. For example, according to the *Household impacts of COVID-19 survey* undertaken by the Australian Bureau of Statistics (ABS), one in three Australians now prefer to do more of their shopping online.[89]

Remote and hybrid work

Before the COVID-19 pandemic, jobs with high levels of social contact were often thought to be 'future proof'; however, jobs with high social contact and a low scope to be performed at home were more negatively impacted in the short term. Research conducted by the NSC during the height of the pandemic found that 39% of Australian jobs can be done remotely, and these were less negatively impacted by the pandemic. The analysis was conducted by using data and methods from a study by Dingel and Neiman and adapted to the Australian context using the *Census of population and housing.*[90]

Hybrid working arrangements are likely to be in demand among employees. PwC found that while 19% of Australian workers say their ideal future work environment is entirely virtual, 72% prefer a mix of in-person and virtual working – known as hybrid working.[91] Hybrid working arrangements can also help address concerns about productivity and well-being that come with an entirely remote working arrangement, and employers will need to implement creative ways to create a sense of community, connection and belonging in the workplace.

A global survey by PwC of 32,500 workers in 19 countries found that only 10% of Australians wanted to go back to the traditional workplaces that existed before last year's COVID-19 lockdown and almost 75% wanted a mix of face-to-face working and remote working. A further 16% said they wanted to work only from home or a remote location on a permanent basis.[92]

Although remote working was embraced during the height of the pandemic, some organisations have already foreseen a future of hybrid work with a mix of in person and remote work. A 2020 survey by the Boston Consulting Group found that employers expect about 40% of their employees to follow a remote-working model in the future.[93] The British multi-national bank HSBC announced in February 2021 that it expects to shrink its property footprint by 40% with about 85% of its employees having the ability to work from home.[94]

However, the increasing trend towards remote work may not be clear cut. Research by the McKinsey Global Institute found that some tasks are done more productively in person than remotely.[95] There is no loss of productivity in activities such as updating knowledge and interacting with computers when they are performed remotely, whereas training and coaching, selling and influencing and caring for others are less productive remotely than in person. This may suggest that as the world emerges from the pandemic, we are still likely to see a trend of hybrid work in the workplace.

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[88] ABS, *Online sales, January 2021 – supplementary COVID-19 analysis,* 2021
[89] ABS, *Household impacts of COVID-19 survey, November 2020,* 2020
[90] JI Dingel and B Neiman, 'How many jobs can be done at home', Working paper 26948, National Bureau of Economic Research, 2020; unpublished NSC research.
[91] PwC, Hopes and fears 2021, 2021.
[92] PwC Australia, *Changing Places: How hybrid working is rewriting the rule book,* 2021.
[93] A Dahik et al., 'What 12,000 Employees Have to Say About the Future of Remote Work', Boston Consulting Group, 2020
[94] H Wilson, 'HSCB sees its future 40% less office space After COVID', Bloomberg, 23 February 2021.
[95] McKinsey Global Institute, 'What's next for remote work: An analysis of 2,000 tasks, 800 jobs, and nine countries', 2020.`

If this trend continues, the increasing popularity of remote and hybrid working for occupations where that is possible will continue to reshape day-to-day activities for these jobs. For example, activities such as holding a design meeting or engaging with clients will rely more on digital collaborative tools such as video-conferencing software and cloud-based project planning software.

The pace and implementation of remote and hybrid working policies will vary across each organisation. However, given the interconnectedness of organisations in the supply chain, the reliance on remote working capabilities will continue to increase. For example, a line manager at a recycling plant who works full time on premises may still require the capability to effectively use video conferencing to engage in weekly meetings with senior management who are working remotely part-time.

Employers have implemented new technologies

Additional questions were added to the NSC's Recruitment Experiences and Outlook survey to evaluate the impact of COVID-19 on businesses. Between 16 November 2020 and 5 February 2021, around 2000 employers from 19 industries (based on the Australian and New Zealand Standard Industrial Classification – ANZSIC) responded to additional research questions in the survey.

Overall, 33% of employers reported that they had brought in automation or new technology due to COVID-19. The uptake of automation and technology was reported by employers across all business sizes.

The industries with the highest proportion of employers surveyed who implemented new technology or automation due to COVID-19 were arts and recreation services (56%), health care and social assistance (51%), education and training (50%), professional, scientific and technical services (46%) and financial and insurance services (44%).

Although 7% of all employers responded that they had been using technology to conduct at least part of their business where it was usually done by a human, the vast majority of these (85%) responded that there was no impact on their staffing levels due to automation or new technology.

Remote working was the most reported uptake of new technology due to COVID-19, and was mostly implemented by employers in the professional, scientific and technical services industry. Some employers in manufacturing and construction also reported the implementation of remote working technology. Among employers, 12% reported the implementation of technology outside of the survey categories. The most common 'other' response was the uptake of QR codes, which was particularly common in the accommodation and food services industry.

The high-level findings from this survey may suggest that the acceleration of technology implementation in the workplace is likely to affect most industries, but not directly affect staffing levels. This suggests that the differences in the impact of technology and automation are more likely to be task and skill specific.

Automation has been manageable and should remain so

As noted previously in this report, automation has varying effects within occupations and industries.[96] It can replace labour in some jobs and tasks that humans used to perform, as well as creating new tasks and demand for labour.

Skills based automation modelling

Automation and technological change have played out across the Australian economy over the past few decades resulting in some structural adjustments, with effects unevenly distributed across certain industries, regions and occupations. Overall, however, the economy has managed these changes well. This section explores a new skills-based approach to consider how automation and technological change might affect the skills needed in the future.

Previous analysis of automation has either focused on occupations or tasks within a job using the United States Department of Labor's O*NET.[97] The specialist tasks in the Australian Skills Classification (ASC) have been adapted to the Australian context from O*NET and therefore provide a strong base for conducting a more granular skills-based view on how technology is reshaping jobs in the labour market.

Measuring automatability: The Work Task Automatability Model

The methodology used by the NSC to measure the automatability of occupations is based on the Work Task Automatability Model developed by Duckworth et al.[98]

The data model is based on a survey of 156 academic and industry experts and estimates the likelihood of tasks in an occupation being automated. The estimated automatability of a task was scored between 1 and 4 (1= not at all automatable, 2= mostly not automatable, 3= mostly automatable, 4= completely automatable). Based on the survey, the researchers used a probabilistic machine learning model to estimate the automatability score for over 10,000 Detailed Work Activities specified by O*NET.

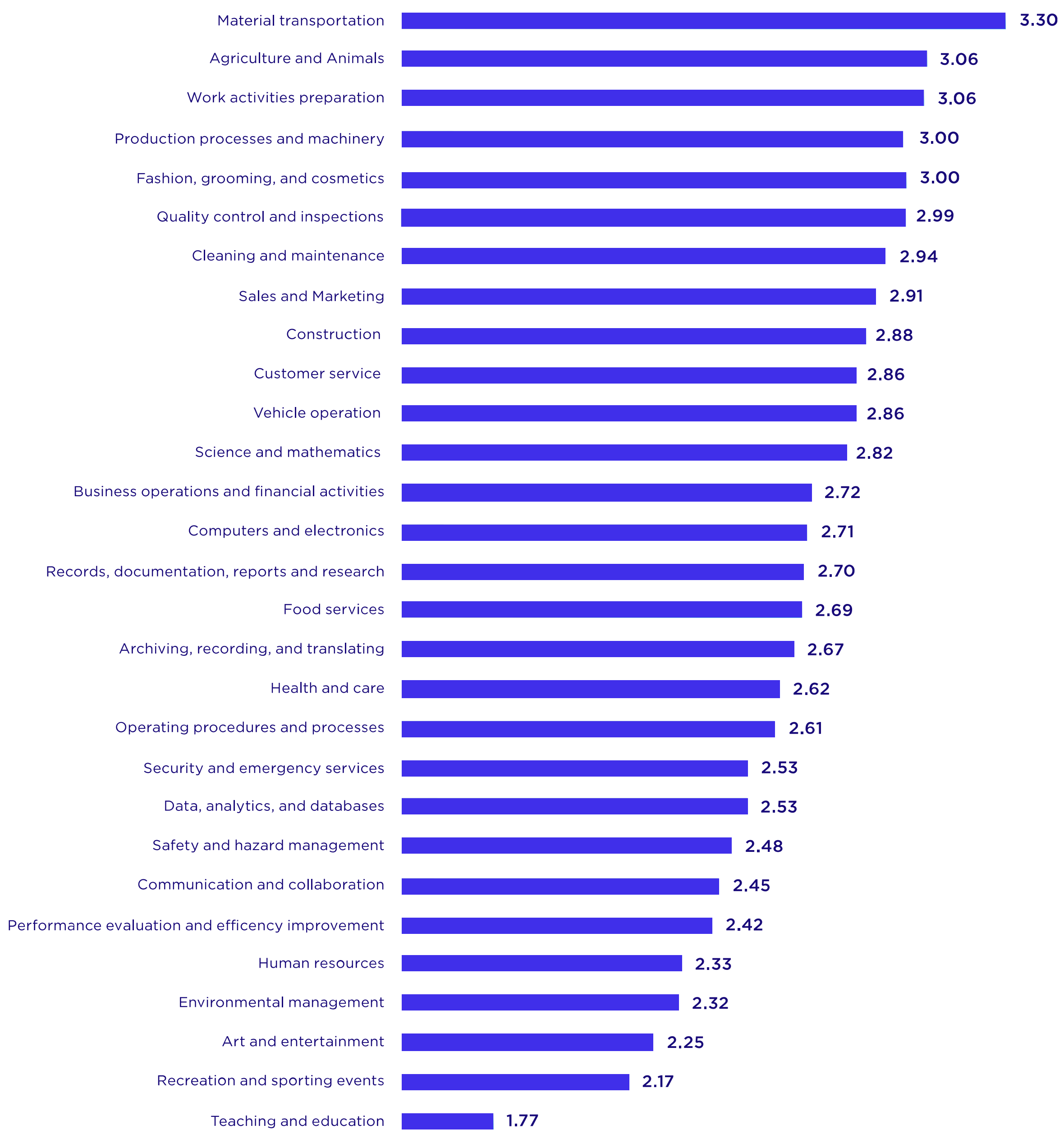
From this dataset, automatability scores of O*NET 'detailed work activities' were used to derive the automatability scores of specialist tasks for each occupation in the ASC using a data match of their equivalent pairs. The automatability scores of the specialist tasks were grouped at different occupational levels based on ANZSCO and weighted by the proportion of time spent on each task to derive a weighted automatability score. The weighted automatability score was derived for 600 occupations at the ANZSCO 4 and 6-digit levels and this was grouped further to derive an average weighted automatability score for 23 occupational groups. The automatability score for 29 cluster families was derived by calculating the average of all specialist tasks under each cluster family.

[96] D Acemoglu and P Restrepo, 'Automation and New Tasks: How Technology Displaces and Reinstates Labor', *Journal of Economic Perspectives, 2019, 33(2):3-30*
[97] O*NET is a database of occupation characteristics and worker requirements across the US economy. The database is collected and updated through ongoing surveys of workers in each occupation supplemented in some cases by occupation experts. These data are incorporated into new versions of the database on an annual schedule.
[98] P Duckworth, 'Inferring Work Task Automatatiblity', 2019.

Automatability of specialist tasks within the ASC

The weighted automatability score of specialist tasks within the ASC varies. The most automatable specialist tasks are manual and routine such as sorting and distributing mail, ship or deliver objects and operate material handling machinery while the least automatable tasks are highly cognitive such as teach classes in area of specialisation, create or perform music and undertake environmental and sustainability research. Figure 75 groups each specialist task under their skills cluster family. When measuring the weighted automatability scores for 29 cluster families in the ASC, the NSC found that the median automatability score across all skills cluster families was 2.70 with material transportation being the most likely to be automated (3.30), compared with teaching and education (1.77) which is the least likely to be automated.

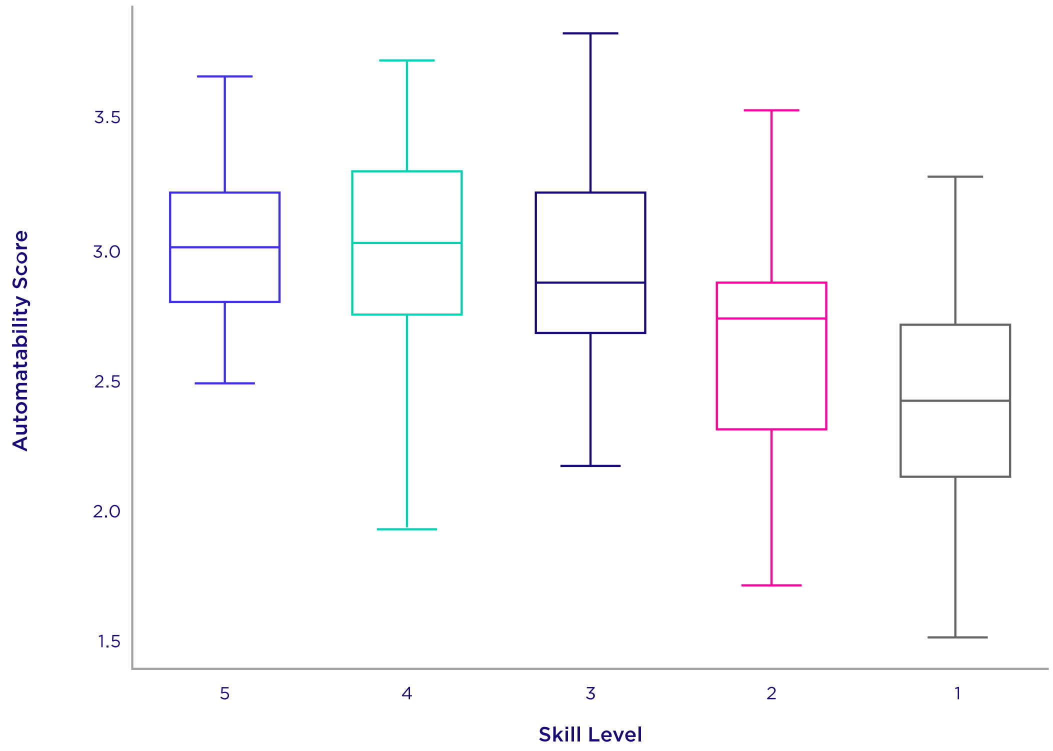
Figure 75: Weighted automatability score of specialist tasks by their skills cluster family



Source: NSC analysis, 2021

In general, the weighted automatability score is higher for lower skilled occupations compared with higher skilled occupations. In the boxplot shown in Figure 76, the median weighted automatability scores decline as the ANZSCO skill level increases.

Figure 76: Average weighted automatability scores of occupations by ANZSCO Skill levels 1—5



Source: NSC analysis, 2021

Note: The horizontal bar near the centre of each box is the median.

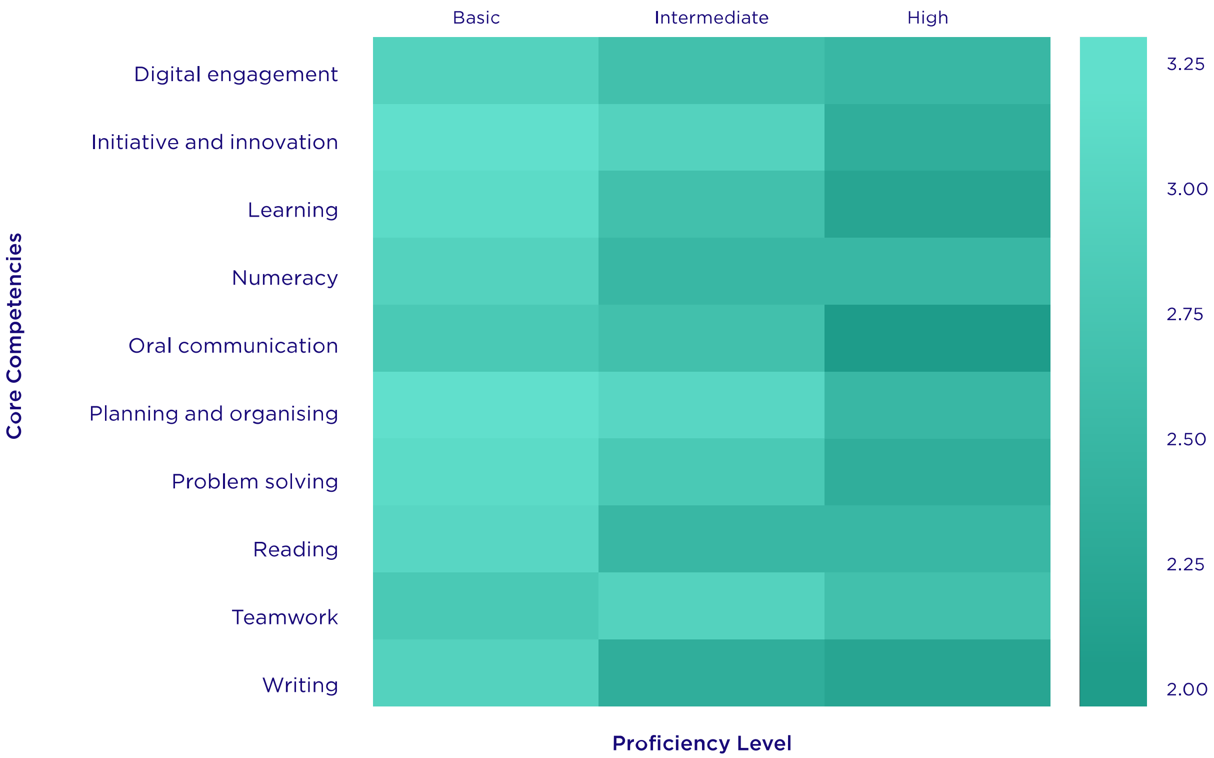
Automatability of core competencies within the ASC

The weighted automatability scores of each occupation can be further grouped by their proficiency levels of core competencies. Occupations that require a higher proficiency in core competencies are generally less automatable.

The heat map in Figure 77 plots the 10 core competencies in the ASC across their proficiency levels (basic, intermediate and high). The colour gradient of the heat map indicates the level of automatability with the lighter shade being most likely to be automated and darker shades the least likely to be automated.

Across all core competencies, high proficiency correlates with a decrease in the likelihood of automation. Within that, high proficiency in oral communication and writing are the least likely to be automated – a finding that sits behind the NSC's view that communication is a core skill of the future. Occupations with a low proficiency in a core competency are generally more likely to be automated, for example a customer service script that can be automated by a pre-programmed chatbot on a website.

Figure 77: Automatability score vs core competency and proficiency levels



Source: NSC analysis, 2021

By pairing automatability scores to specialist tasks, the scores can be grouped and averaged for each occupation in the ASC. Using the approach, the overall automatability of each occupation can be derived to identify those that are most likely or least likely to be automated. The top 10 occupations at most risk of automation are:

- dressmaker or tailor
- clothing patternmaker
- upholsterer
- sewing machinists
- jewellers
- mail sorters
- mail clerks
- stone processing machine operator
- furniture finisher
- graphic pre-press trade workers.

The top 10 occupations least likely to be automated based on their weighted automatability scores are:

- university lecturer
- ministers of religion
- education psychologist
- nurse educator
- education advisers and reviewers
- ICT trainers
- actor
- entertainer or variety artist
- judicial and other legal professionals
- early education (pre-primary school) teachers.

Automatability trends based on scenario modelling

The automatability of specialist tasks and occupations in the ASC can be applied to the outputs of NSC scenario modelling exercises. The automatability of occupations by their occupation groups were compared with their projected employment growth in the Economic Restoration and Accelerated Digitisation scenarios modelled by the Centre of Policy Studies at Victorian University in partnership with the NSC. These scenarios were analysed to support the identification and analysis of potential pathways to recovery following the onset of the COVID-19 pandemic.

Scenario modelling

Scenario modelling was conducted using the Victoria University Employment Forecasting (VUEF) model, underpinned by a computable general equilibrium (CGE) model. CGE models are large numerical models that combine real world economic data with economic theory to computationally derive estimates of how an economy may react to a change in policy or external shock. The data in CGE models typically come from national input-output tables, which contain detailed information about the supply and use of products in the economy and the structure of and inter-relationships between industries. The data are fitted to a set of equations that ascribe behavioural rules determining the way firms, governments and households respond to change. CGE models are used to derive measures of an economy before and after a shock. The differences between the two generate projections of the potential impacts of the shock.

The paths for key macroeconomic variables in the baseline Economic Restoration scenario were developed to broadly align with the macro-economic outlook depicted in the 2020–21 *Mid-year economic and fiscal outlook* (MYEFO).

Figure 78 and Figure 79 show the weighted automatability score and projected growth of occupations groups between 2019 and 2028 under the Economic Restoration and the Accelerated Digitisation scenario respectively.[99] The size of each bubble represents the projected employment size of each occupation group at the end of the projection period of the second quarter of 2028.

The purple bubbles represent occupations which have a weighted automatability score above the median and projected growth below the median. The scenario modelling results indicate that there are occupation groups such as manufacturing and mining that are relatively more automatable and at risk of potentially lower growth than others across both the central Economic Restoration scenario and the Accelerated Digitisation scenario. However, there are some occupations that, should digitisation accelerate, are at a potentially greater risk of a high automatability and lower projected growth. These include occupations across sales, retail, wholesale and real estate.

The pink bubbles represent occupation groups which have a weighted automatability score below the median and projected growth above the median. Groups such as ICT and health and community services are less likely to be automated, and experience higher growth than other groups.

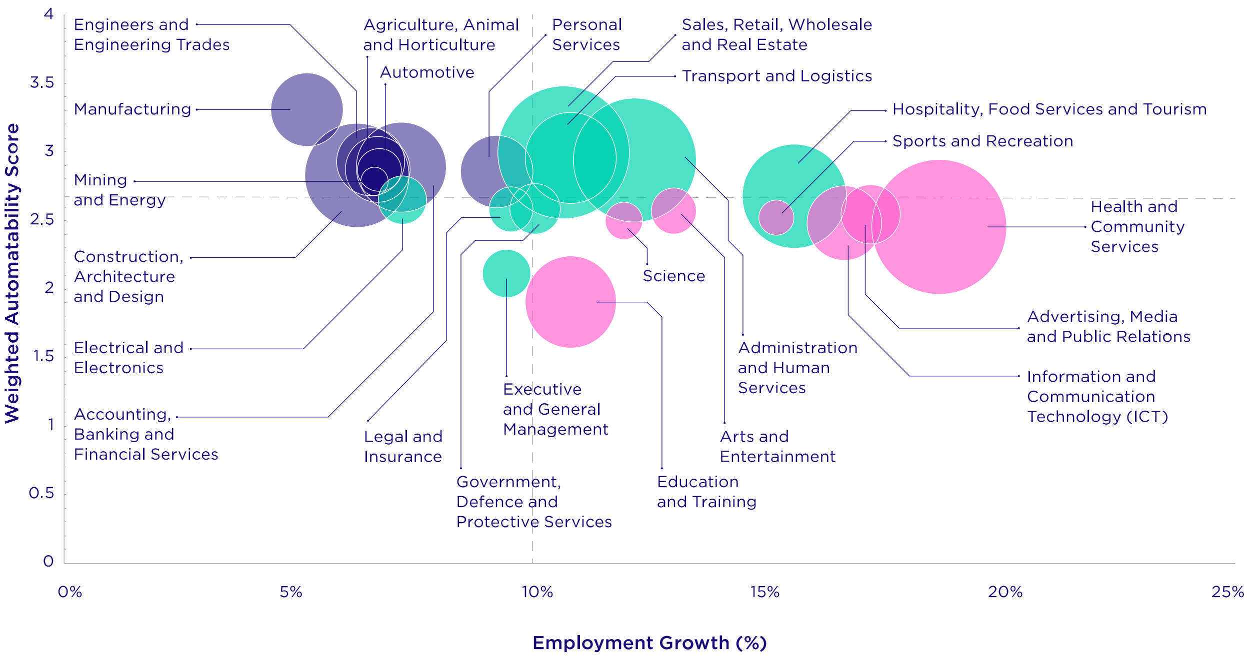
The occupation group of difference under the Accelerated Digitisation scenario is executive and general management, which is considered to have relatively high growth under that scenario, indicating that the demand for these occupations may be higher if trends in digitisation continue to accelerate. Although digital transformation will require technical and digital skills, there will also be a need for skills in planning, governance, and strategic oversight to manage and evaluate the implementation of technology. For example, an accounting firm integrating video conferencing software for staff to communicate with clients will require policy and planning mangers to plan and evaluate the financing, resources and the skills required to implement the digital transformation.

The green bubbles represent occupation groups that have either a below-median or above-median weighted automatability score and projected growth between 2019 and 2028. They show that some highly automatable occupations are projected to experience relatively high growth, such as hospitality, food services and tourism, and transport and logistics.

Under both scenarios, the highest growing occupation groups, such as health and community services, are relatively less automatable and those that are likely to experience the lowest growth, such as manufacturing, are relatively more automatable. However, this effect is not observed in all occupation groups, with some highly automatable occupations, such as hospitality, food services and tourism, projected to experience relatively high growth. This highlights the importance of doing a deep dive into occupations assessing automatability at the level of specialist tasks to determine which skills are the most likely to be augmented or replaced by automation.

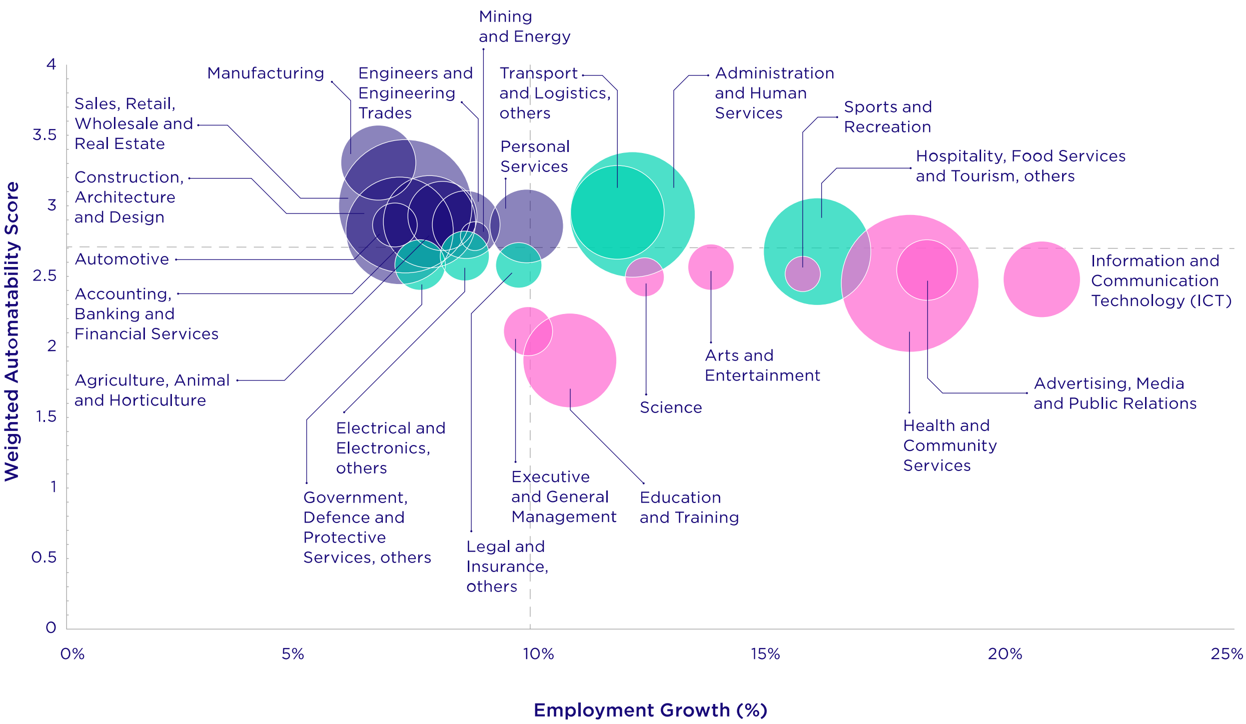
[99] These occupation groups are based on the NSC occupation matrix which differs to the more commonly used Australia and New Zealand Standard Classification of Occupations. More information on the occupation matrix can be found in Department of Jobs and Small Business, *Australian Jobs 2019.*

Figure 78: Automatability compared with growth of occupations in Economic Restoration scenario 2020-2028



Source: NSC analysis, 2021

Figure 79: Automatability compared with growth of occupations in Accelerated Digitisation scenario 2020-2028

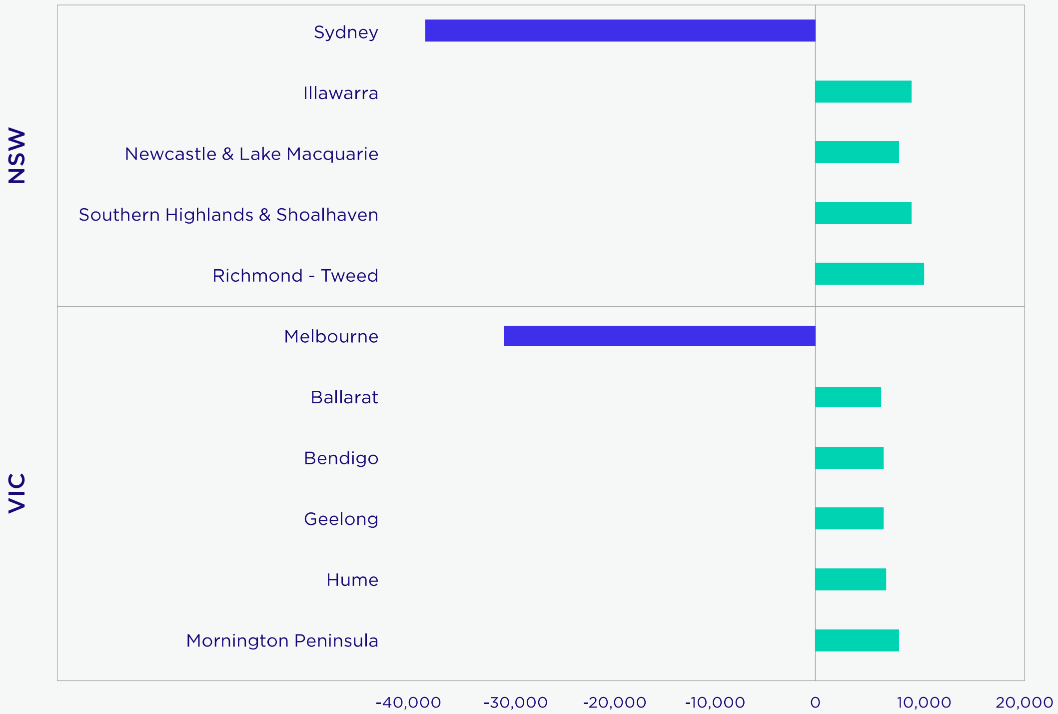


Source: NSC analysis, 2021

The regional impacts of accelerated digitisation

In addition to the baseline Economic Restoration scenario discussed in the previous box, the NSC has undertaken modelling on the accelerated impacts of digitisation that may emerge as a result of COVID-19. The scenario assumed: efficiency gains for the economy through the increased use of computer services, reduced business travel, and increased use of tele-services and wholesale trade. The model also assumed that some regions would experience an increase in population growth driven by more people moving from metropolitan centres into surrounding regions, as well as an increase in the number of people choosing to stay in regional areas rather than migrate to cities for work or study. Regions where this could be expected to occur include Newcastle, Geelong the Gold Coast and other regions surrounding urban centres.

Figure 80: Regional impacts of accelerated digitisation



Source: NSC scenario modelling, conducted in partnership with the Centre of Policy Studies, Victoria University

Note: The figure shows the difference in employment growth for the period Q1 2021 to Q1 2024 under the Accelerated Digitisation scenario compared with the baseline (Economic Restoration) scenario for selected regions.

The increased use of computer and tele-services creates substantial growth in the number of people employed in finance, insurance and professional services. As technology increases the mobility of these workers, many find themselves relocating from metropolitan areas to surrounding regional areas. This population growth then further boosts employment growth in these regions, particularly in the construction, health care and education and training industries, which record stronger growth as they respond to the requirement to service a larger local population. Meanwhile, the reduced population in metropolitan areas results in decreased employment in these industries. This finding is consistent across the impacted regions.

For example, as Figure 80 shows, employment growth for Sydney is expected to be around 35,600 lower under the Accelerated Digitisation scenario when compared with the baseline Economic Restoration scenario. However, employment growth will be comparatively stronger under the Accelerated Digitisation scenario in surrounding regional areas such as the Illawarra (up by 8,900) and Newcastle and Lake Macquarie (up by 7,900).

Risk and implications of automation in care occupations

With an ageing population, it is crucial to have a workforce that can meet the needs of the community. More importantly, it is essential to identify the future skills that are required for the health workforce.

Using automatability as a measure, we can identify the effects that future trends such as technological changes are likely to have on the future care workforce. The cluster family of health and care has a weighted automatability score of 2.62, which is relatively less automatable compared with other skills cluster families such as cleaning and maintenance, quality control and inspections, and customer service.

Table 22 lists the specialist tasks and their automatability scores for aged and disabled carers. The average automatability score for this occupation is 2.46. When comparing these automatability scores with ratings in the Duckworth et al. study, the specialist tasks for aged and disabled carers are in between the rating of 'mostly not automatable' (2.0) and 'mostly automatable' (3.0).

This may seem confusing, but it does signal tasks closer to the score of 3 are the ones more likely to be automated and therefore less important in the future. 'Maintaining client information or service records' has the highest score of 2.78 and this is intuitively correct, given it is a task that is less cognitive, more routine and easily automated using computer software. The scores provide insights into what tasks will be more important in the future for the care workforce – that is, tasks with human interaction.

Table 22: Specialist tasks and automatability scores for aged and disabled carers

Specialist Task	Skills Cluster Family	Automatability Score
Monitor health or behaviour of people.	Assist and support clients	2.08
Develop plans for programs or services.	Establish organisational policies or programs	2.35
Teach health or hygiene practices.	Teach health management or hygiene practices	2.37
Perform housekeeping duties.	Clean work areas or dispose of waste	2.39
Drive vehicles to transport patrons.	Direct or drive passenger vehicles	2.41
Prepare food.	Undertake food preparation	2.43
Assist individuals with accessibility needs	Assist individuals with accessibility needs	2.43
Provide counsel, comfort or encouragement to individuals or families.	Assist and support clients	2.52
Document client health or progress.	Provide customer service and communicate information	2.59
Administer health care or medical treatments.	Provide health care or administer medical treatment	2.69
Maintain client information or service records.	Verify personal information and maintain records	2.78
	Average	**2.46**

Source: NSC analysis

Non-routine cognitive jobs continued to grow – a pointer to the future

Australian labour market economist Professor Jeff Borland suggests that the longer-term force of technological change appears to have remained influential during the pandemic.[100] Technological change has shifted demand for labour away from routine tasks (repetitive physical labour that can be replicated by machines) towards non-routine (non-repetitive or non-codifiable) work.

Borland suggests that the variables representing the scope for a job to be performed at home, and the level of social contact it involves, may be proxies for the impact of 'routinisability' of jobs on employment. Technological change favours cognitive and non-routine jobs, and this explains why jobs which can be done at home – which are likely to be non-routine cognitive jobs – experienced job growth during the pandemic.

In the longer term the demand for human contact, including many jobs in the health care and social assistance industry, will continue to be a source of job growth. This had led to a renewed attention to future of work efforts being focused on workforce development, to understand the demand for roles in the future and how the economy can better match the supply and demand of people with these skills.

The greater difficulty in automating non routine cognitive jobs and tasks (at both high and lower skill levels) also suggests these types of jobs will remain in high demand into the future.

Technological change methodology

The Routine Based Technological Change model is a well-accepted methodology for explaining changes in the employment structure, focusing on the impact of technology on different tasks performed by workers.[101]

Different studies use different data sets and different definitions of tasks, which means their results cannot be compared.[102] In general, the model uses very broad categories of tasks, for example:

- *Routine manual tasks:* repetitive physical labour that can be replicated by machines and automated, including occupations like assemblers and machine operators.
- *Routine cognitive tasks:* repetitive labour involving the processing of information, including clerical and administrative occupations like bank tellers or switchboard operators.
- *Non-routine cognitive tasks:* non-repetitive or non-codifiable work involving the production, processing and manipulation of information. These tasks are usually included in higher skilled occupations including managerial, professional and creative occupations.
- *Non-routine manual tasks:* non-repetitive physical tasks including occupations such as bus driver, cabinet makers or plumbers.[103]

The Reserve Bank of Australia has observed that technology has led to the automation of routine tasks which, whether mental or physical, were previously performed by medium skill workers. Jobs requiring lower-level qualifications have also declined, although not by as much. These jobs may involve tasks that have not yet been automated. For example, they may involve non-routine physical work in unpredictable environments or involve a significant component of human interaction.

At the same time technology may complement the type of non-routine cognitive-based work undertaken by jobs requiring a bachelor degree, improving their productivity and hence the demand for such workers.

[100] J Borland, 'Who lost jobs (and got them back) in 2020?', Labour Market Snapshots, 75, 2021.
[101] Sebastian, R & Biagi, F (2018): The Routine Based Technical Change Hypothesis: a critical review. JRC Technical Reports, European Commission.
[102] R Sebastian, 2018.
[103] R Sebastian, 2018.

A shortage of work or a shortage of workers?

The conclusion that is often drawn from descriptions and characterisations about the future of work – albeit not always stated – is that the economy may end up with too little work, and hence the risk of higher levels of unemployment. The fear is that automation, AI and robots are taking jobs.

In contrast to the thinking of some future of work theorists, economic agencies are usually more inclined to worry not about a shortage of work, but a shortage of workers into the future. This reflects a number of factors, but most significant is the changing demographic profile of the population. As an example, the *2015 Intergenerational Report* noted:

> There will be fewer people of traditional working age compared with the very young and the elderly. This trend is already visible, with the number of people aged between 15 and 64 for every person aged 65 and over having fallen from 7.3 people in 1974-75 to an estimated 4.5 people today. By 2054-55, this is projected to nearly halve again to 2.7 people.[104]

That declining share of working age people compared with the entire population has significant implications for future economic growth. And it is these implications for economic growth that stem from demographic change which see a further divergence between some of the more alarmist views about the future of work and automation versus the analysis of economic agencies considering the long run outlook for the Australian economy.

These divergences reflect the need – as expressed in the succession of intergenerational reports over almost two decades – to increase participation in the labour market. It's also reflected in a more positive view around technology, with the *2015 Intergenerational Report* making the following reflection:

> Technology is changing the way we interact with each other and how we live our lives. It is changing the face of business, markets, governments and social engagement.
>
> In the 1970s, the Internet, mobile phones and social media did not exist as we know them today. Now they are integral parts of our lives and IT-related industries employ nearly as many people in Australia as the mining industry.
>
> Technological advances, such as advanced robotics, 3D printing and self-navigating vehicles have the potential to unlock quality of life improvements.[105]

That is, technology is seen as a positive force to boost productivity and hence both economic growth and living standards over the long run.

These sentiments aren't unique to the series of Intergenerational Reports from the Treasury. In a 2015 speech the then Governor of the Reserve Bank, Glenn Stevens argued that:

> There are no prizes for guessing that the share of services in most economies will continue to increase. Health and aged care are obvious areas for expansion – another effect of demographics. It may be that jobs will be 'robotised'. But on the other hand, in the long run we may need that to some extent. Demographic factors suggest strongly that, all other things equal, the problem isn't going to be a shortage of jobs, but instead a shortage of workers.[106]

[104] Treasury, *2015 Intergenerational Report*, 2015

[105] Treasury, *2015 Intergenerational Report*, 2015.

[106] G Stevens, 'The long run', [speech], Australian Business Economists Annual Dinner, 24 November 2015.

Understanding the big forces at work

Stevens also observed that:

> While small forecast changes get a lot of attention, the far more important question is whether we have recognised and understood the big forces at work. Even if we cannot predict the outcomes with great accuracy, an understanding of these forces ought to help us get policy responses roughly right. And that, in the real world, is probably about as much as we dare hope.[107]

Throughout this report a key focus has been on drawing out the big forces: a shift to higher skill jobs and an ongoing shift toward services; the resilience of non-routine and cognitive jobs in the face of automation and AI; the opportunities and new jobs being created by technology; and an acknowledgment that many of those forces likely to shape the future have also shaped our recent past.

It is through understanding these big forces, the implications for jobs and skills, and understanding the transferability between and across jobs and skills that we can best mitigate the risks inherent in using any set of forecasts – or an overreliance on any set of forecasts.

Encouragingly, the Australian labour market has, on the whole, managed the impacts of these big forces well over the past few decades. The labour market has also emerged from the COVID-19 pandemic in robust fashion. Overall, Australia now has a relatively low unemployment rate and a more highly skilled population than was the case decades earlier. The higher skill base of the population occurred at the same time as jobs across the economy became more highly skilled. Although past performance is no guarantee of future success, the ability of the Australian labour market to respond and reshape itself over the past few decades, as highlighted in Chapter 2, provides some grounds for optimism about our ability to do so into the future.

[107] G Stevens, 'The long run', 2015.

09

Concluding comments

Concluding comments

The aim of this report is not just to outline the current, emerging and future workforce skills needs, but also outline how the NSC approaches that task.

That approach includes both not just a traditional occupational-based lens, but also a skills-based lens using the Australian Skills Classification (ASC). In other words, what are the skills that sit within the occupations that are likely to grow, and what does that imply for the portfolio of skills the economy might need. Thinking about the portfolio of skills an economy might need provides a practical way to mitigate the risks involved in forecasting the outlook for hundreds of individual occupations.

It's important to acknowledge, however, we cannot be driven by data alone. Data can be noisy, and different sets of data may conflict.

The Treasury noted in the 2020-21 Budget: 'The Government's macroeconomic forecasts are prepared using a range of modelling techniques including macroeconomic models, spreadsheet analysis and accounting frameworks. These are augmented by survey data, business liaison, professional opinion and judgment.'

Similarly, the NSC's analysis of skills shortages makes use of survey data, business liaison and judgement, as well as forecasts and projections.

And although we can bring a strong data lens to the question of skills shortages and the economy's current, future and emerging workforce skills needs, data cannot, of itself, resolve all the economy's skills needs or shortages.

Indeed, as the Productivity Commission noted in its review of the National Agreement for Skills and Workforce Development, data from the predecessors to the National Skills Commission 'suggest highly persistent skill shortages in a range of occupations.'[108]

There is a range of factors, beyond the provision of formal training, that might result in skills shortages and that might see those persist.[109]

Some examples include:

- Employers may want staff who are job-ready, with a mix of the right personal skills and on-the-job experience, things that are difficult to provide through formal training alone.
- Skill mismatches may occur geographically, with a mismatch between where those seeking work are located and the work itself.
- An employer might need a highly technical or specialised skill which is emerging and might not yet be reflected in the training system.
- There may be mismatches between the preferences of employers and potential employees.

These highlight the importance of flexibility in labour markets, in labour mobility, in jobs themselves and in the training system – as well as the importance of the insights offered by the NSC – if we are to effectively prepare our workforce for the future and respond to current skills shortages and mismatches.

The final conclusion to impart is that the key – especially when it comes to looking forward – isn't a rigid focus on a specific forecast or number, but a sense of what the big picture dynamics at play are.

It's by understanding these bigger picture dynamics, and by focussing on the portfolio of skills the economy might need in response to them, that will best enable us to assess the skills needs of today, and tomorrow.

[108] Productivity Commission, *National Agreement for Skills and Workforce Development review: Productivity Commission study report*, 2020.
[109] Skill shortages exist when employers are unable to fill or have considerable difficulty filling vacancies for an occupation, or when there are significant specialised skill needs within that occupation at current levels of remuneration and conditions of employment and in reasonably accessible locations.

Appendix: Emerging and trending skills by occupation

Table 23 (1 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Accountant (General)		T								
Actor			T		T					
Actuary		T						T		
Acupuncturist							T (Telehealth)		T (Treatment planning)	
Admissions Clerk	T						T (Patient Preparation)			
Advertising and Marketing Professionals			T		T					
Aeronautical Engineer						E				
Aged and Disabled Carers	T									
Agricultural Technicians				T (Hydraulics)						
Agricultural and Horticultural Mobile Plant Operator				E (Predictive / Preventative Maintenance)		E				
Airconditioning and Refrigeration Mechanics						T				
Aircraft Maintenance Engineer (Avionics)				E (Mechanical Maintenance)						T
Aircraft Maintenance Engineer (Mechanical)				E (Mechanical Maintenance)						T
Ambulance Officers and Paramedics							E (Ambulatory Care)			
Amusement, Fitness and Sports Centre Managers	E		T						T (Physiology)	
Anaesthetic Technician	T									

Table 23 (2 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Analyst Programmer		T								
Arborist			E					E		
Architectural Draftsperson					T					T
Archivist					T			T		
Artistic Director					T					T
Audiologist	T						T (Medical Assistance)		E (Primary Care)	
Author			T		T					
Autoglazier				T (Predictive / Preventative Maintenance)						
Automotive Electricians				T (Predictive / Preventative Maintenance)						
Betting Clerks			T							
Biochemist		T								
Biotechnologist		T								
Book or Script Editor			T		T					E
Bookkeepers						T				
Botanist		T								
Broadcast Transmitter Operator			T		T					
Building Associate						T				
Business Machine Mechanic				T (Predictive / Preventative Maintenance)		T				
Cafe and Restaurant Managers			T							
Call or Contact Centre Manager			T							

Table 23 (3 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Call or Contact Centre Operator			T							
Camera Operator (Film, Television or Video)			T		T					
Car Detailers										T
Cardiac Technician	E									
Caretakers						E				
Chemical Engineer		T								T
Chemist		E								
Chemistry Technician	E								E (Physiology)	
Chief Executives and Managing Directors			T							
Chief Information Officer								T		
Child Care Centre Managers			T							
Chiropractors and Osteopaths							T (Telehealth)		T (Treatment Planning)	
Civil Engineer										T
Civil Engineering Draftsperson					T					T
Civil Engineering Technician					T					T
Clinical Coder	E	T					T (Patient Care)	T	T (Physiology)	
Clinical Psychologist							T (Telehealth)		T (Treatment Planning)	
Commercial Cleaners						E				
Commodities Trader		E	E							

Table 23 (4 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Communications Operator				T (Predictive / Preventative Maintenance)		T				
Community Worker	E		T							
Complementary Health Therapists							T (Telehealth)		T (Treatment Planning)	
Composer			T		E					
Conference and Event Organisers			T							
Conservator		T							T (Physiology)	T
Construction Estimator					T					T
Contract Administrator		T				T				
Copywriter			T		T					
Corporate Services Managers						T				
Corporate Treasurer		T				T		T		
Cost Clerk						T		T		
Counsellors	T								T (Treatment Planning)	
Courier	T									
Crane, Hoist and Lift Operators						E				
Credit and Loans Officers		T								
Customer Service Manager			T							
Customs Officer		T						T		
Dancer or Choreographer			T		T					
Data Entry Operator		T						T		

Table 23 (5 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Database Administrator		T						T		
Dental Assistants	T						T (Patient Preparation)			
Dental Hygienist	T						T (Patient Assistance)		T (Treatment Planning)	
Dental Practitioners	T									
Dental Technician									E (Anatomy)	E
Dental Therapist	T								T (Clinical Reasoning)	
Dermatologist	T									
Detective	E								T (Anatomy)	
Diagnostic and Interventional Radiologist							T (Telemedicine)			
Diesel Motor Mechanic				T (Mechanical Maintenance)						
Diver		E								
Diversional Therapists	E						T (Medical Assistance)			
Doorperson or Luggage Porter	T			T (Equipment Cleaning)						
Drainer	T									
Dressmaker or Tailor						E				
Driller				E (Equipment Inspection)						
Driving Instructors							T (Skin Care)			
Drug and Alcohol Counsellor	T								T (Treatment Planning)	
Earth Science Technician	E								E (Physiology)	

Table 23 (6 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Educational Psychologist							T (Telehealth)		T (Treatment Planning)	
Electrical Distribution Trades Workers						T				
Electrical Engineering Draftsperson		E						E		T
Electrical Engineering Technician						T				
Electrical Engineers						T				T
Electricians						T				
Electronic Engineering Draftspersons and Technicians				T (Test Equipment)						E
Electronic Equipment Trades Worker				T (Test Equipment)						
Electronic Instrument Trades Worker (General)				T (Predictive / Preventative Maintenance)		T				
Electronics Engineers										T
Engineering Managers						T				T
Engineering Production Workers				T (Predictive / Preventative Maintenance)						T
Engineering Technologist						T			T (Treatment Planning)	T
Enrolled Nurse	T						T (Interaction with Patients / Medical Personnel)		T (Primary Care)	

Table 23 (7 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Entertainer or Variety Artist			T		E					
Environmental Consultant		T						T		
Environmental Engineer		T		T (Hydraulics)		T		T		T
Environmental Health Officer	T						T (Medical Assistance)			
Environmental Research Scientist								T		
Facilities Administrator				T (Predictive / Preventative Maintenance)		T				
Facilities Manager				T (Predictive / Preventative Maintenance)						
Family Support Worker	E									
Family and Marriage Counsellor							E (Telehealth)	E	E (Physiology)	
Fashion Designer			T		T					T
Fast Food Cooks	E									
Fibrous Plasterer				E (Predictive / Preventative Maintenance)						
Filing and Registry Clerks								T		
Film and Video Editor			T		T					
Film, Television, Radio and Stage Directors			T		T					
Financial Brokers			E							
Financial Dealers						T		E		

Table 23 (8 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Financial Investment Adviser		T				T				
Financial Investment Manager		T						T		
Fire Fighter						E			E (Anatomy)	
Fitness Instructors			T							
Fitter (General)				T (Equipment Moving)		T				
Fleet Manager		T				T				
Floor Finishers				E (Equipment Cleaning)						
Food Trades Assistants				T (Equipment Cleaning)						
Food and Drink Factory Workers				T (Predictive / Preventative Maintenance)						
Freight and Furniture Handlers						T				
Funeral Workers							T (Skin Care)			
Furniture Finisher				E (Predictive / Preventative Maintenance)						
Gallery or Museum Curator			T					T		
Gallery or Museum Technician		E			E					E
Gallery, Museum and Tour Guides							E (Skin Care)			
Gas or Petroleum Operator				T (Predictive / Preventative Maintenance)		T				
General Clerks			T							
General Practitioner							T (Telehealth)		T (Primary Care)	

Table 23 (9 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Geologists, Geophysicists and Hydrogeologists		T						T		T
Graphic Designer			T		T					
Graphic Pre-press Trades Workers					T					
Handypersons				T (Predictive / Preventative Maintenance)						
Health Information Manager	T				T			T		
Health Practice Manager	T									
Health Promotion Officer							T (Medical Assistance)		T (Primary Care)	
Historian		T						T		
Hospital Orderly	T			E (Equipment Maintenance)			E (Patient Positioning)			
Hospital Pharmacist	T						T (Medical Assistance)			
Hotel Service Managers				E (Predictive / Preventative Maintenance)				E		
Hotel and Motel Managers			T							
Housekeepers	E									
Human Resource Adviser		T								
Human Resource Clerks		T								
Human Resource Managers						T				
ICT Business and Systems Analysts		T								

Table 23 (10 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
ICT Quality Assurance Engineer		T		T (Predictive / Preventative Maintenance)		T				
ICT Support Engineer						T				
Illustrator			T		T					
Immigration Officer		T								
Importers, Exporters and Wholesalers		T								
Indigenous Health Workers	T						E (Telehealth)		T (Primary Care)	
Industrial Designer		T								
Industrial Engineer										T
Information Officers			T							
Inspectors and Regulatory Officers		T						T		
Integration Aide								E		
Intelligence Officer		T								
Interior Designers					T					T
Internal Auditor		T								
Journalists and Other Writers			T		T					
Laboratory Manager		T								
Landscape Architect										T
Laundry Workers				T (Equipment Cleaning)						
Library Assistants			T							
Library Technician		E			E					E
Life Science Technician	E								E (Physiology)	

Table 23 (11 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Life Scientist (General)		T								
Lifeguard				T (Equipment Maintenance)		E				
Lift Mechanic						T				
Locksmith	E									
Make Up Artist			T		T					
Management Accountant		T								
Management Consultant								T		
Market Research Analyst			T		T					
Marketing Specialist			T		T					
Massage Therapists	E								T (Anatomy)	
Materials Engineer		T								T
Mathematician		T								
Mechanical Engineer						T				T
Mechanical Engineering Draftsperson				T (Predictive / Preventative Maintenance)		T				T
Mechanical Engineering Technician				E (Equipment Moving)		T				E
Media Producer (excluding Video)			T		T					
Medical Diagnostic Radiographer	T						T (Medical Assistance)			
Medical Laboratory Scientists	T									
Medical Laboratory Technician	T									

Table 23 (12 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Medical Radiation Therapist							T (Medical Assistance)		T (Treatment Planning)	
Medical Receptionist			T				T (Patient Preparation)		T (General Practice)	
Metal Fabricator				T (Predictive / Preventative Maintenance)						T
Metal Machinist (First Class)										T
Metallurgist		T		E (Equipment Inspection)						
Meteorologist		T							T (Physiology)	T
Microbiologist	E			E (Equipment Maintenance)						
Midwives	T									
Miner				T (Predictive / Preventative Maintenance)						
Mining Engineer (excluding Petroleum)					T			E		E
Mixed Crop and Livestock Farm Workers				T (Predictive / Preventative Maintenance)						
Model		T			E			E	T (Anatomy)	E
Mothercraft Nurse	T						T (Interaction with Patients / Medical Personnel)		T (Primary Care)	
Motor Mechanic (General)				T (Predictive / Preventative Maintenance)						
Motor Vehicle Parts Interpreter						T				
Motor Vehicle Parts and Accessories Fitters				T (Predictive / Preventative Maintenance)						

Table 23 (13 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Motorcycle Mechanic				T (Predictive / Preventative Maintenance)						
Multimedia Designer					T				T (Anatomy)	
Musician (Instrumental)			T		E					
Naturopath							T (Telehealth)		T (Treatment Planning)	
Network Analyst			T							T
Neurologist	T						T (Inpatient Care)		T (Internal Medicine)	
Nuclear Medicine Technologist	T						T (Medical Assistance)		T (Clinical Reasoning)	
Nurse Educator	T						T (Interaction with Patients / Medical Personnel)			
Nurse Managers	T									
Nurse Practitioner	T						T (Patient Care)		T (Primary Care)	
Nurse Researcher	T						T (Interaction with Patients / Medical Personnel)			
Nursing Support Worker	T			T (Equipment Cleaning)			T (Patient Care)			
Nutrition Professionals	T						T (Medical Assistance)		T (Clinical Reasoning)	
Obstetrician and Gynaecologist	T									
Occupational Health and Safety Adviser		T								
Occupational Therapists							T (Telehealth)		T (Treatment Planning)	
Operating Theatre Technician	T									

Table 23 (14 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Ophthalmologist	T									
Optical Dispenser							T (Patient Assistance)			
Order Clerk		T								
Organisation and Methods Analyst		T						T		
Organisational Psychologist							T (Telehealth)		T (Treatment Planning)	
Orthotist or Prosthetist	T								T (Treatment Planning)	
Outdoor Adventure Guides			T							
Paediatrician	E						E (Telehealth)			
Painting Trades Workers				T (Equipment Cleaning)						
Park Ranger		T						T		
Parking Inspector			E			E				
Pathologist	T						T (Medical Assistance)			
Pathology Collector	T									
Paving and Surfacing Labourers						E				
Personal Assistants			T							
Personal Care Assistant	T									
Pest Controller								E		
Pet Groomer	T								E (Anatomy)	
Petroleum Engineer		E			E			E		T
Pharmacy Sales Assistants							T (Medication Dispensation)			

Table 23 (15 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Pharmacy Technician	T									
Photographers			T		T					
Physicist		T							T (Physiology)	T
Physiotherapists									T (Treatment Planning)	
Plumber (General)				T (Predictive / Preventative Maintenance)						
Podiatrists	T						T (Medical Assistance)			
Police Officer	E									
Policy Analyst		T								
Policy and Planning Managers						T				
Power Generation Plant Operator				T (Predictive / Preventative Maintenance)		T				
Precision Instrument Maker and Repairer	E									
Print Finisher				E (Equipment Moving)	T					
Printers				E (Equipment Moving)	T					
Prison Officers						E				
Product Assemblers			E							
Production Clerk		T								
Program or Project Administrator		T						T		
Proof Reader		T		T (Predictive / Preventative Maintenance)				T		
Property Manager					T					

Table 23 (16 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Psychiatrists							E (Telehealth)			
Public Relations Manager		T	T		T					
Public Relations Professionals			T		T					
Quality Assurance Manager		T						T		
Quantity Surveyor										T
Radio Despatcher		E	T		T					
Radio Presenter			T		T					
Real Estate Agent			T							
Real Estate Representative	E						T (Home Management)			
Receptionist (General)			T							
Records Manager					T			T		
Recreation Officer	E									
Recruitment Consultant						T				
Recycling and Rubbish Collectors				T (Predictive / Preventative Maintenance)		T				
Registered Nurse (Critical Care and Emergency)	T						T (Interaction with Patients / Medical Personnel)			
Registered Nurse (Mental Health)	T						T (Patient Care)		T (Treatment Planning)	
Registered Nurse (Surgical)	E						T (Interaction with Patients / Medical Personnel)			
Registered Nurses	T								T (Primary Care)	

Table 23 (17 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Rehabilitation Counsellor	T								T (Treatment Planning)	
Research and Development Managers		E								T
Resident Medical Officer	T								T (Internal Medicine)	
Residential Care Officer	T								T (Primary Care)	
Retail Pharmacist	T									
Roof Plumber										E
Sales Demonstrator			T							
Scaffolder						T				
School Principals		T								
Screen Printer				E (Equipment Moving)	T					
Secretary (General)						T				
Sewing Machinists			E							
Sheetmetal Trades Workers										T
Shelf Fillers						T				
Singer			T		E					
Small Engine Mechanic				T (Predictive / Preventative Maintenance)						
Social Professionals		T						T		
Social Workers	T									
Software Engineer						T				
Solid Plasterer				E (Predictive / Preventative Maintenance)						

Table 23 (18 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Sonographer							T (Medical Assistance)		T (Clinical Reasoning)	
Sound Technician			T		T					
Special Care Workers							E (Patient Preparation)			
Specialist Physicians	T						T (Inpatient Care)		T (Internal Medicine)	
Speech Pathologist							T (Telehealth)		T (Treatment Planning)	
Sports Coaches, Instructors and Officials			T							
Sportspersons						E				
Statistical Clerk								T		
Statistician		T								
Sterilisation Technician	T						T (Medical Assistance)			
Stock Clerk						T				
Street Vendors and Related Salespersons		T	T		E					
Structural Engineer					T	T				T
Surgeons	T									
Survey Interviewers								E		
Surveying or Spatial Science Technician		T				T		T		
Surveyors and Spatial Scientists								T		
Switchboard Operators			E		E					
Systems Administrator						T				

Table 23 (19 of 20): Top 10 fastest spreading trending and emerging skills by occupation

T denotes trending skills, E emerging skills

Occupation	Infection Control	Data Analysis	Social Media	Equipment Repair and Maintenance	Graphic and Visual Design Software	Enterprise Resource Planning (ERP)	Patient Care	Data Management	General Medicine	Engineering Design / Drafting
Taxation Accountant						T				
Taxation Inspector		T						T		
Technical Writer			T							
Telecommunications Engineering Professionals										T
Telecommunications Linesworker				T (Equipment Maintenance)		T				
Telecommunications Trades Workers				T (Equipment Maintenance)		T				
Telemarketers			T							
Therapy Aide	E									
Thoracic Medicine Specialist	T						T (Inpatient Care)		T (Internal Medicine)	
Toolmaker				T (Mechanical Maintenance)		T				T
Train Driver			E							
Training and Development Professionals						T				
Translator		T						T		
Transport Company Manager				T (Equipment Maintenance)		E				
Transport Engineer										T
Transport Operations Inspector		T						T		
Travel Attendants							T (Skin Care)			
Urban and Regional Planners		T								
Vehicle Body Builders and Trimmers					T					T

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