Australian Government

Jobs and Skills Australia

Our Gen AI Transition

Implications for Work and Skills

Analysis Papers

2 September 2025

Acknowledgement of Country

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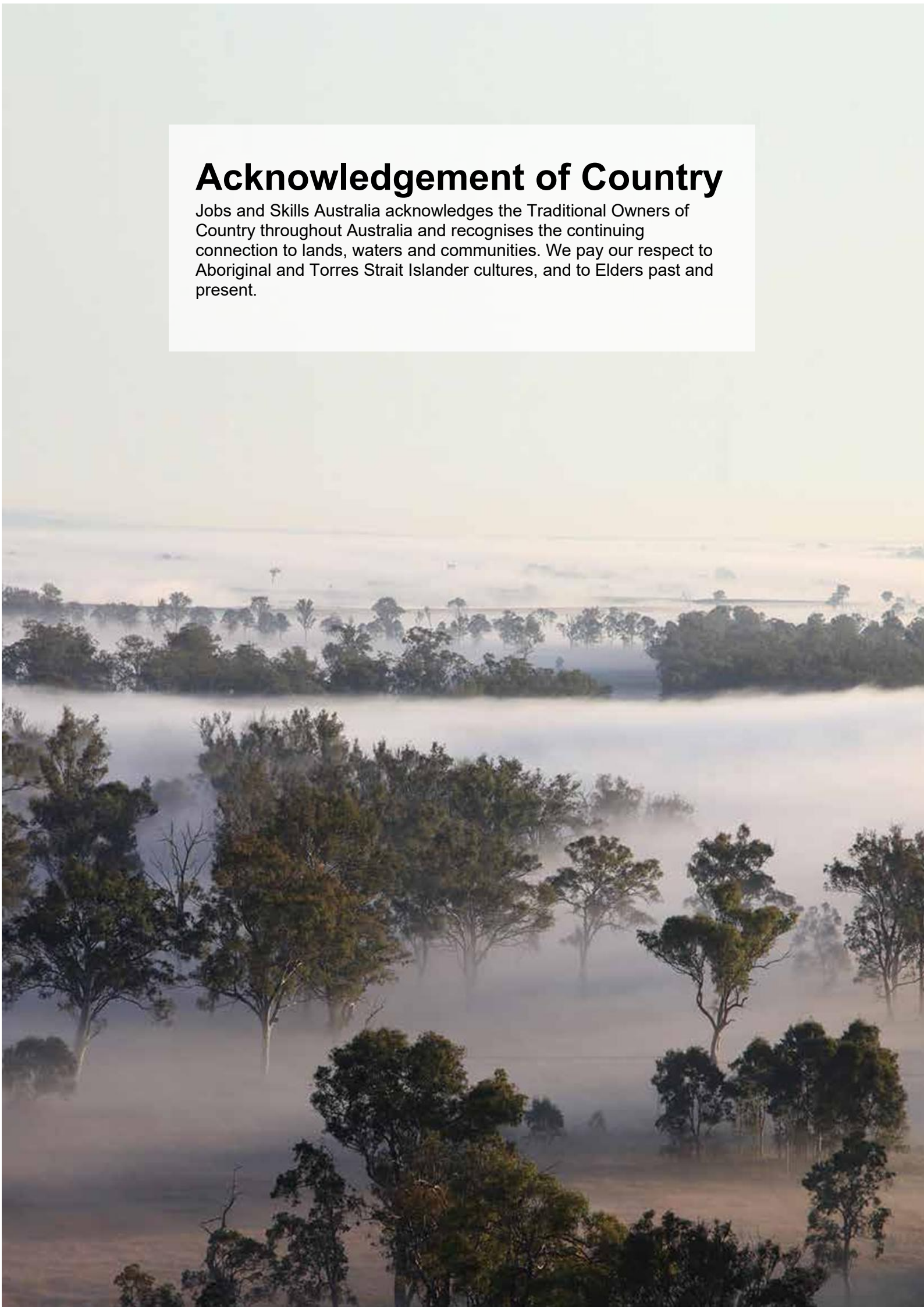

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Foreword

This compendium of five Analysis Papers provides the more detailed analytical findings that were summarised in JSA's Gen AI Study's Overarching Report.

These papers cover the discrete, including novel, pieces of quantitative and qualitative analysis that were undertaken by JSA across five themes – exposure, adoption, adaptation, labour market dynamism and skills.

- **Paper A: Exposure** explores exposure to Gen AI of tasks within occupations. It highlights where exposure skews more towards augmentation and where automation potential is concentrated, including for particular groups in the workforce.
- **Paper B: Adoption** explores adoption among firms, industries and workers, and across the capability spectrum (from adoption to integration to maturity). It includes insights into the conditions that support adoption, including governance, workforce practice, and implementation. Examines how technology and the workforce interact for meaningful uptake and productivity gains.
- **Paper C: Adaptation** explores vertical and horizontal adaptation: within occupations, within sectors, across sectors, and into new occupations. It considers how new specialised or hybrid roles could emerge, which may play a critical role in enabling deep adoption, and new options for workers impacted by disruption in the labour market.
- **Paper D: Labour market dynamism** explores the labour market implications of the AI transition in terms of entry level roles, labour mobility, displacement, and for those outside the labour force. This work extends some previous JSA research on emerging roles, to consider new definitions of work and adaptation.
- **Paper E: Skills** explores Gen AI's implications for skills in the labour market and skills system responses. It considers capability, from foundations to competence to fluency, and how the skills system can support a timely response, including on qualifications, short-form learning, industry and education partnerships, and educator capability.
- **Case Studies**: In addition to these five Analysis Papers, a separate compendium of Case Studies is part of this release, to provide useful experiences and perspectives. Accompanying **Data Releases** and a **Chart Pack** are also available on our website.

Third and final release from this study: This will include non-market, cohort & intersectional perspectives and analysis, as well as any technical matters. Our final **Case Studies** will also be included, with a focus on adoption and hybrid co-design in the non-market sector.

A. Exposure

Augmentation versus automation

Exposure across the labour market

Cohorts & exposure

1. Introduction

This paper outlines JSA's methodology for estimating the potential exposure of occupations to Generative AI (Gen AI) as well as key results. Exposure describes the feasible application of technology to existing work tasks – reflecting the state of technological progress in AI and related fields. Estimates of exposure give an indication of how technologies could be applied, including the extent to which tasks could be *either* augmented or automated.

In practice, many tasks that are 'exposed' to Gen AI could not be automated for reasons related to social norms, inherent value of human interaction, or regulations affecting adoption. For example, while communication tasks might technically be exposed to automation, it is unlikely that this would apply to the delivery of a legal judgment or the communication of sensitive news.[1] These practicalities are not captured in the exposure scores below. As such, the scores provide a useful frame at best, for considering where scope of work could evolve with technological change. The scores do not provide direct insights on labour market outcomes such as wages or employment levels.

While exposure analysis helps inform our understanding of the potential implications of Gen AI for labour market outcomes, this should be supplemented by consideration of how the technology is actually being adopted and used (Analysis Paper B) and how the labour market and economy might adapt over time (Analysis Paper C).

2. Exposure of tasks and occupations to Gen AI

Several recent reports have examined exposure to Gen AI in Australia using a method based on Felten (2021).[2] This study extends these analyses by implementing a method developed by the International Labour Organization (ILO) (Gmyrek, Berg, & Bescond, 2023) and enhancing it for the Australian and New Zealand Standard Classification of Occupations (ANZSCO) (Box 1). This reflects a more up-to-date understanding of Gen AI technology than Felten's and offers a more granular estimate of its effects than the ILO's.

Essentially, the method estimates and interprets exposure as follows:

- Estimated scores show both the potential to augment (augmentability) and automate (automatability) each work task within an occupation, with two scores per task ranging from 0 to 1.[3]
- The exposure scores of a particular occupation reflect the average potential automatability and augmentability for all work tasks within that occupation.

[1] Moreover, given Gen AI technology has not been adopted in full, real effects will be lower than theoretical estimates of exposure.

[2] For example, see Tech Council of Australia (2023) and Future Skills Organisation (2023).

[3] The scores also reflect a non-zero potential of no augmentation or automation of each task, as all exposures are below 1.

- To assess the spread in task-level scores within an occupation, we then use the standard deviation of scores across tasks. That is, within the same occupation, some tasks could be highly automatable or augmentable and some the opposite.[4]

Exposure scores therefore allow us to compare how different tasks and occupations might interact with Gen AI across the labour market, rather than estimating the percentage of all tasks potentially automated or time saved per task.

For simplicity, we have not differentiated between 'core' and 'other' tasks, as this would require significantly more information than is available in formal datasets.[5] Nor have we weighted the tasks in order of complexity, priority or importance.[6][7]

Moreover, exposure scores do not reflect the practical context of the task (including the inherent value of human involvement) which may prevent the use of AI.

Finally, these exposures are measures of the potential for automation and augmentation, and they assume that current Gen AI technologies are implemented in full to their peak potential. Actual automation and augmentation will be lower and more variable where the technology is only partially adopted and evolving (Section 3).

All these factors together explain why exposure estimates cannot, with any certainty, be taken as definitive measures of expected employment or wage effects.

Further results and methodological notes will be released as part of the Technical Release for this study.

[4] A small number of occupations have only one task descriptor, therefore the standard deviation is zero for those.

[5] For instance, the job of a surgeon is made up of several tasks including undertaking surgery. If the surgery itself is the only task that is augmented by Gen AI, the occupation could show a low average score – even though the most important task is affected.

[6] Measuring potential exposure at the task level, rather than human ability or skill levels (as the Felten methodology does) avoids applying strong assumptions about Gen AI performance or the complexity of an occupation. This means we avoid exaggerating exposure across occupations with abilities that are more correlated to language modelling.

[7] We have undertaken analysis by applying time taken for each task as a weight or to rank tasks within an occupation. We found the weighted scores were not more statistically significant than, nor did they vary greatly overall from, the unweighted scores. At this stage, this analysis has been treated as experimental and a check of the robustness of the ILO methodology, as we assessed the time weightings potentially assumed more (or false) accuracy than warranted. Even so, evaluating the complexity and priority of tasks could improve the exposure framework, giving better insight into how well Gen AI could handle tasks and impact work.

Box 1 An improved method for estimating exposure in Australia

Felten – an agnostic measure of exposure

Several recent studies of AI exposure use the method proposed by Felten et al. (2021) for the US labour market. This is based on mapping of AI applications (such as Language Modelling and Image Generation) to 52 human abilities using a crowd-sourced online survey that indicates how each AI application and human abilities relate.

Felten et al. (2023) focuses on Image Generation and Language Modelling for Gen AI specific impact. The key results are that Gen AI exposure rates are highest for high-skilled, white-collar workers such as Professionals and Clerical and Administrative Workers, and lower for unskilled work.

- The method does not distinguish between augmentation and adaptation, meaning the generated scores do not clarify how the technology might be implemented. This raises key questions as to what 'exposure' means.
- Occupations with abilities correlated to the 'Language Modelling' AI task have the highest exposure scores. This can exaggerate exposure of some occupations relative to others, and could be augmentation-biased – for instance, Judges and Barristers have higher scores than Legal and Court Clerks.
- The database used by Felten et al. (2023) may not capture the abilities of current technology. They select Language Modelling and Image Generation as Gen AI tasks from a list of 10 tasks from 2010 based on the Electronic Frontier Foundation (EFF). There have been several AI tasks that have been identified since then, such as 'Learning to Learn' and 'Safety and Security'.

Accounting for automation as well as augmentation

The latest method used by the ILO addresses these concerns to some degree. The ILO study focused on exposure of occupations to Gen AI via a tasks- and occupation-based analysis (Gmyrek, Berg, & Bescond, 2023).

Measuring potential exposure at the task level (rather than human ability or skill levels as Felten does) means the ILO method does not make assumptions about Gen AI performance or the complexity of an occupation.

The ILO method used GPT-4 to understand which tasks could be augmented or automated for each occupation – by first generating tasks for each occupation and then evaluating the tasks' exposure.

Our chosen methodology involves a replication of the ILO approach. However, instead of using AI generated tasks as the ILO method does and mapping the International Standard Classification of Occupations (ISCO) to ANZSCO, we use the ANZSCO tasks data that the Australian Bureau of Statistics has identified for each occupation, at a point in time.

We thus adapt the ILO methodology to the Australian labour market. Exposure is then calculated for each task within the ANZSCO occupation (example below). We also include *an additional direct and ordinal* measure of augmentation, as opposed to the residual binary measure the ILO applies. Our method estimates two exposures for each

task. The ILO's method, in comparison, infers relative augmenting potential for an occupation from task-level automation exposure spreads alone.

Interpreting exposures

As noted above, the scores are largely to aid comparison between tasks and occupations. Our interpretation of the scores are as follows: for a given task – say, *ensuring the centre is a safe area for children, staff and visitors* – a low automation score suggests that very little (if any) of that task could be automated. This suggests that a human worker would have to undertake most of that task in most situations. The medium augmentation score suggests that the worker completing the task would benefit from working *with* Gen AI tools (for instance, in undertaking risk assessments or analysing safety data). The scores cannot be used to infer the quality with which Gen AI might acquit a task.

Table B1.1: Gen AI exposure scores for Child Care Centre Managers (ANZSCO 1341)

Tasks for Child Care Centre Managers (ANZSCO 1341)	Automation	Augmentation
Directing and supervising child carers in providing care and supervision for young children	Low (0.2)	Medium (0.6)
Ensuring the centre is a safe area for children, staff and visitors	Low (0.2)	Medium (0.6)
Providing care for children in before-school, after-school, day, and vacation care centres	Low (0.2)	Medium (0.4)
Complying with relevant government requirements and standards	Low (0.3)	High (0.7)
Developing and implementing programs to enhance the physical, social, emotional, and intellectual development of young children	Low (0.3)	High (0.7)
Liaising with parents	Low (0.3)	High (0.7)
Recruiting staff and coordinating professional development	Low (0.3)	High (0.7)
Maintaining records and accounts for the centre	High (0.7)	High (0.8)
Average	**Low (0.31)**	**Medium (0.65)**

Source: JSA analysis, Census 2021 (TableBuilder).

Critical caveats

The analysis here also replicated four of the ILO's original assumptions. First, the framework is based on assuming full technological potential (100% adoption). Second, tasks are performed in high-income countries (how tasks are acquitted varies based on infrastructure, institutional and other settings). Third, GPT-4 predictions likely skew towards technological optimism, missing practical limitations. Fourth, the framework focuses on current automation and augmentation potential without speculating on future job creation (adaptation potential).

Despite these strong assumptions, its large database of tasks and use of standard deviations mean the ILO's framework is cautiously robust. Moreover, the Australian results in this Study align strongly with what we have heard from our consultations – that a transformation in how work is done is more likely than widespread automation of work and transitional strategies should capture this.

Exposure to augmentation far outweighs automation in the Australian labour market

The averaged augmentation and automation scores show that Gen AI could affect most occupations in the labour market, though to different degrees and in different ways. Our analysis suggests that it is more likely that most workers across the labour market would experience augmentation in their occupation than automation (Figure 1).

Accounting for the number of workers in each occupation group, overall, around 4% of the workforce has high automation exposure to Gen AI, whereas 79% has low automation exposure (Table 1). Nearly half of all workers have low automation and medium augmentation scores, suggesting that it would not be feasible for most workers to have tasks automated. That is, if Gen AI were implemented and used to its potential, then only a relatively low percentage of occupations would incur a significant automation of tasks within them.

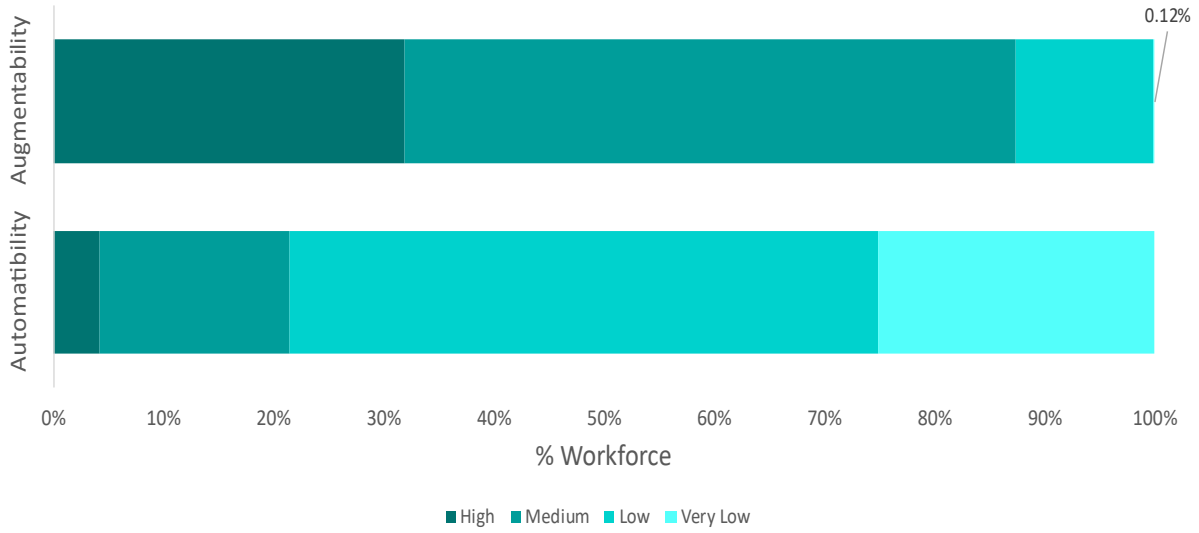
The results also show that medium exposure to potential automation and augmentation is somewhat correlated, as seen in Figure 2. This may indicate that increasingly augmentable tasks (that make use of knowledge or technical skills) tend to be accompanied by routine, standardised or repetitive tasks (such as administrative tasks).

Many clerical tasks – that were not affected by previous waves of automation – could now be undertaken in large part by Gen AI (Figure 3). Gen AI has a higher propensity to augment most tasks than to automate them – it is easier for technology to undertake part of a task than to undertake the task in its entirety. For more standardised and routine tasks, both automation and augmentation exposure scores may be high – such as for data entry and transcription (Figure 3).

Generally, exposure scores would be expected to shift as Gen AI technologies further evolve, especially with more integration of robotics and complementary technologies.

Figure 1: Most of the workforce are in jobs with low automation but mid to high augmentation exposure

Percentage of workforce, across occupations, by exposure to automation and augmentation



Note: High, medium, low and very low refer to exposure scores. In this chart, exposure scores of 0.7 and above are labelled ‘high’; scores between 0.5 and 0.7 are labelled ‘medium’; scores between 0.25 and 0.5 are labelled ‘low’, and scores below 0.25 are labelled 'very low'.

Source: JSA Analysis; ABS ANZSCO, Version 1.3 (v1.3), ABS Census 2021 (TableBuilder).

Table 1: Distribution of workforce by exposure of occupation to Gen AI

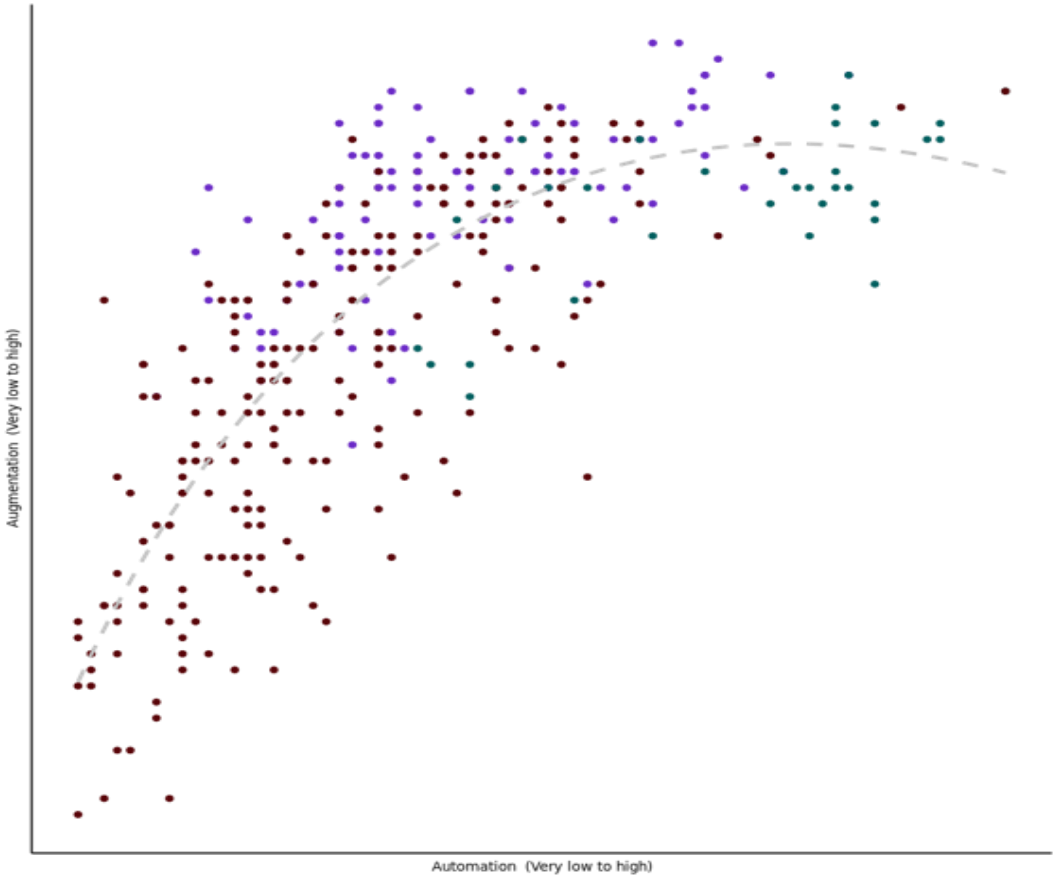
	Low and Very Low automation	Medium automation	High automation	Total
Low and Very Low augmentation	13%	0%	0%	13%
Medium augmentation	49%	5%	2%	56%
High augmentation	17%	12%	2%	31%
Total	79%	17%	4%	100%

Note: High, medium and low refer to exposure scores. In this simple summary table, exposure scores of 0.7 and above are labelled ‘high’; scores between 0.5 and 0.7 are labelled ‘medium’ and scores below 0.5 are labelled ‘low and very low’.

Source: JSA analysis, Census 2021 (TableBuilder).

Figure 2: The Professional occupation group skews towards augmentation

Potential augmentation versus automation of occupations

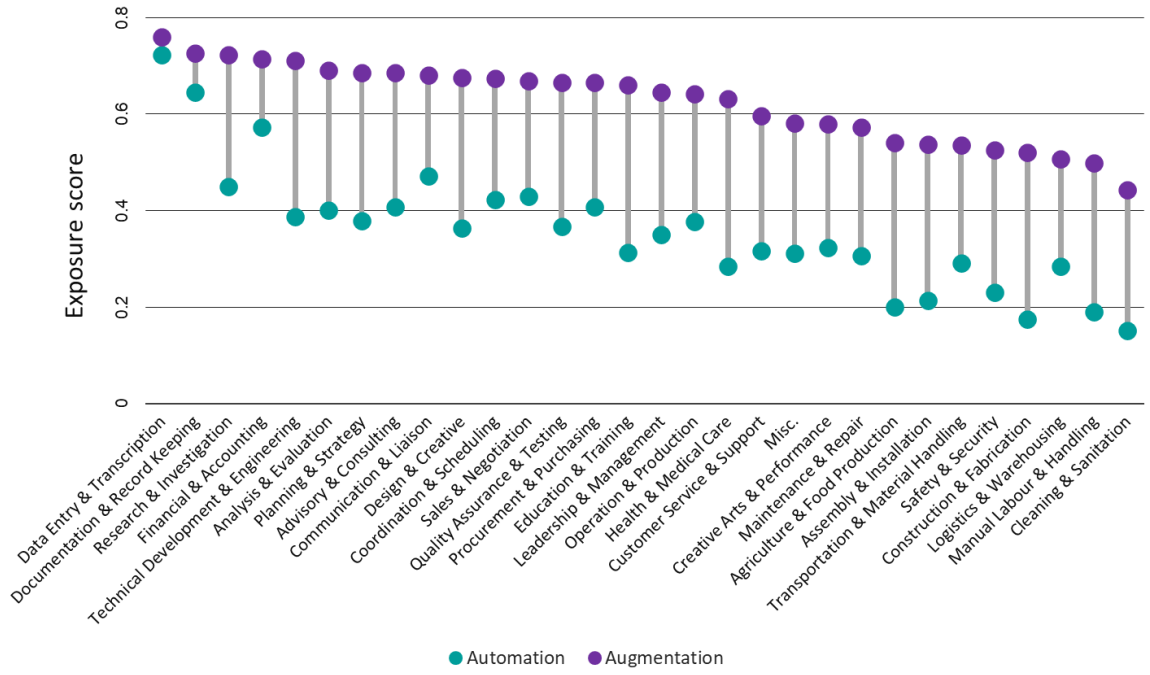


Note: Professional occupations (ANZSCO Major Group 2; purple), administrative and clerical occupations (ANZSCO Major Group 5; teal), and other (ANZSCO Major Groups 1, 3, 4, 6, 7, 8; brown).

Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Figure 3: Exposure varies by task routine and labour intensity

Exposure to augmentation and automation by task type



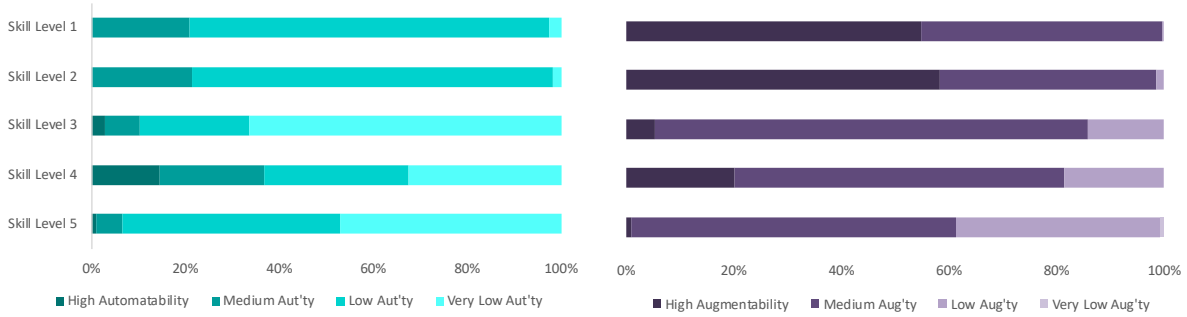
Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Knowledge work and higher-skilled occupations are more augmentable

While the estimated exposures vary between occupations, their distributions show that potential augmentation outweighs potential automation across all skill levels and occupation major groups (Figure 4) and is highest for the most skilled and some specialised groups.

Figure 4: Highest skill levels are most exposed to Gen AI

Potential automation (blue) and potential augmentation (red) – % workforce (x axis) exposed to Gen AI by occupation skill level



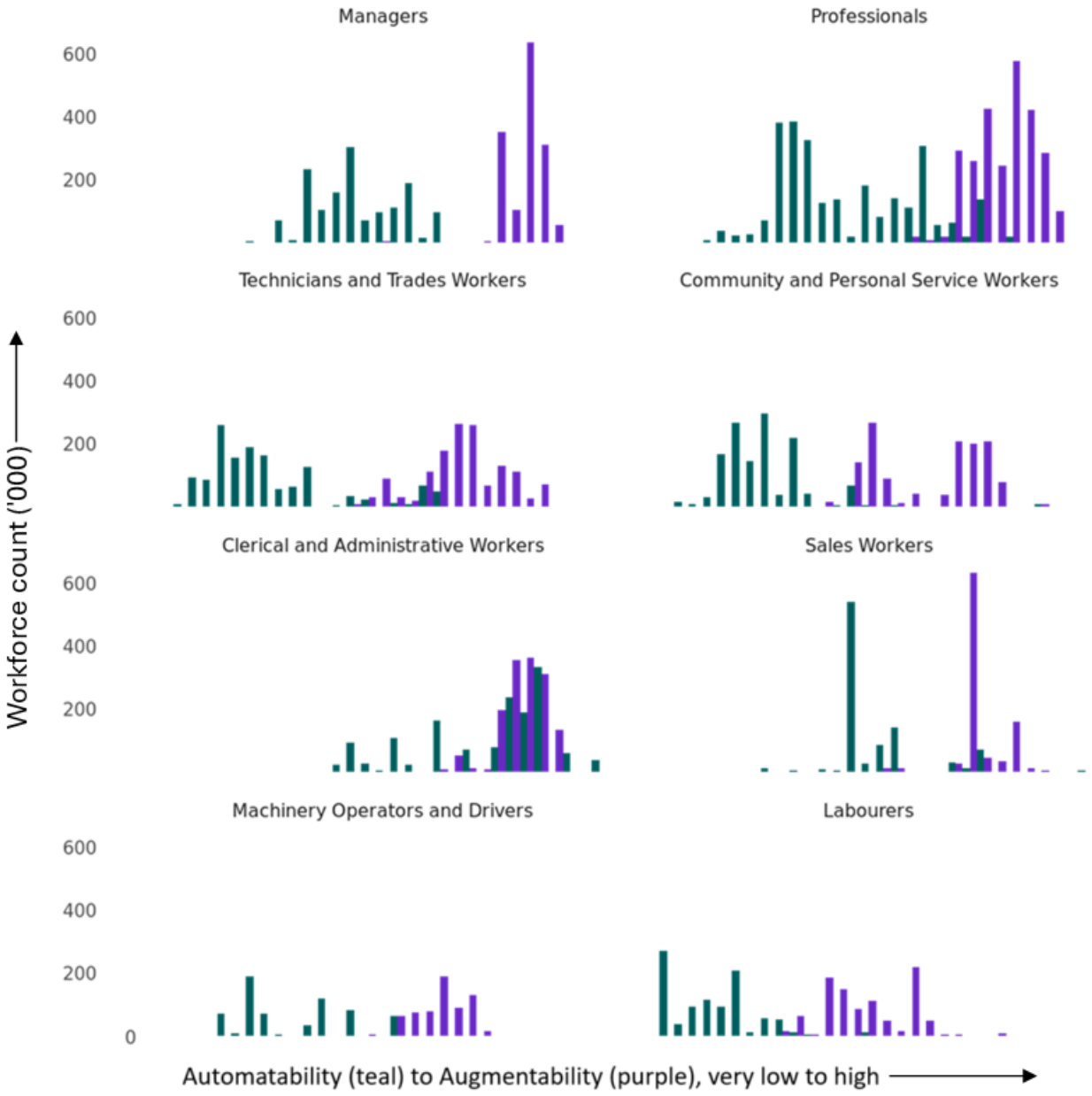
Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Gen AI has a higher propensity to augment work in higher-skilled occupations and for the *Managers* and *Professionals* occupation major groups (Figure 5). This likely reflects the

opportunities for the technology to be incorporated into knowledge-based work, as well as technical tasks.

The potential to automate tasks is highest for the middle-skill occupations, particularly at ANZSCO skill level 4, which includes several forms of clerical work. Many clerical tasks – that were not affected by previous waves of automation – could now be undertaken in large part by Gen AI. Occupations with low augmenting and automating potential often involve tasks that require physical action that Gen AI could not carry out (at various skill levels). Higher skill level occupations record greater exposure to medium automation potential, suggesting highly skilled occupations could discover new efficiencies based on the current technology. These scores would be expected to shift as Gen AI technologies evolve, especially with more integration of robotics and complementary technologies.

Figure 5: More skilled and technical occupations are more augmentable than automatable
Number of workers exposed to automation (green) and augmentation exposure (purple), by occupation major group



Note: Each column represents a single occupation (4-digit ANZSCO) within the occupation major group.
Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

3. Implications of occupation-based exposures for industries, cohorts and trajectories

Our task-based method for calculating Gen AI exposure scores for each occupation in turn provides the basis for considering exposure for different industries, geographies and cohorts. The potential applicability of Gen AI in different industries or locations can be estimated based on their current occupational compositions. Cohort-specific implications can be estimated by examining the workforce composition of each occupation. These implications will be specific to the Australian labour market at a given point in time.

Exposure analysis can also be useful in considering the trajectory of Gen AI adoption over time. This can be modelled across various scenarios using assumptions about when the technology would be worth implementing.

Industry composition and Gen AI exposure

By calculating the weighted average exposure scores for each industry, it is clear that all industries have some potential to apply Gen AI technologies. Overall, the Construction industry contains a greater share of occupations with low exposure (given the importance of physical tasks such as machine operation) compared to the Financial and Insurance Services or Professional, Scientific and Technical Services industries.[8] However, industry-level averages are limited in what they can show about likely implications for the respective workforces.

Table 2: Weighted average Gen AI exposures by industry

Weighted average Gen AI exposures by industry, based on occupation-specific exposure scores

Industry	Augmentation score	Automation score	Proportion of workforce
Accommodation and Food Services	0.58	0.33	0.1%
Administrative and Support Services	0.56	0.32	0.2%
Agriculture, Forestry and Fishing	0.61	0.31	0.2%
Arts and Recreation Services	0.63	0.37	0.3%
Construction	0.59	0.27	0.1%
Education and Training	0.65	0.38	1.0%
Electricity, Gas, Water and Waste Services	0.65	0.38	0.4%

[8] The average automation score for occupations in the Construction industry is 0.27, while the average augmentation score is 0.59. This is lower than the Financial and Insurance Services industry (average automation score of 0.54, average augmentation score of 0.72) or the Professional, Scientific and Technical Services (average automation score of 0.47, average augmentation score of 0.70).

Financial and Insurance Services	0.72	0.54	0.4%
Health Care and Social Assistance	0.63	0.34	0.2%
Information Media and Telecommunications	0.69	0.46	1.2%
Manufacturing	0.62	0.34	0.3%
Mining	0.61	0.31	0.2%
Other Services	0.58	0.32	0.2%
Professional, Scientific and Technical Services	0.70	0.47	0.6%
Public Administration and Safety	0.66	0.41	0.2%
Rental, Hiring and Real Estate Services	0.69	0.47	0.1%
Retail Trade	0.63	0.42	0.2%
Transport, Postal and Warehousing	0.60	0.38	0.2%
Wholesale Trade	0.67	0.45	0.1%

Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

A more detailed understanding of each industry can be gained by focusing on the 10 largest occupations by workforce count. This shows how much, and how, each industry's workforce is exposed to Gen AI (Figures 6-8, bubble sizes indicate workforce size per occupation). For example, in the Financial and Insurance Services industry, the 10 largest occupations have medium to high augmenting potential (Figure 6) suggesting that a significant proportion of that workforce, and indeed that industry, could undertake their work tasks with the help of Gen AI.

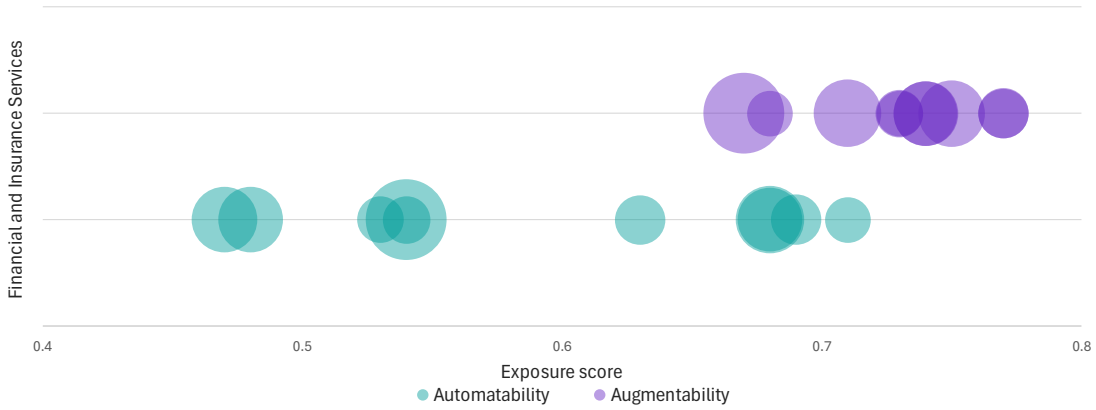
Extending this analysis to all industries provides a useful comparison of how Gen AI could affect the workforce in each industry. Not only do industries differ in terms of exposure, but so too do occupations within that industry (Figure 7). In the Health Care and Social Assistance industry, for example, several occupations have medium to high levels of augmentation potential, while also having a relatively large workforce in an occupation that has low augmentation potential. Other industries such as Accommodation and Food Services and Agriculture, Forestry and Fishing are comprised of occupations with relatively diverse levels of Gen AI exposure.

Automation potential also varies across the most common occupations in each industry (Figure 8). Industries focused on knowledge work, information and services are more likely to have occupations with automating potential. Industries that involve working more directly with physical materials, such as the Construction industry, have low automating potential for most of its largest occupations (Figure 8, bubbles skew left).

Both the occupations and industries that are more exposed to automation account for significantly smaller workforce numbers (smaller red bubbles). This reinforces the observation that the automating potential of Gen AI currently seems less material than augmentation. Exposure to augmentation is higher across all industries overall, particularly the non-market sector and information-based industries (Figure 8, purple panel's bubbles skew more right).

Figure 6: Largest occupations in Financial and Insurance Services have mid to high augmentability

Gen AI exposures from low to high (x-axis, left to right) by workforce size (size of circle) for 10 largest occupations in the Financial and Insurance Services industry

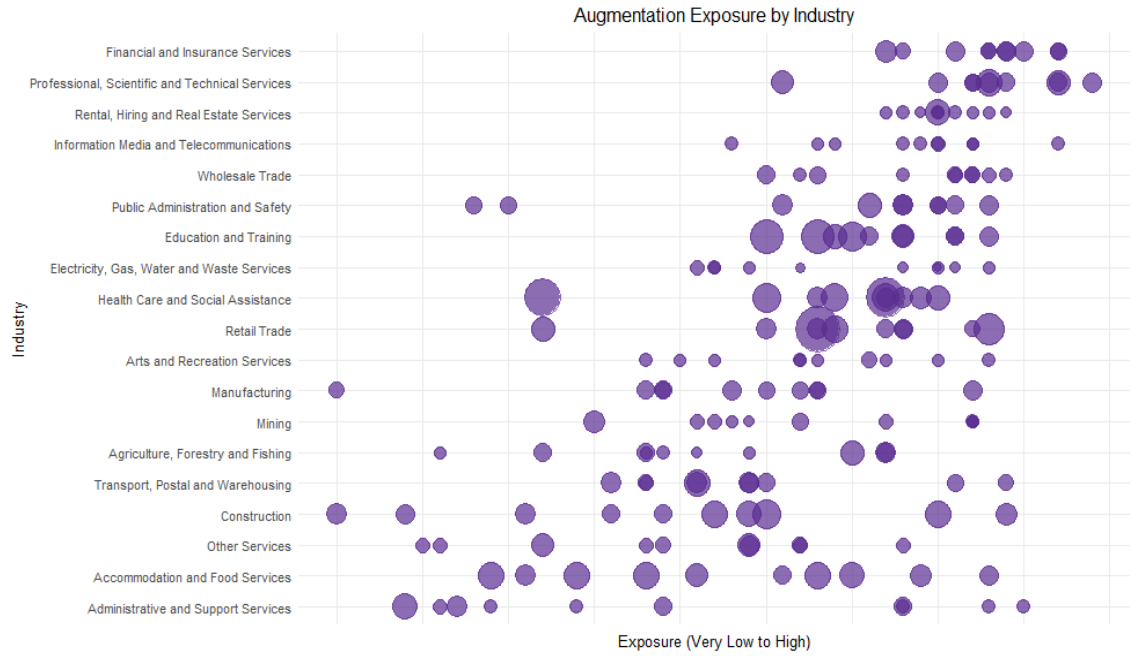


Note: Bubble sizes reflect relative workforce size per each of the top 10 occupations within each industry, across the whole labour market. This means (1) an occupation can appear in more than one row and (2) the bubble sizes can be compared across rows. The industries in each panel are ordered from highest aggregate automation exposure to lowest aggregate automation exposure (y axes). Along each row, where the bubbles are evenly (unevenly) sized, the top 10 occupations within that industry have similar (different) workforce sizes; and therefore if the bubbles along a row skew to the left (right), then the industry's workforce faces relative low (high) exposure. Where the bubbles are evenly spread along a row, more variety and extremes in exposure are more likely in that industry (for example, automation exposure of the Arts and Recreation services industry). Bubble sizes apply 2021 Census occupation weights.

Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Figure 7: Industries and occupations within them differ in Gen AI augmentation exposure

Gen AI exposures from low to high (x-axis, left to right) by workforce size (size of circle) for 10 largest occupations per industry



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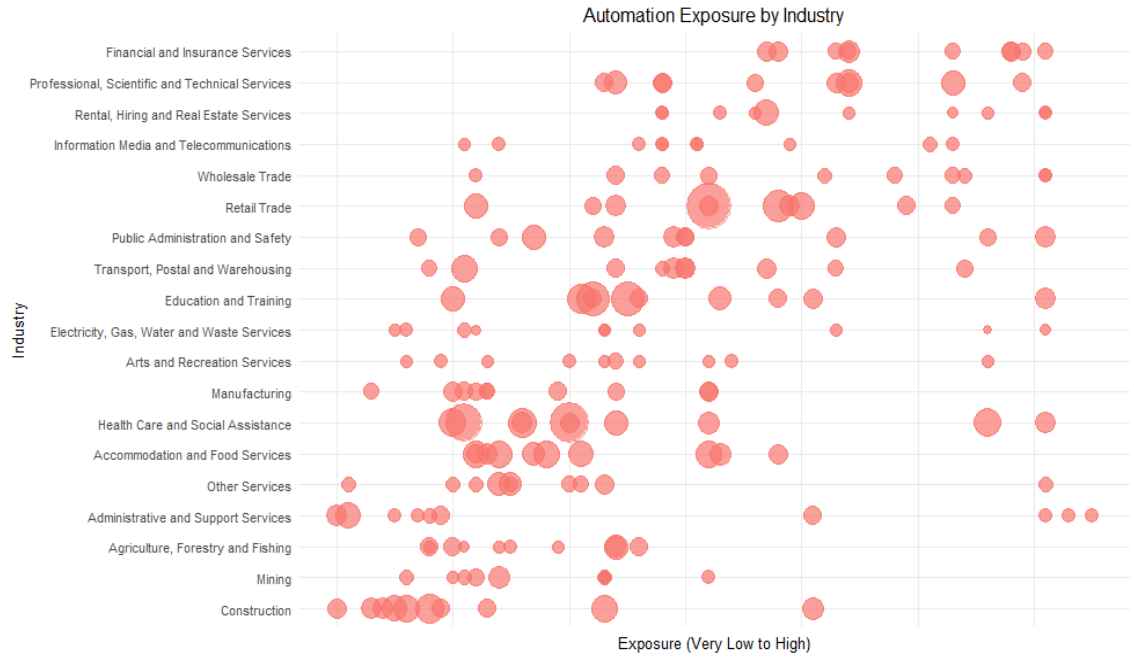
Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Figure 8: Industries and occupations within them differ in automation exposure

Gen AI exposures from low to high (x-axis, left to right) by workforce size (size of circle) for 10 largest occupations per industry



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Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Exposure across geographies

Based on the workforce composition of different geographic regions, exposure to Gen AI is typically higher for inner city areas compared to regional and remote areas. At the SA4 level, the average exposure scores were comparable in each state and territory, with an augmenting potential ranging from 60% to 68% and automating potential at a much lower level, from 31% to 45%.

We analysed the most common occupations in regional and remote areas, which collectively employ 50% of people in those workforces. From these lists, the only common occupation in remote areas that was highly exposed to Gen AI automation (i.e. exposure score above 0.7) was General Clerks. In regional areas it was General Clerks and Accounting Clerks.

In regional and remote areas, the occupational makeup is less prone to automation or augmentation than in urban centres. While this suggests less scope for disruption, it may also suggest less scope for labour-augmenting uses of Gen AI and its productivity-improving effects.

Table 3: Gen AI exposures of largest occupational workforces in regional areas

Common occupations in inner- and outer-regional areas	Automation score	Augmentation score	Proportion of regional workforce
Sales Assistants (General)	Low	Medium	4.74%
Aged and Disabled Carers	Very Low	Low	2.52%
Registered Nurses	Low	Medium	2.40%
General Clerks	High	Medium	2.17%
Truck Drivers	Very Low	Medium	1.98%
Livestock Farmers	Low	Medium	1.87%
Retail Managers	Low	High	1.76%
Primary School Teachers	Low	Medium	1.55%
Commercial Cleaners	Very Low	Low	1.46%
Secondary School Teachers	Low	Medium	1.45%
Receptionists	Medium	Medium	1.42%
Metal Fitters and Machinists	Very Low	Medium	1.31%
Electricians	Very Low	Medium	1.29%
Child Carers	Very Low	Medium	1.26%
Education Aides	Low	Medium	1.21%
Carpenters and Joiners	Very Low	Medium	1.10%
Kitchenhands	Very Low	Medium	1.09%
Motor Mechanics	Low	Medium	1.08%
Office Managers	Low	High	1.05%
Crop Farmers	Low	Medium	0.99%

Note: Regional for the purposes of this analysis is defined as areas that are classified as 'Inner Regional' or 'Outer Regional' per ABS remoteness areas.

Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Table 4: Gen AI exposures of largest occupational workforces in remote areas

Common occupations in remote or very remote areas	Automation score	Augmentation score	Proportion of remote workforce
Livestock Farmers	Low	Medium	4.15%
Drillers, Miners and Shot Firers	Very Low	Medium	3.08%
Sales Assistants (General)	Low	Medium	2.89%
Mixed Crop and Livestock Farmers	Low	Medium	2.35%
Metal Fitters and Machinists	Very Low	Medium	2.32%
General Clerks	High	Medium	2.29%
Truck Drivers	Very Low	Medium	2.10%
Livestock Farm Workers	Very Low	Low	1.97%
Registered Nurses	Low	Medium	1.92%
Crop Farmers	Low	Medium	1.91%
Education Aides	Low	Medium	1.85%
Primary School Teachers	Low	Medium	1.80%
Commercial Cleaners	Very Low	Low	1.77%
Electricians	Very Low	Medium	1.58%
Retail Managers	Low	High	1.49%
Welfare Support Workers	Low	Medium	1.35%
Receptionists	Medium	Medium	1.21%
Aged and Disabled Carers	Very Low	Low	1.18%
Secondary School Teachers	Low	Medium	1.14%
Motor Mechanics	Low	Medium	1.10%

Note: Remote for the purposes of this analysis is defined as areas that are classified as 'Remote' or 'Very Remote' per ABS remoteness areas.

Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Workforce composition and implications for worker cohorts

Gen AI exposure will vary for different cohorts of people in the workforce, according to the occupations they work in. Some high-level demographic results are observed across gender, age and educational attainment.

Based on the current gender makeup of occupational workforces, women face greater exposure to both automation and augmentation from Gen AI (Figure 9). Women are overrepresented in highly automatable roles (Figure 10). However, there are many occupations that are growing and have strong potential for augmentation, more than automation, including a range of female-dominated occupations.

This aligns with past Australian research that has shown that in the financial services sector, for example, female participation is high in low-projected-growth occupations, including Accounting Clerks, Bookkeepers, Payroll Clerks, and Bank workers, all of which face significant exposure to

Gen AI (Future Skills Organisation, 2024). Analysis by Mandala has also pointed to occupations in other sectors, such as Medical Administrative Assistants as well as Legal Assistants as being particularly exposed (Mandala, 2024).

Based on the current composition of occupational workforces, people in all age groups work in occupations that are exposed to augmentation and automation (Figure 11). Exposure is marginally lower for the youngest age groups, likely due to their comprising a smaller share of the workforce in higher-skilled occupations.

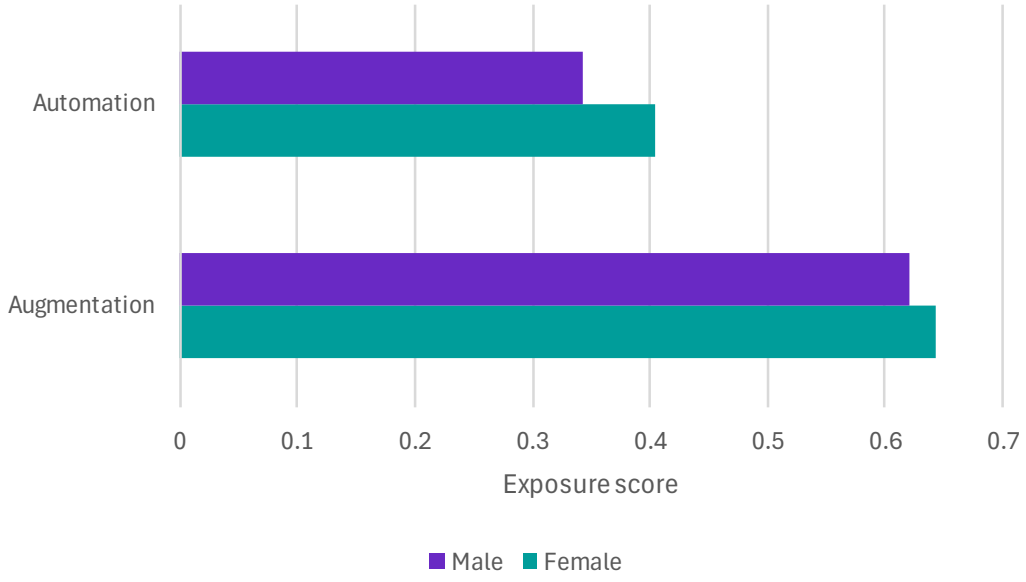
However, these results do not account for any differences between workers in the same occupation. It will be important to compare these results to other evidence of how people actually interact with technology, and the extent to which this changes over time. Recent survey evidence shows people in different age groups vary in their frequency of and reason for using Gen AI (ACCC, 2025). Fusion Digital Agency (2024) found that white-collar workers aged 58 years or more were the least likely to use AI, with only 75% identifying as AI users. In contrast, those aged 27-42 years were the most likely to adopt AI tools at work, with 90% of respondents in this age group indicating they used AI.

People with higher levels of education are more likely to work in occupations with greater exposure to Gen AI on average (Figure 12). The skew towards tertiary educated workers likely reflects their greater share in medium and higher skilled occupations. This marks Gen AI as different to some of the previous waves of automation.

As such, exposure analysis provides useful information on the cohorts of workers who would be affected by occupation-level changes, given the current composition of the workforce. This is an important part of ensuring an understanding of the particular implications that Gen AI will have on the Australian labour market as it stands today.

Figure 9: On average, women face greater augmentation and automation

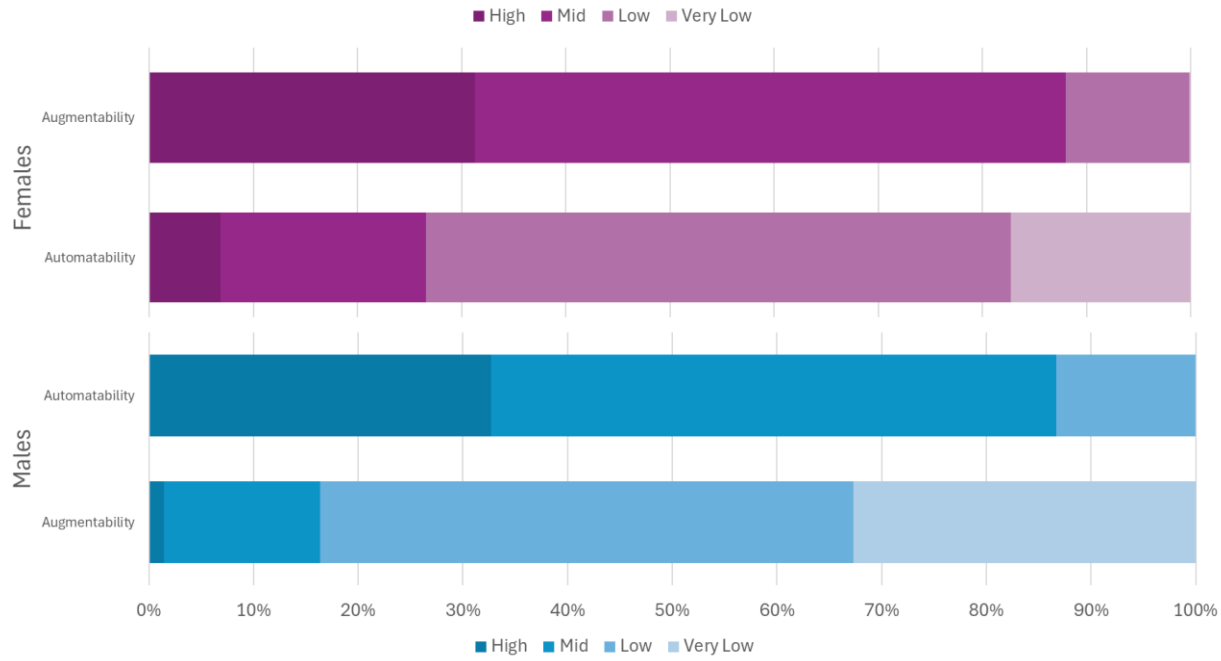
Weighted average automation and augmentation scores by gender



Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Figure 10: Augmentability is similar and automatability is higher for female workforce

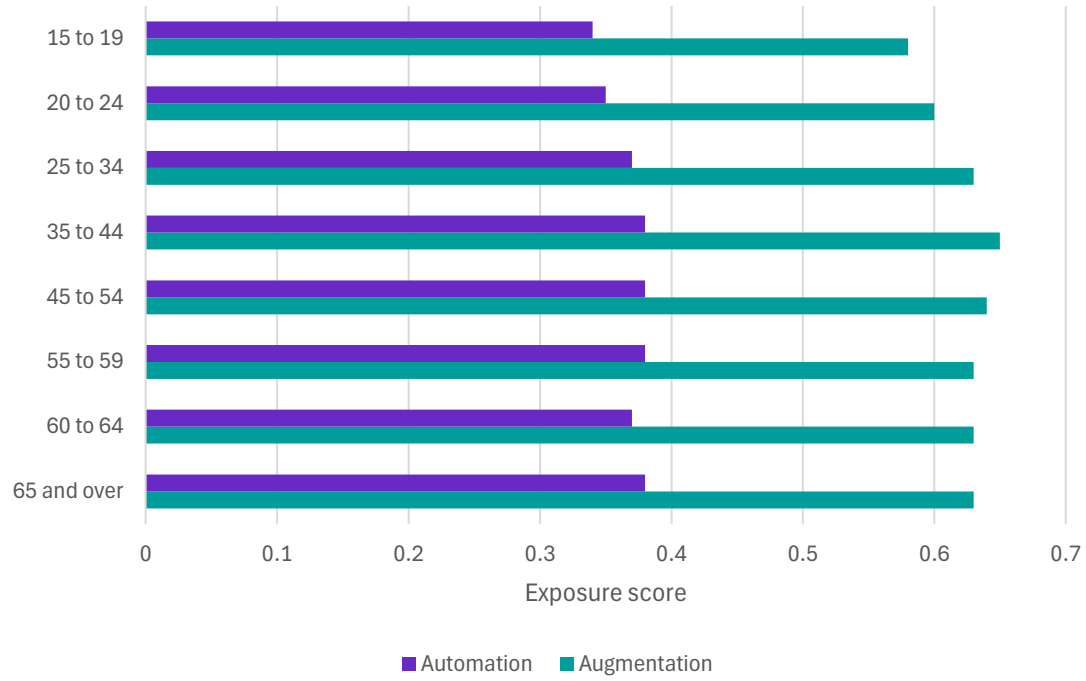
Female and male workforce exposure to automation and augmentation in current occupations



Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Figure 11: All age groups are exposed to augmentation more than automation

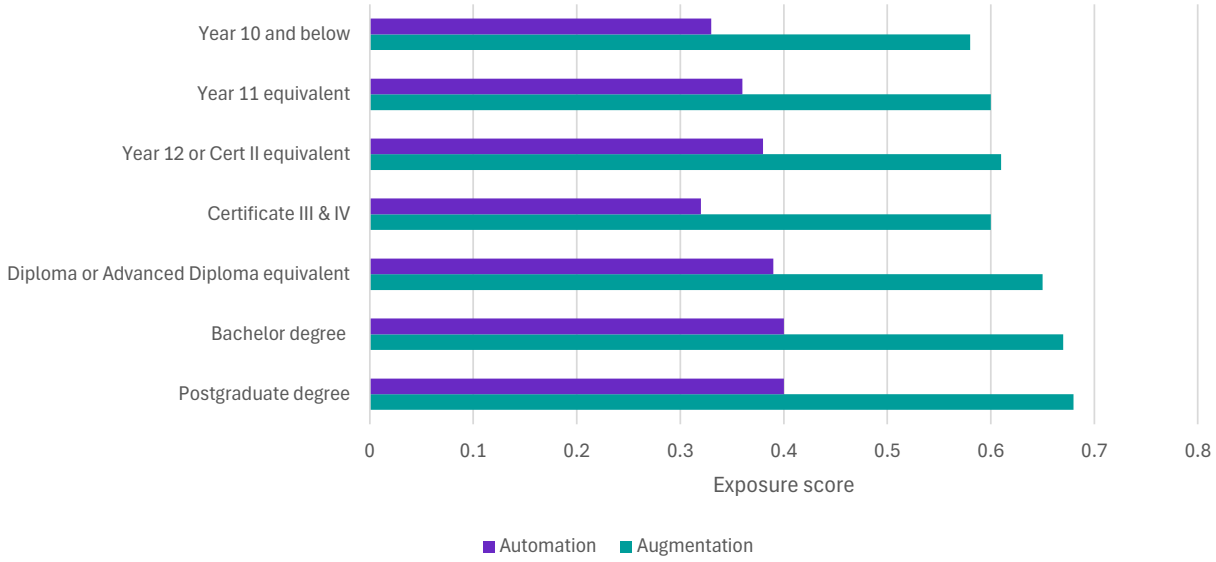
Weighted average automation and augmentation scores by age group



Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

Figure 12: Higher education levels face more augmentation

Weighted average automation and augmentation scores by highest level of education



Source: JSA Analysis; ANZSCO (v1.3), Census 2021 (TableBuilder).

4. Conclusion

Most occupations in Australia have the potential to interact with Gen AI technology. For some tasks, work could potentially be enhanced by the use of AI tools. In other tasks, there is potential for Gen AI to produce the output with little or no human involvement. A relatively small percentage of occupations are comprised of highly automatable tasks affecting a small proportion of the workforce. Overall, this points to a significant potential for Gen AI to change how work is done in Australia across a broad range of occupations, but more through the augmentation of tasks.

These findings also underscore that the transformative potential of Gen AI is largely dependent on situations where people work with or alongside it. Even where certain tasks could be automated, workers may be needed to check and verify those outputs, in addition to carrying out tasks that are less amenable to Gen AI use. As such, the exposure scores suggest that skills and capabilities will be important for workers in a Gen AI-enabled labour market.

Importantly, exposure scores can only provide a theoretical measure of Gen AI's potential. They are likely to overstate the potential application of Gen AI, as they do not directly account for practical barriers to use. Neither do they consider what organisations and individuals might consider reasonable and valuable uses of Gen AI given risks, costs, and potential benefits.

By the same token, while exposure analysis shows that Gen AI could change how work is done across the labour market, it does not suggest how employment levels would be impacted. Exposure scores do not directly reveal short-run productivity or cost implications of adopting Gen AI into work (Acemoglu & Restrepo, 2022). We cannot assume from exposures alone that Gen AI will undertake a task more quickly, better or more cheaply, observing which relies on evidence on the real effects of technological adoption. Moreover, it will be important to consider how the labour market and aggregate demand adapt (that is, create new work) to emerging

technology. As such, our exposure framework alone cannot capture Gen AI's full potential, including the emergence of new occupations and outputs.[9]

Findings from the Overarching Paper that this analysis supports

Finding 1: Gen AI could be applied to most occupations but to different extents, and there is generally greater potential for task augmentation than automation

At this stage, Gen AI could be applied to some portion of the tasks in the majority of occupations. Overall, there is far greater potential for occupations to be augmented than to be automated.

The potential impact of Gen AI is uneven across the economy. There is more potential for augmentation in medium- and higher-skilled occupations and to knowledge-work. There is more potential for automation in repetitive, structured and routine clerical tasks.

Exposure will change over time where new technological developments allow AI to be applied differently or to different tasks (including improvements in the capabilities of Gen AI and robotics, or the ongoing emergence of Agentic AI).

Exposure scores do not capture all the practicalities that may make Gen AI more or less applicable in a given situation. Neither does it reflect the implications for the replacement of previous technologies and retirement of assets.

[9] The current occupational taxonomy, which underpins the exposure framework, places well-defined limits on speculating about emerging occupations.

Finding 2: Adoption and adaptation will determine how Gen AI's labour market impacts and its potential are realised

The quality of adoption and implementation will be instrumental in achieving the benefits of labour-augmenting tools. Implementing Gen AI requires adaptability for both employers and the workforce.

More broadly, adaptability and dynamism in the labour market (and the economy) will dictate how any saved time could be redeployed and reallocated. This will ultimately determine how the use of Gen AI influences employment growth, both positively and negatively (as modelled).

Over time, the use of Gen AI and other technologies will lead to various forms of adaptation. This includes changes within-occupations, across occupations and with regard to working arrangements. As such, the effect of technology on the labour market will continue to evolve.

Considering "first order" adaptation – where automation and augmentation may cluster tasks – can help identify where specialised or hybrid roles could emerge within existing occupations and roles.

Given the complexity of dynamics of Gen AI use, a wide range of labour market outcomes is possible in the medium term (around 15 years, for the purposes of this Study). This will require regular monitoring, to inform effective strategy and planning across the labour market and skills system.

Finding 7: Gen AI adoption is reshaping skill demand and roles. Large-scale job displacement is yet to emerge, with current impacts limited to early-adopters.

Among early-adopting firms in Australia, Gen AI use has been linked to increased demand for certain skills and roles, while reducing demand for others, particularly in routine or clerical functions.

There is evidence of only limited job displacement to date. Some task-specific occupations, such as voice-over artists, have seen reduced demand overall. Most observed impacts involve the evolution of roles, upskilling, and redeployment of workers, rather than widespread job loss.

Many organisations have yet to adopt the technology in significant ways. And some firms are only early in the process of large-scale change-management projects, meaning that any employment effects have not yet emerged.

Finding 10: The number of entry level roles hasn't declined even as the work has, and should continue to be monitored closely

Entry-level recruitment has been relatively stable, based on job advertisements data. Anecdotally, in early adopting sectors, employers are changing or considering changes to their entry-level intake. This includes changes to the nature of entry-level roles in workplaces where Gen AI is being used for routine tasks.

Overall, entry-level roles should remain an area of focus given the capabilities of Gen AI and the emerging capabilities of agentic AI to undertake structured, routine tasks.

Finding 17: Gen AI exposure has important implications for education and training pathways, based on their common destination occupations

The Gen AI exposure of education and training pathways varies across fields of education, training package, and qualification types.

Alongside other considerations, such as the volume of completers and evidence of AI adoption, the Gen AI exposure of education and training pathways provides a useful guide for prioritisation to those with responsibilities for qualification design and delivery.

B. Adoption

Depth of use & implementation across sectors

A spectrum of capability, from adoption, integration, maturity

Gen AI ‘personas’ support dynamic adoption & adaptation

1. Introduction

This paper explores the adoption and implementation of Gen AI, both in conceptual terms and in terms of the practical realities of the Australian labour market. While exposure analysis (Analysis Paper A) usefully estimates how Gen AI might apply to existing work tasks, it reflects the *potential* for change, and does not account for practical barriers and complications that affect the extent to which this potential is realised and how quickly this occurs. In practice, the adoption and use of Gen AI is influenced by such factors as the capabilities and adaptability of firms and workers (including managers), regulation, social norms, and the inherent value of human interaction.

Technology adoption can be considered a simple, binary concept, which is useful in understanding how many firms, organisations, and workers have begun to use Gen AI (Section 2). It is also useful to consider the extent or depth of adoption and implementation, in order to understand how Gen AI is being used and how this may change over time (Section 3). Gen AI adoption will have differing trajectories across the economy, and will involve adaptation of roles and work processes (Section 4). Each of these considerations has implications for how Gen AI is experienced in the labour market (Section 5).

2. Considering the depth of adoption

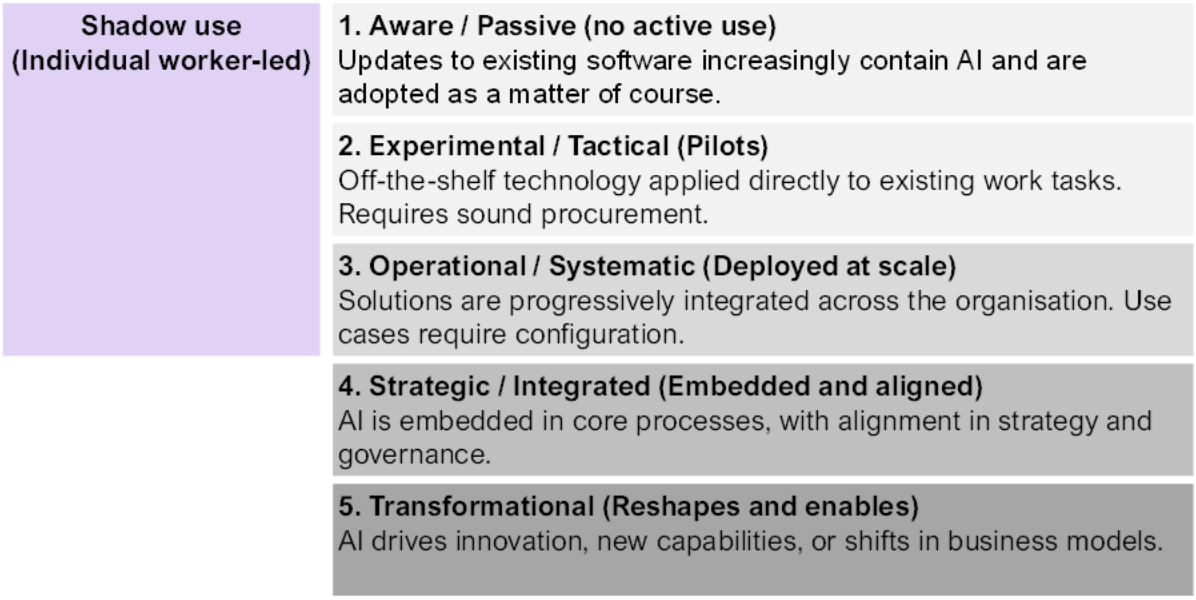
Gen AI can be adopted in many different ways, given the various applications of the technology, and different options for how it can be implemented in a workplace. To understand the implications of Gen AI for the labour market and productivity, it is vital to consider the extent and nature of its use.

Depth of adoption

Observing the adoption of Gen AI is informative in terms of how diffusion of the technology is progressing as compared to its theoretical potential. Monitoring the spread of Gen AI over time will be vital to identifying barriers to implementation or challenges that affect its effective implementation.

A growing body of research is moving beyond the binary view of adoption (i.e. whether technology has been adopted or not), given this view fails to capture the extent of integration, use, and impact. Different stages of technology maturity can be identified by the extent or depth of adoption (Figure 1).

Figure 1: AI adoption is not a simple concept



Individual-led and 'shadow' adoption comprises workers who adopt the technology in order to realise individual productivity benefits. This type of adoption may stem from personal, non-work use of Gen AI. Individual adopters typically source their own tools and training, and manage the risks involved with their use. Responsibility for governance and risk management is therefore shared or transferred to the worker. Individual workers may recoup time or be rewarded for productivity (although performance expectations may be updated over time).

Organisation-level adoption is likely to be more uniform across the workplace. It will also involve consideration of centralised governance of data and AI, typically requiring investment in the re-design of work processes.

A range of practical factors influence adoption

The adoption of Gen AI will depend on its performance against particular tasks – both in comparison to workers and as a complement to workers. Evidence suggests that accuracy is a common perceived and experienced risk associated with AI use (KPMG, 2025). Others note that AI will increasingly be used for tasks where it can perform tasks in ways that humans cannot, even if accuracy is sacrificed:

> *When a system has a bottleneck related to speed, scale, scope or sophistication, or when one of these factors poses a real barrier to being able to accomplish a goal, it makes sense to think about how AI could help. Equally, when speed, scale, scope and sophistication are not primary barriers, it makes less sense to use AI. This is why AI auto-suggest features for short communications such as text messages can feel so annoying. They offer little speed advantage and no benefit from sophistication, while sacrificing the sincerity of human communication. (Bruce Schneier, 2025)*

Where productivity allows for more time to be allocated to more valuable tasks, this can have different effects on worker experiences and quality of work as well as scope of practice. For instance, if automation occurs for repetitive, low-intensity tasks, this could allow workers more time and space to work towards high-value objectives (i.e. freeing up time for more important and specialised uses). This could allow workers to devote more time to tasks that benefit most from human involvement and align more closely with their expertise.

> *Customer service remains a vital component of the shopping experience, as two-thirds of Australian consumers view brick-and-mortar stores as a key touchpoint between a business and its customers. As such, interpersonal skills such as empathy, problem-solving and communication will become increasingly valuable as they complement AI capabilities. This shift underscores the need for both technical expertise and human-centric skills*. (Gen AI Capacity Study Consultation Hub Response – SaCSA)

Importantly, the role of Gen AI technologies in work processes – and whether they automate a task, provide assistance to workers, or are not used at all for particular tasks – will vary across use cases and situations. The degree of human involvement required is likely to be high in some aspects of patient care in health services, or interactions with students in education, or some creative tasks in the arts.

> *The sector consistently tells us that workers enter the care and support sector for its relational and human centred nature—supporting older people, people with disability, helping secure housing, and educating children. However, rising administrative burden has become a source of dissatisfaction, as it reduces the time available for the person-centred work, they value most*. (Gen AI Capacity Study Consultation Hub Response – HumanAbility)

Others point out that allowing workers to tend to human-centred tasks is also critical for quality of service in many aspects of care.

> *While these technologies can be used to support workflows, they cannot and should not replace the human workforce required in many sectors, particularly healthcare. The use of Gen AI in healthcare requires human oversight to ensure accuracy and the presentation of information that accounts for human element of healthcare (such as responsiveness, assurance, courtesy, empathy, communication, and understanding*). (Gen AI Capacity Study Consultation Hub Response – ANMF)

HumanAbility also noted that Gen AI use could improve staff retention in some care occupations, given survey evidence found administrative burden to be a significant factor in engagement and burnout in the NDIS; and that carers are often highly motivated by client interaction.

How often Gen AI is used and for how many tasks

There is limited evidence in Australia to show the extent to which Gen AI is being applied to specific tasks. However, globally, a recent study by Anthropic estimated that use of Claude.ai is concentrated for tasks related to software development and technical writing, and more likely for augmentation than automation.[1]

[1] Handa et al. (2025) note that usage is suggestive of marginally less automation (43%) than augmentation (57%) of human capabilities.

Box 1 Task-level use of Gen AI

A research study from Anthropic has analysed task-level use of Gen AI with an unprecedented level of detail – using over four million user 'conversations' with Gen AI tool Claude.ai and mapped them to tasks and occupations via the U.S. Department of Labor's O*NET Database (Handa, et al., 2025). They also note the importance of analysing usage at the task level rather than at the occupation level, given that, for example, not all people who search for nutritional advice would be employed as nutritionists. Overall, they note that:

> *Currently, we observe usage concentrated in specific tasks … rather than wholesale automation of occupations. If this pattern persists—with AI affecting only a subset of tasks within jobs—it suggests occupations will evolve rather than disappear.*

While the work of Handa et al. (2025) presents a leap forward in assessing the use of Gen AI for particular work tasks, it presents relatively limited inferences for the Australian experience.[2] In part this is because it focuses on Claude.ai (which has less than 3% of market share in Australia) and uses a global sample of conversations. The authors also recognise that, given O*NET is a 'US-centric classification', this may 'overlook significant occupational categories and tasks from other regions.'

If the study by Handa et al. (2025) were to be replicated for Australia using the ANZSCO classification system, it would still only provide an understanding of a small proportion of AI users. Moreover, the strength of its estimates would depend heavily on the ability to map conversations to tasks and occupations. Overall, however, this kind of analysis would be invaluable for the future monitoring of Gen AI adoption in Australia.

A similar study was undertaken by Microsoft using 200 000 anonymised conversations with Copilot from users in the United States (Tomlinson, Jaffe, Wang, Counts, & Suri, 2025). They also used O*NET as a means of classification and found that Copilot is mostly used to provide 'information and assistance, writing, teaching, and advising', making it most directly applicable to knowledge work, administrative support, and occupations involving communicating information.

Even where Gen AI has been implemented in a given workplace, its use can vary by task (Digital Transformation Agency, 2024). Moreover, early adoption rates may still reflect an experimental phase – survey evidence suggests that for 70% of firms trialling AI technologies, only 30% of the experiments were put into production (Lynch, 2024). Moreover, early adoption rates may still reflect an experimental phase – survey evidence suggests that for 70% of firms trialling AI technologies, only 30% of the experiments were put into production (Lynch, 2024).

Workers who use AI more frequently have been found to be more trusting of the AI.[3] This may reflect a dynamic where increased use results in greater trust, or alternatively, it may indicate

[2] In addition, Handa et al. (2025) does not consider the quality or depth of Gen AI use, or whether the use is individual or firm led. The authors also do not explicitly identify whether the tasks Claude undertook were undertaken within an employment context or otherwise.

[3] Among those using AI for less than one hour per week, 25% think we should trust AI, 34% believe it has a positive impact, and only 64% feel it gives correct and accurate answers. Among workers using AI 10+ hours per week,

that people who trust AI more are more willing to use it. The extent and frequency of use in turn will have implications for the quantum of productivity gains that are realised. And while evidence suggests significant lack of trust of AI technologies,[4] the *trustworthiness* of AI tools is likely to improve they becomes more accurate and effective.

3. Observed adoption in Australia

Simple binary adoption rates

The ABS Business Characteristics Survey measured the use of AI through a survey of businesses, most recently for 2021-22. The survey showed that in 2021-22, immediately prior to the public release of ChatGPT, around 1% of Australian businesses reported using various types of AI, to some extent.

While at that early point only 1% reported using AI, this varied across businesses:

- By size (9.5% for those with 200 or more employees, 3.3% for 20-199, 1.4% for 5-19, and 1.1% for 0-4)
- By industry (7.7% for Information Media and Telecommunications, 3.6% of Professional, Scientific and Technical Services, and through to industries with virtually no adoption).

While AI adoption data is not yet available from more recent large and representative ABS surveys of businesses, which is planned for the coming years, a variety of surveys from other sources suggests that AI adoption has increased significantly in the past two years (Table 1). Surveys of this kind, focused on AI in businesses, are prolific and partial. Nevertheless, the diversity of results provides some insight, at least into why businesses are considering adoption, as well as seemingly disparate rates of adoption at industry or occupational levels.

A monthly survey of Australian businesses conducted for the National AI Centre showed that for the September quarter 2024:

- 35% of respondents had, were in the process of adopting, or planned to adopt AI
- 42% of businesses reported no intention of adopting AI
- 23% were unaware of how AI could be applied to their operations.

78% believe we should trust AI, 76% think it has a positive impact, and 78% believe AI gives correct and accurate answers (Fusion Digital Agency, 2024).

[4] Many reports have noted the lack of trust that workers have for Gen AI tools. Around 53% of respondents to the Fusion Digital survey were ‘wary’ or ‘unsure’ about trusting AI (Fusion Digital Agency, 2024).

Table 1: Estimates of AI Adoption in Australia

Adoption rates of AI technologies, which may or may not include Gen AI, as measured by various surveys of Australian businesses. Non-ABS survey samples are not balanced and therefore not representative of whole-of-economy trends.

Survey	Year	AI Adoption rate[D]	Sample
ABS Characteristics of Business Survey[A]	2021-22	1%	70,000 Australian businesses
MYOB (2024)[B]	2024	19%	1,012 Australian SMEs
NAB (2024)[B]	2024	23%	700 Australian SMEs
PwC (Pagram, 2024)[C]	2024	25%	116 Australian businesses
Ai Group (2024)[B]	2024	52%	182 Australian businesses
NAIC (2025)	Jan – Jun 2025	27%	400 Australian businesses

[A] Results predate introduction of ChatGPT. While at an early point in adoption, the 2022 ABS Characteristics of Business Survey showed that adoption already varied by size (9.5% for those with 200 or more employees, 3.3% for 20-199, 1.4% for 5-19, and 1.1% for 0-4) and industry (7.7% for Information Media and Telecommunications, 3.6% of Professional, Scientific and Technical services, and through to industries with virtually no adoption). [B] Reporting on data and results covers various AI technologies and does not identify Gen AI explicitly but Gen AI is taken as being included in the definition of AI applied given responses. [C] Reporting on data and results explicitly identifies Gen AI. [D] Reporting on data and results covers various AI technologies.

Source: ABS *Characteristics of Australian Businesses*; Ai Group (2024); NAIC (2025); Pagram (2024); NAB (2024); MYOB (2024).

Survey evidence reviewed by the Australian Chamber of Commerce and Industry (2024) showed more momentum among medium-sized businesses, as they found that:

- larger businesses, while adopting, had yet to fully leverage AI, due to data management and adoption strategy issues
- medium-sized businesses were leading adoption, with 90 per cent planning to implement AI by 2026
- smaller businesses were lagging in AI adoption with training being a key barrier (Australian Chamber of Commerce and Industry, 2024).

The NAIC (2025) survey also highlighted that larger businesses are more likely to adopt AI than smaller ones. A similar trend in use is evident in surveys of individual workers, where respondents were more likely to use of AI tools if they were employed by larger businesses.[5]

Organisation-led and worker-led adoption

Unlike the adoption of many other disruptive technologies in recent decades, Gen AI has been implemented both at the behest of employers and proactively by individual workers.

Organisation-level adoption is likely to be more uniform across the workplace. It will also involve consideration of centralised governance of data and AI, typically requiring investment in the re-design of work processes.

[5] Survey evidence from Fusion Digital Agency (2024) found that 81% of white-collar employees used AI tools in small businesses (1–100 employees), compared to 87% in medium-sized businesses (100–500 employees), 88% in large businesses (500–5,000 employees), and 93% for enterprises with over 5,000 employees.

There is increasing evidence that AI adoption in Australia has been led by workers in a number of workplaces across Australia. Many employees have reported using Gen AI without the knowledge of management: Deloitte Access Economics (2024) found that around 27% were using Gen AI secretly at work, while another study (Fusion Digital Agency, 2024) found 21% of white collar workers were doing so.

> *We heard in our consultations from employees who had proactively implemented Gen AI – across health, financial, legal, and other professional occupations, often without their employers' involvement or knowledge. We also heard that some individuals deliberately avoided using Gen AI due to personal views of the technology, including among academics and workers in creative industries.*

Workers may be using AI in an unofficial capacity for different reasons. For instance, a survey conducted by Slack listed the most common reasons why employees hide their AI usage were: that they 'feel that using AI is cheating'; they have a 'fear of being seen as lazy'; and they have a 'fear of being seen as less competent'. These findings align with survey evidence from Microsoft that found 19% of respondents reported feeling like they are 'cheating' when they use Gen AI to undertake their work tasks (Microsoft, 2024).

The Fusion Digital Agency (2024) survey also showed that transparency around AI use increases with company size. For example, 83% of white-collar employees at large enterprises (over 5,000 employees) reported being open about their AI use with employers, compared to only 57% at small businesses.

Adoption also appears to vary according to age. Fusion Digital Agency (2024) found that white-collar workers aged 58 years or more were the least likely to use AI, with only 75% identifying as AI users. In contrast, those aged 27-42 years were the most likely to adopt AI tools at work, with 90% of respondents in this age group indicating they used AI.

Observed investment in technology and skills

Adoption patterns are inseparable from the broader drivers of technological and capability diffusion.

The OECD (2023) noted that the pace and locus of AI advances are largely determined by private R&D, venture capital and open-source collaboration. The World Economic Forum (2024) found that Gen AI uptake is heterogeneous across sectors and geographies, shaped by firm-level strategies and global model proliferation. Even when public funding seeded breakthroughs (e.g., ARPANET), corporate innovation and consumer uptake determined the spread of computing and the internet (David, 1990; Mokyr, 1992; Bresnahan & Trajtenberg, 1995).

Firms investing in technology and related skills

An analysis of ASX200 company 2024 reports showed that the vast majority of Australia's largest employers are actively investing in some form of digital technologies, including many that underlie the use of Gen AI. More than half had mentioned investments in AI technologies specifically, suggesting movement toward the implementation of AI. To the extent that such investments are part of longer-term projects, they may not be translating into observable uses of AI, or at scale.

In 2024, the vast majority of the ASX200 mentioned technology investments in their annual reports (84%) with more than half of ASX200 companies mentioning AI-related investments (57%). Those mentioning investments in AI tended to be larger companies, representing 77% of market capitalisation.

Investing in technologies that could eventually facilitate Gen AI use, including cloud infrastructure and platform services (85 companies); cybersecurity and data protection (167 companies); enterprise software and digital automation (134 companies); data analytics and business intelligence (63 companies).

Investments in AI and related technologies have taken various forms. In 2024:

- 86 companies had allocated resources to developing AI capabilities in-house, including establishing AI research teams or developing projects with internal staff.
- 61 companies had purchased rights to use existing AI technologies developed by other organisations.
- 25 companies had purchased one or more startups specialising in AI technology to integrate their capabilities, IP and talent.
- 37 companies had an official agreement with established AI technology providers to implement technology together.

The reasons for investment have also varied, focusing on different forms of productivity improvement, including improved customer service, new products, and risk management.

- For 57 companies, AI investment focused on improving interactions with customers, e.g. chatbots and customer insights tools.
- For 84 companies, AI investment focused on streamlining internal processes, reducing manual tasks and generally improving efficiency.
- For 56 companies, AI investment focused on enhancing existing offerings by creating new products or new features for existing products.
- For 35 companies, AI investment focused on identifying, assessing or mitigating business risks or adherence to regulatory requirements.

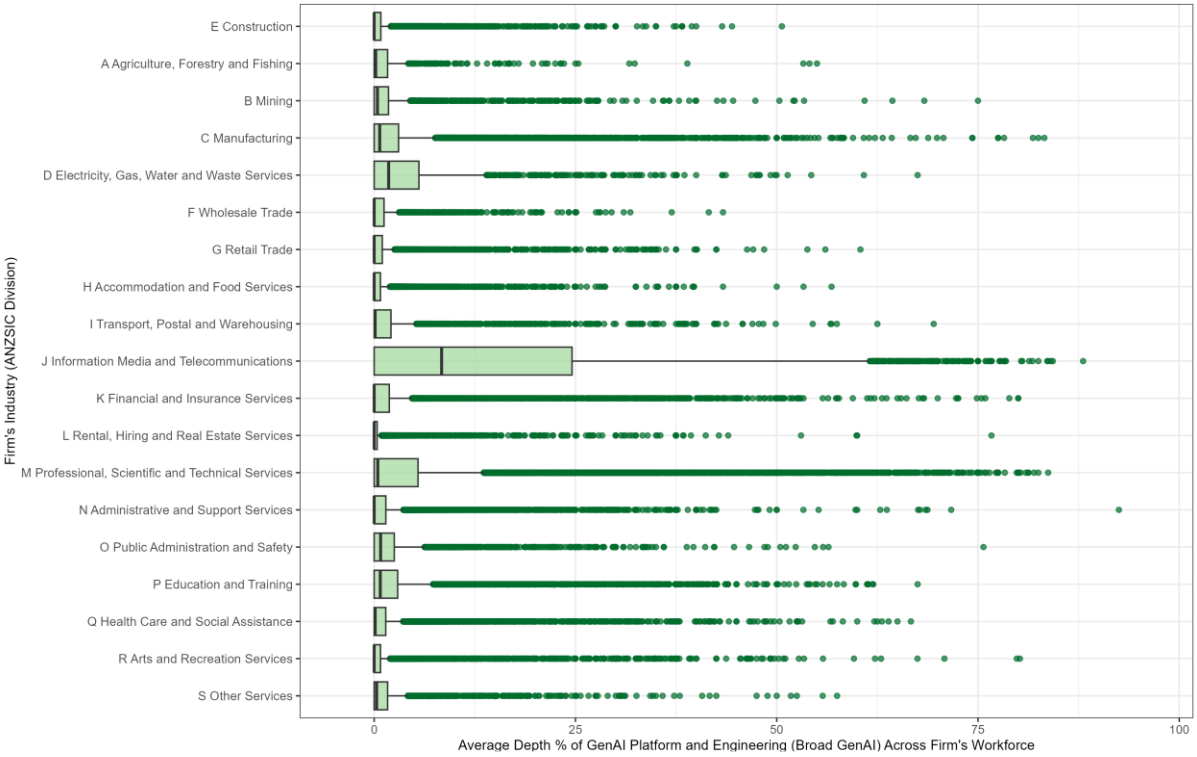
These reasons illustrate to some degree to what extent further AI use will depend on the design of internal work processes, and to what extent customer preferences will affect adoption trajectories.

As might be expected, some of the earliest and quickest adopters of technology are within the technology sector itself. These experiences show how the impact of Gen AI on a firm's workforce can develop rapidly, particularly if the use case is well-developed and straightforward to implement; and if the organisation is well-equipped to work with advanced technology.

However, experiences in the technology sector are not always easily generalised to other industries. Simple measures of adoption consistently find diverse rates of AI use and awareness across industries (National AI Centre, 2025) (FSO, 2025). Our analysis of Revelio worker profiles data shows that workers with skills relating to Gen AI platforms and engineering are concentrated in the technology sector, with varying levels and distributions in other industries (as can be seen in the relative size of the boxes in Figure 2).

Figure 2: Specialist AI skills depth varies among firms and across industries

Depth of Gen AI platform and engineering skills in individual firms by industry



Note: This chart shows the distribution of firms in each industry with regard to the depth of specialist AI-related skills in their workforce, proxied by a worker's average specialist AI skills stock as a % of total skills. The boxes show the mean and inner quartiles of firms in each industry, with individual outlier firms denoted by dots.

Source: JSA-commissioned analysis of Revelio worker profiles data.

4. Moving to AI Maturity

The extent to which firms are adaptable to changes in technology depends on several interrelated factors, including:

- Their ability to invest in and adopt technology – which frames their productive capacity
- A range of firm-level capabilities – which underpin digital and AI maturity
- The skill mix of their workforce – which underlies adoption, firm capabilities and sustained progress.

These factors help explain the variation in Gen AI adoption already observed across sectors, as well as the different paths to maturity that different firms and sectors are likely to take.

Multi-speed adoption across sectors

Multi-speed adoption is a defining feature of the Gen AI transition. The study finds consistent divergence between the market sector, where adoption is driven by competitive pressures, and the non-market sector, where organisations must meet service delivery mandates within constrained funding structures.

In non-market sectors, the incentives to adopt AI technologies for cost savings and service improvements are just as sharp as in the market sector. These organisations face pressure to deliver more or higher-quality services within fixed funding arrangements. What differs is the extent of rules and regulations that shape how the technology is deployed.

This duality suggests that many factors influencing the multi-speed nature of adoption are structural, such as regulatory frameworks, rather than incidental. This complicates efforts to define the settings needed to drive adoption across sectors, including aggregate measures.

Reaching AI maturity

The evidence demonstrates that organisational capability is a critical determinant of how Gen AI translates into performance. Adoption does not follow a single trajectory. Firms appear to operate at, and progress along, different stages of a spectrum of capability – from tentative adoption, to integration into workflows, to maturity where AI becomes embedded in strategy and governance.

This spectrum encapsulates what has been observed across the evidence considered in this Study. Adoption represents entry into experimentation, integration involves embedding AI into core processes, and maturity reflects adaptive leadership and responsible governance. At each stage, enabling factors such as leadership alignment, hybrid expertise, data readiness, and workforce skills determine whether firms move forward or stall.

A spectrum of firm-level capability

- **Adoption**. The initial stages of adoption can provide a range of lessons for the firm, even if Gen AI use is not yet fully aligned with strategy, governance and training. Adoption is often experimental and fragmented, with firms identifying opportunities, investing in infrastructure, and experimenting with pilots, which may be fragile. Evidence from the ASX200 shows that 57% of large firms mentioned AI-related investment in 2024, though many were still at exploratory stages. Crunchbase data shows concentrated investment in ICT, finance, and professional services. Challapally, Pease, Raskar, & Chari (2025) report that 95% of corporate AI pilots fail to scale, underscoring the risks of shallow adoption. Worker-led “shadow use” further complicates this stage, with around a quarter of employees using Gen AI tools unofficially, but still being critical early drivers of adoption.
- **Integration**. Organisations move from pilots to embedding AI in core workflows. This requires hybrid expertise, data readiness, and structured change management. The evidence at a high level indicates integration in Australian firms is uneven: larger ASX200 companies invest in data infrastructure and skills pipelines, while SMEs often lack the absorptive capacity. Integration depends as much on organisational redesign as on technology. Integration is the threshold where productivity gains emerge, but only where complementary investments are made (McElheran, Yang, Kroff, & Brynjolfsson, 2025).
- **Maturity**. At maturity, AI use would be scaled and governed strategically and responsibly. Adaptive leadership, cross-functional hybrid expertise, and robust data systems would underpin sustained performance in the firm. Maturity is not a steady state but a dynamic capacity to adapt as technologies evolve. Early evidence suggests it is concentrated in frontier sectors, such as ICT, finance and professional services, also where firms are able to mobilise resources, restructure, and manage risks.

At each stage, sectors, organisations and firms would exhibit varying degrees of strength across a range of enabling factors, including:

- Strategic leadership and alignment – whether AI is championed at senior levels or remains siloed.
- Workforce skills and hybrid expertise – ability to blend domain knowledge with technical capability, explored in Analysis Paper E. Personas identified in the Study (leaders, change drivers, professionals, enabled workers) map onto progression along the spectrum.
- Data infrastructure and readiness – access to secure, interoperable data systems.
- Operational integration and change management – embedding tools into processes and ensuring staff buy-in.
- Responsible governance – ethical, legal, and compliance frameworks. In health care, for example, hybrid expertise and governance are decisive; in education, workforce readiness and change management dominate.

Individual-level capability: personas as agents of adoption

The combination of skills and knowledge a sector's or organisation's workforce will need to achieve adoption depth along the spectrum will vary according to the breadth, depth and type of their engagement with AI technologies, and the role that people play around its adoption and use.

This Study identifies seven relevant personas, building on the individual-level capabilities that are explored in Analysis Paper E:

- **Gen AI leaders** – individuals whose role involves senior responsibility for decision-making regarding the adoption, deployment and governance of Gen AI within organisations. This persona includes board members, business owners, senior executives and other leadership roles such as heads of relevant departments (e.g. Head of Innovation).
- **Gen AI change drivers** – individuals whose role serves to enable adoption and implementation of Gen AI by others within a firm or organisation. This persona includes those tasked with optimising business processes and workflows; identifying, recruiting and/or developing the skills required by the firm, and ensuring the use of Gen AI is compliant with legal and regulatory requirements. Roles characterised by deep technical skills in AI are excluded from this persona and are instead captured below.
- **Gen AI professionals** – individuals with deep technical skills whose role involves developing, deploying and maintaining foundational AI models or the applications built on top of these models. This persona includes roles such as AI engineers, data scientists and other specialist technical roles.
- **Gen AI enabled workers** – individuals whose role involves working with or alongside Gen AI technologies to accomplish work tasks and processes. This persona encompasses a broad range of roles where non-specialist Gen AI skills and knowledge are applied alongside domain expertise.
- **Gen AI affected workers** – individuals whose role or function is affected by the implementation of Gen AI in other areas of an organisation.
- **Gen AI informed citizens** – other members of the public. This persona includes workers in roles where use of Gen AI is not expected, the unemployed, and those outside the labour

force. This persona may interact with Gen AI as consumers and/or require AI and digital skills to participate in work, study and the community now and in the future.

- **Gen AI educators** – individuals whose role relates to developing the skills and knowledge required by others to operate effectively in a Gen AI-enabled society and economy. This persona includes educators across formal, non-formal and informal education and training settings.

Depending on the complexity and sensitivity of the work setting, a 'hybrid expertise' (bringing together two or more of the personas above) may be required. For instance, in complex settings in the health sector AI adoption may be best championed by individuals who combine clinical expertise with technical expertise in Gen AI.

Spectrum of capability, personas as scaffolding, and sectoral variation

The spectrum of organisational capability and the individual-level personas are interdependent. The spectrum describes how firms progress in their use of AI, while the personas describe how individuals act as the agents of this progression. **Enabled workers** are often the persona associated with early adoption, **change drivers** with integration, and **leaders** and **hybrid experts** with maturity. These examples are illustrative rather than deterministic: different configurations of personas may support progression depending on sectoral context.

Sectoral variation reinforces this point. To illustrate, larger firms may be more likely to have **leaders**, **professionals**, and **educators** in place, which helps move them toward integration and maturity. Smaller firms and non-market organisations may often rely more heavily on **enabled workers** or **change drivers**, making their progression slower and more uneven, and bringing into focus the different kinds of skills and investments required across the sectors.

These patterns are indicative rather than conclusive, with the distribution of personas across sector as drivers of adoption potentially worth investigating further, as the transition progresses.

Together, the spectrum and personas provide a layered picture of capability. Firm-level or organisational maturity depends on firm-level enablers, but progression is enacted by individuals – and groups of individuals - especially when working with augmenting or 'collaborative' technologies. The personas illustrate how workers adapt, shape, and in some cases accelerate adoption.

Other critical factors influencing employer adaptability

Employer adaptability is also mediated by capital flows and institutional settings. Crunchbase data this Study considered show that financial and professional services account for the largest share of AI-related investment. SMEs without access to venture capital or internal reserves struggle to sustain projects. Non-market organisations depend on government funding streams, which are far less likely to reward digital innovation.

Governance maturity around AI is also varied. Some ASX200 firms have instituted AI ethics committees and data governance protocols. In contrast, most SMEs lack formal governance frameworks, and in care sectors, ethical risks are more likely to be pushed down to frontline workers. This divergence underscores that governance is an important systemic enabler that should be considered early, and not as an afterthought.

Employer adaptability is decisive in translating adoption into productivity. Where firms invest in hybrid expertise, redesign work, and manage governance risks, productivity effects extend

beyond efficiency gains to innovation in services and products. Where adaptability is weak, AI remains peripheral, with risks shifted onto workers or clients.

This also aligns with what we saw in the illustrative CGE scenarios, which assume productivity gains where there are no impediments to labour market mobility in a market-clearing setting.

5. Adoption over time

As the earlier analysis has highlighted, Australia is still early in its Gen AI transition. Its future adoption – both its extent and pace - and the degree to which there is effective adaptation will all be shaped by how all labour market actors, including Australian governments, respond to the opportunities and challenges.

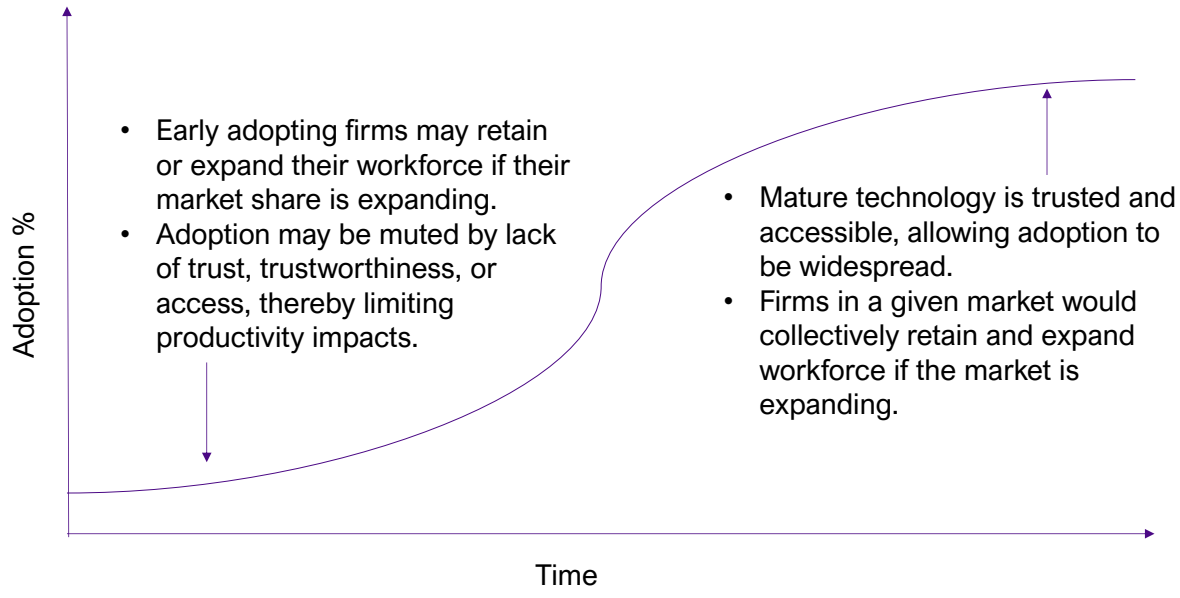
Here, we explore how different potential adoption paths could translate into different changes in the labour market. Actual adoption will be critical to monitor over time, supported by reliable, accurate, frequent and timely data. This will be important for understanding future adoption and adaptation.

The effects of Gen AI at different phases of adoption

The labour market implications of Gen AI adoption will differ between early and late stages of adoption. If early adopters are able to improve productivity and increase their market share, this may have different implications for their workforce than in a more mature phase of adoption, where all competitors have adopted the technology (Figure 3).

The implications for displacement, or the extent of labour market disruption, are particularly difficult to assume at this stage. Early experiences may be more useful as examples of what could or should be done, rather than illustrations or expectations of what will be done.

Figure 3: Factors influencing Gen AI adoption and employment will likely vary over time



Through different phases of adoption, there will be interactions between the quality of technology; the degree of trust people have in the technology; the extent to which people use the technology; and productivity.

It is unclear how quickly these factors will evolve or how the adoption of Gen AI will unfold. As such, while technologies may become standard practice in the long term, the medium term may still be characterised by leaders and laggards.

Gen AI adoption through task-based modelling

The Computable General Equilibrium (CGE) analysis developed for this Study illustrates how the pace and depth of Gen AI adoption may affect employment across industries and occupations. This took the form of CGE scenarios, which were designed to be illustrative rather than predictive: they impose a stylised adoption path, with full uptake within 25 years (a generation), and hold many factors constant.

Rather than assuming an exogenous productivity uplift, the scenarios illustrate how automation and augmentation reduce the labour input for certain tasks and reallocates resources across the economy, allowing productivity effects to emerge endogenously. This approach connects technology adoption to changes in task composition rather than to an assumed shift in efficiency.[6]

Several simplifications are important to note. Adoption rates and final levels are imposed mechanically rather than derived from firm behaviour; there is no explicit cost for AI technology; labour markets are assumed to clear even in public services; and the model does not distinguish between automation and augmentation based on cost or regulation.

In addition, the ‘adjustment’ and ‘recovery’ phases identified in the scenarios are modelling constructs rather than predictions of a real-world cycle or phases. Real labour markets may adjust in more continuous or intermittent ways, and the timing of peaks and troughs will depend on a broad range of factors outside the model, such as adaptation, institutional frictions and policy interventions. Consequently, the results show how employment trajectories may diverge from the base case scenario used in the 2024 JSA Employment Projections, under different adoption pathways – they do not seek to come up with specific forecasts of job destruction or job creation.

Three illustrative scenarios for adoption

Gen AI adoption alters not just which jobs exist but how tasks within jobs are performed. The three illustrative scenarios explore the share of tasks in the labour market that are augmented by AI, automated and manual (that is, neither augmented or automated).

- In the ‘simultaneous adoption’ case (Scenario 1), augmentation and automation expand together, steadily reducing manual tasks across sectors. Under this scenario, augmentation and automation would reach 50% of the full potential Gen AI use (as defined by the exposure analysis) at 8 years.
- In the ‘non-market lag’ case (Scenario 2), market sectors adopt AI earlier, so augmented and automated task shares rise sooner in industries like finance, manufacturing and retail, but public services, such as health, education and administration, rely on manual tasks for

[6] The model we used adapts the production-function framework developed by Acemoglu and Restrepo in 2021, treating AI as a task-displacing technology. Details will be released at Technical Release.

longer. Under this scenario, augmentation and automation in the non-market sector would reach 50% of the full potential use by 12 years, compared to 8 years in the market sector.

- In the ‘augmentation first’ case (Scenario 3), augmented tasks increase rapidly from the mid-2020s as workers use copilot tools and assistants, while automation arrives later. Manual tasks decline more gradually in the 2030s. Under this scenario, augmentation occurs faster (reaching 50% of the full potential use by 5 years) than automation (reaching 50% of the full potential use by 10 years), to provide an illustration of different effects from augmentation and automation through adjusting their respective timing.

These patterns all illustrate where AI complements labour and where it may substitute for it.

Importantly, any assumptions around timing in these models are that – assumptions. It is important to note that neither JSA or VU are forecasting that these adoption rates would necessarily occur by these dates, but they illustrate how change could progressively occur in the labour market, as the exposure of tasks to potential augmentation and automation progressively translate into changes for occupations.

Employment adjustments under different adoption pathways

All three illustrative scenarios assume eventual full adoption of AI by the same point (within 25 years) but assume different pacing and sequencing of adoption. The table below summarises key parameters and impacts relative to the base case.

Table 2: Key parameters in CGE modelling across three illustrative scenarios

Dimension	Scenario 1: Simultaneous adoption	Scenario 2: Non-market lag	Scenario 3: Augmentation first
Adoption assumptions	100% adoption of AI in 25 years across all sectors	100% adoption of AI in 25 years, with delayed adoption for specified non-market sectors	100% adoption of AI in 25 years; augmentation reaches widespread use earlier than automation (mode-based sequencing)
Adoption velocity assumptions	Medium; automation and augmentation progress together across sectors	Market sectors adopt at baseline speed; non-market sectors lag by ~5 years	Fast initial augmentation; automation lags; adoption curves staggered by mode but not by sector
Adjustment pattern observed	Sharp mid-transition dip with rebound by 2050; contraction and recovery coincide across sectors	Milder mid-transition dip; market recovery ahead of non-market; second dip in non-market sector smaller	Less pronounced mid-transition dip; early augmentation cushions impacts; later automation still causes adjustments
Occupational exposure (high automatable)	Clerical and routine office roles show reduced employment growth	Hospitality workers, personal service & sales support see the largest reductions in employment growth in market sectors	Mid-skill automatable roles see a later drop when automation arrives (after 2035)
Occupational exposure (high augmentable)	Some clerical and administrative occupations benefit modestly from augmentation	Clerical and administrative roles with high augmentable task shares show pockets of growth	Clerical, sales, care and education occupations gain earlier; employment growth rises in care & education sectors
Observed industry effects (greatest decline)	Public administration, financial services, retail, professional services, real estate	Retail trade, public administration & safety, finance & insurance, professional services, real estate	Delayed automation reduces early declines; later reductions in employment growth are more sector-wide
Observed industry effects (greatest growth)	Construction, accommodation & food, manufacturing, education & training, agriculture	Construction, accommodation & food, manufacturing, education, agriculture	Care, education, administration and service roles gain earlier and maintain higher employment growth

Source: JSA analysis of illustrative Computable General Equilibrium scenarios conducted with Victoria University.

Industry outcomes across scenarios after full potential is realised

The table below summarises the effect on employment in selected industries, relative to the base case across the three adoption pathways, after the full potential of Gen AI, as reflected in the exposure scores, has been realised by 2050.

‘Stronger’ indicates employment growth above the base case; ‘Weaker’ indicates employment growth below the base case; ‘Moderately weaker’ indicates a smaller fall relative to more automated scenarios (and the reverse for ‘Moderately stronger’).

Table 3: Implications of Gen AI on employment in CGE modelling across three illustrative scenarios

Industry	Scenario 1 Outcome: relative to the base case projection	Scenario 2 Outcome: relative to the base case projection	Scenario 3 Outcome: relative to the base case projection
Agriculture	Stronger relative to base	Stronger relative to base	Stronger relative to base
Manufacturing	Stronger	Stronger	Moderately stronger (augmentation early, automation later)
Construction	Stronger	Stronger	Stronger (early augmentation benefits)
Accommodation & Food	Stronger	Stronger	Stronger (early augmentation benefits)
Retail trade	Weaker relative to base	Weaker relative to base	Moderately weaker (augmented early, automation later)
Public administration & safety	Weaker	Weaker	Moderately weaker (augmented early, automation later)
Finance & insurance	Weaker	Weaker	Moderately weaker (augmented early, automation later)
Professional & technical services	Weaker	Weaker	Moderately weaker (augmented early, automation later)
Real estate	Weaker	Weaker	Moderately weaker (augmented early, automation later)
Education & training	Stronger	Stronger	Stronger (early augmentation)
Health & social care	Moderately stronger	Stable to moderately stronger (delayed adoption)	Stronger (early augmentation)

Source: JSA analysis of illustrative Computable General Equilibrium scenarios conducted with Victoria University.

Focusing on adoption over the next 15 years

Although the model provides projections out to 2050, the 2025–2040 window is far more relevant for policymaking. Gen AI technologies, regulatory frameworks and adoption patterns will evolve quickly, so looking beyond 15 years may be less useful for informing Australia's approach to the immediate opportunities and challenges.

Across scenarios, employment trajectories diverge from the JSA base case during this medium term period.

- In Scenario 1 the adjustment dip extends through the 2020s and early 2030s before growth moves above the baseline.
- Scenario 2 cushions the early decline but the rebound would be delayed: employment growth remains below the base case until the late 2030s.
- Scenario 3 keeps growth close to the baseline in the 2020s thanks to early augmentation; a dip occurs when automation arrives in the mid-2030s but employment growth catches up by 2040.

These patterns suggest that decisions taken in the next decade and a half, including those related to skills, AI governance and labour market support, will determine whether the rebound from when labour market disruption is greatest is delayed or accelerated. The timing and shape of recovery will also depend on factors outside the model, such as organisational choices, macroeconomic conditions and policy interventions.

Skills, adaptation and recovery

In assuming in the CGE modelling that the skills system remains constant over time, we are inevitably exaggerating the duration and depth of any early negative impacts and understating the potential for early positive impacts. Actual recovery is not just about employment catching up to the base case; it involves redeploying workers into new roles, building new occupations and raising productivity. Targeted investment in training and education can shorten the adjustment period and increase the share of work that is augmented rather than automated.

In sectors where firms can choose between automating and augmenting tasks, the availability of skilled labour may tilt the balance towards augmentation, sustaining employment growth. Conversely, without new skills, workers may struggle to find roles in growing industries such as health care, education, construction and digital services.

One important limitation of the model is that it does not capture adaptation, understood here as how firms and workers change tasks, create new roles or develop new work structures in response to AI. This unavoidable omission is significant: analysis elsewhere suggests that adaptation could offset some of the displacement effects of automation and reshape the transition pathway. The scenarios therefore provide a baseline view of how employment growth might evolve if adoption occurs without significant adaptation.

The scenarios also assume investment in labour productivity is unchanged. They show where employment diverges from the base case, not how productive workers become once redeployed. Their value lies in highlighting where early support and skills investment could make the biggest difference.

Implications for workforce planning

The CGE scenarios present a structured way to consider how Gen AI adoption might affect employment growth relative to the JSA employment projections. The impacts are uneven: employment growth in routine clerical and lower skilled service roles lags, while growth in interpersonal, care-based and manual roles stays closer to or above the baseline. The timing and magnitude of divergences depend on the rate and sequencing of adoption and differ between market and nonmarket sectors.

For policymakers and workforce planners, the scenarios underscore the importance of monitoring adoption signals and digital maturity across sectors. They highlight the need to build dynamic workforce planning capabilities, including scanning for emerging roles, anticipating

where employment growth may fall below baseline projections, and targeting support to groups and industries most affected.

Crucially, the scenarios show that outcomes are not predetermined. By investing in the skills system and supporting firms to adopt augmentation tools, Australia can accelerate recovery and ensure that workers share in productivity gains. CGE modelling is one useful input into this strategic planning; it helps us to frames the scale and sequencing of change. Coupling it with continuous monitoring, an understanding of adaptation pathways and flexible policies will enable Australia to navigate the Gen AI transition with foresight and resilience.

6. Conclusion

Gen AI adoption in Australia is progressing along multiple, overlapping dimensions. Depth of adoption ranges from individual-led experimentation to organisation-wide integration, while sectoral pathways diverge between market and non-market domains, and between complex and non-complex settings. Organisation-level capability guides progression from adoption to integration to maturity, shaped by leadership, data systems, and hybrid expertise. Individual personas act as agents of this progression, driving uptake in different ways across contexts.

These patterns of divergence and diversity are likely structural in some cases, reflecting characteristics specific to, and producing uneven trajectories across sectors and firms. This highlights the importance of adaptability, governance settings and workforce capability in shaping how productivity gains are realised and shared.

Findings from the Overarching Paper that this analysis supports

Finding 2: Adoption and adaptation will determine how Gen AI's labour market impacts and its potential are realised

The quality of adoption and implementation will be instrumental in achieving the benefits of labour-augmenting tools. Implementing Gen AI requires adaptability for both employers and the workforce.

More broadly, adaptability and dynamism in the labour market (and the economy) will dictate how any saved time could be redeployed and reallocated. This will ultimately determine how the use of Gen AI influences employment growth, both positively and negatively (as modelled).

Over time, the use of Gen AI and other technologies will lead to various forms of adaptation. This includes changes within-occupations, across occupations and with regard to working arrangements. As such, the effect of technology on the labour market will continue to evolve.

Considering "first order" adaptation – where automation and augmentation may cluster tasks – can help identify where specialised or hybrid roles could emerge within existing occupations and roles.

Given the complexity of dynamics of Gen AI use, a wide range of labour market outcomes is possible in the medium term (around 15 years, for the purposes of this Study). This will require regular monitoring, to inform effective strategy and planning across the labour market and skills system.

Finding 3: Adoption is advancing in digitally mature industries and sectors, slower in the non-market sector, and broadly well below its exposure potential.

Australia's Gen AI adoption is accelerating in digitally mature industries and large firms. This reflects a multi-speed transition, where uptake is shaped by sectoral readiness, organisational capability, and risk tolerance.

Advanced adoption is concentrated in technology, finance, and other knowledge-intensive sectors, where firms possess the data infrastructure, technical expertise, and strategic intent to integrate Gen AI at scale. In these sectors, larger organisations have been able to leverage investments, expertise, and experimentation, applying Gen AI for productivity gains in areas like software development, customer service, and administrative workflows.

The non-market sector, including government, health, education, and social services, faces higher barriers to adoption despite high exposure potential. These sectors are slower to adopt due to complex outcomes, coordination and implementation risks, ethical and regulatory constraints, and more limited digital maturity.

Across the economy, adoption in Australia is tracking well below its exposure potential.

Finding 4: The multi-speed adoption and transition has important implications.

The multi-speed adoption risks widening digital divides and investment gaps between industries and firm sizes, and between market and non-market domains.

Multi-speed capital investment in digital and AI technologies can also lead to workforce capability gaps across the sectors.

Targeted technology and workforce capability uplift can help close these gaps and manage future disruptions, especially where readiness is low but exposure is high.

Because adoption is complex in some sectors, coordination and stewardship are needed to guide (but not dictate) the transition.

Finding 5: Shadow use shows workers driving adoption and experimentation.

The rise of shadow use, where workers adopt Gen AI tools without formal organisational approval, demonstrates that the workforce is actively driving bottom-up innovation in some sectors. While this signals initiative and experimentation, it also shifts governance and risk management responsibilities onto individuals.

Without responsive organisational strategies, shadow use may lead to uneven implementation and missed opportunities for structured capability building.

Finding 6: Early evidence of productivity impacts is mostly positive.

Early experiments and workplace data from overseas show that Gen AI tools can improve productivity, particularly in routine, text-heavy tasks and among less experienced workers.

In Australia, most Gen AI users surveyed in early adopting workplaces self-report task-specific productivity gains. This has had varied effects on overall workload depending on how saved time is used.

But full-scale adoption remains limited. Many firms that are aware of Gen AI have not implemented it, and many AI-related projects do not proceed to full implementation.

Finding 9: Different ‘personas’ are being observed in Gen AI adoption

New Gen AI-related workforce personas are emerging through the transition, each requiring skills and knowledge relevant to the role they play in Gen AI adoption and use.

Relevant personas include Gen AI leaders, Gen AI change drivers, Gen AI professionals, Gen AI enabled workers, Gen AI affected workers, Gen AI informed citizens, and Gen AI educators. These personas can support the development of new hybrid capabilities within organisational settings.

Finding 15: Firms progress through a spectrum of digital and AI capability – from adoption, to integration, to maturity.

Organisations move through three broad stages along a spectrum of capability:

- Adoption: identifying relevant AI opportunities, investing in infrastructure, and building foundational workforce skills.
- Integration: embedding AI into workflows, supported by data readiness, hybrid expertise, and change management.
- Maturity: scaling AI use, applying adaptive leadership, and embedding responsible governance.

At each stage, organisations demonstrate varying depth and breadth across a set of enabling factors: strategic leadership and alignment, workforce skills and hybrid expertise, data infrastructure and readiness, operational integration and change management, as well as responsible AI governance.

Organisations follow different paths to maturity, shaped by sectoral context, workforce composition, and organisational priorities. This also applies to sectors.

Early adopters offer insights into implementation, but readiness is also shaped by broader economic conditions, regulatory settings, and the ability to redesign work and invest in skills as well as technology.

C. Adaptation

Adaptation from technology adoption

Forms of adaptation

Adaptation potential of Gen AI

1. Introduction

As technological advances are harnessed into new production processes, various forms of adaptation (including the re-organisation of work) are a normal feature of changes in the labour market. These effects can be profound and widespread, particularly when involving general-purpose technologies. For example, when electricity was introduced, it was first integrated into existing plants and factories but in subsequent periods it led to the major redesign of plants and factories (to best harness electricity), to new products and processes, and ultimately, to the next waves of innovation in work and output (Agrawal, Gans, & Goldfarb, 2022).

In this early stage of the Gen AI transition, the adaptation effects of Gen AI are not easily identifiable in data. For example, adaptation effects are not fully captured in either the exposure analysis (Analysis Paper A) or economy-wide illustrative scenarios (Analysis Paper B) undertaken for this study. Considering adaptation requires a different approach.

This paper will demonstrate why adaptation effects matter, with reference to evidence of past adaptation in the context of the Australian labour market. In doing so, it provides insight based on past examples into how the adaptation effects of Gen AI – though difficult to predict with certainty – are likely to have substantial implications for our labour market and skills system.

This paper will then explore the adaptation potential associated with Gen AI as an emerging general-purpose technology. This will include presenting a theoretical indication of potential occupation change related to Gen AI, as well as considering the implications of the adaptation potential of Gen AI for labour market and skills system actors.

2. Adaptation in the labour market

Changes within the skill and task content of jobs

Analysis of job advertisements data is well suited for investigating adaptation effects within occupations in a way that is dynamic, current, and granular. Accordingly, we consider adaptation through an analysis of job advertisements data (Box 1). Results from this analysis for select occupations are presented below as illustrative real-world examples of observable adaptation effects.

Box 1 Exploring adaptation effects through online job advertisements

Our approach to exploring adaptation effects through Australian online job advertisements involves two main steps.

- First, capturing the prevalence of specific skills in online job advertisements for select occupations in 2012 and 2024, using the Lightcast skill taxonomy.
- Second, comparing the composition of skills demanded by employers for select occupations between the two periods, enabling us to identify: a) which skills have substantially risen (or fallen) in demand; and b) which skills are listed in 2024 which were not listed at all in 2012 and vice-versa.

While this approach does not directly measure changes in production processes and the reorganisation of work, by examining which specific skills are rising and falling in demand we can draw reasonable inferences about changes within in a given occupation.

We then extend on the analysis by examining the implications of adaptation for the skill level of the occupation. This involves:

- First, assigning each unique skill in the Lightcast skill taxonomy as skill level based on the weighted average of the ANZSCO Skill Level of the occupations in which that skill is demanded in job advertisements.
  - For example, if a particular skill is listed only in Skill Level 1 occupations then its skill level would be 1. Whereas if 80% of occupations listing a particular skill are Skill Level 2 occupations and the other 20% are Skill Level 3 occupations, the skill level for that skill would be 2.2.
- Second, analysing select occupations to determine whether the newly appearing skills in online job advertisements since 2012 have tended to increase the skill complexity of the occupation.

Arts and Media Professionals

Focusing on Arts and Media Professionals as an example, ‘Communication’ is the skill that has grown the most in percentage point terms for this group of occupations, appearing in 43% of job ads in 2024 compared to 32% in 2012.

Considering the 14 high-growth skills which grew by at least 5 percentage points, we can see broad groups of skills that highlight some important patterns.

- First, **many high-growth skills relate to how workers apply digital skills in a domain-specific context**. High-growth skills with an explicit connection to digital technology include Social Media, Search Engine Optimisation and Digital Content. This may signal the growth of digital arts and media focused specialisations as production processes evolve in response to the digital transformation. The other high-growth domain expertise skills for Arts and Media Professionals (Editing, Writing, Content Creation and Marketing) may also commonly involve the application of digital skills.[1]
- Second, **the remaining high-growth skills are human skills**. The remainder of the 14 high-growth skills for Arts and Media Professionals were Communication, Detail Oriented,

[1] For example, the ABC (2023) is transitioning to a digital-first approach to its content and operations.

Teaching, Mentorship, Leadership, Ability to Meet Deadlines. A few of these skills (Teaching, Mentorship, Leadership) are related to the management, supervision or development of others.

Of skills that were not listed at all for Arts and Media Professionals in 2012, the most common in 2024 were TikTok, Canva, Numeracy and Artificial Intelligence. This suggests that technological developments were a key driver behind newly appearing skills.

The weighted average skill level of newly appearing skills for Arts and Media Professionals (1.63) skews more heavily towards the highest skill level than the result for all skills for this occupation (1.77). This may point to effects of skills-biased technological change, with the diffusion digital technologies in recent decades typically considered to be complementary to those with higher skills (discussed in more depth in Analysis Paper E).

Business, Human Resources and Marketing Professionals

Between 2012 and 2024, there were 11 high-growth skills (i.e. skills that grew in prevalence in online job advertisements by at least 5 percentage points) for Business, Human Resources and Marketing Professionals. These high-growth skills were:

- Detail Oriented
- Problem Solving
- Communication
- Data Analysis
- Leadership
- Operations
- Decision Making
- Innovation
- Continuous Improvement Process
- Interpersonal Communication

This set of high-growth skills may indicate a trend towards routine-biased technology change, with computer-based technologies historically tending to substitute for human labour in undertaking routine cognitive tasks while also complementing workers performing non-routine cognitive tasks.[2]

> *Because repetitive, predictable tasks are readily automated, computerisation of the workplace raises demand for problem-solving and communications tasks such as responding to discrepancies, improving production processes, and coordinating and managing the activities of others (Autor, Levy, & Murnane, 2003).*

As with Arts and Media Professionals, the weighted average skill level of skills that have newly appeared since 2012 for Business, Human Resources and Marketing Professionals (1.48) skews more heavily towards the highest skill level than the result for all skills for this occupation (1.83).

This result was predominantly driven by newly appearing technology related skills such as Power BI, Canva, TikTok, and Microsoft Azure.

Secretaries

Between 2012 and 2024, there were 21 high-growth skills for Secretaries where the prevalence in online job advertisements grew by at least 5 percentage points. As with earlier groups of occupations, we see broad groups of skills that highlight some important patterns.

[2] The concept of routine-biased technological change is discussed further in Analysis Paper E.

- First, **multiple high-growth skills relate to the efficiency of business operations and project management**. This includes skills such as Coordinating, Business Support Systems, Operations, Project Management, Governance, Executive Information Systems and Scheduling. This may reflect a shift in the role of Secretaries towards more complex or strategic organisational tasks as digital tools and technologies streamline routine administrative tasks such as file management.
- Second, **multiple high-growth skills are human skills**. These include Communication, Problem Solving, Planning, Leadership, Time Management, and Detail Oriented.

The weighted average skill level of skills that have newly appeared since 2012 for Secretaries (1.92) skews more heavily towards the highest skill level than the result for all skills for this occupation (2.26).

Software skills such as Xero, Microsoft Teams, Microsoft Office 365 and Google Workspace feature prominently among newly-appearing skills for Secretaries.

Job hybridisation: Secretaries and General Clerks

Job hybridisation' refers to the process of jobs becoming more similar over time, with the potential for previously distinct jobs to merge. Where it occurs, job hybridisation may enable workers to move between relevant occupations more easily.

In 2012, the top 10 most-demanded skills for Secretaries and General Clerks respectively included 4 skills in common (Management, Communication, Detail Oriented, and Microsoft Office), with the occupation Secretaries being distinguished by the higher prominence of skills such as Typing, Billing, and Filing (Table 1).

By 2024, the two occupations included 8 skills in common across the top 10 skills, including all of the same top 5 skills (Table 2).

Table 1: In 2012, top skills for Secretaries and General Clerks varied considerably

Top 10 skills in online job advertisements for Secretaries and General Clerks, 2012

Secretaries - 2012	General Clerks - 2012
Management	**Communication**
Communication	Customer Service
Typing	Administrative Support
Detail Oriented	Data Entry
Billing	**Management**
Organisational Skills	**Detail Oriented**
Lawsuits	Computer Literacy
Filing	Administrative Functions
Microsoft Office	Web Navigation
JavaScript (Programming Language)	**Microsoft Office**

Note: Bold text represents skills in common across the top 10 skills of both occupations.

Source: JSA analysis of Lightcast job advertisement data.

Table 2: By 2024, top skills for Secretaries and General Clerks had largely converged

Top 10 skills in online job advertisements for Secretaries and General Clerks, 2024

Secretaries - 2024	General Clerks - 2024
Communication	**Communication**
Management	**Customer Service**
Detail Oriented	**Administrative Support**
Administrative Support	**Detail Oriented**
Customer Service	**Management**
Coordinating	**Administrative Functions**
Administrative Functions	**Microsoft Office**
Microsoft Office	Operations
Business Support Systems	Data Entry
Time Management	**Time Management**

Note: Bold text represents skills in common across the top 10 skills of both occupations.

Source: JSA analysis of Lightcast job advertisement data.

In part, the increasing similarity between the two occupations has been driven by a decline in the share of online job advertisements for Secretaries listing skills that previously distinguished the occupation from General Clerks such as Typing (down 25.8 percentage points), Billing (down 12.9 percentage points) and Filing (down 2.3 percentage points).

Welfare Support Workers

Between 2012 and 2024, there were 10 high-growth skills for Welfare Support Workers where the prevalence in online job advertisements grew by at least 5 percentage points.

- **Multiple high-growth skills for Welfare Support Workers are certification skills**. This includes the highest growing skill in the occupation (Working with Children Check) as well as other certification skills (Cardiopulmonary Resuscitation (CPR) Certification and First Aid Certification). This may indicate a greater emphasis from governments and/or employing organisations on ensuring workers have certified skills relevant to the health and safety of those they are supporting.
- **The two highest-growing non-certification skills are related to mental health and wellbeing**. The two highest-growing non-certification skills for Welfare Support Workers are Trauma Care (up 12.1 percentage points from 0.8% to 12.1%) and Mental Health (up 12.1 percentage points from 6.0% to 14.7%). This may indicate increased demand for Welfare Support Workers specialising in mental health in line with greater overall demand for mental health support and services.
- **Multiple high-growth skills are human skills**. High-growth skills for Welfare Support Workers include Empathy, Interpersonal Communication and Resilience.

The weighted average skill level of skills that have appeared since 2012 for Welfare Support Workers (2.06) is broadly consistent with the result for all skills for this occupation (2.08).

While some explicitly technology-related skills such as Smartphone Operation are included among the newly-appearing skills for Welfare Support Workers, technological change does not appear to be a primary driver of adaptation in this occupation. For example, the most prevalent

newly-appearing skill – with more than twice the growth of the next most prevalent newly-appearing skill – is Trauma Informed Approaches. This is consistent with the increased demand for mental health-related skills identified above.

As the example of Welfare Support Workers illustrates, technological change is not the only catalyst of adaptation in the labour market. Instead, adaptation may occur as a result of a range of factors including from social, demographic and regulatory changes.

Adaptation effects: job specialisations, hybridisation and emerging trends

The select occupations above provide real-world examples of within-occupation adaptation effects. These effects can manifest in multiples ways, such as:

- **Job specialisations**: Specialisations can emerge within an occupation as adaptation effects increase the prominence of a subset of specialised tasks within an occupation (e.g. digital focused specialisations among Arts and Media Professionals)
- **Job hybridisation**: As existing jobs become more similar – and potentially merge – as a result of adaptation effects (e.g. increased similarity between the skill sets of Secretaries and General Clerks)
- **Emerging trends**: Common directions of change in the skill and task content of jobs (e.g. increased demand for human skills, skill-biased technological change, and routine-biased technological change).

Changes within the skill and task content of jobs have a range of implications for the labour market and skills system. These include:

- the need for education and training pathways to keep pace with changes in relevant occupations and build the resilience of graduates to future adaptation
- the need for workers already in changing jobs to update their skills over time
- the emergence of demand for new combinations of skills and knowledge, and
- the potential for changes to the scope and complexity of workers' responsibilities.

Changes in the composition of the labour market

Adaptation effects of technology adoption contribute to changes in the composition of the labour market, including by creating new occupations and shaping demand for existing occupations in the new production processes enabled by technology. The widespread diffusion of information and communication technology (ICT) in the Australian economy over recent decades provides an example of how adaptation effects can lead to changes in the composition of the labour market.

Creation of new occupations

The diffusion of ICT in the Australian economy has created demand for labour in new tasks and occupations. Most conspicuously, this includes tasks directly related to:

- managing ICT functions and activities within organisations (e.g. ICT Managers)
- performing analytical, conceptual and practical tasks that support the efficient and secure provision of ICT services (e.g. ICT Professionals)

- supporting the development and maintenance of computer infrastructure and software, including diagnosing and resolving technical problems (e.g. ICT Technicians and Support Officers)
- selling ICT-related goods and services (e.g. ICT Sales Assistants).

ABS Labour Force Survey data shows that employment in the occupation ICT Professionals alone increased by nearly 360,000 employed persons (or 751%) between August 1986 and May 2025. This represents the second highest percentage growth over the past four decades among the 43 occupations at the 2-digit level, behind only Carers and Aides. Over this period, ICT professionals went from 0.7% of employed people in 1986, to 1.7% by 2006 and 2.8% by May 2025.

This strong growth in ICT Professionals, relative to almost all other occupations, has contributed to an overall trend in growth in Skill Level 1 and non-routine cognitive occupations, which are now the dominant types of job in the Australian labour market.

Beyond these explicitly ICT-related occupational categories, new occupations have also emerged as a result of changes that the diffusion of ICT enables. For instance, the occupations Data Analyst and Data Scientist were added as part of the 2022 ANZSCO update, informed by evidence from National Skills Commission (2020) that emerging skills in using data visualisation applications and big data analytics had sufficiently changed the nature of some traditional statistician roles to warrant the creation of new occupations.

The reinstatement of labour in new tasks – and potentially new occupations – is a key counterbalance to the displacement effects of automation which increases demand for labour and the labour share of national income (Acemoglu & Restrepo, Artficial intelligence, automation and work, 2019).

Shaping demand for existing occupations

Technology can impact demand for labour in tasks through multiple effects, including:

- **displacement effects**: where demand for labour decreases in tasks that are automated
- **productivity effects**: where demand for labour may increase in non-automated tasks
- **reinstatement effects**: where new tasks are created in which human labour has the competitive advantage over technology (National Academies of Science, Engineering, and Medicine, 2024).

ABS Labour Force Survey data reveals that only 6 out of 43 occupations at the 2-digit level experienced an absolute decline in employment between August 1986 and May 2025. The diffusion of ICT is likely to have played a notable role for two of these occupations: Personal Assistants and Secretaries, and Clerical and Office Support Workers.[3] Collectively, employment in these two occupations declined by over 138,000, from nearly 306,000 employed persons in August 1986 to around 167,000 employed persons in May 2025. Over this period, they went from 4.4% of employed people in 1986, to 2.6% by 2006 and 1.1% by May 2025.

The contraction of employment in these two occupations may indicate that displacement effects at the task level have outweighed productivity and reinstatement effects. However, adaptation effects – and the reorganisation of work across occupations – may also have played a role.

[3] The other four occupations with declining employment over this period were Farmers and Farm Managers, Machine and Stationary Plant Operators, Factory Process Workers, and Farm, Forestry and Garden Workers.

For instance, filing and file management was previously a core task performed by Secretaries and one of the top 10 skills listed in online job advertisements in 2012. The diffusion of ICT – and a digital-first approach to filing taken across a broad section of the labour market – has not reduced the amount of filing taking place. However, the streamlining of file management through ICT has enabled a range of occupations to undertake filing tasks as a small component of their jobs and reduced the extent to which filing is a core task concentrated in any one occupation. It has also likely contributed to freeing up the capacity of Secretaries to take on more strategic coordination tasks and responsibilities.

The evolution of the task and skill content of jobs is one level at which skill-biased and routine-biased technological change is evident. Another level at which these trends can be observed is across occupations as production processes within an industry adapt in order to harness technology.

Within-industry changes towards higher skilled and non-routine cognitive work have been evident across the most heavily computerised industries – such as Professional, Scientific and Technical Services, Financial and Insurance Services, Public Administration and Safety, and Information, Media and Telecommunications. While these trends are not solely attributable to technological change, the interplay between the displacement, productivity and reinstatement effects as technology has been harnessed into production processes in these industries are likely to have been a significant contributor to these trends. (Figure 1).[4]

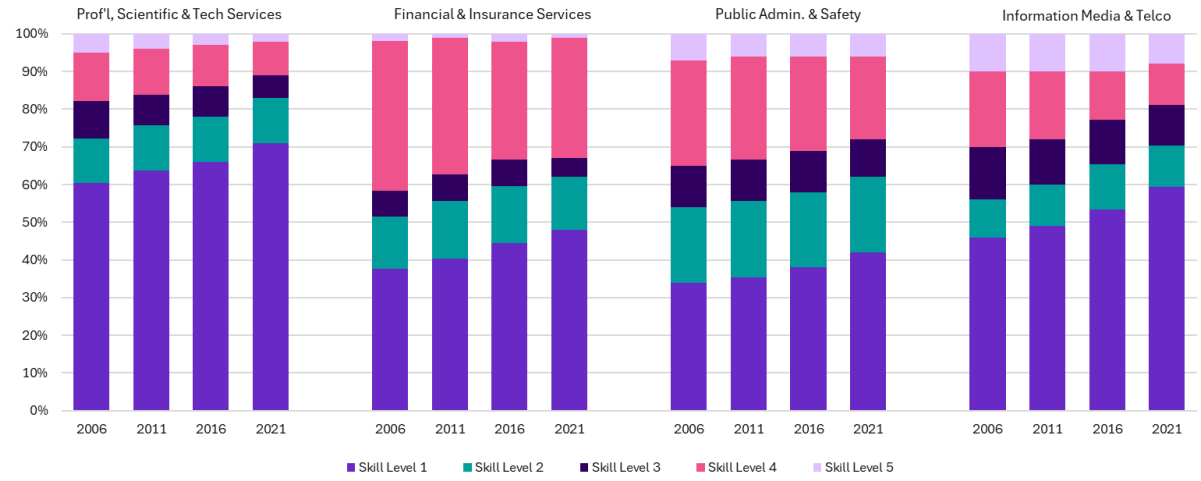
While these trends are not solely attributable to technological change, the interplay between the displacement, productivity and reinstatement effects as technology has been harnessed into production processes in these industries are likely to have been a significant contributor to these trends.

[4] Per the ABS Australian System of National Accounts, these four industries have the highest capital stock of computer software.

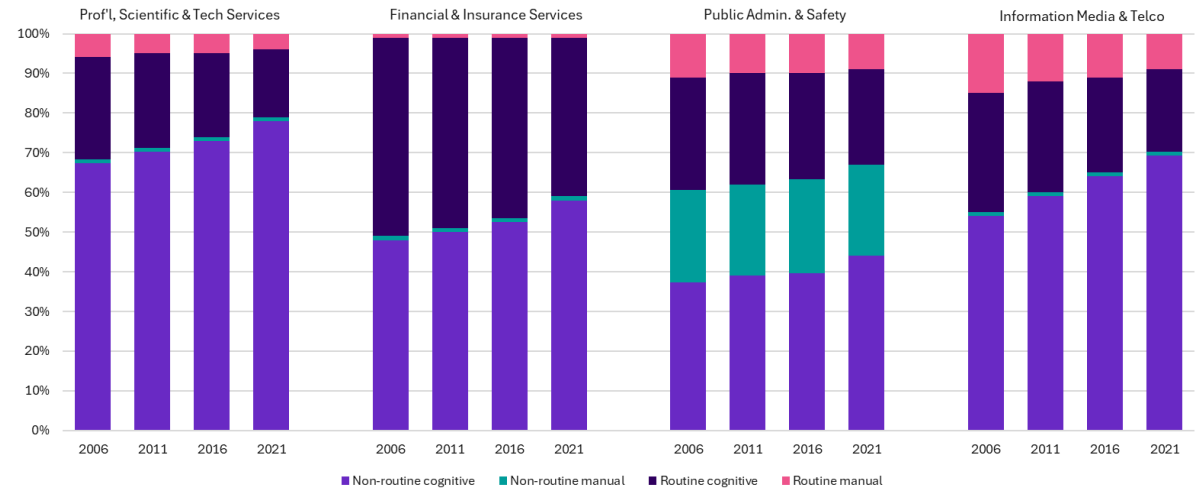
Figure 1: Computerised industries have trended over time toward higher skilled and non-routine work

Share of employment by skill level (Panel A) and job type (Panel B) by select industries, 2006-2021

Panel A



Panel B



Source: ABS Census of Population and Housing, 2006, 2011, 2016 and 2021.

Changes in work arrangements

Adaptation effects from technology are not limited to changes to the skill and task content of jobs. Adaptation effects can also disrupt traditional working arrangements and forms of employment, as we have seen with the emergence of digital platform work.

> *Such platforms are leading to changes not just to the organisation of enterprises and work processes but in many cases to the relationship between workers and businesses as well (International Labour Organization, 2021).*

Digital platform work is defined in various ways internationally. The ABS (2023) defines digital platform work as 'the provision of fixed duration labour services, in the form of tasks/jobs which are accessed by the worker through digital platforms and are paid per unit of work delivered through the same platform.'

Applying this definition, ABS data on working arrangements in Australia show that, in 2023-24, 1.2% of employed people had undertaken digital platform work in the last 12 months.

While a relatively low percentage at a whole-of-population level, digital platform work has a significant observable impact in the task types where it is most prevalent, i.e. delivering food

and other goods, and providing personal transport (e.g. rideshare services). While these task types collectively account for over 80% of digital platform work in Australia, digital platform work is also present in relation to other activities including professional services, home maintenance, caring for people or minding children.

Changes in work arrangements and forms of employment made possible through technological change such as digital platform work present opportunities and challenges for workers and businesses.

- For workers, digital platform work may provide flexible working hours or locations, an opportunity to supplement income from other sources, or an avenue to earn money where finding other work is difficult. Challenges for digital platform workers can include limited job security and labour representation, difficulty accessing enough work, and worker wellbeing concerns associated with new forms of monitoring and algorithmic management.
- For businesses, opportunities in relation to use of digital platforms may include dynamic matching of labour and skills supply and demand, increased productivity, reduced costs, shorter time schedules, and improved visibility to customers. Challenges associated with digital platforms may include competition issues (e.g. due to platform monopolies or dominance), limited access to digital skills or infrastructure, high commission fees, and data security and privacy concerns.

3. Adaptation potential of Gen AI

Gen AI has potential as an emerging general-purpose technology to:

- be used in a wide range of tasks, industries and use cases
- improve over time, i.e. to become faster, more accurate and/or cheaper as the technology develops, and
- give rise to complementary innovations, facilitating deeper, ongoing changes to how work is undertaken, as the technology is further harnessed into new production processes or leads to labour being reallocated or reinstated to new tasks.

Expanding on our task-based exposure analysis (Analysis Paper A), we consider theoretically how occupational change patterns *could* occur as a result of Generative AI (Box 2). We also acknowledge that AI has the potential to lead to the creation of new roles and occupations. As the Australian Council of Trade Unions (2024) highlighted in relation to AI in their submission to the Inquiry into the Digital Transformation of Workplaces:

> *Other jobs will be created that were not previously possible – and will require dynamic training and development to ensure workers are not left behind.*

Box 2 A theoretical framework for job adaptation from Gen AI

Our method for exploring potential job hybridisation and job specialisation as a result of Gen AI is grounded in task-level analysis at the unit group level of ANZSCO (i.e. at the 4-digit level of the classification).

Our approach involves three main steps:

- First, we estimate similarity scores for occupations based on the similarity of the words in the description of their tasks (using the sentence embedding technique). All tasks are weighted equally. These similarity scores represent the baseline scenario, with a similarity score of 1 meaning the occupations are the most similar and a score of 0 meaning they are the least similar.
- Second, we investigate candidates for job hybridisation. We do this by estimating the similarity of occupation pairs with a revised weighting, with higher automation exposure tasks weighted lower to reflect potential changes in the task content of the job due to automation. Close clusters of jobs under this scenario compared to the baseline may be candidates for hybridisation.
- Third, we investigate candidates for AI-related job specialisations. In this case, tasks with higher augmentation scores are weighted higher to reflect potential changes in the task content of the job due to augmentation. Close clusters of jobs under this scenario compared to the baseline may be candidates for new AI-related job specialisations.

This approach provides a conceptual view of 'first order' adaptation – where automation and augmentation may cluster tasks – can help identify where specialised or hybrid roles could emerge within existing occupations and roles. It does not account for the creation of entirely new tasks.

Hybridisation potential

Job hybridisation refers to the process of jobs becoming more similar – and potentially merging into one – over time. Where job hybridisation occurs, it may enable workers to move between relevant occupations more easily. We explore hybridisation by weighting higher automation-exposed tasks lower to account for potential changes in the task content of jobs due to Gen AI automating certain tasks.

When we give less weight to tasks that are more likely to be automated, most jobs appear less similar to each other. This indicates that automation potential is higher in tasks that are common across many occupations, rather than the tasks which make each occupation unique. Out of the 358 occupations considered, around 40 occupations show increased similarity to other jobs under this approach.

There are two lenses through which to consider pairing occupations that may potentially be candidates for hybridisation.

- The first lens is to consider which occupation pairs have the closest similarity scores (after tasks exposed to higher automation are weighted lower). However, this approach skews heavily towards occupation pairs that are highly similar, irrespective of the impact of Gen AI, such as Middle School Teachers and Secondary School Teachers, and ICT Sales Assistants and Sales Assistants.

- Second, and more usefully in the context of the potential impact of Gen AI, to consider which occupation pairs exhibit the greatest increase in similarity if automation exposed tasks are automated.
- Table 3 presents the occupation pairs with the greatest increase in similarity scores with a score of 0.60 or above (that is, where the similarity score is above a minimum threshold that indicates hybridisation may be relevant).

Table 3: Some occupation pairs would become more similar if automation-exposed tasks are automated

Occupation pairs with greatest increase in similarity – higher automation exposed tasks weighted lower

Occupation 1	Occupation 2	Similarity score (*similarity score increase*)
Gallery, Library and Museum Technicians	Visual Merchandisers	0.75 *(+0.10)*
Inspectors and Regulatory Officers	Other Clerical and Office Support Workers	0.66 *(+0.07)*
Electronic Engineering Draftspersons, Technicians	Electronics Trades Workers	0.76 *(+0.07)*
Human Resource Professionals	Policy and Planning Managers	0.63 *(+0.06)*
Other Miscellaneous Labourers	Ticket Salespersons	0.67 *(+0.06)*
Importers, Exporters and Wholesalers	Telemarketers	0.72 *(+0.06)*
Electronics Trades Workers	Mechanical Engineering Draftspersons, Technicians	0.76 *(+0.06)*
Conference and Event Organisers	Supply, Distribution and Procurement Managers	0.71 *(+0.06)*
Gallery, Museum and Tour Guides	Security Officers and Guards	0.60 *(+0.06)*
Gallery, Library and Museum Technicians	Gallery, Museum and Tour Guides	0.66 *(+0.05)*

Note: Excludes occupation pairs with a similarity score below 0.60.

Source: JSA analysis; ABS ANZSCO v1.3.

Specialisation potential

New specialisations can emerge within an occupation as adaptation effects increase the prominence of a subset of specialised tasks within an occupation. New specialisations can generate demand for new combinations of skills and knowledge and require a dynamic response from the labour market and the skills system.

We explore specialisation potential by weighting higher augmentation-exposed tasks higher to account for potential changes in the task content of jobs due to Gen AI augmenting human labour in these tasks.

When we give greater weight to tasks that are more likely to be augmented, most jobs become moderately more similar. Out of the 358 occupations considered, 220 occupations show increased similarity to other jobs under this approach.

The greatest increases in average similarity scores under this approach are exhibited by Sales Workers and Clerical and Administrative Workers (Figure 2). This indicates that augmentation exposure is typically higher in tasks that are common across jobs within these occupation groups, rather than in the tasks that distinguish most occupations from each other.

Figure 2: Augmentation exposure is higher in tasks that are common across jobs in the same occupation group, especially for Sales Workers and Clerical and Administrative Workers

Comparison of average similarity scores between the baseline and where higher augmentation exposure tasks are weighted higher

Source: JSA analysis; ABS ANZSCO v1.3.

Clusters of jobs that become more similar under this approach are potentially candidates for AI-related job specialisation, where there may be increased opportunities for those with the ability to work effectively with and alongside Gen AI. This could be similar to the specialisation example provided above with respect to opportunities for Arts and Media Professionals with the ability to work with and alongside digital technologies.

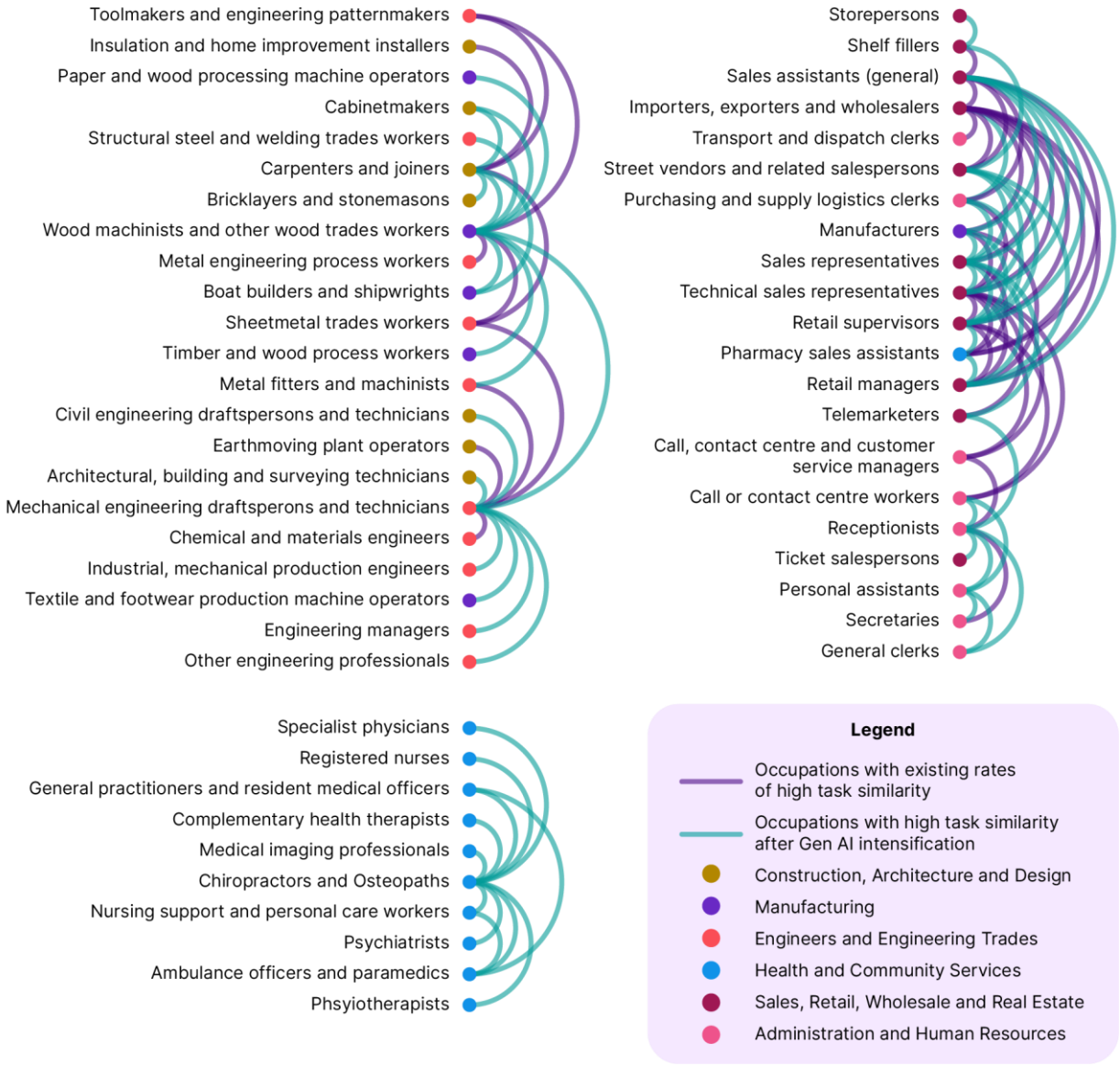
While a conceptual exercise, it is possible through network analysis to visualise potential specialisation clusters at a more granular level where tasks with higher augmentation exposure are at the intersection of jobs. While clusters already exist between occupations with similar tasks (nodes connected by purple lines in Figure 3) the use of Gen AI to augment particular tasks could lead to occupations becoming more similar, creating new connected clusters or opening new pathways (nodes connected by teal lines in Figure 3).

Figure 3 shows there may be potential for AI-related job specialisations in a range of domains including:

- engineering and engineering trades; construction, architecture and design; and manufacturing (top left)
- health and community services (bottom left)
- sales, retail, wholesale and real estate; and administration and human resources (top right).

Figure 3: Some occupation pairs would become more similar if augmentation potential is realised

Potential specialisation clusters as a result of Gen AI augmentation



Source: JSA analysis; ABS ANZSCO v1.3.

In addition to this conceptual exercise, stakeholders in our consultations, from across multiple industries, raised the prospect of AI-related job specialisations combining domain expertise with technical AI skills emerging in their sectors.

> *The Personal Services sector is using AI and Augmented Reality (AR) to personalise offerings, with workers increasingly needing both technical skills and digital literacy, highlighting the need for new training pathways and growing demand for workers equipped with both service and digital capabilities (Service and Creative Skills Australia, 2025).*

> *There's been a big growth in Health IT; it essentially is its own sort of specialty now. [This includes] people, you know, I guess, like myself [who] have a clinical background. So we can speak the [clinical as well as IT] language[s], which is really important to implement change because clinicians [treat] it like it is a different language. (Consultation participant, Union Member)*

In the Retail sector, large retailers are leading AI adoption to reduce costs and improve value offers to consumers. As AI automates more routine tasks, demand is growing for higher-skilled workers who can interpret complex data analytics, and those with strong interpersonal skills (Service and Creative Skills Australia, 2025).

4. Conclusion

The adaptation effects from technology adoption can be profound, particularly in relation to general-purpose technologies such as Gen AI.

Specialised or hybrid roles – including where people integrate technical AI skills and knowledge plus domain expertise in engineering and trades, sales and logistics, hospitality and customer service, administration or health – may play a critical role in enabling deep adoption and the creation of new roles that provide an important countervailing force to displacement effects.

In addition to its important role in shaping how the use of Gen AI influences employment growth, adaptability and dynamism in the labour market and the economy will also be instrumental in achieving the benefits of labour-augmenting tools. This includes adaptations that could deliver more or better services (including in the non-market sector) to achieve workforce capacity gains to meet unmet demand for services and/or reduced costs.

Like previous digital technologies, Gen AI may also contribute to the disruption of traditional working arrangements.

Through our consultation, some stakeholders also raised the possibility of Gen AI leading to greater ‘taskification’ of work, with potential to intensify the opportunities and challenges discussed above in relation to digital platform work. This could involve a greater proportion of jobs being divided into distinct tasks, with certain tasks being automated by AI and others being performed on-demand through the medium of a digital platform.

The possibilities considered here are not pre-determined by technology, and a wide range of labour market outcomes remain possible. Decisions made across the economy by labour market and skill system actors will shape how Australia experiences the Gen AI transition.

Findings from the Overarching Paper that this analysis supports

Finding 2: Adoption and adaptation will determine how Gen AI's labour market impacts and its potential are realised

The quality of adoption and implementation will be instrumental in achieving the benefits of labour-augmenting tools. Implementing Gen AI requires adaptability for both employers and the workforce.

More broadly, adaptability and dynamism in the labour market (and the economy) will dictate how any saved time could be redeployed and reallocated. This will ultimately determine how the use of Gen AI influences employment growth, both positively and negatively (as modelled).

Over time, the use of Gen AI and other technologies will lead to various forms of adaptation. This includes changes within-occupations, across occupations and with regard to working arrangements. As such, the effect of technology on the labour market will continue to evolve.

Considering 'first order' adaptation – where automation and augmentation may cluster tasks – can help identify where specialised or hybrid roles could emerge within existing occupations and roles.

Given the complexity of dynamics of Gen AI use, a wide range of labour market outcomes is possible in the medium term (around 15 years, for the purposes of this Study). This will require regular monitoring, to inform effective strategy and planning across the labour market and skills system.

Finding 7: Gen AI adoption is reshaping skill demand and roles. Large-scale job displacement is yet to emerge, with current impacts limited to early-adopters.

Among early-adopting firms in Australia, Gen AI use has been linked to increased demand for certain skills and roles, while reducing demand for others, particularly in routine or clerical functions.

There is evidence of only limited job displacement to date. Some task-specific occupations, such as voice-over artists, have seen reduced demand overall. Most observed impacts involve the evolution of roles, upskilling, and redeployment of workers, rather than widespread job loss.

Many organisations have yet to adopt the technology in significant ways. And some firms are only early in the process of large-scale change-management projects, meaning that any employment effects have not yet emerged.

Finding 20: The skills system will need to focus even more on building adaptive capacity to respond to the pace of change

The skills system will need to develop graduates with strong adaptive capacity while responding to the pace of change. Formal qualifications and short-form learning each have important and often distinct roles to play in achieving these objectives.

A dynamic skills response requires support for educators, flexible program design, and a well-functioning ecosystem of formal and informal learning pathways.

D. Labour Market Dynamism

Entering: Changes to entry-level roles

Participating: Career pathways and illustrative scenarios

Displacement and people outside the labour market

1. Introduction

Understanding how each stage of the worker life cycle could be affected by Gen AI is critical to understanding how Australia can transition equitably and efficiently to a Gen AI-enabled economy. This paper provides insights into how Gen AI is expected to affect workers and firms at each stage of the worker life cycle.

Section 1 of the paper examines the implications of a Gen AI-enabled workplace for those entering the labour force, looking in detail at how trends in entry-level job ads have evolved over the last seven years and discussing how the workplace and hiring is starting to change for junior staff in a world with Gen AI. Section 2 looks at the mid-stage of the worker life cycle and focuses on the typical career paths that are taken in Australia's largest occupations, and what a changing nature of work could look like in a Gen AI-enabled economy. The section also covers expected long term trends in employment and includes a segment on how new jobs arise with adaptation to Gen AI. Section 3 of the paper addresses the process of leaving the labour market and how technological change can affect retrenchments, departures, and attrition in the workplace. The last section focuses on people outside of the workforce, such as the long-term unemployed.

Given the early stage of Gen AI adoption (and the pace of technological and other developments) the insights in this paper reflect a point in time and will need to be updated over time as increasing information on Gen AI adoption becomes available (Box 1). The implications of Gen AI for labour market dynamism will remain an important area for ongoing monitoring and analysis.

Box 1 Analytical challenges when producing early insights into the labour market implications of Gen AI

Technological progress outpacing data collection

Gen AI technology is developing far more rapidly than is able to filter through to official statistics, and its effects are not yet being fully felt across industry. As a recent innovation, there are few data sources available which can account for how this technology is affecting the labour market. While we expect this to change in the future as the effects of Gen AI filter through to the official statistics, at this early stage we need to draw on alternative sources to provide insights. These include a mix of historical, small sample, and extensive qualitative research data (with over 40 hours of survey and focus group interviews conducted by JSA) as well as, where possible, larger administrative and other data sets.

In addition, whether Gen AI is used to augment or automate work will have varying impacts across the economy (for further discussion, refer to Analysis Paper A). Both will lead to the creation of new tasks and occupations and the decline of others, neither of which can be observed directly at this early stage of adoption.

The effect of the COVID-19 pandemic and post-pandemic period

A further limitation of the data is the recency of the COVID-19 pandemic and how this extraordinary event affected the labour market. Between 2020 and 2024 the Australian labour market experienced a series of extreme shocks, followed by a period of historically tight labour market conditions. The extent of the changes in labour market conditions over this period makes it challenging to disentangle the effects of a new technology from other factors.

Limitations of online job advertisements data

Online job advertisements data allow us to analyse aspects of labour and skills demand. However, online job advertisements are not representative of the whole of the labour market. They are generally skewed toward higher-skilled and more digitally-oriented jobs, white collar occupations, particular industries, and jobs in the major cities.

Occupation titles and tasks listed in job ads may not always be adequately matched to those in a pre-existing government taxonomy. Further, the data suffers from self-selection bias as advertising online is optional; it may be easier (for example, in hospitality) to advertise in local newspapers, on the door of a business itself, or elsewhere (Sostero & Fernández-Macías, 2021). Finally, a single job ad may advertise for multiple roles and may not specify the industry. Jobs ads alone thus do not provide 1:1 information about labour demand. Nonetheless, online job ads do provide real time insight into hiring trends and are useful for an enhanced, if incomplete, understanding of the labour market.

2. Entering the workforce: Changes to entry-level roles

Gen AI is best suited to reproducing repetitive, routine tasks, which are often undertaken by people who are relatively new to an occupation or to the workforce. This makes entry-level roles particularly susceptible to disruption by Gen AI. Entry-level roles often specifically target recent graduates, or may simply require little to no experience. They can include internships and vacation jobs, as well as any roles in which the worker is expected to undergo significant training on the job.

Changes to the demand for or the nature of entry-level work can have far-reaching implications for particular cohorts of the workforce, as well as for the pipeline of workers in the labour market. Entry-level roles are where workers begin their career and enter the workforce. They are roles that allow the development of key skills and capabilities for recent higher education and VET graduates, other new entrants to the labour market, as well as people re-entering the labour market.

Internationally, entry-level roles are typically not monitored as part of official labour market statistical collections. As such, it is difficult to reliably ascertain what effect if any Gen AI is having on new entrants to the workforce. Some estimates and surveys indicate potential future impacts on entry-level roles.[1] In other cases, specific firms have cited AI as a reason for changing their hiring practices, although these indications do not generalise easily into other firms or industries.[2] One study of US data from 2022 to 2025 finds declining employment for people aged 22-25 to be correlated with occupations of greater automation exposure (Brynjolfsson, Chandar, & Chen, 2025).[3]

Gen AI has begun to affect some entry-level roles in certain industries and occupations across Australia. In focus groups, we heard that some employers have shifted their recruitment patterns toward hiring more senior and experienced workers, and away from hiring as many junior staff. We also heard that the nature of entry-level work is changing, as is the use of alternative recruitment and development pathways.[4]

We also heard in our consultations that entry-level work increasingly involves checking of AI output for errors. This is consistent with surveys done widely, such as CapGemini (2024) who reported that 71% of managers and new hires expect junior roles to pivot toward

[1] In the United States, Bloomberg Intelligence estimated that 200,000 back and middle office roles in banking and finance would be replaced by Gen AI and that those most vulnerable to replacement would be entry-level workers engaged in financial calculations and customer service (Shaw, 2025). Also in the United States, a survey from Clarify Capital found 86% of executives were planning to replace entry-level roles (Parker, Gerson, & Baynes, 2025).

[2] While job ads for white collar workers decreased slightly between 2024-2025 in the USA, there was no clear evidence of this with regards to entry-level roles, the share of which only declined very slightly between Q4 2024 and Q1 2025 (Munyikwa, 2025). At the same time, specific firms have noted AI as a reason for changes in hiring. Among respondents to a survey from Clarify Capital 1 in 12 executives in the same sample had stopped hiring junior staff altogether due to AI (Parker, Gerson, & Baynes, 2025). In the UK, several large accounting firms have cut graduate intakes through 2025 citing AI automation of junior audit tasks specifically (Young, 2025).

[3] Brynjolfsson, Chandar and Chen (2025) use exposure scores as measured by Handa et al. (2025) and Eloundou et al. (2024). They find that employment levels between younger and older workers changes over this period among highly exposed occupations rather than wage differentials changing.

[4] Case study: Gen AI adoption and adaptation at ReadyTech.

reviewing and curating Gen AI output over the next three years. These trends will also influence the skill mix an entry-level worker will need. For example, a higher level of digital and AI fluency will be required so that junior staff can work effectively with Gen AI, and an increased responsibility for error checking and quality control of outputs will require high levels of domain expertise.

Trends in entry-level job ads

To study whether the demand for entry-level roles has decreased as Gen AI has become more mainstream (since around the end of 2022), we took a novel approach to identifying and quantifying the change over time of entry-level roles by using the Lightcast online job ad database.

While listings for graduate roles, apprenticeships, and internships have been studied internationally (for example, in the UK, where recently the number of these job ads was found to have declined since 2022)[5] our analysis is novel in the Australian context. To assess the state of job availability for entry-level workers, we considered job ads targeting *all* new entrants to the job market including graduate roles, internships, apprenticeships, and those jobs where the job ad specifies low/no qualifications.

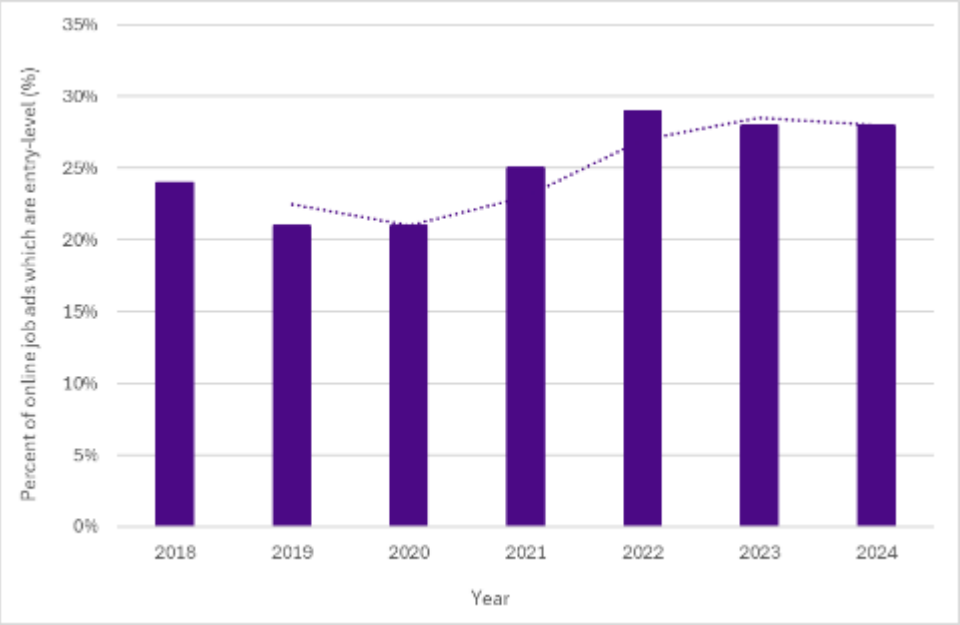
We found that entry-level roles declined in 2019-2020, in line with an overall reduction in job ads across the board, as a result of the COVID-19 pandemic. However, in 2021 the proportion of entry-level roles rose to 25% of all job ads, peaking in 2022 at 29%, as the labour market recovered from the pandemic and entered a period of unusually tight conditions. Following this, the share of entry-level job ads declined in 2023 but have subsequently remained elevated and relatively steady (Figure 1).

While we do not yet see evidence that Gen AI has affected entry-level roles in the online job ads data at the aggregate level, the composition and volume of entry-level jobs may yet shift as the integration of Gen AI into business becomes more widespread. Any changes will also vary by industry as some sectors adopt and integrate Gen AI more quickly and deeply than others.

[5] Per the UK Job Market report from job matching platform, Adzuna, online job ads for graduates and entry-level roles have both declined and are at their lowest levels since 2020 in the UK (McCulloch, 2025).

Figure 1: The share of entry-level job ads increased post-COVID and remains stable

Share of entry-level jobs as a proportion of all job ads, 2018-2024



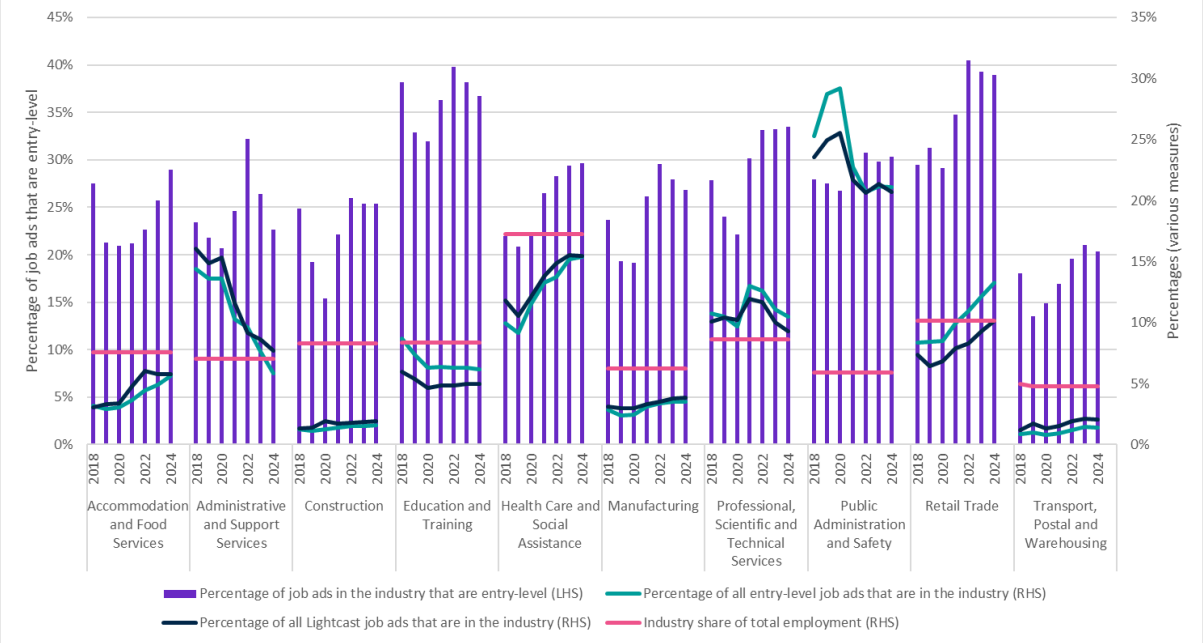
Source: JSA analysis of Lightcast Australian job ads (2018-2024).

Looking across industries, we see similar trends to the whole-of-economy level of pandemic impacts, which were then followed by elevated demand during a tight labour market. Entry-level job ads have by and large followed this trend, with the exception being the Construction industry, where entry-level job ads decreased while job ads overall increased during 2019-2020 (Figure 2).

In the Health Care and Social Assistance, Accommodation and Food Services, and Retail Trade industries, both job ads overall and the proportion of entry-level job ads have continued to rise. In contrast, the share of entry-level roles appears to be decreasing in the Transport, Postal and Warehousing, in Manufacturing, and in the Education and Training industries, while the share of job ads overall is increasing, suggesting that these industries are hiring disproportionately fewer entry-level workers (Figure 2).

Figure 2: The share of entry-level roles in larger industries have mostly recovered since the COVID-19 pandemic

Entry-level roles trend by 10 largest industry divisions 2018-2024 (largest share of entry-level ads in 2024)



Source: JSA Analysis of Lightcast Australian job ads (2018-2024), ABS Labour Account Australia (2025).

For the smaller industry divisions, the share of entry-level job ads and job ads overall appears to be mostly stable or increasing. In the Financial and Insurance Services industry the share of job ads overall has been volatile, with a decline from 2019 onwards and a longer post-COVID recovery. In the Information, Media and Telecommunications industry, job ads overall have been decreasing since before the pandemic, with the share of entry-level job ads decreasing as well from 2023 onwards (Figure 3).

Figure 3: Post-pandemic experiences in entry-level hiring vary significantly across smaller industries

Entry-level roles trend by 10 smallest industry divisions 2018-2024 (smallest share of entry-level ads in 2024)

Source: JSA Analysis of Lightcast Australian job ads (2018-2024), ABS Labour Account Australia (2025).

Every occupation has a different exposure to automation and augmentation (Analysis Paper A). Within each occupation, workers of different levels of seniority are likely to have different potential use of Gen AI, and hence may have different experiences of changes early in the transition.[6] Junior staff are often trained through completing repetitive, routine tasks to learn their craft, which are the same tasks which an AI can more easily take on.

However, we do not yet see a consistent trend of decreasing entry-level job ads for occupations that are highly exposed to Gen AI automation (Figure 4). Trends in entry-level job ads across most of these occupations mirrored that of job ads overall: job ads declined in 2018-2019 during the pandemic and then recovered in 2021-2022. Interestingly, General Clerks, the largest of these occupations, and Accounting Clerks recovered the most successfully post-pandemic, though the share of job ads overall, along with the share of entry-level job ads, have been declining since 2022.

[6] In addition, JSA heard that some occupations, such as those in the creative industries, tech occupations, finance, and the legal sector, are already experiencing changes in hiring and the treatment of juniors (see Case Study: Gen AI and entry-level roles in legal, health care and creative industries). For example, from representatives of the legal sector we heard that the work of a junior law graduate could be 'almost entirely' completed by Gen AI, though other representatives argued that this would not affecting hiring. Instead, firms are changing how they train junior lawyers and incorporating more error checking into tasks to manage the work Gen AI has done.

Figure 4: The share of entry-level roles has generally decreased among the top 10 exposed occupations

Entry-level jobs in the most exposed occupations (ANZSCO 4), 2019-2024

Source: JSA Analysis of Lightcast Australian job ads (2018-2024), JSA Occupational Profiles (2025).

Overall, however, there is no consistent pattern in the share of entry-level job ads, even for the occupations that might be expected to first experience tasks being shifted away from junior workers to Gen AI. Evidence overseas on junior hiring is similarly mixed. Given how early Australia is in its transition to a Gen AI-enabled economy, it may be too soon to see evidence of a decline in entry-level demand. However, it is worth monitoring these trends to better understand how they may evolve.

Gen AI's effects on new entrants and new hires in the labour market

Any shifts in demand away from hiring junior staff may not be evident yet, either in job advertisement data or in official labour market statistics, and some firms may not even be thinking about the potential for AI in this context.[7] However, with the same tasks used to upskill junior staff often involving repetition, there is the potential for these types of tasks to be the first disrupted by AI. These demand shifts may also show up in adaptation, for example, in the form of new jobs (e.g. 'AI engineer') that are emerging in the labour market.

Gen AI may also be affecting new hires in other ways. For example, Gen AI is being used widely in recruitment. It can auto-generate job advertisements, create talent maps from candidates submitting their information and from scraping their online public profiles,

[7] In the JSA Recruitment and Experiences Outlook survey for February-April, most businesses reported that even with the adoption of Gen AI, firms would expect their recruitment activity over the next 12 months to remain the same. A small number suggested that with the adoption of Gen AI, they would hire more workers, with these concentrated at the entry or mid-level, and only a very small number of firms suggested they would decrease the number of workers.

schedule and chat with candidates, and assess them for the role.[8] There is evidence that use of Gen AI in recruitment can introduce new biases from various models which may make it difficult for labour market entrants with certain characteristics to pass a screening (Nakano, et al., 2024).[9]

New entrants to the labour market may also benefit from using Gen AI to help them write applications or resumes, but may incur difficulties in the job search process, where, for example, AI-generated resumes inundate recruiters and authentic applications get lost, or AI-generated applications are too similar to one another (Hoover, 2024). Firms may also require more of junior hires to begin with (including a higher level of minimum digital and AI capability).

Once hired, the role of junior staff may change in a Gen AI-enabled economy. New hires may face expectations of higher productivity once they do find employment, as employers now expect them to augment their work with Gen AI. With AI-augmented tasks, studies have reported that new hires reach performance benchmarks sooner, and this may change the expectations around the performance of entry-level workers. For example, Hitachi implemented a buddy chatbot to help new employees learn about the business and reduced onboarding time by four days (Kapadia, 2025). Another study found that augmenting with AI can also help junior staff produce output similar to that of more highly experienced workers (Brynjolfsson, Li, & Raymond, 2023).

These diverging patterns underscore that while Gen AI does not appear to be resulting in fewer entry-level roles in the aggregate, it may be too early to tell how it is actually impacting new labour market entrants (either positively or negatively). Changes in demand may also filter down through other means, such as adaptation, with new roles created (for example, Project Officers instead of General Clerks) as other occupations become automated. The decline in entry-level roles is also likely to be different across industries and occupations.

Any shifts in demand for entry-level workers may limit workforce mobility and participation for younger cohorts, especially those without access to tailored education or internship pathways aligned with industry needs. Modest drops in the number of entry-level staff can also erode future career pipelines, raising supply issues for long-term talent.

It will be important to continue monitoring entry-level job creation in all industries – particularly those with a higher exposure to AI. Additionally, it will be critical to ensure that training continues to align with evolving employer expectations, and that there are appropriate pathways for new entrants into the labour market, and its industries and occupations.

[8] See Zheng et al (2023), Nakano et al (2024) and Karakeben, Sorotos, Milchevskaya, & Assaf (2024) for academic discussions of Gen AI's ability with regards to automating HR processes. Practical examples of how companies are actively using Gen AI in recruitment include LinkedIn Help (2025) and Seek (2023) for recruitment and Seek (2024) for jobseekers).

[9] Overseas, bias audits are now mandated in some areas before any automated recruitment tools can be used (see, for example, New York City Council (2021)**)**.

3. Participating in the workforce

New entrants to the labour market will not be the only ones affected by the adoption of Gen AI. To help explore dynamism in the labour market for those already in the workforce, we analysed career pathways through both analysis of historical data and illustrative modelling.

- Understanding the career journeys typically undertaken by workers can provide insight as to where workers may go in the event of being displaced by Gen AI, even though the data are likely not yet showing actual, consequential changes in career paths.
- Looking at the whole of the labour market, this section further discusses analysis undertaken using a computable general equilibrium model (CGE) to examine the effects of Gen AI exposure and identify the industries and occupations which may require more attention in policymaking (as well as workforce planning processes) in the future.

Gen AI exposure in the context of historical patterns in occupational mobility

To examine typical career transitions, we use information from two datasets; PLIDA administrative data which incorporates self-reported occupations from tax returns, and self-reported occupations as listed in online worker profiles (Box 2). Historically, per the linked administrative data, around 85% of workers tend to stay in the same roles between years, on average, and approximately 15% will change occupations (Jobs and Skills Australia, 2024). This figure has remained relatively consistent over the years and is line with ABS survey data.

For people who change roles, a typical career trajectory varies between occupations. We examined occupational mobility using a measure that combines churn rates and the diversity of destination occupations (Box 2).

A key benefit of career pathways data is that it shows the next career move a worker might make, allowing us to examine the exposures of a worker's likely *next* occupation. It is important to not just consider the exposure of each occupation in isolation, but also the extent to which people in these occupations face higher compounding exposure, based on both exposure of their current occupation and the common destination occupations that people typically move to. This allows a more holistic view when considering potential labour market impacts.

Box 2 Data sources, limitations and Gen AI visibility

Measuring mobility

We created an index of occupational mobility as a function of observed measures of churn, entropy and outflow destinations. Churn was calculated as the rate of turnover for a given occupation. Diversity was calculated as the number of occupations that a given occupation flows to or from. Entropy represents the degree of concentration of flows amongst outflow or inflow occupations.

Higher scores of this mobility index mean that workers in this occupation have historically been more likely to transition to other occupations.

Measuring exposure potential using historical mobility patterns

We extend our exposure analysis (discussed in Analysis Paper A) by considering the exposure of each occupation in the context of the occupations it is typically linked to in historical mobility patterns. That is, we take a weighted average of the exposure score of a given occupation as well as all other occupations that workers would historically move toward.

Data sources, limitations and Gen AI visibility

The PLIDA data is uniquely informative in that it takes real-time tax inputs to show actual career progressions by Australian workers over time. This occupation data can be combined with data from the Census and administrative datasets to hone in on particular cohorts and further investigate career paths with respect to variables of interest such as location, age, remoteness, and many other useful variables.

In online worker profiles, career progressions are also available, in addition to self-reported skills that a worker can ascribe to their profile. These are often updated frequently and can reflect real-time labour market trends, such as emerging skills and occupations, that have not yet appeared in administrative datasets or been incorporated into official occupation and skill taxonomies.

The self-reported nature of online worker profiles data may limit its reliability, including regarding how frequently it is updated. However, similar limitations can apply to some administrative datasets. For instance, self-reported data in tax returns suffers from around 10% unreliability per Hathorne and Breunig (2022). Further, not all workers may submit tax returns in any given year due to submitting late, compliance issues, or not earning income during a given period. Online worker profiles data is also known to be skewed towards white-collar occupations and certain industries, such as the technology industry. They don’t capture information around age and gender well, and suffer from self-selection bias, as reporting is optional (Lehner, 2024).

The most pressing limitation of these data is of course that since Gen AI is such a new technology, its effects are not yet clearly visible. PLIDA data in particular, is limited in this way. Some of the data we used is based on the most recent Census, in 2021, whereas Chat GPT and other LLMs became mainstream in late 2022. On the other hand, worker profiles data is a more recent source of information but is limited to those who opt in to creating a profile in the first place, which is not only a subset of all occupations but also a subset of all workers in an occupation. Importantly, the data

from these sources are not directly comparable, and in each case, the story we can tell from the data is partial and does not reflect the whole of labour market experience.

We examine these trajectories using administrative and profiles data and classify each occupation as per the definitions in Table 1 and Table 2 based on their exposure scores and mobility indicators.

Table 1: Administrative data augmentation and mobility classification

Augmentation and mobility features	Intuition
High Augmentation & High Mobility	These occupations are both highly augmentable and exhibit high mobility. Workers are well-positioned to benefit from AI tools and adapt to changing roles.
High Augmentation & Low Mobility	Jobs can be enhanced by AI, but structural rigidity or low job switching could limit the full benefits.
Low Augmentation & High Mobility	These occupations are mobile, suggesting workers can shift roles, but AI is unlikely to be a major productivity driver.
Low Augmentation & Low Mobility	Occupations unlikely to be enhanced by AI and with low movement.

Table 2: Administrative data automation and mobility classification

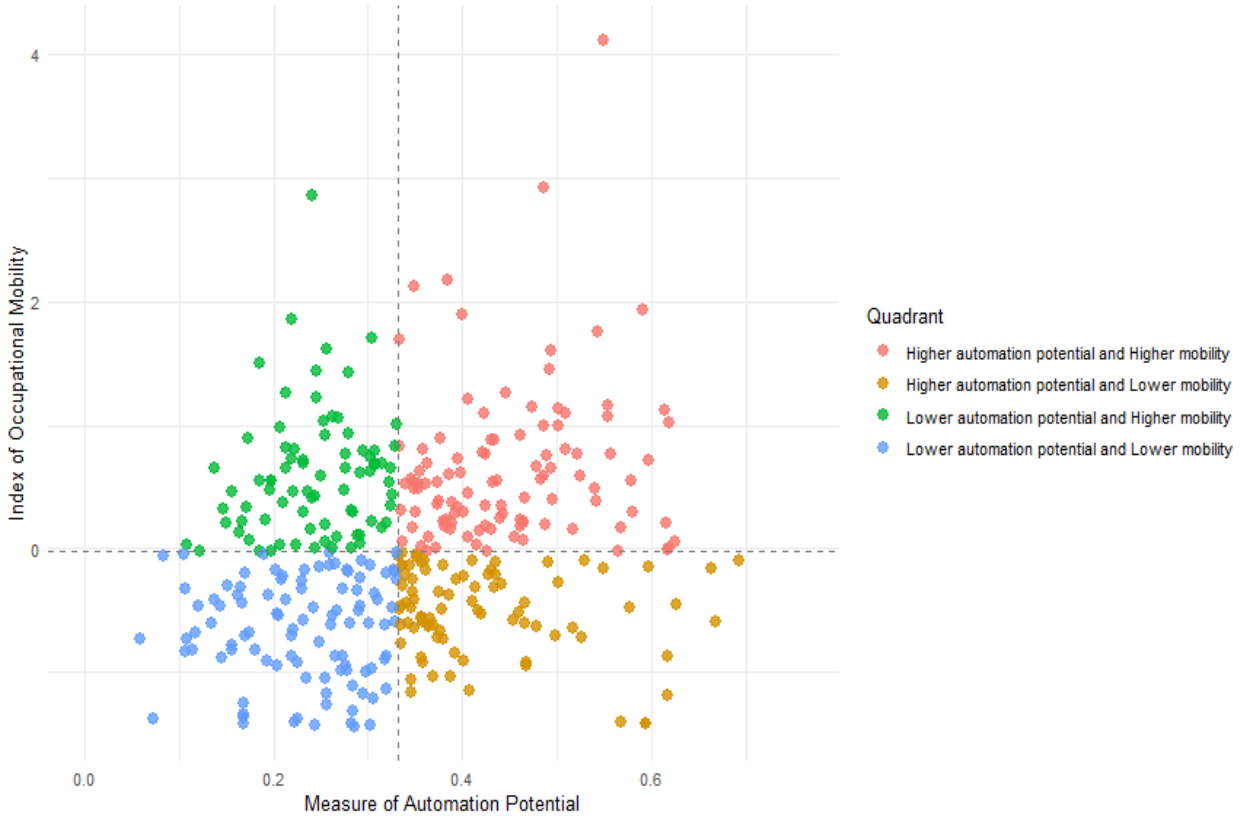
Automation and mobility features	Intuition
High Automation & High Mobility	These occupations contain several highly automatable tasks and historically exhibit high mobility.
High Automation & Low Mobility	These occupations contain several highly automatable tasks, with typically low rates of occupation switching.
Low Automation & High Mobility	These occupations are mobile, suggesting workers can shift roles, but AI is unlikely to be a major productivity driver.
Low Automation & Low Mobility	Occupations unlikely to be enhanced by AI and with low movement.

Although based on pre-Gen AI period data, the findings show that some occupations may already have limited and narrow mobility, often concentrated in roles with higher exposure to automation (the bottom right quadrant of Figure 5). This does not imply displacement, but highlights occupations in which people may need to adapt their mobility patterns if automation becomes more widespread.

Occupations with low mobility and high pathway exposure could be considered more vulnerable. It's also important to note how many occupations sit near the boundaries of these categories, suggesting that transitions may be possible with the right support.

Figure 5: Job mobility compared with pathway exposure to automation

Historical occupation mobility 2021-2022, compared with pathway exposure to Gen AI automation



Note: The measure of automation potential (x axis) is a weighted index of automation exposures of starting and destination occupations to understand how dynamic a transitional pathway might be when exposed to automation. The index of occupational mobility (y axis) is a composite of churn, entropy, and diversity – partial measures of labour mobility. Churn measures turnover rate in occupations. Diversity captures the number of unique occupations people move to/from. Entropy captures the concentration of flows (whether people move to a few or many different jobs). These calculations have also been undertaken for augmentation potential, but are not presented here.

Source: JSA analysis of Data on Occupation Mobility; ANZSCO (v1.3), Census 2021 (TableBuilder).

Focusing on the bottom right quadrant, our analysis over the period 2024 to 2025 indicated that there are 76 occupations in this cluster. Of these occupations, 66 typically transition into jobs that are not projected to grow over the next decade[10] (Table 3). Of the remaining 10 occupations, 8 typically transition to similar occupations with an equivalent or higher skill profile and similarity score.[11] This provides some indication of the nature of skill acquisition that could be needed.

[10] Defined as occupations for which employment could be at least 0.5% higher in 2035 under scenario 1 compared to the base scenario (100% adoption of automating and augmenting Gen AI in JSA's CGE illustrative scenario 1, compared to 2024 JSA Employment Projections.)

[11] Based on JSA's similarity scores as described in Box 4, these occupations scored less than 0.75.

Table 3: Mobility patterns in occupations vulnerable to repeated automation disruption

	Typically transition into growing jobs	Typically transition into declining jobs
Typically transition into high job-similarity jobs (high similarity and into equally or higher skilled job)	8 occupations • Secretaries • Electronics Engineers • Architects and Landscape Architects	18 occupations • Artistic Directors, and Media Producers and Presenters • Authors, and Book and Script Editors • Interior Designers
Typically transition into non-similar jobs (low or medium similarity or into lower skilled job)	2 occupations • Surveyors and Spatial Scientists • Caravan Park and Camping Ground Managers	48 occupations • Telemarketers • Librarians • Keyboard Operators

Source: JSA analysis of Data on Occupation Mobility & illustrative CGE scenarios conducted with VU; Revelio worker profiles data; ANZSCO (v1.3), Census 2021 (TableBuilder).

The mobility of workers during the ongoing Gen AI transition will have significant implications for skills. Workers may face repeated scenarios in their career where automation occurs to *part* of the occupation, increasing the importance of skills used in the remaining tasks.

Whole of Labour Market Adjustments over time

To explore how the entire labour market might adjust as Australia transitions to complete Gen AI adoption, JSA and VU conducted a CGE analysis exploring the whole-of-labour-market impacts of augmenting and automating tasks with Gen AI. Economy-wide modelling can be useful to explore how exposure and Gen AI adoption may influence the labour market over time.[12]

As summarised in Analysis Paper B, our analysis used Computable General Equilibrium (CGE) modelling similar to what currently underpins the JSA employment projections, but with a novel design that accounts for the potential augmentation and automation effects of Gen AI. Importantly, the model allows for the fact that occupations are subject to both automation and augmentation to different degrees.

Implications for occupations and roles

If the full potential of Gen AI is realised the CGE model suggests increases in employment and the size of the economy compared to the base case scenario by 2050.[13] Given Gen AI is assumed to automate on average 13% of tasks and augment around 55% of tasks, this

[12] Other long-term studies on the impact of Gen AI on the whole of the Australian economy are sparse, but include Occhipinti et al (2025) who use a system-dynamics model to explore how more AI (or technology) per worker could affect labour underutilisation (those unemployed and those underemployed), disposable income, and consumption through to 2050. They explore three scenarios (low, moderate, and high uptake of Gen AI) find that in the absence of policy action, moderate AI uptake could increase the underutilisation rate by around 130%, reduce disposable income by around 30%, and reduce consumption by 30%. In particular, to avoid an economic contraction (reduced consumption) Occhipinti et al (2025) state that Australia would require around 11x the current new-job creation rate. Importantly, these measures are different to those considered in our CGE analysis.

[13] Noting that this model was geared toward exploring the effects of Gen AI adoption across the labour market, rather than on macroeconomic outcomes.

creates the opportunity to apply the workforce to other tasks. This creates a productivity gain, which increases overall output.

The adaptability of employers and the workforce, as well as the degree of dynamism in the labour market and economy more broadly, will be critical to facilitating greater allocation and redeployment of labour to support these potential gains, and in reducing the scope for displacement to lead to increases in unemployment.

This will vary according to the exposure of different occupations to augmentation and automation, and the different occupational composition of industries and groups of workers (Box 3). The modelling suggests that employment in occupations with high AI exposure indices, particularly the clerical occupations and some professional occupations, will be below projected employment in base case scenario, and that employment would increase in occupations less subject to automation or augmentation, particularly the trades and community service occupations.

A direct interpretation of the illustrative modelling would suggest the following occupation-specific results:

- The five **occupations** (3-digit ANZSCO level) which would lose the most employment in 2050 relative to the base case are General clerks, Receptionists, Accounting clerks and bookkeepers, Sales, Marketing and public relations professionals, and Business and systems analysts, and programmers. The five **industries** with the greatest losses are Retail trade, Public administration and safety, Financial and insurance services, Professional, scientific and technical, and Rental, hiring and real estate.
- The five **occupations** which would gain the most employment in 2050 relative to the base case are Cleaners and laundry workers, Midwifery and nursing professionals, Business administration managers, Construction and mining labourers, and Hospitality workers. The five **industries** with the greatest gains are Construction, Accommodation and food services, Manufacturing, Education and training, and Agriculture, forestry and fishing.

In addition to illustrating how the exposure scores could translate into changes in occupations across the labour market over time, the modelling also supports analysis of different stages of the transition, and the extent to which different adoption trajectories will lead to different long-term results.

Moreover, a modelling approach that considers augmentation and automation provides insights into both effects. For example, in our third illustrative scenario we assumed augmentation occurred faster than automation, which resulted in different phasing to the other two scenarios (Box 3).

Box 3: Implications for occupations where augmentation leads automation (based on the third illustrative scenario explored in Analysis Paper B)

During the adjustment phase (2025–2032 in this illustrative scenario), occupations heavily reliant on routine support work experienced the earliest losses, relative to their projected growth in the base case scenario. These impacts could reflect an initial wave of augmentation-led restructuring, where technologies displaced low-complexity human tasks before creating offsetting demand.

Conversely, occupations tied to leadership, decision-making, or specialist expertise saw marked growth. These results suggest that augmentation complemented rather than replaced roles that involve non-routine judgement, supervision, or human development.

By the early recovery phase (2032–2038 in this illustrative scenario), many of the impacts observed during the adjustment period had become established, suggesting that augmentation-led displacement in administrative and support functions were not transitional, but part of a longer-term structural shift.

However, growth became more dispersed and sector-diverse, including a range of emerging roles, indicating occupational growth into new functions aligned with AI-enabled workflows.

In the expansion phase (2038–2041 in this illustrative scenario), the bifurcation of outcomes became more pronounced. Administrative and support roles continued their softening trajectory, reflecting the consolidation of AI's capabilities in automating routine documentation, finance, and clerical tasks.

In contrast, occupations with a strong interpersonal, physical, technical, or educational component experienced sustained growth. These patterns reflect AI's ongoing role as a productivity enhancer in settings that still rely on human judgement and emotional intelligence.

By the final phase (2041–2050 in this illustrative scenario), the cumulative effect of delayed automation was clear. Administrative and support roles continued to reflect impacts at accelerating rates. By the time peak exposure potential is reached, these occupations, all tied to task environments easily codified and routinised, appear to have been structurally replaced by mature AI systems.

In contrast, health, education, and public service roles showed ongoing and expanding demand.

The additional long-term economic demand generated by the AI transition also resulted in strong growth in interpersonal, physical, technical or educational roles, beyond the base case scenario.

4: Displacement of workers

Where the use of Gen AI contributes to displacement in the labour market, people might move to new jobs/occupations (as discussed in Section 3) or they might exit the workforce.

There have been several prominent international examples of retrenchments occurring where Gen AI is cited as a reason for displacement.[14] The story in Australia to date has been limited and has varied by occupation and industry. This may partly reflect the early stage of adoption, as well as the approaches to retraining and redeployment in Australia.

Some Gen AI-related adjustments in the labour market may not take the form of redundancies. Some may instead appear in the form of changes to hiring practices, which are more likely to affect new entrants to the labour market or job switchers, as opposed to incumbents.

There are also questions about how older workers, particularly those already closer to retirement, interact with Gen AI. Workers who can pick up effective Gen AI skills may find it easier to prolong their working life. On the other hand, for those older workers who may struggle to obtain the necessary skills to interact with Gen AI in the workplace, it could be a factor that influences an earlier exit from the workforce.

Restructuring and retrenchments

Internationally there have been announcements about job loss due to replacement of workers by Gen AI and these layoffs have not been limited to the technology industry. In Australia, however, there is limited evidence that similar retrenchments are occurring.

While some Australian firms over the past year have reported retrenchments of workers due to Gen AI or related to technological change, many of these companies also retained a portion of the affected workforce and upskilled employees, ultimately transferring them to different roles within the company.

Table 4 summarises the roles made redundant for a group of companies who registered their reasons for the retrenchments as either being due to incorporation of Gen AI or related technological improvements during the 2024 calendar year. During this period, the companies (referred to as ‘A’ to ‘L’) described below were the only companies that reported AI-related retrenchments.

While most job losses occurred in the Information, Media and Telecommunications industry division, the largest number of companies retrenching workers were in the Financial and Insurance Services industry. Other companies have conducted retrenchments but did not specifically state that these were related to Gen AI.

[14] Among others, Dropbox retrenched 20% of its workers in 2024 (Esther, 2024), Apple cut 2000 jobs in 2024 with redundancies where redeployment wasn’t possible (Disotto, 2024), education company Chegg retrenched 22% of its workforce in (Louise, 2025), Salesforce cut 1000 workers in early 2025 (Semjonova, 2025), Google cut 6% of its global workforce in 2023 (Napolitano, 2024), Duolingo retrenched 10% of translator employees through to January 2024 after it replaced them with ChatGPT (Forristal, 2024), and Meta famously announced its ‘Year of Efficiency’ with over 20,000 jobs cut in 2022 and 2023 (Hammers, 2023).

Table 4: Reported redundancies resulting from Gen AI during 2024

Company	Industry	Number of roles reported made redundant by AI
A	Administrative and Support Services	<50
B	Financial and Insurance services	<50
C	Financial and Insurance services	50-100
D	Professional, Scientific and Technical services	<50
E	Manufacturing	50-100
F	Administrative and Support Services	200-300
G	Financial and Insurance services	50-100
H	Financial and Insurance services	<50
I	Financial and insurance services	<50
J	Professional, scientific and technical services	<50
K	Information, Media and Telecommunications	1500-1600[A]
L	Computer System Design and Related Services	50-100

[A] This figure relates to net retrenchments, given the majority of affected workers were redeployed into other roles within the firm.

Source: Retrenchments information provided to DEWR 2024.

The propensity for the use of Gen AI to result in significant change or displacement is not evenly spread across the workforce, given differences in the workforce composition of each occupation, including gender differences (Table 5). Several occupations with high automation exposure scores are female dominated.

Policymakers should pay particular attention to workers in occupations with high exposure to automation, as their risk of job displacement by Gen AI is likely to be highest. Further, workers in these occupations whose tasks are routine and easily automated by AI may need targeted upskilling programs to ensure that they gain new or different, transferable, skills to allow them to move into other less-impacted jobs.

Table 5: Top 10 occupations with the highest exposure to automation by Gen AI

Occupation Title	Automation exposure level	Augmentation exposure level	Share of total workforce	Female share of occupation workforce	Median Age (years)
Accounting Clerks	High	High	1%	81%	45
Betting Clerks	High	Medium	0%	N/A	42
Call or Contact Centre Workers	High	High	0%	68%	32
Filing and Registry Clerks	High	High	0%	71%	43
General Clerks	High	Medium	1%	84%	42
Human Resource Clerks	High	High	0%	74%	39
Keyboard Operators	High	High	0%	79%	43
Survey Interviewers	High	Medium	0%	N/A	53
Telemarketers	High	High	0%	53%	32
Tourism and Travel Advisers	High	High	0%	78%	44

Source: JSA analysis of exposure (2025), JSA Occupational Profiles (May 2025)

Several highly automatable occupations involve administrative tasks that may be more routine and easily replicable. This includes clerks and administrative workers, who work in various industries.

In our submissions and focus groups, JSA heard that job loss due to displacement has already begun in some industries with a large customer service focus, such as banking. A submission from the Finance Sector Union further warned that those working in susceptible roles already have lower education and training than others, and that these workers may find it difficult to transition to other occupations. Submissions from nursing and midwifery groups also pointed out the likelihood of customer service roles being displaced first, but warned that Gen AI cannot replace the psychosocial support, empathy, and compassion of human care.

In some instances, human expertise and intervention remain critical to managing risks, despite high automatability. For example, the legal workforce also undertake a range of knowledge-based, routine tasks (as discussed in Section 1). However, particular concerns arose in multiple cases where legal teams cited non-existent cases in court, thought to be AI-generated (Ali, Sampson, Dunne, McGill, & Langoya, 2025). In response, the Victorian and NSW Supreme Courts both issued statements in late 2024-early 2025 prohibiting the use of AI generated material in court, and notably, put the onus on judges as well as barristers to maintain a Gen AI-free courtroom (Supreme Court of NSW, 2025) (Supreme Court of Victoria, 2024).

In other cases, Gen AI is becoming increasingly capable of substituting for human output. For instance, many workers in creative industries have raised concerns about reduced demand and revenue impacts, which were echoed in our focus group discussions. Participants reported that they would likely need to take other, less preferred work outside of the creative field. Some also felt that those with less training would be able to do the same roles as others with higher skills due to assistance from Gen AI.

> *[Gen AI] is taking the probability of making 100% of your income in the arts less likely, so you have to supplement your income in areas like hospitality. (Creative industry professional, focus group)*

Although imitations have always been a concern for artists, Gen AI is also able to generate new versions of artist-inspired work, and these can skew the art market even further, potentially driving the price of original goods and services down. This is of particular concern with regards to First Nations artists, who not only rely heavily on their artwork for income, but for whom the art also has cultural significance (Productivity Commission, 2022).

While, in some cases, Gen AI may lead to job augmentation instead of displacement as demand increases for workers who can create alongside AI (see, for example Erickson (2024)), Australian creatives are still concerned about their job prospects. Other submissions to this study discussed an Australian radio network that is actively investing in technology to replace human voice actors with synthetic voices, and a film studio where expansion was paused due to the release of Sora, OpenAI's text-to-video generator. Furthermore, 65% of creative artists surveyed by the Media, Entertainment and Arts Alliance (MEAA) worried they would be replaced entirely by AI (Media Entertainment and Arts Alliance (MEAA), 2024).

Gen AI's effects on retirement and attrition

There is mixed evidence on older workers and their interactions with Gen AI (see also the summary in Table 6). This is particularly important considering Australia's ageing population and the higher proportion of older workers in the labour force as the typical retirement age increases (Australian Bureau of Statistics (ABS), 2024a) (Australian Bureau of Statistics (ABS), 2024b).

While older workers might be considered to be more likely to leave the workforce when faced with a new technology to master, evidence suggests this is only the case for some and it is important to avoid over-emphasising age-related factors. Casas & Román (2024) found that in occupations with high likelihood of future AI exposure in which AI is also advancing rapidly, the likelihood of early retirement falls for workers with tertiary education qualifications. In these occupations, Gen AI is seen as sufficiently productivity boosting as to increase the opportunity cost of exiting the workforce. On the other hand, the study found the opposite effect for less educated workers for whom the cost of learning how to use Gen AI increases.

For older workers, access to appropriate training will also be important – either to keep up with changes to their existing roles or to pursue new roles in an adapting labour market. One Australian survey reported that 36% of older workers cite training and development opportunities as an incentive to remain in the workforce longer (Australian HR Institute, & Australian Human Rights Commission, 2025).

Table 6: Factors influencing retirement in the Gen AI enabled economy

Factors encouraging early retirement	Factors encouraging later retirement
Perception of job insecurity in roles that are highly automatable by Gen AI	Gen AI boosts productivity for workers increasing the incentive to stay in the workforce
Insufficient (or lack of) adequate training resources for Gen AI upskilling	Adequate upskilling/reskilling initiatives available to employees
Retrenchment packages for older workers	Flexible work arrangements better facilitated by Gen AI
Workers with weak digital skills already close to retiring not willing to engage in additional training	AI UX tools in workplace increase accessibility

In addition, Australia's older workforce is predominantly employed in occupations facing a medium-high augmentation exposure to Gen AI, but few occupations facing a medium-high automation exposure (Table 7). This suggests that, on average, many tasks undertaken by older workers are likely to be augmented by Gen AI but only a few of the occupations with older workers will have many of their tasks automated.

However, each case has its own implications. Where many tasks are augmented by Gen AI, there will be mixed outcomes. For example, workers using AI may be more productive, increasing demand for labour as firms can produce more output. Firms may also decide to hire fewer workers as they can create the same amount of output with fewer staff, leading to a reduction in employment.

Automating tasks, in contrast, is more directly linked with job displacement, as workers whose tasks are now completed by Gen AI are less likely to retain their jobs. The displacement due to automation may also not filter through as retrenchments, and instead manifest as a reduction in hiring.

Table 7 shows the 20 largest occupations with the most workers aged 55 or above, and they account for close to a third (32%) of all older workers. While almost all roles have medium-high augmentation exposure, only General Clerks (2.63% of all older workers) and Accounting Clerks (just over 1% of all older workers) have a high automation exposure. Receptionists, Bookkeepers, and Accountants (respectively representing 1.61%, 1.30%, and 1.15% of the older workforce) all have a medium exposure to Gen AI automation. Cumulatively, this represents fewer than 8% of workers older than 55.

To analyse the level of Gen AI proficiency among older workers, we compared findings from self-reported online job profiles data looking at the number of users who list Gen AI related skills on their profile. For the different categories and definition of Gen AI skills, see Analysis Paper E for a more detailed discussion.

People who had been in the workforce for 30 years or more were more likely to report a proficiency in both narrow and domain expert skills in Gen AI, compared to other groups. On the other hand, fewer of these older workers listed soft skills on their profiles compared with younger workers, particularly those who had been in their career for 10 years or more. Older workers were also the least likely to report any foundational literacy skills on their profiles as compared to all workers in younger cohorts.

Online worker profiles data is known to be biased towards white collar occupations (Lehner, 2024). Older workers in blue collar occupations may not be as STEM savvy or digitally fluent as their white collar counterparts. Policymakers would do well to pay particular attention to this group to ensure that in a Gen AI enabled economy, the growing requirements for digital fluency (even in less STEM related jobs) do not become a disincentive to remain in the workforce.

Another issue facing firms with an ageing workforce is the knowledge transfer between older workers and those remaining in the workforce as the older group retires. Some companies are using Gen AI to help facilitate the retirement process. For example, Canadian infrastructure company Enbridge is using AI to smooth the exit process for late-career employees as they transition into retirement by implementing digital expert systems to integrate their employees' know-how before they retire (Laguerquist, 2024). Hitachi has a Gen AI assistant which works with older workers in the field to take notes and uses it as input to train a diagnostic tool which helps teach new hires to identify product faults (Humphries, 2023).

Table 7: Top 20 occupations Australian workers aged 55+ are likely to work in are highly augmentable but only a few are at risk of automation by Gen AI

Occupation Title	Automation level	Augmentation level	Percent of workers aged 55+ in occupation	Percent of all workers aged 55+
Sales Assistants (General)	Low	Medium	13.85%	2.98%
General Clerks	High	Medium	25.60%	2.63%
Aged and Disabled Carers	Very Low	Low	25.36%	2.42%
Registered Nurses	Low	Medium	20.97%	2.31%
Truck Drivers	Very Low	Medium	32.12%	2.17%
Commercial Cleaners	Very Low	Low	31.89%	1.88%
Retail Managers	Low	High	20.81%	1.70%
Livestock Farmers	Low	Medium	58.44%	1.61%
Receptionists	Medium	Medium	23.96%	1.61%
Secondary School Teachers	Low	Medium	21.76%	1.42%
Office Managers	Low	High	29.88%	1.40%
Bookkeepers	Medium	High	38.84%	1.30%
Primary School Teachers	Low	Medium	17.69%	1.22%
Chief Executives and Managing Directors	Low	Medium	36.62%	1.17%
Accountants	Medium	High	17.41%	1.15%
Accounting Clerks	High	High	25.92%	1.13%
Education Aides	Low	Medium	24.16%	1.05%
Nursing Support and Personal Care Workers	Low	Medium	23.65%	1.04%
Construction Managers	Low	High	22.58%	1.03%
Real Estate Sales Agents	Low	High	26.38%	0.95%

Source: JSA analysis of ABS Person Level Integrated Data Asset (PLIDA) (2025), Customised data, ABS Datalab. Findings based on use of PLIDA data.

5: People outside of the workforce

In a Gen AI enabled economy, the benefits of new productivity tools are more likely to accrue first to those who are already online, well-connected, and digitally confident.

Prospective job seekers without these traits run the risk of being left behind. People who have stepped away from paid work or those on low incomes may lack access to devices, as well as the digital fluency, that AI-augmented roles may require. Bridging the gap is essential if Gen AI is to widen the pathways into meaningful work.

The digital divide

Gen AI tools assume a baseline level of connectivity, affordability, and digital ability. However, the latest Australian Digital Inclusion Index (ADII), an inclusion score between 0-100 which measures access to and use of digital devices, shows almost a 30 point gap between those in the highest income and those in the lowest income groups (Thomas, et al., 2023).

Findings from the focus groups run by JSA also largely reinforced this, with older Australians citing cost as the primary concern with accessing Gen AI tools. On the other hand, a long-term unemployed participant appreciated that Gen AI tools were largely free (didn't require a paid subscription for use) once an individual could access an internet connection. In line with the ADII, all participants suggested that benefits to Gen AI will not be felt evenly through the economy without targeted support, and that clear regulations and training opportunities should be provided by governments and employers, respectively.

Implications for those outside the workforce

In the last quarter of 2024, 1.9 million people with a long-term health condition and 1.2 million people with a disability were not in the workforce but around a third of each group would like a job (Australian Bureau of Statistics (ABS), 2025). When questioned on how these individuals could better rejoin the workforce, the most frequent responses related to needing to 'find work that matched their skills and experience' (33%) and 'needed training or study to improve their skills' (25%). However, to find meaningful work in a Gen AI enabled economy, proficiency in Gen AI could increasingly be treated as a foundational or required skill.

Familiarity with Gen AI tools including how to prompt, verify, and integrate outputs will be required for candidates to reach the shortlist in many roles. Jobs which those outside of the workforce hope to get will be shaped by Gen AI workflows which will increasingly require at least foundational digital and AI capabilities that long-term absentees from the market may not have had the chance to build. In this context, health, care, and location-based barriers to entering the workforce will be compounded by a widening digital ability gap.

Beyond health-related absences, many Australians step away from the workforce to meet caring responsibilities. Caring for children is now the leading reason women who want a job cannot start within 4 weeks, while caring for an ill, disabled, or elderly relative ranks third (Australian Bureau of Statistics (ABS), 2025). Together these caring roles account for more than half of women's short-term unavailability to work (Australian Bureau of Statistics (ABS),

2025). Many women spend extended time on parental or carers' leave and may pause their careers entirely with the intention of returning once their caring responsibilities ease.

When asked what would help carers re-enter the workforce, primary carers echo those with health conditions. They emphasise the need for finding roles which match their skills and to access training to refresh their skills (Australian Bureau of Statistics (ABS), 2025). The jobs these individuals are planning to return to in a Gen-AI enabled economy will likely be AI augmented, and without current digital and AI skills, the temporary caregiving career break risks turning into a long-term earnings gap.

Discouraged workers in a Gen AI Enabled Economy

Discouraged job-seekers are those looking for a job, are available to start within four weeks, but have stopped looking because they believe there is no suitable work available, employers will not hire them, or they lack the appropriate experience (Australian Bureau of Statistics (ABS), 2025). There were around 73,000 Australians classified as discouraged workers in February 2024, making 'discouragement' one of the reasons potential workers did not search for work even though they were ready to take on paid work (Australian Bureau of Statistics (ABS), 2025).

Discouraged workers may already have doubts about their ability to re-enter the workforce, and Gen AI may reinforce this negativity for several reasons. Firstly, Gen AI may lead to less transparency in recruitment. Use of automated resume screening and interview bots may more quickly filter out those without a consistent career history or a non-standard career trajectory. As with other workers who are out of the workforce for long periods, the lack of necessary skills and insufficient work experience may act as a barrier to even entry-level positions as Gen AI literacy becomes a foundation skill requirement. Finally, discouraged workers tend to be older, live in regional areas, have lower income households, and also record lower digital ability scores than other groups (Australian Bureau of Statistics (ABS), 2025) (Thomas, et al., 2023). Combined with low confidence and potentially outdated devices, it may be more difficult for these individuals to learn Gen AI skills on their own.

To the extent that rapid changes in the use of technology impose additional hurdles for those rejoining the workforce, this increases the importance of a number of services and mechanisms. For instance, it would be important to ensure training is made available to cohorts outside the workforce, to build both foundation skills and more advanced capabilities according to contemporary industry practice. There would also be an important role for employment services to aid in labour market matching (including those provided through Workforce Australia or through not-for-profit organisations). Employers themselves play a critical role in identifying opportunities to hire from alternative pathways (such as through the NSW Digital Skills and Workforce Compact).

More broadly, a range of economic policy levers will be relevant to managing movement into and out of the labour force, including incentives in the tax and transfer system.

6: Conclusion

The effect of Gen AI on labour market outcomes will depend on a range of factors, including the extent of its adoption, and whether its use is geared toward automation or augmentation.

Concerns about the impact of Gen AI on entry-level jobs – partly borne of emerging international examples – have not yet translated into observable effects in the Australian labour market. Evidence suggests that entry-level hiring remains active across many industries and firms, including those with higher exposure to AI. However, this will be important to monitor over the coming years.

Gen AI will influence a range of labour market dynamics, not limited to job creation, displacement, mobility, and participation. It is clear that upskilling and reskilling will be vital. It will need to be appropriately tailored – to ensure that workers across the life cycle and access spectrum are able to obtain the necessary skills to meet minimum job requirements.

Findings from the Overarching Paper that this analysis supports

Finding 2: Adoption and adaptation will determine how Gen AI's labour market impacts and its potential are realised

The quality of adoption and implementation will be instrumental in achieving the benefits of labour-augmenting tools. Implementing Gen AI requires adaptability for both employers and the workforce.

More broadly, adaptability and dynamism in the labour market (and the economy) will dictate how any saved time could be redeployed and reallocated. This will ultimately determine how the use of Gen AI influences employment growth, both positively and negatively (as modelled).

Over time, the use of Gen AI and other technologies will lead to various forms of adaptation. This includes changes within-occupations, across occupations and with regard to working arrangements. As such, the effect of technology on the labour market will continue to evolve.

Considering "first order" adaptation – where automation and augmentation may cluster tasks – can help identify where specialised or hybrid roles could emerge within existing occupations and roles.

Given the complexity of dynamics of Gen AI use, a wide range of labour market outcomes is possible in the medium term (around 15 years, for the purposes of this Study). This will require regular monitoring, to inform effective strategy and planning across the labour market and skills system.

Finding 7: Gen AI adoption is reshaping skill demand and roles. Large-scale job displacement is yet to emerge, with current impacts limited to early-adopters.

Among early-adopting firms in Australia, Gen AI use has been linked to increased demand for certain skills and roles, while reducing demand for others, particularly in routine or clerical functions.

There is evidence of only limited job displacement to date. Some task-specific occupations, such as voice-over artists, have seen reduced demand overall. Most observed impacts involve the evolution of roles, upskilling, and redeployment of workers, rather than widespread job loss.

Many organisations have yet to adopt the technology in significant ways. And some firms are only early in the process of large-scale change-management projects, meaning that any employment effects have not yet emerged.

Finding 10: The number of entry level roles hasn't declined even as the work has, and should continue to be monitored closely

Entry-level recruitment has been relatively stable, based on job advertisements data. Anecdotally, in early adopting sectors, employers are changing or considering changes to their entry-level intake. This includes changes to the nature of entry-level roles in workplaces where Gen AI is being used for routine tasks.

Overall, entry-level roles should remain an area of focus given the capabilities of Gen AI and the emerging capabilities of agentic AI to undertake structured, routine tasks.

Finding 14: Workers experience the opportunities and challenges of the digital and AI transition differently, in application and outcomes

The effect of Gen AI will vary between different groups of workers and according to different circumstances and identities. In some cases, groups of people will be more acutely exposed to Gen AI by virtue of their skills and occupations. In other cases, workers within the same occupation may face different access, opportunities, pressures, and challenges.

A focus on different groups (that is, an intersectional lens) will be important when considering which workers may be more likely to experience negative labour market impacts – either earlier or to a greater extent. An intersectional lens – including in monitoring the transition – can therefore also reveal new insights on how Gen AI technologies can adapt to varied contexts.

E. Skills

Direction and pace of change

Digital and AI capability

Skills system response

1. Introduction

This paper explores the implications of Gen AI for the skills system in Australia. It first examines how the demand and supply of skills have adapted over recent decades in the context of technological change (Section 2). In doing so, it provides an overview of key frameworks and concepts on the interaction between technology and the labour market.

This paper then explores the implications of Gen AI for demand and supply of skills (Section 3). It examines the early practical impacts of Gen AI in the context of adoption to date.

Finally, it examines the response of the skills system so far and considers the demands that will be placed on the skills system into the future (Section 4). This includes exploring the Gen AI exposure of higher education and VET pathways, in order to provide insight into where the potential implications of Gen AI are greatest.

2. Technology and skills – demand and supply

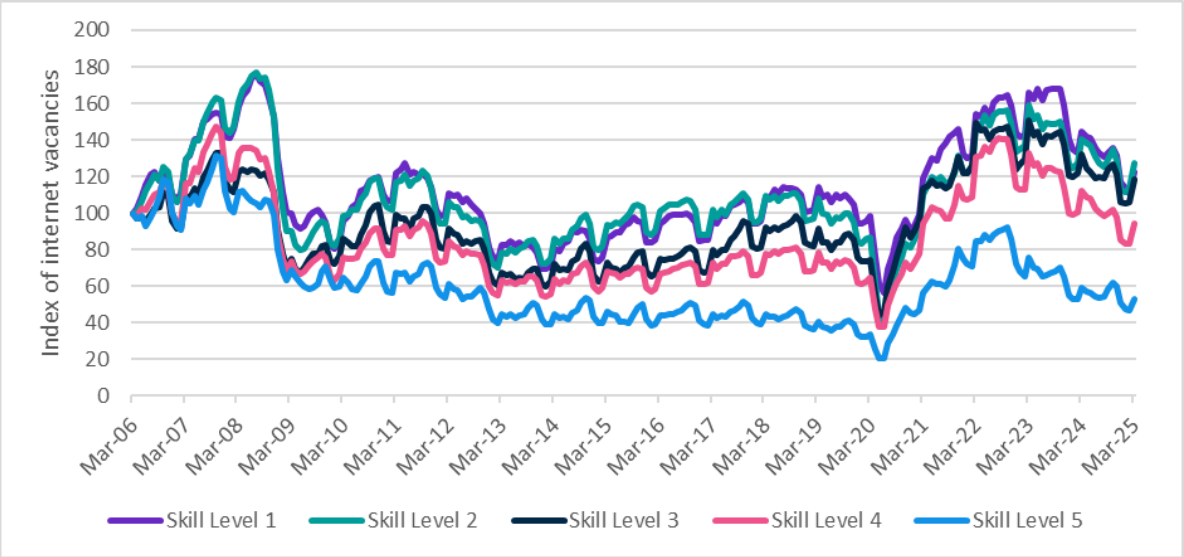
The direction of skill change

Our analysis of job advertisements data[1] illustrates two key trends in recruitment demand in the Australian labour market over the past two decades. First, there has been **increased demand for higher skilled occupations relative to lower skilled occupations** (Figure 1). While levels of recruitment activity have experienced peaks and troughs over the decades for which IVI data is available, demand relative to 2006 levels has consistently been greater in higher skilled occupations compared to lower skilled occupations.

[1] Based on data from the Internet Vacancy Index (IVI) – a monthly count of online job advertisements compiled by JSA.

Figure 1: Demand for higher skilled occupations is higher relative to lower skilled occupations

Index of internet vacancies by skill level, 2006 to 2025 (March 2006 = 100)

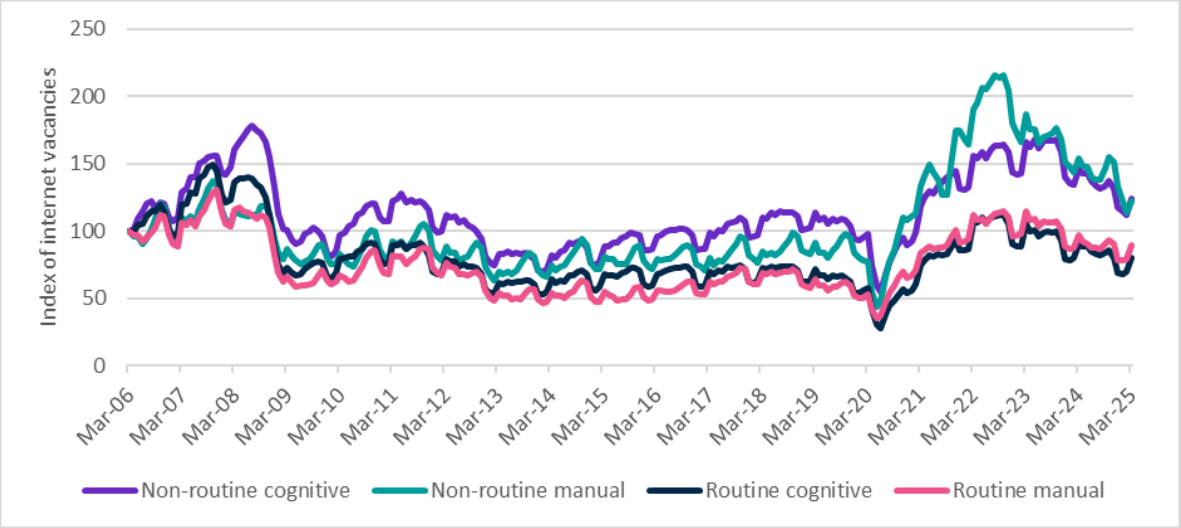


Source: JSA analysis of internet vacancy data, 2006 to 2025.

A second key trend in the Australian labour market has been **increased demand in non-routine occupations relative to routine occupations** (Figure 2).[2] This trend has been consistent since mid-2011 and particularly pronounced following the initial pandemic shock.

Figure 2: Demand for non-routine occupations is higher relative to routine occupations

Index of internet vacancies by job type, 2006 to 2025 (March 2006 = 100)



Source: JSA analysis of internet vacancy data, 2006 to 2025.

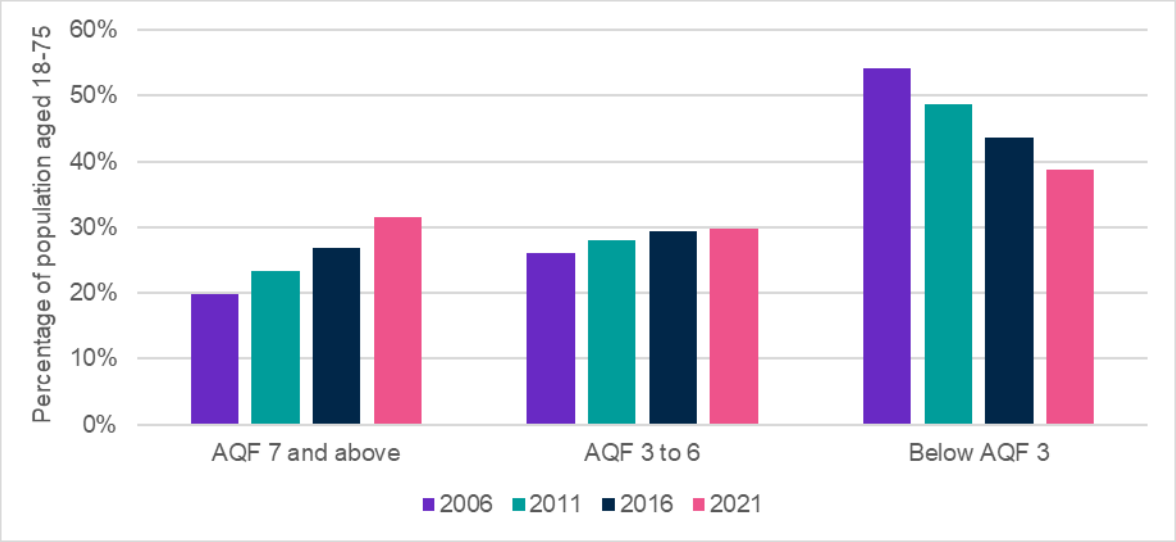
On the supply side, the workforce has also adapted over time in terms of the supply of skills – notably, through increased tertiary education attainment. The period between 2006 and 2021 witnessed a 15.5 percentage point increase in the share of the working age population with at least a Certificate III Level qualification (AQF 3 and above).

[2] This paper applies the work of Coelli and Borland (2023) in classifying occupations as non-routine cognitive, routine cognitive, non-routine manual and routine manual.

As Figure 3 shows, most of this increase has been seen in the share of the working age population with a Bachelor Degree Level or above qualification (AQF 7 and above) and most of the decline relates to the proportion without at least a Certificate III (Below AQF 3). The share of the working age population with an AQF Level 3 to 6 qualification – aligned with key vocational qualifications – as their highest qualification has witnessed more moderate growth.

Figure 3: Increased tertiary education attainment has largely been concentrated in Bachelor Degree and above qualifications

Percentage of population aged 18-75 by AQF level of highest qualification, 2006-2021

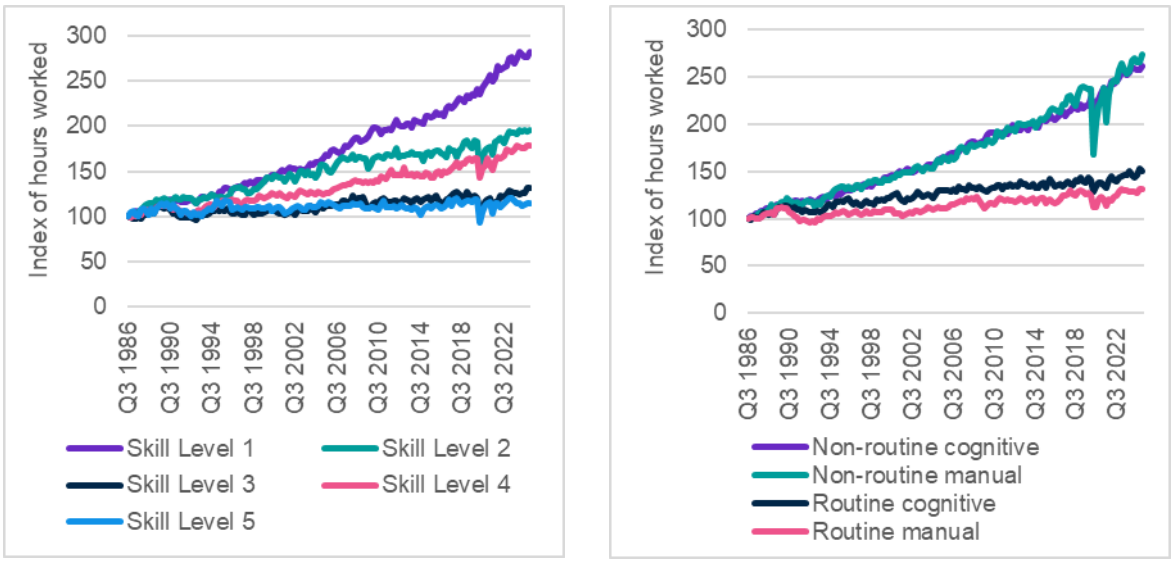


Source: JSA analysis of ABS Census of Population and Housing, 2006, 2011, 2016 and 2021.

These longer-term trends in employer demand for higher skills are also reflected in changes in the composition of the Australian labour market. As ABS Labour Force Survey data reveals, the share of hours worked in the Australian economy has been trending towards higher skill and non-routine work since at least the mid-1980s (Figure 4).

Figure 4: Growth in hours worked is greatest in higher skill and non-routine work

Index of hours worked by skill level and job type of main occupation, 1986 to 2025 (Q3 1986 = 100)

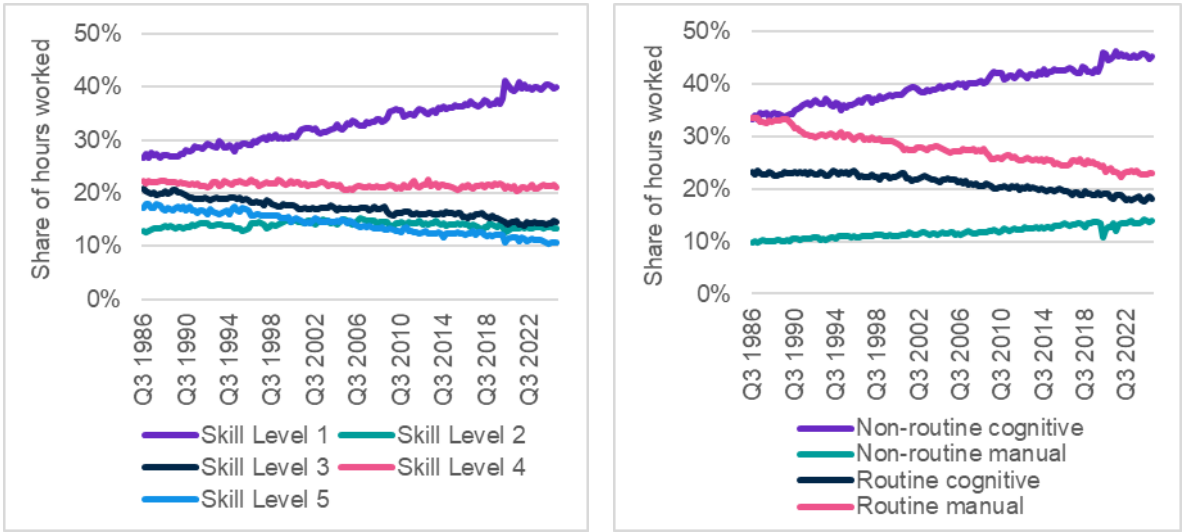


Source: JSA analysis of ABS Labour Force Survey data, 1986-2025.

These pronounced and continuing changes in skills in the labour market over recent decades have seen Skill Level 1 and non-routine cognitive occupations become the clearly dominant types of jobs (Figure 5). For instance, while non-routine cognitive and non-routine manual job have been growing at a similar rate over the past 4 decades, non-routine cognitive jobs started from a much higher base and now account for around 45% of all hours worked in the Australian economy.

Figure 5: Skill Level 1 and non-routine cognitive occupations are the most common types of job

Share of hours worked by select job characteristics, Q3 1986-Q1 2025



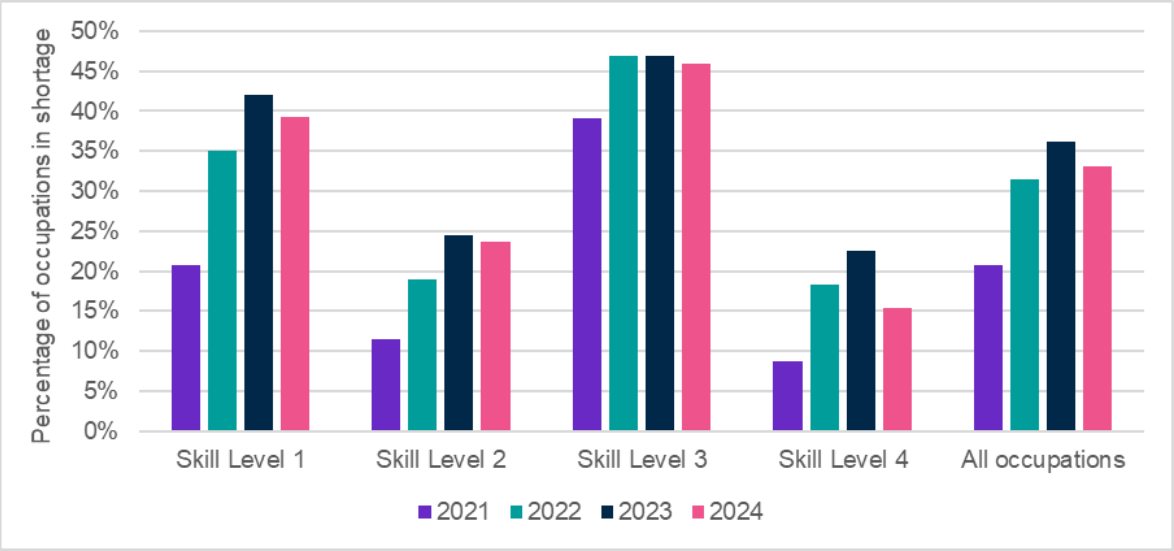
Source: JSA analysis of ABS Labour Force Survey data, 1986-2025.

Notwithstanding improved tertiary education attainment and the contribution of skilled migration, imbalances between skill supply and demand persist. JSA's Occupation Shortage List shows that a relatively high percentage of Skill Level 1 and Skill Level 3 occupations are in shortage (Figure 6).[3]

[3] Skill Level 5 occupations are excluded from the scope of the Occupation Shortage List. Skill Level 5 occupations have fewer barriers to entry and unlike other in-scope occupations, they generally do not require significant post-school education and training.

Figure 6: Skill Level 3 and Skill Level 1 have the highest concentration of occupations in shortage

Percentage of occupations in shortage by skill level, 2021-2024



Source: JSA Occupation Shortage List, 2021–24.

Skill-biased and routine-biased technology change

These trends collectively align with the concept of skill-biased technological change (SBTC). The SBTC framework posits that changes in the capabilities and cost of technologies – and associated changes to production processes and the organisation of work – are important drivers of the relative demand for more-skilled or lower-skilled labour.

While the skill bias of technology can be in either direction, the diffusion of digital technologies in recent decades has typically been found to complement those with higher skills.[4] For example, Jackson, Michelson and Munir (2020) observed:

> *The accounting profession has experienced significant technological change which has impacted on how accountants acquire, analyse and interpret data to inform organisational decision-making. Key trends in technology have meant that tasks traditionally performed by early career accountants are often automated. Accountants are now expected to have the expertise and skills to leverage technology to complete tasks and make decisions far earlier in their careers than before.*

Building on the SBTC framework, task-based approaches have sought to make more explicit the interactions between technology, workers' skills and the application of skills and capital to work tasks. Task-based approaches often point to routine-biased technological change (RBTC) as a key trend. The RBTC framework is grounded in the observation that computer-based technologies:

- can most feasibly automate routine tasks involving abstract information that can be accomplished by following explicit, pre-defined rules, and

[4] Whether this will remain the case in relation to Gen AI remains an open question, and may depend on the particular use case and setting. Some early evidence points to AI reducing the productivity differential between most and least productive individuals in relation to customer support, software development, and writing tasks (Brynjolfsson, Li, & Raymond, 2023), (Peng, Kalliamvakou, Cihon, & Demier, 2023), (Noy & Zhang, 2023).

- may augment or reinstate labour in non-routine cognitive tasks where data and information are a key input but not sufficient to accomplish the task (Coelli & Borland, 2023).

Software and Applications Programmers is an occupation that provides a useful window into understanding routine-biased technological change. Programmers have not only played a significant role in developing software and applications that automate routine and augment non-routine cognitive tasks across a range of industries and occupations. They also provide a clear example of the reinstatement of labour in non-routine cognitive tasks, with Software and Applications Programmers growing over time and by 2025 have become of one the top 10 employing occupations in Australia.

Of course, trends in labour market composition are not solely attributable to technological change. Other contributing factors include:

- changes in demand for products and services – which could potentially shift the composition of the labour market towards relatively high skill industries, and
- changes in trade and global supply chains – which help to shape domestic demand for particular forms of work.

Within-industry changes towards higher-skilled and non-routine work were more likely to take place in more heavily computerised industries – such as Professional, Scientific and Technical Services, Financial and Insurance Services, Public Administration and Safety, and Information, Media and Telecommunications (explored in Analysis Paper C).[5]

The pace of skill change

Official statistics, such as from the ABS Labour Force Survey, allow us to measure changes in the composition of the labour market across different occupations and skill levels. However, to observe changes in skill requirements within occupations requires alternative data sources, such as job advertisements.

We analysed job advertisement data from Lightcast in order to measure change in the skill content of jobs over time (i.e. the rate of skill change) using an approach adapted from that of Deming and Noray (2020) (Box 1). Table 1 presents occupations (at the occupation sub-major group level) with the highest and lowest rates of skill change.

[5] Per the ABS Australian System of National Accounts, these four industries have the highest capital stock of computer software.

Box 1 Rate of skill change

Our approach to calculating the rate of skill change by occupation follows the example of Deming and Noray (2020) in relation to the US labour market. Our approach replicates Deming and Noray's methodology, making only necessary adjustments to apply the methodology to the current Australian labour market including:

- using data on Australian job advertisements from Lightcast between 2012 and 2024, and
- mapping job advertisements to the Australian and New Zealand Standard Classification of Occupations (ANZSCO) rather the US Standard Occupational Classification system.

By its nature, this exercise is dependent on specific definitions of skills. Our approach is based on a skills taxonomy provided by Lightcast, which is one of many possible taxonomies rather than a nationally recognised or agreed one.

While the rate of skill change provides a useful, objective measure of the pace of skill change by occupation, two limitations should be noted.

Firstly, while the sample of job advertisements is extensive (at almost 1 million advertisements in 2024) it does not represent all job advertisements in Australia.

Secondly, in occupations with mandatory qualifications (or other certification required under legislative, licensing and regulatory arrangements), skill change can occur through changes in training rather than changes to the requirements listed in job advertisements (Deming & Noray, 2020).

Table 1: Some occupations experience faster change in skill requirements than others

Occupations with the highest and lowest rates of skill change, 2012-2024

Panel A. Fastest skill change occupations	Rate of skill change	Panel B. Slowest skill change occupations	Rate of skill change
ICT Professionals	10.5	Storepersons	1.5
Arts and Media Professionals	6.2	Farm, Forestry and Garden Workers	1.6
Business, Human Resource and Marketing Professionals	5.4	Hospitality Workers	1.9
Design, Engineering, Science and Transport Professionals	5.3	Food Preparation Assistants	1.9
Engineering, ICT and Science Technicians	5.2	Other Labourers	2.0
Specialist Managers	5.1	Road and Rail Drivers	2.0
Education Professionals	4.8	Construction Trades Workers	2.2
Sales Representatives and Agents	4.8	Mobile Plant Operators	2.2
Office Managers and Program Administrators	4.7	Cleaners and Laundry Workers	2.2
Sales Support Workers	4.6	Carers and Aides	2.3

Note: Skill change refers to the absolute value of the differences in the share of job ads in which each skill appears in each year, summed up by occupation. The average rate of skill change across occupation sub-major groups is 3.5.

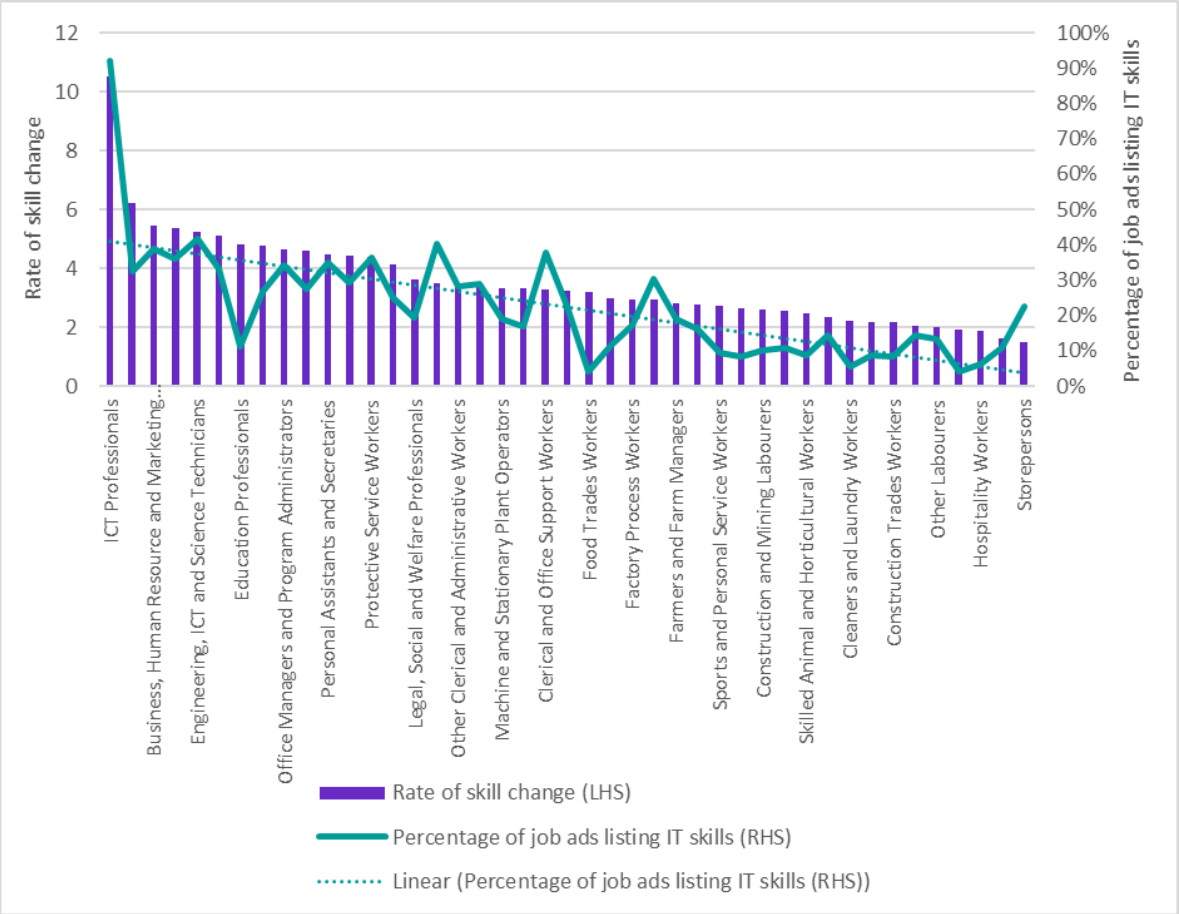
Source: JSA analysis of Lightcast job advertisement data.

One clear inference that can be drawn from Table 1 is that the rate of skill change varies significantly across occupations. For instance, the skill change in the fastest changing occupation of ICT Professionals is 7 times faster than the rate of skills change evident in the slowest changing occupation.

A second inference that can be drawn is that technology-intensive occupations appear to demonstrate a higher rate of job skill change. This can be seen by correlating the rate of skill change with the percentage of job advertisements – by occupation – requesting at least one skill in the Information Technology category per the Lightcast skills taxonomy (as a measure of the technology intensity of the occupation). Figure 7 presents the results of this analysis and provides evidence of a strong correlation between more technology-intensive occupations and faster skill change.

Figure 7: Technology-intensive occupations tend to exhibit faster skill change

Rate of skill change and percentage of job advertisements requesting Information Technology skills by occupation



Source: JSA analysis of Lightcast job advertisement data.

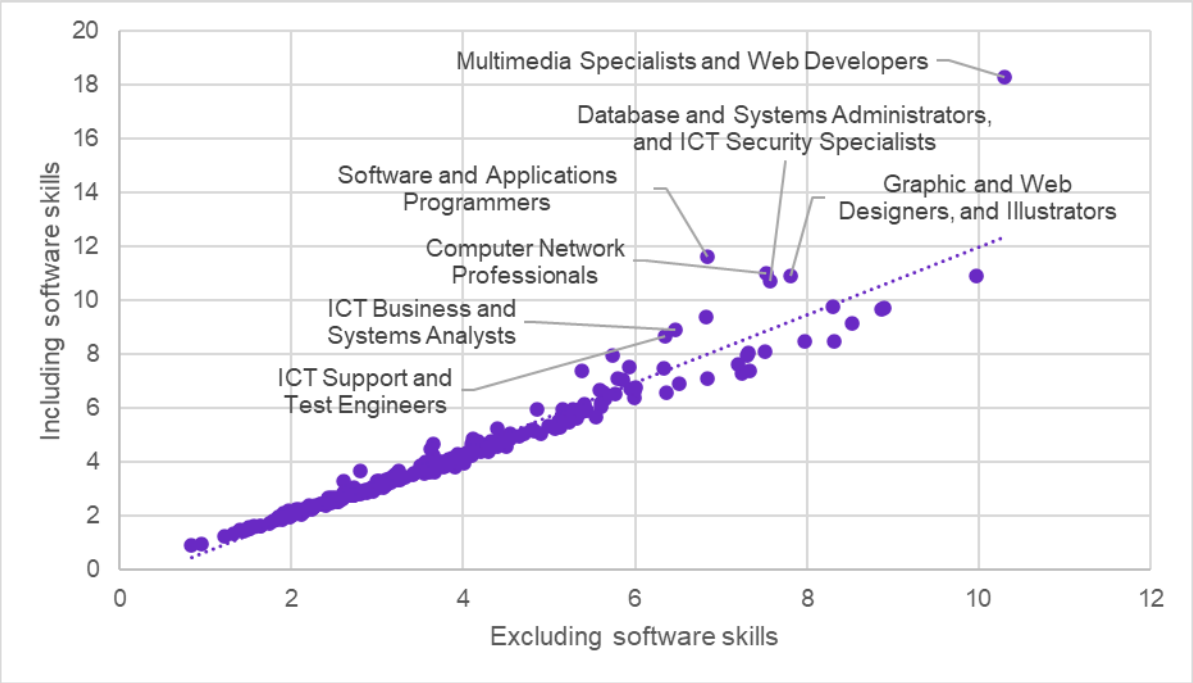
To unpack the implications of technology-intensive occupations appearing to demonstrate a higher rate of job skill change, we extend on the work of Deming and Noray and explore the sensitivity of the rate of skill change to the exclusion of software skills.[6] When software skills are excluded, this reduces the rate of skill change in some technology-intensive roles (Figure 8). However, the reduction is marginal. Even with the exclusion of software skills, the rates of skill change for technology-intensive roles remain among the highest of all occupation groups.

This suggests high rates of skill change in technology-intensive occupations are not only related to the capability to use new software tools, but also that new software tools and technologies help shape the broader skill requirements of the role.

[6] Defined by Lightcast as any software tool or programming component used to help with a job

Figure 8: Faster skill change in technology-intensive roles is about more than software skills

Rate of skill change by occupation unit group, with and without software skills



Source: JSA analysis of Lightcast job advertisement data.

3. Gen AI and skills – demand and supply

AI skills

For the purposes of this paper, we define AI skills as encompassing the approximately 350 specific skills in the Lightcast skills taxonomy that are grouped under the two subcategories of Artificial Intelligence and Machine Learning, and Natural Language Processing.

Examining job ads and worker profiles through the lens of this definition means we capture instances where AI skills are sufficiently valued by employers and employees for them to be specifically listed. While this will capture some instances of AI use by workers in non-tech roles, we can expect this lens to skew towards capturing jobs where specialist AI skills are required.

AI skills by occupation

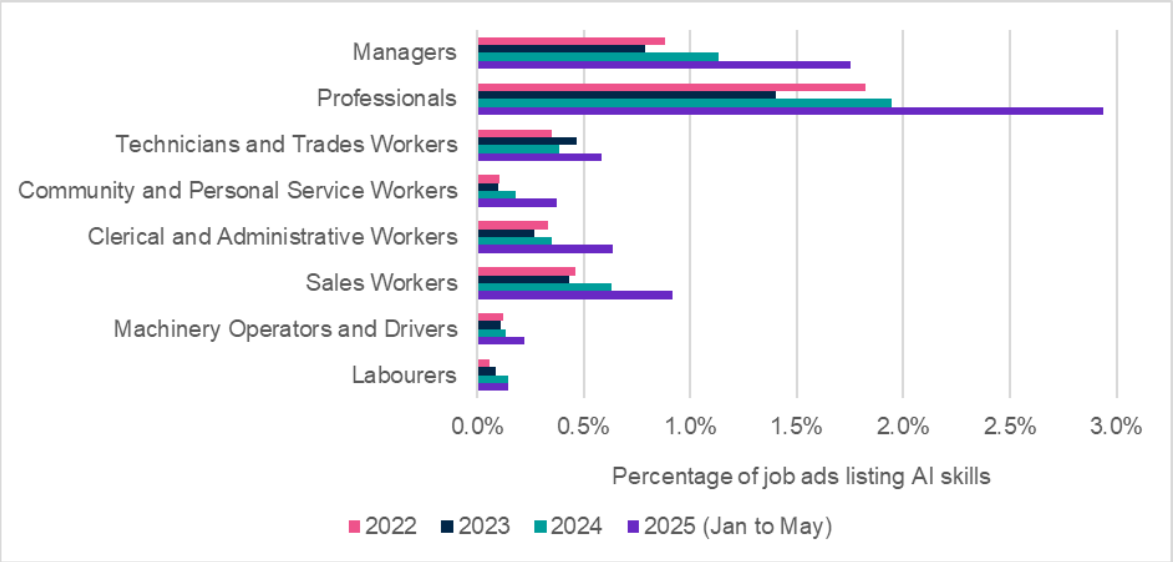
The proportion of job ads listing AI skills is highest among Professionals, followed by Managers and Sales Workers (Figure 9).

Notably, the proportion of job ads listing AI skills was elevated in the early months of 2025 compared with previous years across all occupation major groups except Labourers. This increase may suggest that the period of January to May 2025 witnessed either a new wave of firms seeking AI skills for the first time, previous adopters seeking to deepen their existing base of AI skills, or a combination of the two. Where Gen AI adoption broadens or deepens,

the associated demand for AI skills – as well as the interaction of the technology with other skills – will likely contribute to an accelerating pace of skill change.

Figure 9: AI skills are more often advertised for Professionals and Managers

Percentage of job advertisements listing AI skills, by occupation major group and year

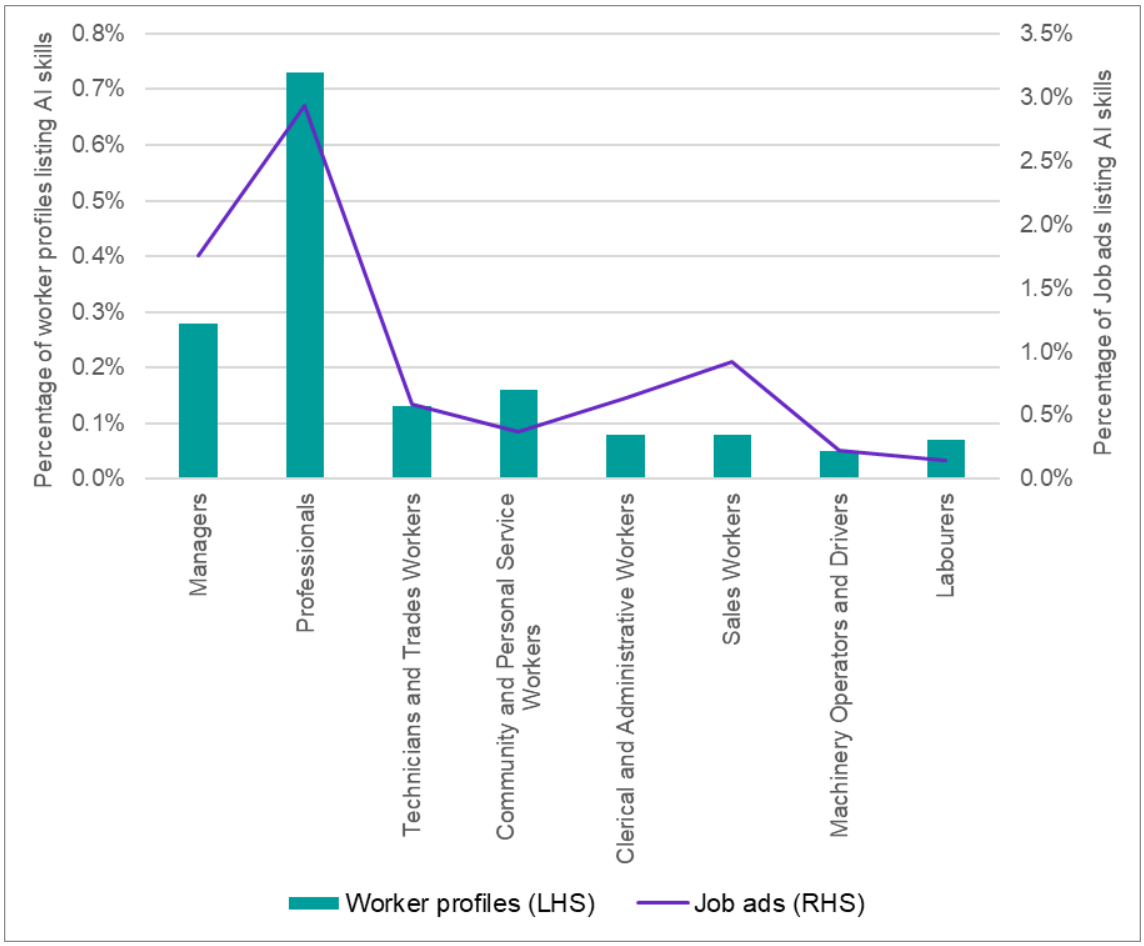


Source: JSA analysis of Lightcast job advertisement data.

The share of Revelio worker profiles and Lightcast job ads listing AI skills by major occupation groups follows broadly similar patterns (Figure 10). However, one notable difference is that Community and Personal Service Workers are the third most likely group to list AI skills on their worker profile whereas job ads for this group are only the sixth most likely to demand AI skills. This may indicate a level of individual initiative among Community and Personal Service Workers relating to the potential of AI to augment their existing work or to develop skills that could be applied in other occupations.

Figure 10: AI skills listings in worker profiles follow a similar pattern to job advertisements

Percentage of worker profiles and job ads listing AI skills by occupation, 2025

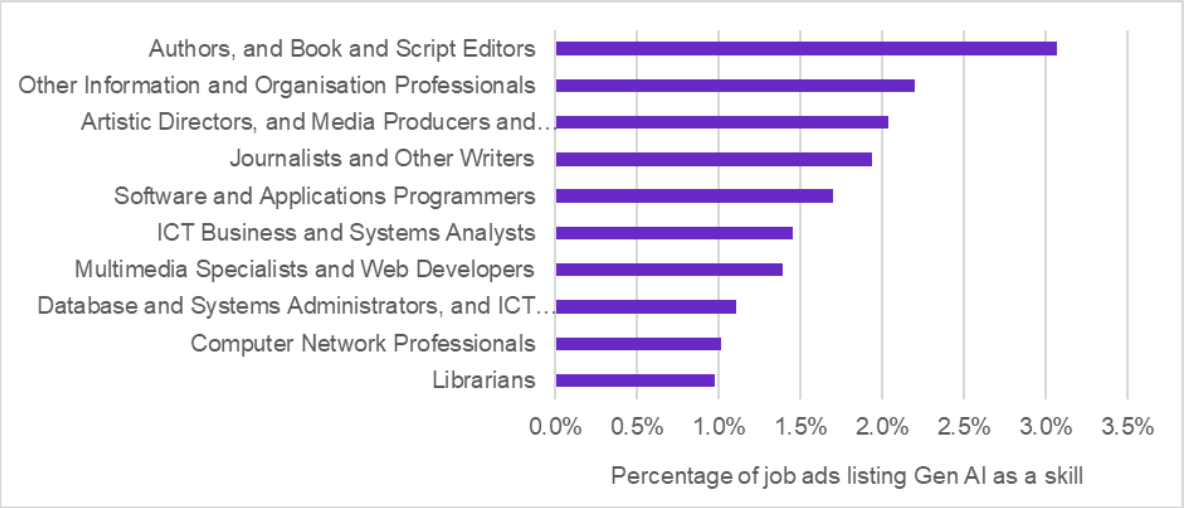


Source: JSA analysis of Lightcast job advertisement data and Revelio worker profiles data.

Generative AI skills were the third most commonly listed AI skill (behind only the broad skills of Artificial Intelligence and Machine Learning). At the occupation unit group level, we can see that the top occupations by share of job ads listing Generative Artificial Intelligence as a skill in 2025 include a mix of tech and non-tech roles (Figure 11).

Figure 11: Generative AI is a skill demanded in both tech and non-tech roles

Top 10 occupations by percentage of job ads listing Gen AI as a skill, Jan to May 2025



Note: Excludes occupations with fewer than 100 job ads in 2025.

Source: JSA analysis of Lightcast job advertisement data.

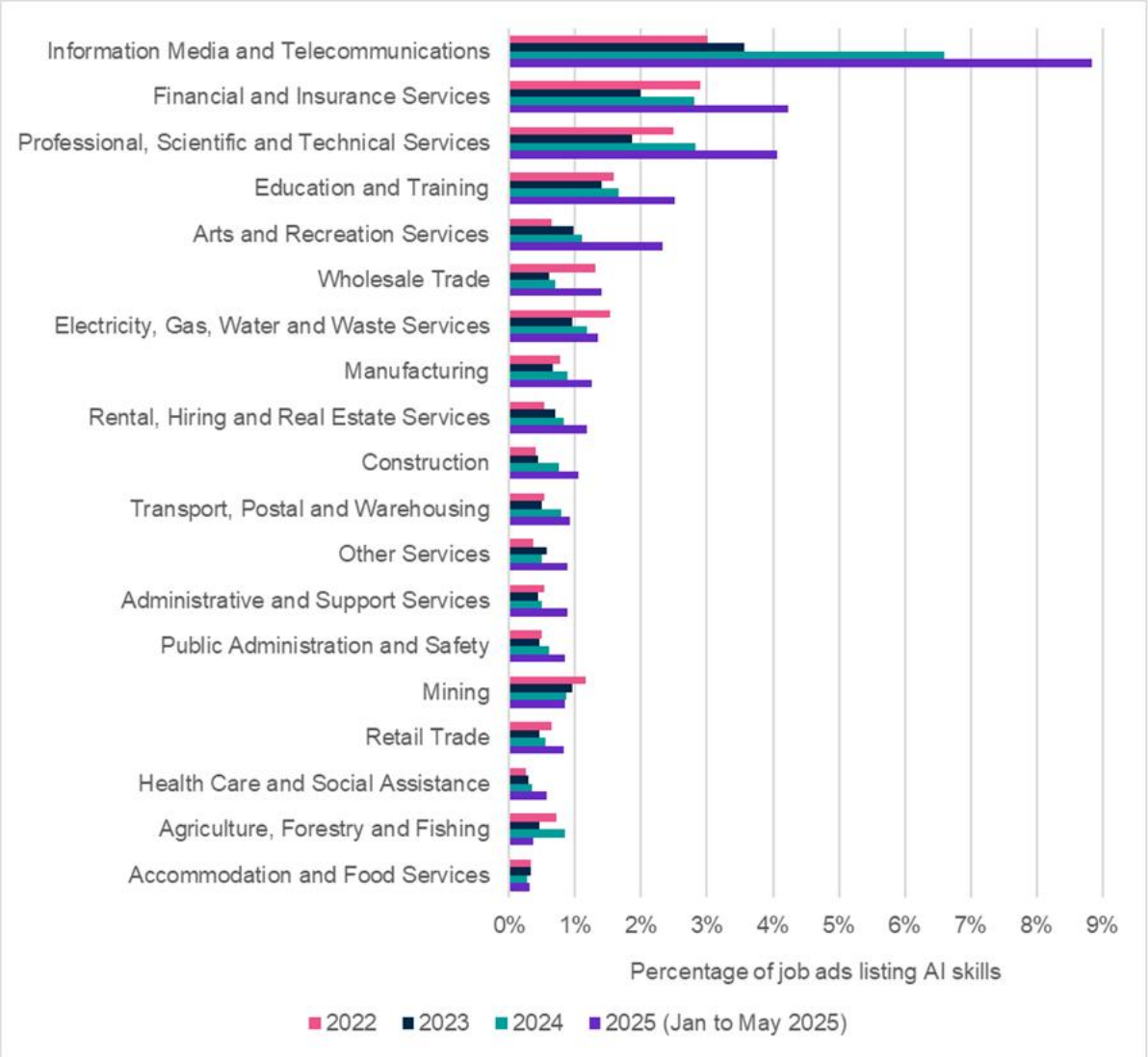
AI skills by industry

An industry lens provides another useful window into where step-changes in employer demand for AI skills have occurred. As shown in Figure 12, the largest percentage point increases in demand for AI skills between 2024 and 2025 were in:

- information-intensive industries such as Information Media and Telecommunications; Financial and Insurance Services; Professional, Scientific and Technical Services; and Education and Training, and
- Arts and Recreation Services, where the ability of Gen AI to generate text, images, videos and music may contribute to elevated demand.

Figure 12: Demand for AI skills is growing across most industries, albeit unevenly

Percentage of job advertisements listing AI skills by industry and year



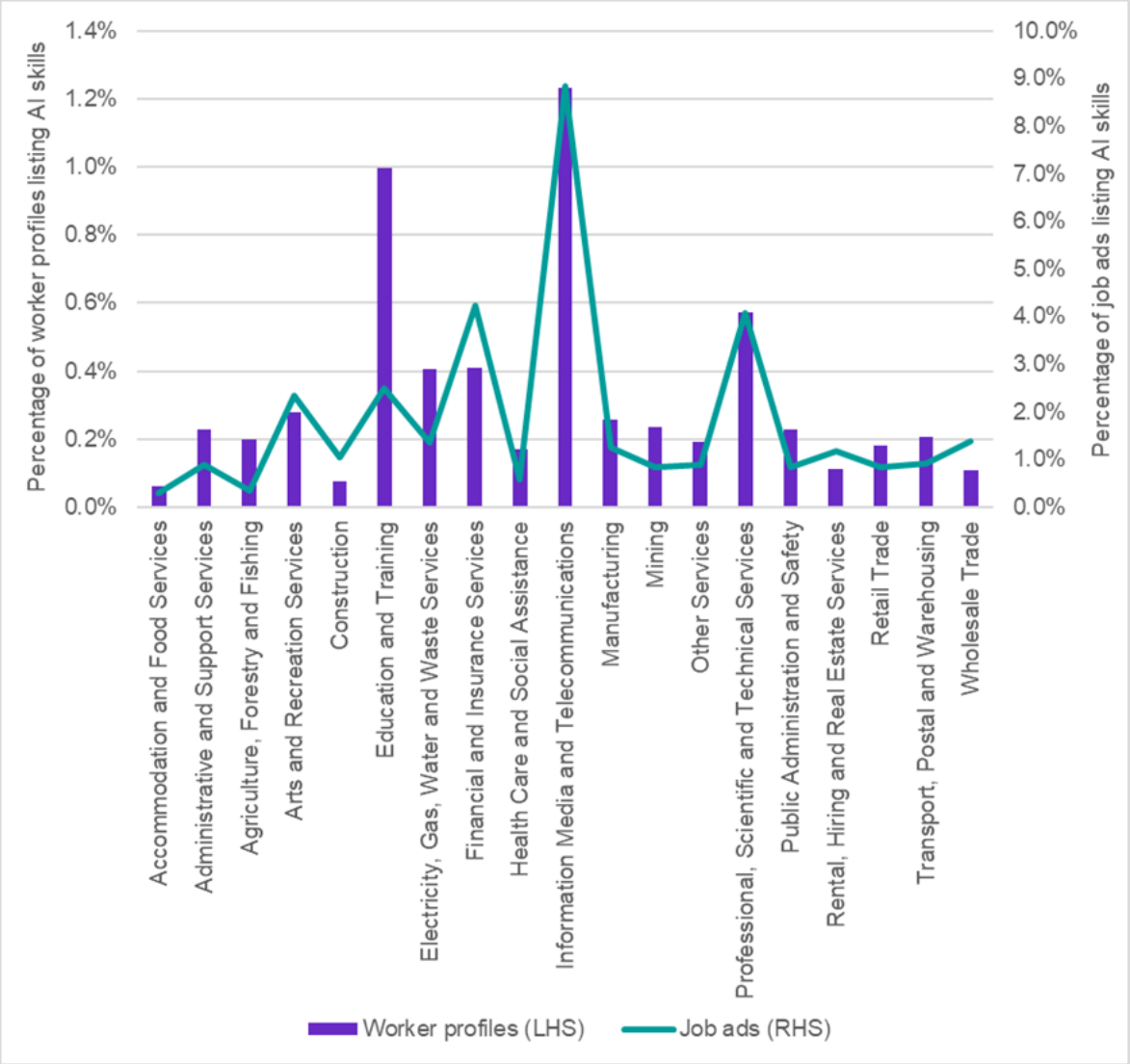
Source: JSA analysis of Lightcast job advertisement data.

Comparing worker profiles and job advertisements data provides useful insights into the current state of adoption in each industry. Our analysis indicates that AI skills are most commonly listed in profiles of those working in Information Media and Telecommunications (including the Software Publishing industry engaged in creating and disseminating AI-enabled applications) and Education and Training (including higher education teaching and research in computer science and AI) (Figure 13).

If the demand for AI skills indicated by job advertisements were met, we would expect to see the supply of skills in early adopting industries such as Financial and Insurance Services and Professional, Scientific and Technical Services increasing in the near term.

Figure 13: Industries vary in terms of their demand and supply of AI skills

Percentage of worker profiles and online job advertisements listing AI skills by industry, 2025



Source: JSA analysis of Lightcast job advertisement data and Revelio worker profiles data.

AI skills by individual and firm characteristics

Evidence from the nearly 6 million Australians whose profiles are captured in the Revelio dataset indicates that 0.5% of males list at least one AI skill on their profile, compared to 0.3% of females. This pattern of males being more likely to list AI skills than females is seen in all industries.

By highest education attainment, the highest share of individuals listing at least one AI skill are those with a postgraduate degree (1.1%). This is nearly four times higher than the next highest category of those with a Bachelor Degree as their highest qualification (0.3%).

AI skills also vary according to characteristics of the firm they work in. Individuals working in large employing firms (0.5%) are the most likely to list at least one AI skill, followed by small firms (0.4%) and medium firms (0.3%). The higher share in small businesses, compared to medium businesses, may partly reflect a relatively high share of AI skills among small start-ups, which could be explored in the future. This may also help explain why AI skills are most prevalent in firms in operation for less than 5 years (0.8%) compared to 5-15 years (0.5%) and more than 15 years (0.4%).

Skills complementary to Gen AI

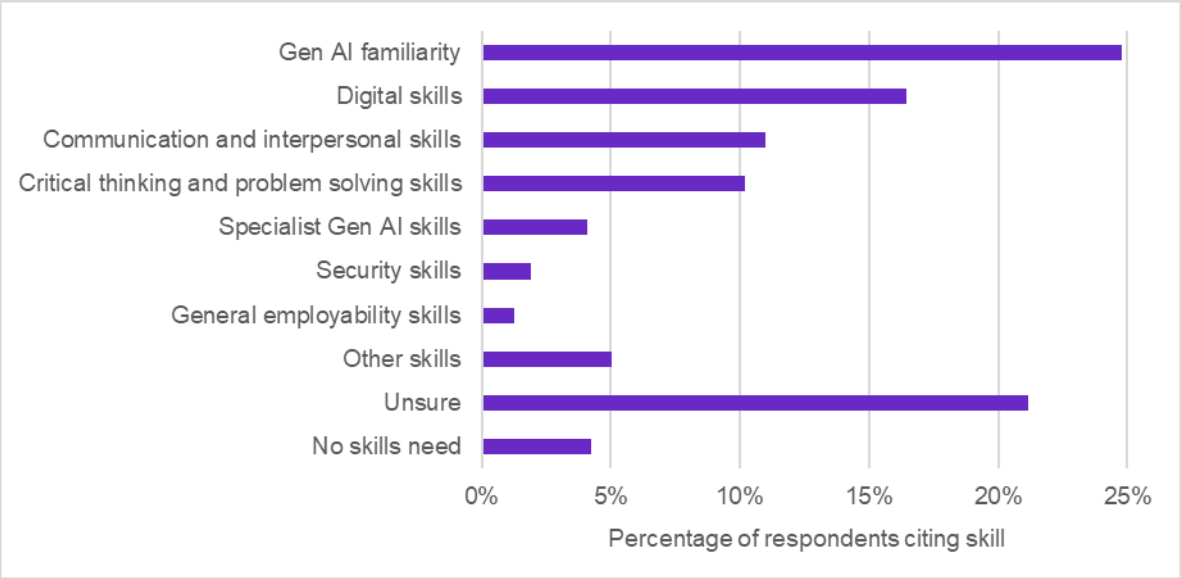
Evidence from JSA's Recruitment Experiences and Outlook Survey provides valuable insight into the skills business consider important when working with Gen AI.

Figure 14 indicates that businesses most commonly consider familiarity with Gen AI as important, followed by digital skills and human skills such as communication and critical thinking skills.

Additionally, around five times as many businesses considered familiarity with Gen AI important, compared with specialist Gen AI skills. This may reflect familiarity with Gen AI being important across a wide range of labour market participants and potential business applications, as opposed to specialist Gen AI skills being concentrated largely among the tech workforce, in addition to reflecting how early most businesses are in their AI adoption.

Figure 14: Businesses consider a range of skills important for workers to have when working with Gen AI

Percentage of business respondents citing select skills as important when working with Gen AI



Note: Based on the categorisation of open-ended survey responses. The same business respondent can include multiple important skills in their response.

Source: JSA, Recruitment Outlook and Experiences Survey: Generative AI module, February 2025.

Gen AI familiarity and fundamentals

Gen AI familiarity and fundamentals can be understood as a base level of skills and knowledge that support non-technical specialists to understand the opportunities, limitations and ethics of using Gen AI in a work setting.

There is little available data on the demand and supply of Gen AI fundamentals across the Australian labour market. Nevertheless, the available survey evidence indicates room for improvement at multiple levels in organisational structures:

- 41% of Australian businesses in a survey conducted for the Ai Group (2024) nominated leaders lacking skills and capabilities as a barrier holding them back from doing more with AI.
- Only 31% of workers surveyed by the Finance Sector Union (2025) reported that they felt prepared to work alongside AI. This is notable given the comparatively high Gen AI

exposure of the financial and insurance services industry and the prevalence of firms in this industry among early adopters.

Digital skills and other foundation skills / literacies

CSIRO research has found that higher levels of digital confidence are significantly associated with more positive experiences with, and attitudes towards, AI (Bentley, Naughtin, McGrath, Irons, & Cooper, 2024). This make sense, given the effective use of AI involves leveraging many of the building blocks of digital ability.

As defined for the Australian Digital Inclusion Index (2021), these building blocks include capability across the following domains:

- basic operational: including downloading and opening files, connecting to the internet, and setting passwords
- advanced operational: including saving to the cloud, determining what is safe to download, customising devices and connections, and adjusting privacy settings
- information navigation: including searching and navigating, verifying trustworthy information, and managing third party data collection
- social: including deciding what to share, how, and who with, manage and monitor contacts, and communicate with others
- creative: including editing, producing, and posting content, as well as a broad understanding of the rules that may apply to these activities
- automation: including connecting, operating, and managing smart devices and IoT technologies.

While the examples provided for each of these domains pre-date the emergence of Gen AI, the domains themselves remain relevant in a Gen AI-enabled era. Implicit within the domains above are the set of literacies and foundation skills that together constitute the kind of digital capability that enables effective Gen AI use. These include:

- language and literacy skills – required to craft prompts and comprehend the outputs of Gen AI technologies. Numeracy skills may also be required in this context where the desired output involves working with numbers.
- information and data literacy – required to search for, manage, organise, and critically evaluate the relevance and reliability of information and data when working with Gen AI.

There are particular limitations in using worker profile or job ad data to examine demand and supply of baseline-level capabilities. This is because baseline-level capabilities are likely to be implicit rather than explicit across most job ads and worker profiles, and tend to be specifically listed when a baseline proficiency (and no higher) is required for a job.

Options for making foundation skills requirements of occupations explicit are being considered as part of the development of the National Skills Taxonomy (JSA, 2024).

Human skills

Evidence from a range of sources highlights a continued – and potentially growing – importance of human skills (also known as soft skills) alongside AI adoption. A global survey of 2,500 workers (including 168 Australian workers) across industries and countries

commissioned by Workday highlighted the following connections between various human skills and business value in AI-enabled workplaces (Table 2).

Table 2: Human skills will remain valuable in AI-enabled workplaces

Skills Group	Qualities	Business value
Adaptability and resilience	• Ability to adjust to changes • Cultural sensitivity and adaptation • Emotional intelligence and empathy	Critical for navigating business disruptions. Demands emotional intelligence, empathy, and readiness for evolving workplaces.
Analytical thinking and decision-making	• Creative thinking and innovation • Critical thinking and problem-solving • Information synthesis and analysis • Strategic planning	A prime area for AI influence: augmenting human-centric critical thinking and problem-solving, innovation, and efficiency.
Interpersonal connection and collaboration	• Collaboration • Communication • Conflict resolution • Human networking and relationship building • Negotiation and persuasion	The most emphasised skills group in the study, highlighting the enduring importance of human connection, teamwork, and healthy conflict resolution.
Leadership and guidance	• Ethical decision-making and moral judgment • Leadership and management • Mentorship	Emphasises ethical reasoning, sometimes without clear precedents to follow, as well as moral judgment rooted in shared values.

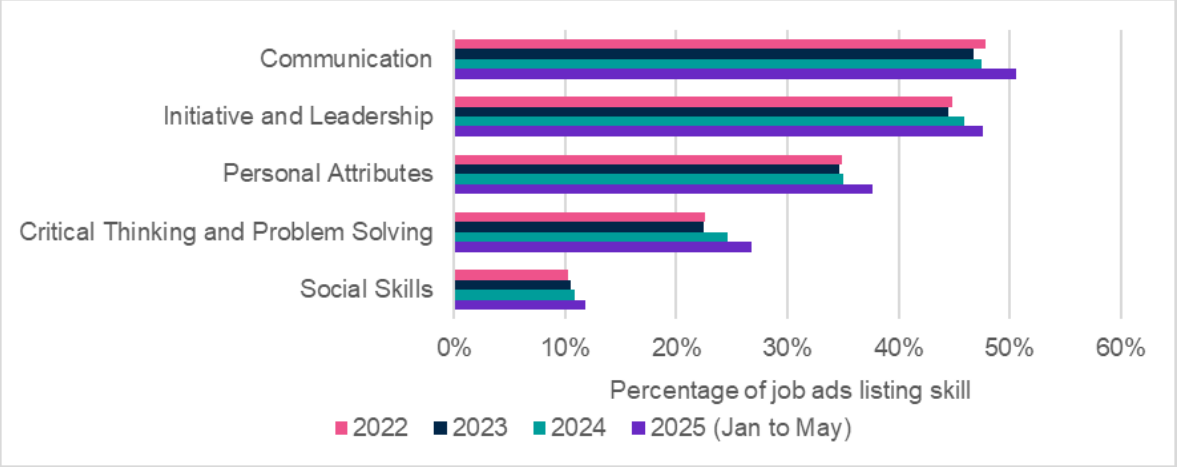
Source: Workday (2025) Elevating Human Potential: The AI Skills Revolution.

While isolating the impact of AI on demand for human skills in job ads is difficult, analysis of Lightcast job ad data reveals two important trends.

Firstly, the proportion of job ads listing human skills is significant and has been trending higher in recent years (Figure 15). So far this year, Communication, Initiative and Leadership, Personal Attributes, and Critical Thinking and Problem Solving have accounted for four of the top five skill sub-categories by the proportion of job ads in which they appeared.

Figure 15: Job advertisements continue to list human-centric skills

Percentage of online job advertisements listing select human skills by year, 2022 to 2025



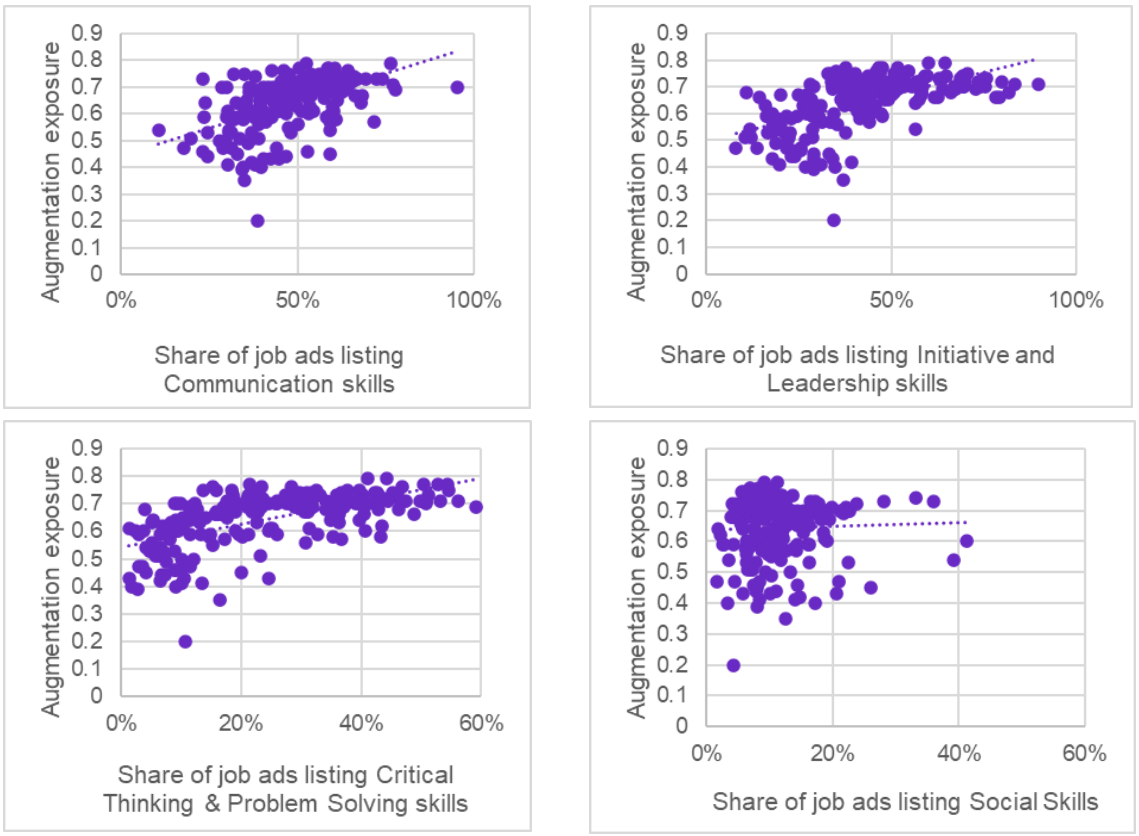
Source: JSA analysis of Lightcast job advertisement data.

Secondly, occupations with higher Gen AI augmentation exposure tend to exhibit higher shares of job ads listing Communication, Initiative and Leadership, and Critical Thinking and Problem Solving skills (Figure 16). This trend is less significant in relation to Social Skills.

As the scatterplots show, the demand for critical thinking and problem solving, and initiative and leadership, both increase alongside an increase in Gen AI augmentation exposure. That is, the dots in the scatterplots – which represent each occupation – generally shift to the right as augmentation increases vertically.

Figure 16: More augmentable jobs are more likely to demand human skills

Percentage of online job advertisements by occupation citing select human skills by augmentation exposure, January to May 2025 (min 100 online job advertisements)



Note: Each dot represents an occupation. Occupations with fewer than 100 job ads are excluded.

Source: JSA analysis of Lightcast job advertisement data.

This aligns with public submissions to a recent Parliamentary Inquiry into the use of generative artificial intelligence in the Australian education system (House Standing Committee on Employment, Education and Training, 2024). At least 30 of these submissions pointed to the importance of critical thinking, while several others referenced human or soft skills. It also aligns with submissions received as part of this study.

> *Customer service remains a vital component of the shopping experience, as two-thirds of Australian consumers view brick-and-mortar stores as a key touchpoint between a business and its customers. As such, interpersonal skills such as empathy, problem-solving and communication will become increasingly valuable as they complement AI capabilities. This shift underscores the need for both technical expertise and human-centric skills. (Service and Creative Skills Australia, 2025)*

Domain expertise

Domain expertise (i.e. the possession of in-depth knowledge and skills relevant to an industry, occupation or field) is an important enabler of effective and responsible Gen AI use in the workplace. This is driven in large part by the limitations of Gen AI, including that outputs are not guaranteed to be factual, accurate and unbiased. This limitation of Gen AI means that domain expertise is likely to be augmented rather than rendered obsolete by Gen AI, particularly in high-stakes settings where tolerance for error is low.

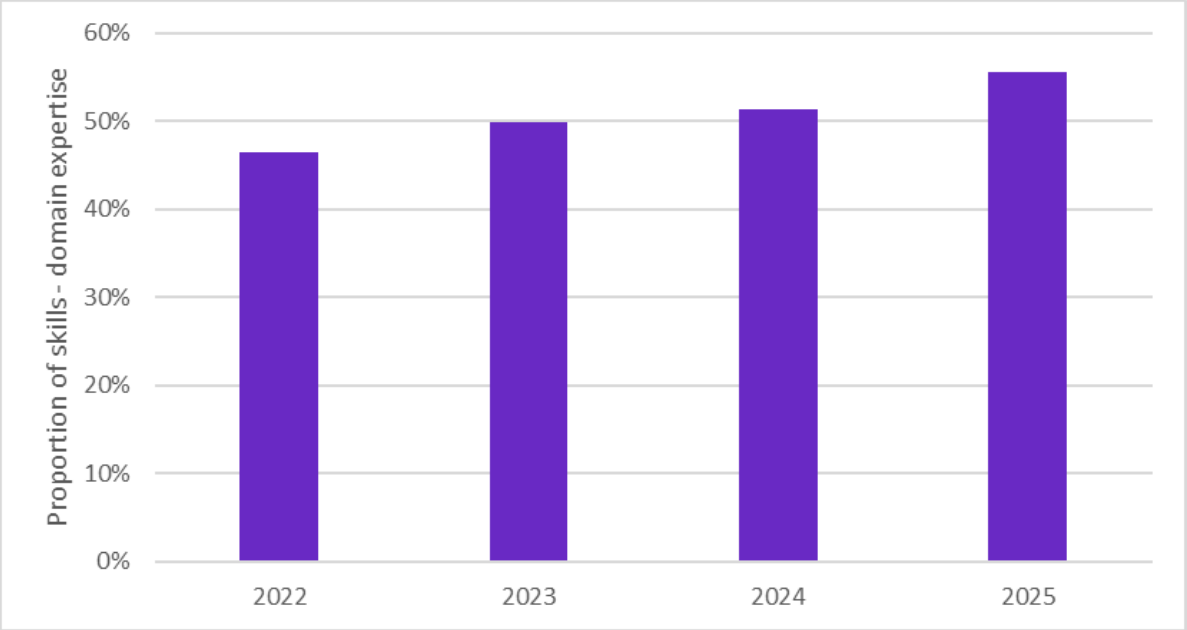
At the industry or organisation-level, domain expertise (alongside an understanding of the potential of the technology) is critical to aligning the right technological solution to the most impactful problem or opportunity. While at the individual level, domain expertise plays a role in enabling high-quality prompts and effective verification of Gen AI outputs. Domain expertise and professional judgment are crucial for sound decision-making, including where AI is involved.

We heard in our consultations that Gen AI can access a multitude of information but often lacks critical context. We also heard recognition of the augmentation potential of Gen AI in many contexts, where Gen AI can assist but is not a substitute for the skills, experience, and the knowledge that people have gained through their study and careers.

Our analysis of Revelio worker profile data indicates that the average share of skills listed by individuals accounted for by domain expertise skills[7] is steadily increasing in recent years and now represents over half of all skills listed in the average profile (Figure 17).

Figure 17: Workers are increasingly promoting their domain expertise

Average proportion of skills in worker profiles comprised by domain expertise skills



Source: JSA analysis of Revelio worker profiles data.

[7] For the purposes of this analysis, domain expertise skills are defined as specialised skills in the Lightcast skill taxonomy that are not software skills.

4. Skills system response

The desired outcomes of the skills system – encompassing higher education, vocational education and training (VET) and other forms of adult education and training – are multifaceted.

Multiple significant agreements and other documents related to the skills system contribute to the articulation of the objectives and desired outcomes for the skills system. These include the National Skills Agreement signed by Commonwealth and state and territory governments in relation to the VET system, and the *Higher Education Support Act 2003* as the main piece of legislation governing higher education in Australia.[8]

Not all objectives of the skills system are directly motivated by labour market outcomes. However, as a labour market focused study of the implications of Gen AI, this study will focus specifically on the outcomes that are orientated towards the labour market.

Gen AI exposure and tertiary education pathways

Applying an exposure lens to education and training pathways based on their destination occupations can provide insight into which pathways may be most impacted by Gen AI.

This study extends on previous work commissioned by the Future Skills Organisation (FSO) (2023), using a method that:

- reflects current Gen AI technology
- draws on real-world post-education and training pathways via linked data in the Person Level Integrated Data Asset (PLIDA), instead of 1:1 conceptual mapping of qualifications to occupations, and
- accounts specifically for augmentation – of critical importance in a skill system context where the implications of augmentation-focused implementation of Gen AI differ significantly from the implications of automation.

Our analysis suggests that across both higher education and VET graduates, augmentation potential is typically higher than automation potential. As a result, for most tertiary graduates the experience of Gen AI in the labour market is likely to be one of working with or alongside Gen AI, rather than one where their skills and knowledge are made obsolete by the technology. Improvements in the capabilities of Gen AI and the ongoing emergence of Agentic AI will influence the extent to which work tasks – and consequently occupations – are further exposed to automation or augmentation.

Our analysis also indicates that, on average, higher education graduates are more likely to enter occupations that are more highly exposed to augmentation and automation than their VET counterparts.

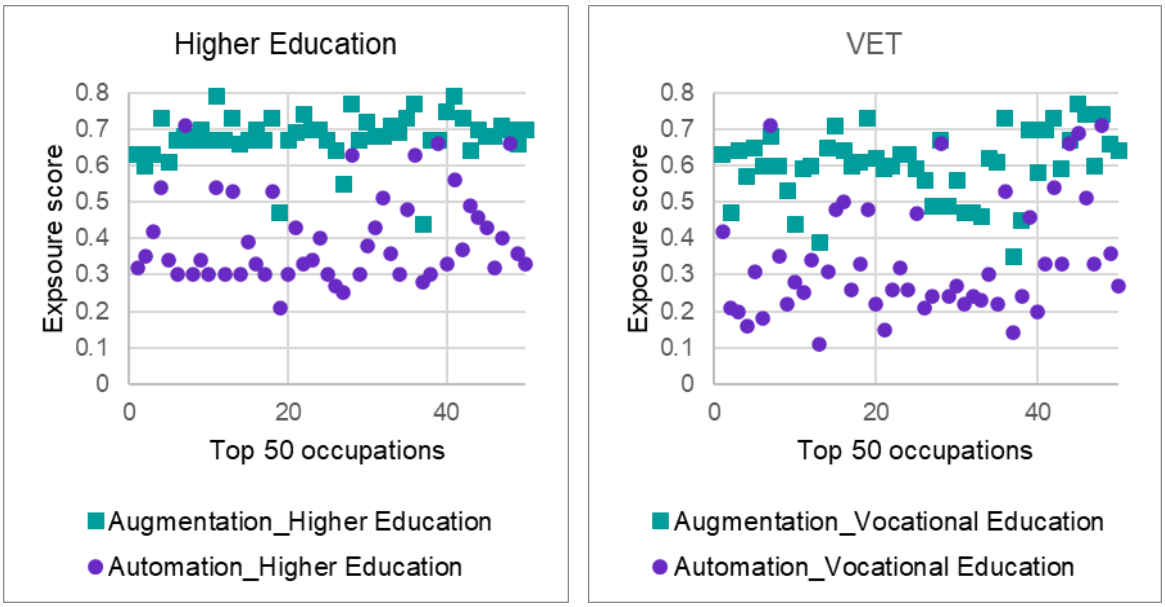
[8] The National Skills Agreement lists 4 population level outcomes (Productivity, Labour supply, Wellbeing and inclusion, and Resilience) and 5 system level outcomes (Industry needs, Student needs, Responsive courses, Quality delivery, and A collaborative and sustainable system).

Meanwhile the *Higher Education Support Act 2003* seeks to support a higher education system that: a) is characterised by quality, diversity and equity of access; b) contributes to the development of cultural and intellectual life in Australia; c) is appropriate to meet Australia's social and economic needs for a highly educated and skilled population; and d) promotes and protects freedom of speech and academic freedom.

Figure 18 illustrates this, with a focus on the 50 most common post-study occupations of our higher education and VET systems respectively.

Figure 18: Both VET and higher education graduates are likely to work in Gen AI-exposed jobs

Exposure scores of top 50 occupations for higher education and VET graduates



Note: Exposure score assigned at the unit group level to which the detailed occupation belongs.

Source: JSA analysis of ABS PLIDA data linking Census, higher education and VET statistics, 2018-20; ANZSCO v1.3.

Occupations commonly associated with higher education graduates are relatively consistent in their exposure to Gen AI augmentation (with an average of 0.68 and 47 out of the top 50 occupations having an exposure score within the 0.6 to 0.8 band). This likely reflects relatively high augmentation exposure of knowledge and information-based tasks common among occupation destinations of higher education graduates.

In contrast, the augmentability of common occupations of VET graduates exhibit a wider spread with an average of 0.60 but only 33 out of the top 50 occupations having an exposure score within the 0.5 to 0.7 band. This wider spread includes multiple common occupations of VET graduates that are highly exposed to Gen AI.

Higher education

One of the key ways in which higher education offerings in Australia are classified is by field of education, that is, the subject matter of an educational activity. By analysing real-world pathways, we can identify the fields of education where higher education graduates transition to occupations with the greatest propensity for augmentation and automation.

Figure 19 presents the weighted average augmentation and automation scores of each broad field of education.[9] With respect to automatability, Information Technology and

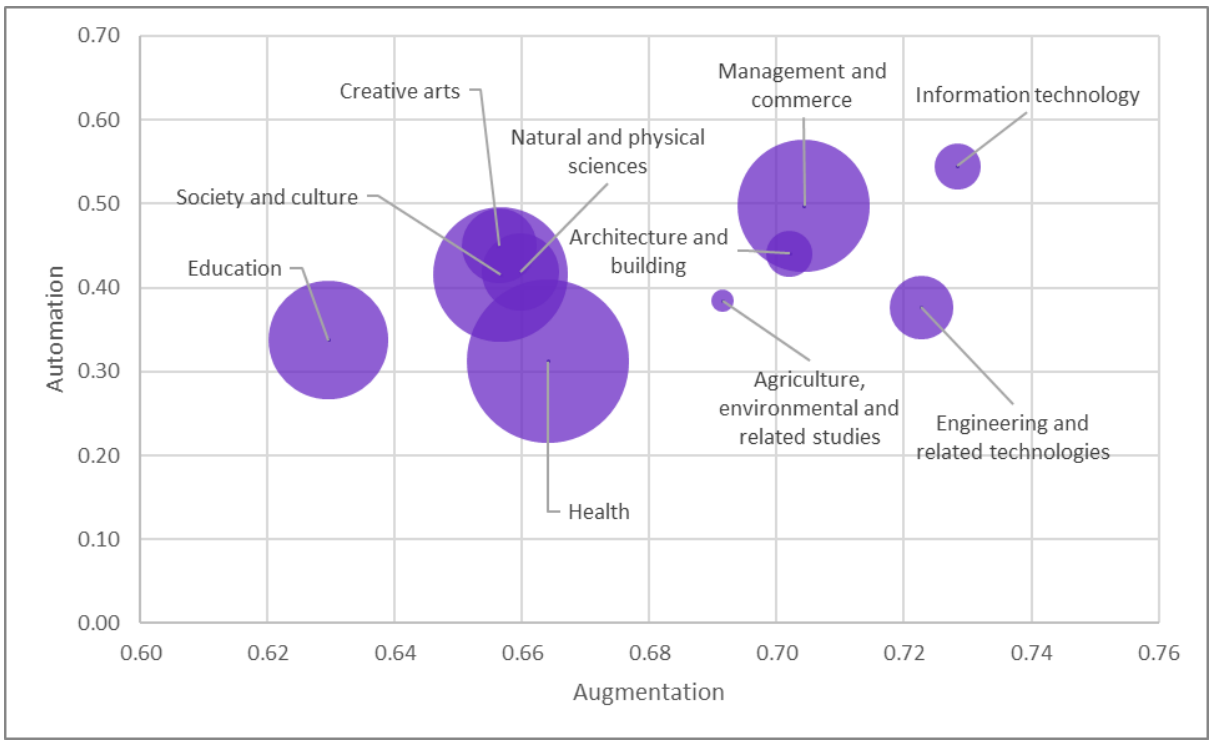
[9] Weighted average exposure scores for fields of education are weighted by the number of graduates from that field of education transitioning to a particular occupation. For example, if 70% of graduates enter an occupation with an augmentation score of 0.75 and the other 30% enter an occupation with an augmentation score of 0.6, the weighted average augmentation score would be 0.71. The weighted average exposure score is calculated with reference to graduates whose occupation unit group can be determined. Graduates who are unemployed, not in the labour force, whose occupation is not stated/inadequately described in the Census etc. are excluded.

Management and Commerce are the only fields with a weighted average automation score of 0.5 or above. Meanwhile, Education and Health exhibit the lowest automatability.

On augmentability, the spread between highest and lowest fields of education is substantially narrower (0.1 as opposed to 0.23). Information Technology has the highest exposure to both augmentation and automation. Meanwhile, Health and Engineering and Related Technologies exhibit the largest increases in their weighted average augmentation relative to their automation scores.

Figure 19: Gen AI exposure varies among broad higher education fields of education

Fields of education by weighted average exposure scores



Note: Bubble size indicates number of higher education completions in the broad field of education, with larger bubbles representing more completions.

Source: JSA analysis of PLIDA data linking Census and higher education statistics, 2018-20; ANZSCO, v1.3.

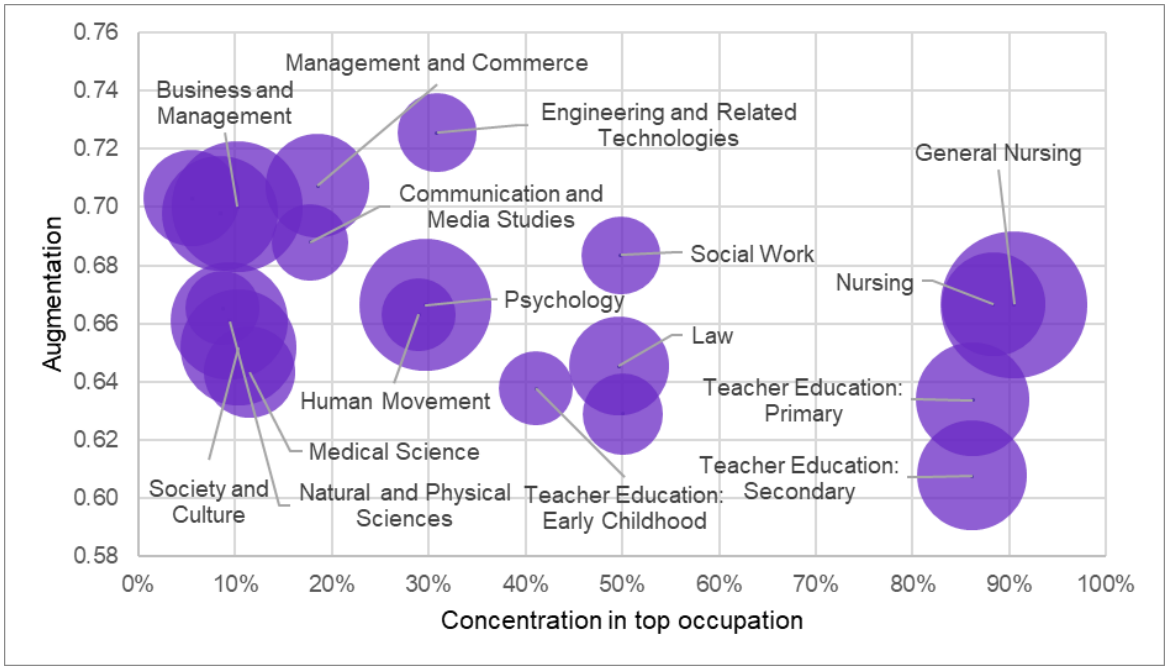
Drilling down to the 20 largest detailed fields of education, we can see significant variation in how different fields of education interact with the labour market.[10] Some detailed fields of education – often those including special courses required to obtain initial or provisional registration in a particular profession – largely funnel graduates into a single occupation. By contrast, other detailed fields of education see graduates widely dispersed across occupations.

Figure 20 overlays how detailed fields of education interact with the labour market with the weighted average augmentation score of post-study occupations from that field.

[10] Collectively, the top 20 detailed fields of education account for around 56% of higher education award course completions.

Figure 20: Augmentation exposure varies among fields of study with broad and narrow pathways

Top 20 detailed fields of education by weighted average augmentation and graduate concentration in the main post-study occupation



Note: Concentration in top occupation represents the percentage of graduates whose post-study occupation unit group is known who pathway to the same occupation unit group. Bubble size indicates number of higher education completions in the detailed field of education, with larger bubbles representing more completions.

Source: JSA analysis of PLIDA data linking Census and higher education statistics, 2018-20; ANZSCO v1.3.

Figure 20 shows that for some fields of education, graduates tend to enter a broad range of related occupations with high augmentability. This is the case for Business and Management, Management and Commerce, and Engineering and Related Technologies. In these fields, equipping graduates with the knowledge, skills and capabilities to work with and alongside Gen AI will support graduates' adaptability, mobility and resilience in the labour market. While exposure to Gen AI refers to potential and does not necessarily imply its actual adoption, it is likely that the ability to work with or alongside Gen AI will be valued in one or more of the common occupation destinations from these fields.

In relation to special courses required to obtain initial or provisional registration (e.g. as a teacher or nurse), the emphasis may be less on individual mobility and resilience and more on the collective capability of the workforce to adopt Gen AI. For occupations where completing a special course is mandatory, Gen AI adoption in the occupation could be significantly enabled or inhibited by extent to which the special course provides the skills, knowledge and capabilities needed to work with and alongside Gen AI productively and responsibly.

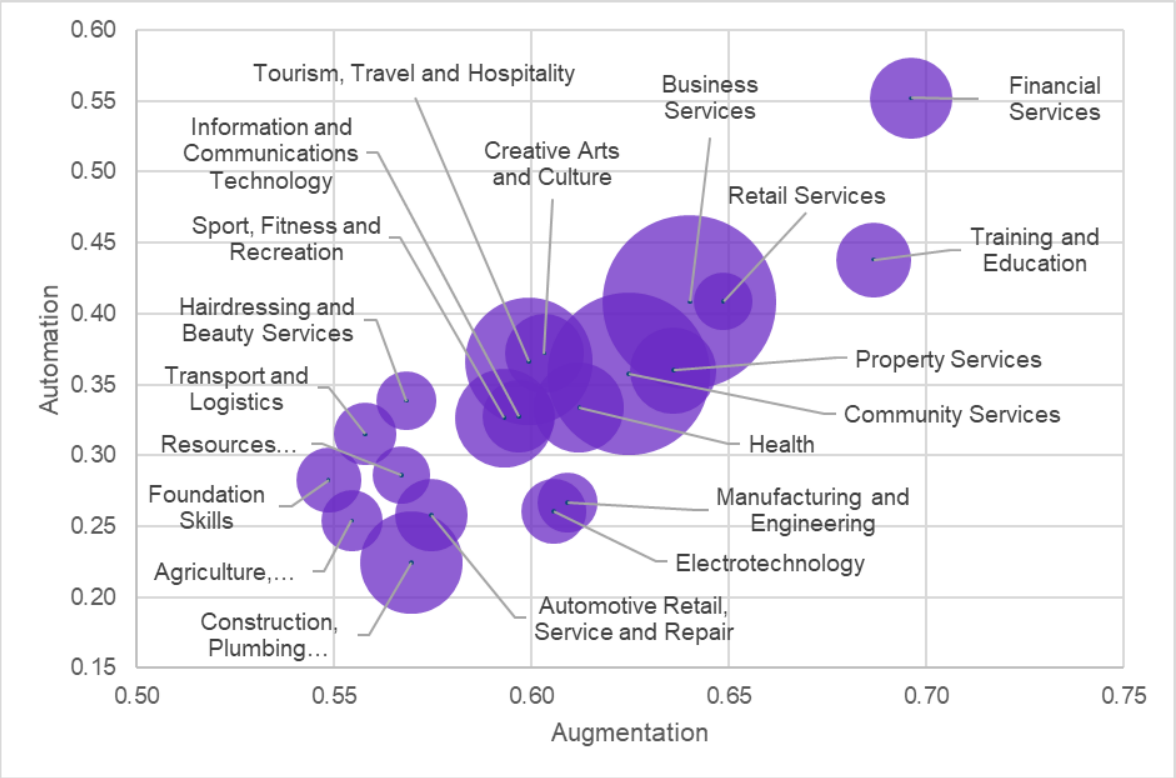
VET

Similar to the above analysis of higher education fields of education, analysing real-world pathways enables us to identify the training packages where VET completers transition to occupations with the greatest propensity for augmentation and automation.

Figure 21 presents the weighted average augmentation and automation scores of the top 20 training packages.[11] Of these training packages, Financial Services emerges as the most exposed across both automation and augmentation metrics. Other training packages with an augmentation exposure score of 0.6 or above include Training and Education; Retail Services; Business Services; Property Services; Community Services; Health; Manufacturing and Engineering; Electrotechnology; Creative Arts and Culture; Tourism, Travel and Hospitality; and Information and Communication Technology.

Figure 21: Gen AI exposure varies across VET training packages

Top 20 training packages by weighted average exposure scores



Note: Bubble size indicates the number of completions by training package, with larger bubbles representing more completions.

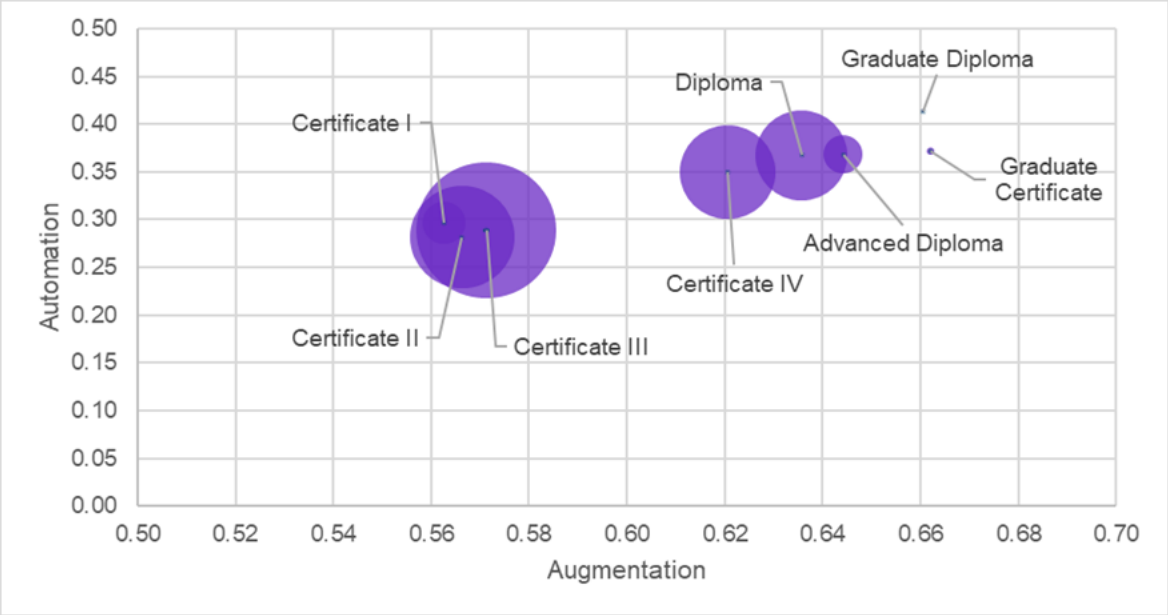
Source: JSA analysis of PLIDA data linking Census and VET statistics, 2018-20; ANZSCO v1.3.

Regarding qualification type, Gen AI exposure on average tends to be higher as the AQF level of the qualification increases (Figure 22). This is consistent with previous analysis which points to higher AQF levels in the VET system broadly leading to occupations with greater cognitive skill demands compared to lower AQF levels relying more heavily on physical skills (Future Skills Organisation, 2023).

[11] The approach for calculating weighted average exposure scores for each training package involved calculating the weighted average exposure score for each qualification before averaging this score for each qualification in the same training package. Collectively, the top 20 training packages account for over 90% of completions in training package qualifications.

Figure 22: Gen AI exposure is higher in higher level VET qualifications

Weighted average exposure scores by VET qualification type



Note: Bubble size indicates the proportion of completions by VET qualification type, with larger bubbles representing more completions.

Source: JSA analysis of PLIDA data linking Census and VET statistics, 2018-20; ANZSCO v1.3.

The response to date

Introducing Gen AI while managing academic integrity risks

The academic integrity risks of Gen AI have been widely noted, including by regulators and education and training providers. These risks are real and will require ongoing management, particularly in relation to areas where approaches to teaching, learning and assessment are most susceptible to Gen AI misuse.

Notwithstanding these risks, there is increasing recognition that blanket prohibitions on Gen AI use are not appropriate or consistent with the educative purpose of equipping students to participate in the Gen AI-enabled society and labour market. As Lodge, Howard and Bearman (2023) observed:

> *There is little value in ignoring AI or implementing blanket bans on particular tools or technologies. These are oversimplified solutions to a complex set of problems and overlook what is already known about good assessment practice. As AI use becomes commonplace across schools and workplaces, it will be increasingly important to consider how these tools are integrated into learning and teaching in higher education in intelligent ways.*

Education and training providers are pursuing a range of approaches regarding when and how Gen AI may be used by students and staff, and the extent to which teaching the skills and knowledge to work with Gen AI is explicitly embedded (Box 2).

Box 2 Example approaches to Gen AI across tertiary institutions

La Trobe University: In 2024, La Trobe University unveiled its 'AI-first' strategy which aims to integrate AI into curricula to prepare graduates for an AI-ready workforce and encourage staff to embrace an AI-first mindset, training them to use AI safely, ethically and responsibly to enhance productivity and improve student experience.

La Trobe's AI-first strategy is supported by partnerships with Microsoft and Cyber CX and will include opportunities to build expertise and experience through guest lecturers, industry participation, scholarships and skills programs, funding for digital transformation, and industry-recognised certifications and micro-credentials.

University of Sydney: From Semester 2 of 2025, the University of Sydney has moved to a two-lane approach to assessment in the age of Gen AI (Bridgeman & Liu, 2025). The two-lane approach summarised below distinguishes between two roles of assessment with different roles for Gen AI:

	Secure (Lane 1)	Open (Lane 2)
Role of assessment	Assessment *of* learning	Assessment *for* and *as* learning
Level of operation	Mainly at program level	Mainly at unit level
Assessment security	Secured, in person	'Open' / unsecured
Role of Gen AI	May or may not be allowed by examiner	As relevant, use of AI scaffolded and supported
TEQSA alignment	Principle 2 – forming trustworthy judgments of student learning	Principle 1 – equip students to participate ethically and actively in a society pervaded with AI

Source: The University of Sydney, The Sydney Assessment Framework

TAFE SA: TAFE SA provide guidance to students to support make informed decisions regarding using AI, including noting that the use of Gen AI tools in assessment is not supported by TAFE SA. TAFE SA Libraries has also compiled information on AI for the reference of students and staff, including in relation to the use of AI for teaching purposes and in the industries taught by TAFE SA.

Some diversity in how the tertiary education sector approaches the opportunities and risks of Gen AI is appropriate, with flexibility important for allowing innovation and room for the exercise of professional judgement. However, some differences in approach are also likely accounted for by varying levels of planning and capability among providers and staff in relation to Gen AI.

At the system level, the higher education system appears to have moved faster and further in planning for Gen AI. In 2024, the Tertiary Education Quality and Standards Agency (TEQSA) issued a request to all Australian higher education providers seeking a credible institutional action plan addressing the risk Gen AI poses to award integrity – a request that received a 100% response rate. In contrast, the results of one recent survey suggest that only 21% of VET providers had a formalised AI strategy (ReadyTech, 2025).

Based on the responses received to their request for information, TEQSA published the *Gen AI strategies for higher education: Emerging practice* toolkit sharing 'practical actions and experiences from across the sector, to uplift capability and support providers in managing the risk gen AI poses to award integrity, while also meaningfully and ethically integrating these tools into teaching and learning practices' (TEQSA, 2024). This resource is one of many available in the Gen AI knowledge hub compiled by TEQSA as part of its educative-led approach to date in protecting and enhancing the quality and integrity of higher education in the context of Gen AI.[12]

ASQA has begun to feature AI in communications to providers (including being referenced in ASQA IQ newsletters In July 2024, March 2025, and April 2025). Nevertheless, over the course of this study, we heard examples of VET practitioners who were hesitant to adopt Gen AI due to uncertainty about what would or would not be permitted from a compliance perspective. This suggests there is scope for ASQA to expand its educative activities in supporting the VET sector to manage risks while integrating AI into vocational education practice. This educative-led approach could include the provision of advice, clear statements of regulatory expectations, toolkits and resources.

New and updated education and training offerings

During consultation for this study we heard about a range of innovative efforts to respond to the pace of change and address skill gaps related to data, digital technologies and AI. The Institute of Applied Technology – Digital (IAT Digital) is a prime example (Box 3).

[12] TEQSA have signalled an intention to shift from an educative-led approach to a regulatory-led approach for 2026 as the risks of Gen AI in relation to assessment integrity and associated risks to compliance with the Threshold Standards in higher education are now widely understood (TEQSA, 2025).

Box 3 Institute of Applied Technology – Digital

The IAT Digital is a New South Wales Government-funded initiative that provides short courses targeting key digital skills including AI. Key features of the IAT Digital model include:

- **Microskills and Microcredentials:** The IAT Digital aims to provide flexible, modular training in the form of microskills (self-directed courses containing a few hours of on-demand content) and microcredentials (practical, assessed short courses providing certification in relevant industry skills. These short courses can serve as an opportunity to springboard into relevant entry-level roles. Alternatively, they can serve as a 'taster course' for those wanting to test their interest in pursuing full qualifications, with options for credit transfer available. Gen AI-focused IAT Digital courses include the microskill Generative AI and its Business Applications and the microcredential Unlock the Power of Gen AI: Prompt Engineering.
- **Co-design of courses by industry and education experts:** The IAT Digital model seeks to ensure a high quality and industry-relevant experience by leveraging the strengths of its foundation partners TAFE NSW, Macquarie University, the University of Technology Sydney and Microsoft.

  Our academic and professional staff are working with industry partners to co-design, co-develop and co-deliver micro-credentials, bringing Macquarie University's expertise and research to new learners. These new offerings fast-track the development of skills and knowledge in exciting and emerging areas (Macquarie University, n.d.)
- **Training for individuals:** The IAT Digital was conceived as a way to scale digital skills training for individuals, irrespective of their current employment status. This approach is consistent with the aim of providing an avenue for individuals to take a first step into work or further study in tech. This has not precluded businesses from identifying IAT Digital offerings as a means to help upskill their own workforce.
- **Speed to market:** Established relationships between industry and education providers and the flexibility of the IAT Digital model (compared to standard practice in higher education and VET settings) meant that the IAT Digital could have microskills in the market within a 6-month process in response to the emergence of Gen AI.

Education and training products focused specifically on Gen AI have tended to be short-form training targeting upskilling in this new technology – including, for example, those offered by the IAT Digital.

At the same time, full qualifications continue to play a central role in training students in the contemporary use of technologies, including AI, in their fields. Processes for identifying where and how Gen AI should be incorporated in full qualifications are underway. These processes differ between the VET and higher education sectors and are shaped by system and institutional-level arrangements related to updating the content of qualifications.

The process for developing new or amending existing training products in the VET sector is prescribed in the Training Package Organising Framework (TPOF). Where a proposed change meets the threshold for a major change, the full training product development and endorsement process applies. The timeframe for this process is estimated in the TPOF as

between 9.5 and 15.5 months, without accounting for the preliminary workforce planning and pre-development steps that Jobs and Skills Councils are required to undertake.

The Future Skills Organisation (FSO) Specialist Artificial Intelligence project – aimed at updating the Information and Communications Technology training package to include new training products related to specialist AI skills – provides a relevant example of the TPOF process in action. This project, which commenced in May 2025, is anticipated to be complete in February 2027. In an effort to accelerate the speed-to-market of training products, the FSO are also trialling a new approach in relation to digital capabilities, including generalist AI (Box 4).

Box 4 FSO Digital Capability Training Product Trial

The Digital Capability Training Product Trial aims to fast-track industry-led, high-quality digital capability skills, including generalist AI and generalist cyber skills, to address Australia's critical digital skills gap.

The trial will involve:

- designing units of competency that define essential digital skills across the economy developed based on the Digital Competence Framework for Citizens 2.2 (DigComp 2.2)
- collaborating with partners to develop and deliver training resources which enable the draft training product to be in the market in parallel with the Training Package Product Development Process.

The early testing enabled by the draft training product will also mean feedback can be incorporated as part of the finalisation of the accredited training products. This approach has the potential to reduce the need for time and resource-intensive updates down the line where issues are identified after the accreditation of the training product is finalised. If successful, the trial could provide a prototype for rapid development and deployment of training in the VET context in response to urgent skills gaps.

Outside the TPOF process, the Australian Skills Quality Authority (ASQA) as the national VET regulator, may also accredit courses designed to meet skills needs that are not covered in nationally endorsed training packages. ASQA has also recently been engaged in piloting delegation of course accreditation authority to a select number of TAFEs, to test where this delegation can be implemented in such a way to allow TAFEs greater flexibility and responsiveness to industry needs while safeguarding the integrity of VET accredited courses.

Self-accreditation is a more established part of the higher education system. As at 19 August 2025, the National Register lists 70 higher education providers (including Australia's major established universities) with either full or partial self-accrediting authority.[13] These institutions enjoy greater autonomy in designing and updating curricula and course content. In this context, the speed of responses to technological developments and changes in skill demands depends upon:

[13] This compares to 193 higher education providers listed as not having either full or partial self-accrediting authority.

- the effectiveness of the institution's mechanisms for identifying relevant changes to technology and skills needs, including the strength of their industry engagement, and
- timeframes of internal processes for approving major changes to qualifications and course offerings.

The time and cost for education and training providers of translating changes to qualification design into delivery can be significant. Factors contributing to translation costs can include developing, testing and quality assuring new resources, professional development for staff, and updating administrative processes.

In relation to fast-evolving digital and AI skills, stakeholders in our consultation identified the importance of avoiding overspecification in the design of qualifications. Alongside this, stakeholders raised a centralised mechanism for making high-quality, up-to-date learning resources available to education and training providers as having potential to enable greater responsiveness of qualification design and efficiency of delivery.

The role of industry and employers

Industry and employers are critical actors within the skills system. In relation to Gen AI, the tech industry – and industry more broadly – play a role in providing direct-to-business, direct-to-student and direct-to-user forms of education and training. These forms of training can include vendor training, industry certifications, online courses, boot camps and others. These and similar delivery models can play a significant role in:

- **providing expertise that has yet to be reflected in other standard qualifications.** Technology companies are providing learning opportunities in emerging skills sets, such as agentic AI. For example, Microsoft partnered with the education provider Akkodis Academy to make free training available to students and educators providing hands-on experience in building, deploying and managing AI agents (Akkodis Academy, 2025).
- **providing those already in the workforce with expertise additional to their existing qualifications.** For example, many professional and industry associations (such as the Australian Computer Society, Certified Practising Accountant (CPA) Australia and the Property Council of Australia) promote and/or provide industry-relevant Gen AI courses and learning resources. Completion of these activities frequently contributes towards meeting continuing professional development requirements and/or results in digital badges or certificates.
- **providing those without other qualifications with expertise that could be applied directly to work situations or lead to further study.** Online courses through learning platforms such as Coursera, Google Learning and others can provide an alternative pathway to developing industry-relevant skills for those considering a career or further study in technology-related fields.

These forms of training are an important source of dynamism in the skills system, with several stakeholders in our consultations observing that the implementation of Gen AI tools in leading firms and industries has moved faster than the integration of relevant skills into formal education and training.

Decisions made by employers about the skills they value and who and what they invest in are directly relevant to enabling AI readiness across different roles or 'personas' in the firm (as summarised in Analysis Paper B). Our analysis of public reports of ASX 200 companies showed that 19% mentioned AI training in their annual reports in 2023, rising to 25% in

2024. It is not always clear what training is being provided, but several companies flagged training focused on leadership development or executive education focused on AI strategy, ethics, or management (18%), with a smaller share allocating resources to training programs focused on how employees can use, operate, or work with existing AI tools, platforms, or applications in their daily work (12%).

Beyond training investment decisions, employers also signal the skills, credentials and attributes they value in their hiring and promotion decisions. We heard examples of businesses explicitly adopting skills-first approaches, which typically involve reduced emphasis on individuals' formal credentials and previous work experience to instead focus on the skills and knowledge they possess and evidence of what they can do.[14]

We also heard examples of firms taking an employment-first approach, employing individuals with potential from any background into roles with lower barriers to entry and working with them to identify and develop the skills required to progress their careers in the firm.[15]

Industry and employers also have an important role in engaging and collaborating with the education and training sector (Box 5). This includes:

- communicating current and future industry skill needs
- making available opportunities for students to participate in work-based and work-integrated learning, and
- supporting knowledge exchange between industry professionals and educators.

[14] Case study: A skills-based approach at Workday

[15] Case study: Gen AI adoption and adaptation at ReadyTech

Box 5 Partnerships between the technology industry and education and training providers

In 2019, Telstra signed Memorandums of Understanding (MoUs) with RMIT University, University of Melbourne, UNSW Sydney, University of Sydney, and University of Technology Sydney (UTS) to jointly develop technology-related short-form training. The partnership created microcredentials on data analytics, data engineering and machine learning. Over 2500 Telstra employees have trained under the collaboration. At the same time, Telstra agreed to work with each university

> *…to enhance student learning through providing input into curriculums, industry placements and integrated work experiences, research and innovation opportunities, and early access to career opportunities (Telstra, 2019).*

The University of the Sunshine Coast has embedded technology industry certifications into each year of its technology degrees. This includes certifications and badges from Microsoft, ITS, CISCO and EC-Council, equipping them with additional professional skills.

> *Students can earn while they learn by using in-demand industry certifications and badges to secure jobs and internships in the booming technology sector as they study – and graduate with high-level, job-ready professional skills (University of the Sunshine Coast, 2022).*

While industry-education engagement and collaboration is occurring, there are opportunities to achieve greater scale, efficiency and sustainability. This is particularly the case in relation to the higher education sector, where such engagements were described by some stakeholders as frequently ad hoc and challenging to scale beyond single institutions. As the Australian Universities Accord Panel (2024) highlighted:

> *there is a need for a forum between industry and universities to support skills delivery, the co-design of both course curriculum and work integrated learning programs, and improved industry utilisation of higher education research and knowledge.*

Given the accelerated pace of skill change that typically occur in the context of widespread adoption of new technologies, this need is only likely to become greater.

Supplementing domestic skills supply with international expertise

The response of Australia's education and training systems in developing our digital skills base will need to continue to be supplemented by the contribution of skilled migration. ICT Professionals figure prominently among Australia's permanent skilled migration intake, with over 9,000 permanent skilled visas granted in 2023-24.[16] Technology occupations Software Engineer and ICT Business Analysts also feature among the top 10 nominated occupations for primary temporary resident (skilled) visas in 2024-25 (Department of Home Affairs, 2025).[17] Overall, the FSO (2025) calculates that migrants constitute 41% of the workforce in technology occupations.

[16] This figure is from the Department of Home Affairs report on the permanent migration program, BP0068 Migration Program, Expert Panel (Family) and Child Outcomes, 2014-15 to 2023-24.

[17] Data for 2024-25 are year to date up to 31 March 2025.

This strong demand for specialist skills in digital technologies, including AI, highlights the importance of efforts to develop these capabilities through Australia's education and training systems.[18] These efforts should not be limited to the pursuit of increased enrolments and completions. As highlighted in our pace of skill change analysis, ICT Professionals is a highly dynamic occupation group which exhibited the highest pace of skill change between 2012 and 2024. Analysis by JSA (2024) – at least in relation to Software and Applications Programmers – identifies a suitability gap as a shortage driver.[19]

Efforts to develop these capabilities through Australia's education and training systems should continue to be complemented as appropriate by skilled migration, given:

- There is a time lag between increasing the pipeline of domestic students and addressing skills gaps in the labour market, particularly for specialist skills which require longer education and training pathways.
- Highly skilled migrants can make significant contributions to innovation and productivity, including in relation to the adoption and diffusion of new technologies such as Gen AI. The contribution of highly skilled migrants can also include helping to uplift the skills and expertise of Australian workers through increased knowledge-transfer.

Skills system challenges

Enabling digital and AI uplift across the capability spectrum

An individual's ability to engage confidently, critically and responsibly with digital technologies including AI has become a key enabler of participation in work, study and society in the 21st century. Given the productive potential of Gen AI and its applicability across a wide range of personal and professional tasks, Gen AI is only likely to make this even more important.

Uplifting digital and AI capability across the labour market requires action across the capability spectrum. Following the example of Cain and Coldwell-Neilson (2024), we unpack this by identifying three key building blocks in the development of individual capability – foundations, competence and fluency.

Foundations

Access to digital technologies and foundational digital skills are pre-requisites for harnessing the productive potential of AI. Although digital inclusion at the national level has improved as measured by the Australian Digital Inclusion Index, 9.4% of the population remained highly digitally excluded as at the most recent data from 2022. Cohorts overrepresented among the highly digital excluded include First Nations people, the unemployed, people with a disability, older Australians, and those living outside major cities.

[18] According to executives surveyed by the World Economic Forum (2025) as part of the Future of Jobs Survey, the jobs expected to grow the fastest in relative terms by 2030 are specialist digital and AI roles such as Big Data Specialist, FinTech Engineers, AI and Machine Learning Specialists, and Software and Applications Developers.

[19] The suitability gap category refers to those occupations where there are enough qualified applicants, but they are not regarded as suitable.

Recent CSIRO research attests to the spill-over effect of existing digital divides onto experiences with AI, reinforcing the importance of digital access and foundational digital skills as building blocks of AI capability (Bentley, Naughtin, McGrath, Irons, & Cooper, 2024).

While the skills system alone cannot solve all barriers to digital inclusion, it can play a major role in bridging digital divides by promoting foundational digital skills and ensuring equitable access for students of digital technologies, including Gen AI.

Effective use of Gen AI also engages other foundation skills such as literacy and numeracy which may be required to craft prompts and understand outputs. In addition to these foundation skills, basic AI literacy also requires a foundational awareness of issues such as bias, hallucination and privacy.

Competence

In addition to supporting a minimum baseline capability for everyone, the skills system should aim to provide and cultivate digital and AI skills, knowledge and attitudes at the right proficiency levels that are relevant for the learner. In addition to generalist digital and AI capability, this will often also involve instruction in domain-specific skills and knowledge for applying AI in a particular context.

The Australian Government recognises DigComp 2.2 as a preferred guide for digital skills and training activities for citizens, learners and workers. This framework identifies 5 areas of digital competence: information and data literacy; communication and collaboration; digital content creation; safety; and problem solving (Vuorikari, Kluzer, & Yves, 2022).

Achieving an appropriate level of proficiency across each of these 5 areas is an important indicator of an individual's AI readiness. What an appropriate level of proficiency looks like will depend on the context. For example, a nursing course where graduates will be expected to handle sensitive personal data may seek to develop a higher baseline with respect to information and data literacy and protection and safety components of digital capability than with respect to digital content creation. As HumanAbility (2025) – the Jobs and Skills Council for the care and support economy – noted in their submission:

> *Role-specific digital capability may include using AI-enabled tools to support communication, manage documentation safely, and apply data privacy and consent principles, while preserving the relational and ethical foundations of care work.*

Other international skills frameworks such as Singapore's Skills Framework for Infocomm Technology (ICT) outline a preliminary set of skills in Gen AI which provide an indication of what digital competence means in the context of Gen AI (Infocomm Media Development Authority and SkillsFuture Singapore, 2025). This includes the differences in skill and knowledge requirements between generalist and specialist users of Gen AI.

Fluency

Fluency refers to applying digital capabilities alongside core non-digital capabilities and domain expertise to achieve positive outcomes through the use of digital technologies and AI.

Our analysis has shown that labour market demand for human skills such as communication, critical thinking and problem solving, and leadership is significant and trending higher in recent years. Moreover, occupations with higher Gen AI augmentation exposure tend to exhibit higher shares of job ads listing these human skills.

This foundations-competence-fluency framing is not the only possible framing of the digital and AI capability spectrum for individuals.[20] Nevertheless, this framing captures some of the common elements across relevant frameworks and digital inclusion literature. This includes acknowledging:

- the three-levels of the digital divide: material access, skills and usage, and outcomes
- multiple levels of proficiency encompassing foundational, generalist and specialist skills and knowledge
- different domains or dimensions of digital and AI competence, e.g. information and data literacy; communication and collaboration; content creation; safety; and problem solving
- the importance of technical digital and AI skills alongside core non-digital capabilities, and
- a balance between general skills and knowledge that support everyone to engage confidently, critically and responsibly with digital technologies and domain-specific skills and knowledge for applying AI in particular contexts.

Multiple pathways to uplift to suit learner needs

The nature of Gen AI exposure makes clear that training needs will face workers at various stages of their careers and in different personal circumstances. It is critical that the training is delivered in formats with appropriate financial and time costs. Multiple methods of education and training delivery will be needed and delivered at scale.

Full tertiary qualifications, particularly those predominantly undertaken by students earlier in their adult life, are a key vehicle alongside school education for promoting adaptive capacity. Such qualifications can prepare graduates for a world of fast-evolving, non-routine work by developing self-regulation skills such as learning to learn. This should be accompanied by mechanisms to equip graduates with skills and knowledge relevant to their domain or field. As Engineers Australia (2025) noted in relation to initial higher education and VET qualifications:

> *These sectors play a foundational role in shaping technical skills and professional judgement. Overreliance on Gen AI at this stage may hinder the development of core engineering capabilities. Focus of education must remain on developing core engineering capabilities and understanding how Gen AI can support – rather than hinder – this process.*

Tertiary qualifications should also familiarise graduates with current industry/professional practice. For example, the responsiveness of qualifications to the use of Gen AI will be critical to ensuring the pipeline of new graduates can uplift the AI readiness of firms and industries across the economy.

Short-form learning – whether delivered as accredited or non-accredited training – serves an essential role in the skills system as a vehicle for rapid and responsive up-skilling or re-skilling. As the QUT Digital Media Research Centre (2025) observed:

[20] The Digital Education Council (2025) AI Literacy Framework is another notable example. This framework includes 3 levels of competency and 5 dimensions of AI literacy: Understanding AI and data, Critical thinking and judgment; Ethical and responsible use; Human-centricity, emotional intelligence, and creativity; and Domain Expertise.

Full qualifications will remain essential for foundational knowledge and regulated professions, but micro-credentials and modular learning will gain importance as AI continues to shift skill requirements at pace.

In many cases, short-form learning will be the most efficient and effective option for developing AI skills and literacy for those in the workforce, or those looking for entry-level work where a full qualification is not required. For example, the Victorian Government's Digital Jobs program has supported over 5,400 mid-career Victorians to complete 12 weeks of industry-relevant training and the opportunity to apply for 12-week paid work placement in the digital economy with a Victorian business.

Alongside full qualifications and short courses, on-the-job training will be required to maximise the productivity benefits of labour augmenting Gen AI. On-the-job training may be most relevant in providing training for workers for particular AI tools and use cases that pertain to their current role or firm.

Providing strong foundations for adaptability and keeping up with the pace of change

The medium-term implications of Gen AI, and the emerging capabilities of agentic AI, on demand for skills in the labour market cannot be predicted with certainty. In part, this is due to uncertainty about the future capabilities of the technology itself. Nevertheless, it is reasonable to expect that technological developments capable of being applied across a wide range of occupations and industries will accelerate the pace of change. In this context, investing in the adaptive capacity of our people is a sensible approach.

Graduate-level outcomes

During our consultations we heard from multiple skill system actors and subject matter experts on what skills and knowledge would be required in an AI-enabled labour market. The messages that emerged from these consultations centred around the following propositions:

Domain expertise and human skills will remain important, though new combinations of skills and knowledge will be necessary

While emphasising the continued need for domain expertise in a Gen AI-enabled economy, stakeholders also raised the likelihood that new combinations of skills and knowledge will likely be required to maximise the adaptation potential of Gen AI. This could include skills and knowledge that cut across domain boundaries as currently defined. For example, stakeholders emphasised in relation to the arts sector 'the growing demand for professionals who can integrate creative and technological skills' (Service and Creative Skills Australia, 2025).

Education and training sectors should aim to develop domain expertise and human skills alongside embedding AI literacy and technical AI skills to avoid overreliance on Gen AI and the associated risks of skill erosion and cognitive atrophy.

Any inclusion of AI literacy training must therefore be carefully balanced and integrated in ways that reinforce, rather than replace, these core competencies. If AI use is prioritised without sustained attention to critical thinking, ethical reasoning, and independent problem-solving, education risks reinforcing the very overreliance it seeks to prevent (QUT Digital Media Research Centre, 2025).

Graduates should be proficient users of relevant technologies

While human skills and domain expertise are critical for adaptive capacity over the medium term, proficiency in the use of relevant technologies remains highly influential in determining the employment prospects of those starting their careers or looking to move into technology-intensive work.

Responding to the pace of change is a critical challenge in this context. Our analysis of Australian online job advertisements has shown that technology-intensive occupations have historically exhibited high rates of skill change. There is no reason to believe this will not continue in the context of broader adoption of Gen AI.

During our consultations we heard about activity underway in various parts of the skill system aiming to deliver and update the technical skills required by students in line with industry/professional practice. However, we also heard concern from a range of stakeholders regarding the capacity of the skills system to respond to the pace of change, in terms of both the level of dynamism and scale required. For example, Service and Creative Skills Australia (2025) noted in their submission:

> *The Tourism and Hospitality sectors are using AI to improve efficiency and guest experience, but current training is not keeping pace with digital needs which may result in a widening skills gap and increasing the risk of skills shortages.*

Greater collaboration and coordination between the technology industry – and industry more broadly – and the tertiary education sector will be vital in ensuring the relevance and responsiveness of education and training in fast-evolving industries and job types. This collaboration could focus on the design and delivery of education and training programs, work-integrated or work-based learning opportunities, and intelligence on the most value technical and human skills that will assist students in working with and alongside Gen AI.

AI capabilities should not be viewed in isolation from data, digital and cybersecurity skills

Stakeholders emphasised that broad capability uplift in relation to AI cannot be achieved in isolation from data, digital and cybersecurity skills at generalist and specialist levels. The 5 areas of digital competence outlined in DigComp 2.2 are relevant here. This includes avoiding assumptions about digital or AI natives and recognising the potential for spiky profiles in skills. For example, individuals whose use of Gen AI has largely been for personal rather than professional reasons may have more developed skills in relation to digital content creation than information and data literacy and safety. Also, while skills, knowledge and behaviours related to the specific characteristics of AI are important, productive and responsible use will be enhanced by broad capability uplift across data, digital, AI and cybersecurity.

System-level outcomes

During our consultations with skill system actors and subject matter experts, we heard the following messages on features that will enable the skills system to be ready for the opportunities and challenges posed by Gen AI:

The capability, capacity and currency of trainers and educators will be key

The capability, capacity and currency of educators and trainers across the tertiary sector play a pivotal role in ensuring high-quality and relevant learning experiences. Targeted

professional development can support educators and trainers to maintain current skills and knowledge with respect to the following:

- **Education, training and assessment:** All educators and trainers will require at least a baseline level of AI skills and literacy. This should include educators and trainers having access to relevant Gen AI tools as well as guidance and training on how to:
  - leverage digital technologies such as Gen AI responsibly to improve teaching and learning while avoiding student overreliance on Gen AI, and
  - ensure high-quality, robust assessment in the era of AI.
- **Industry practice:** Where they are up to date with current and emerging industry practice in the relevant field, educators and trainers can be well placed to contextualise and tailor delivery within the bounds of training products and curricula. This could involve the introduction of contemporary tools, techniques and examples.

Continuing professional development to maintain currency with contemporary educational and industry practices is a familiar concept across VET and higher education. However, Gen AI introduces an additional reason to reinforce and strengthen mechanisms for targeted professional development.

During consultations for this study, we heard that educators and trainers have a desire to act and innovate in relation to Gen AI. In part, this is motivated by an acknowledgement that Gen AI is already available to many students and cannot be simply ignored. Beyond this, there is also an awareness of the opportunities Gen AI presents in many cases to plan and deliver high-quality education and training more efficiently and effectively. The potential of Gen AI also extends to promoting equity in education and training.

> *Generative AI can enhance learning for digitally excluded groups when used appropriately—for instance, through language translation, simplified content creation, or personalised feedback. These benefits are particularly relevant for adult learners, migrants, and individuals with low English proficiency. (QUT Digital Media Research Centre, 2025)*

Agility in responding to emerging skill demands will be important

Responding to the pace of change is a critical challenge. Our analysis has shown that technology-intensive occupations historically exhibit higher rates of change in skills demanded. Gen AI is likely to accelerate the rates of skill change across many occupations in the labour market, particularly as technology use cases continue to evolve.

The ability of higher education and VET to respond to emerging skill demands is shaped by structural arrangements around both training product development and delivery.

In the VET sector, nationally endorsed training packages provide strong alignment with industry-defined competencies and ensure a degree of consistency across providers. However, the formal process for updating these packages is frequently described as too slow to respond to technological developments (Joyce, 2019) (Productivity Commission, 2019).

Higher education institutions have more autonomy in designing and updating curricula, which can allow more responsiveness to technological change. While the Australian Universities Accord Panel (2024) highlights this flexibility as a key strength, it also flags the need for strong integration between universities and industry, including through partnerships and national frameworks.

Mechanisms for identifying, disseminating and scaling good practice are essential

While acknowledging the valuable activity underway being led by multiple skill system actors, stakeholders highlighted the need for strategic coordination if the productive potential of Gen AI is to be realised. Opportunities for greater coordination were identified in relation to:

- workforce planning and skill gap identification – with stakeholders highlighting the value of a coordinated and coherent response to national priorities, acknowledging that no single provider is likely to be able to address national skills gaps on their own
- industry-education engagement and collaboration – the current state of which was described by many stakeholders as fragmented and inefficient, and
- disseminating and scaling good practice across education and training providers – which was described as a potentially limiting functional gap in the existing approach, which currently relies on a dispersed and resource-intensive approach of individual providers developing their own resources and products, with limited mechanisms to share the learnings of early experimentation in relation to Gen AI.

Stakeholders have identified a national network approach to these opportunities as one that merits consideration. This type of approach has been put into practice internationally, including in relation to The Alan Turing Institute – the United Kingdom's national institute for data science and AI. This institute, which has a network of 65 universities from across the United Kingdom and collaborates with Skills England, acts as 'a national convenor in the data science and AI landscape and creates opportunity for meaningful collaboration where interests align across research and innovation, skills and engagement' (The Alan Turing Institute, 2025).

5. Conclusion

Technological change, particularly through automation, augmentation, and adaptation, continues to reshape the demand for skills. The Australian workforce has already seen a shift toward higher-skilled, non-routine work, a trend consistent with skill-biased and routine-biased technological change. Occupations that are more technology-intensive tend to experience faster shifts in skill requirements, underscoring the need for a dynamic and forward-looking skills system that can keep pace with evolving demands.

In this context, building adaptive capacity within the skills system is more important than ever. Both formal qualifications and short-form learning have distinct and complementary roles to play in equipping individuals with the skills they need. Flexibility in learning pathways will be key to supporting lifelong learning and enabling workers to transition across roles and industries as the nature of work continues to change. Educators and trainers will also need support to maintain currency and deliver high-quality, relevant learning experiences in Gen AI-enabled environments.

Gen AI is already influencing both the demand and supply of skills in the labour market. There is growing recognition of the need for a spectrum of AI capabilities – from foundations, to competence, to fluency – alongside complementary human and domain-specific skills. A one-size-fits-all approach to capability uplift will not meet the diverse needs of individuals or

employers. Domestic skill development must be prioritised, supported by targeted skilled migration where appropriate, to ensure Australia can meet the rising demand for digital and AI expertise.

Finally, the role of industry will be critical in shaping the future of skills development. Industry-led training, active engagement with education and training providers, and real-time feedback on emerging skill needs will help ensure the system remains agile and relevant. The Gen AI exposure of education and training pathways offers a valuable guide for prioritisation, helping stakeholders focus efforts where they are most needed. By fostering collaboration, investing in educator capability, and embracing innovation, Australia can build a resilient and future-ready workforce equipped to lead in the age of AI.

Findings from the Overarching Paper that this analysis supports

Finding 8: Gen AI is already being reflected in the demand for skills and supply of skills in the labour market, along with broader digital, AI and complementary skills

Gen AI is already influencing demand and supply of skills. This has included growing demand for AI technical specialist skills.

Both digital and non-digital skills will remain relevant in a Gen AI-enabled labour market, with employers indicating a growing need for higher-order, human-centric skills.

Finding 16: The skills system will be critical in the Gen AI transition

The workforce – and the skills and knowledge they possess – is a key enabler of Gen AI adoption. No single skills system actor can be expected to equip Australians for the digital and AI transformation on their own. Alignment across skills system actors on key objectives and coordination of effort will help ensure the most effective and efficient skills system response.

Finding 17: Gen AI exposure has important implications for education and training pathways, based on their common destination occupations

The Gen AI exposure of education and training pathways varies across fields of education, training package, and qualification types.

Alongside other considerations, such as the volume of completers and evidence of AI adoption, the Gen AI exposure of education and training pathways provides a useful guide for prioritisation to those with responsibilities for qualification design and delivery.

Finding 18: Demand for specialist digital and AI capabilities will require domestic skills development and leveraging international expertise

There is strong demand for specialist digital and AI capabilities. Domestic skill development efforts are required, complemented as appropriate by skilled migration.

Finding 19: There is a spectrum of AI capabilities for individuals – from foundations, to competence, to fluency

A one-size-fits-all approach to capability uplift will not meet the needs of individuals or the labour market. A baseline of digital and AI access and foundational skills is a crucial enabler of participating in work, study and society (foundations). Beyond this, the skills system should aim to deliver learner-centric, purpose-led digital and AI capabilities including developing:

- the competent application of digital and AI skills, knowledge and attitudes (competence), and
- the digital and non-digital capabilities required to achieve positive outcomes with digital technology including AI in relevant settings (fluency).

Finding 20: The skills system will need to focus even more on building adaptive capacity to respond to the pace of change

The skills system will need to develop graduates with strong adaptive capacity while responding to the pace of change. Formal qualifications and short-form learning each have important and often distinct roles to play in achieving these objectives.

A dynamic skills response requires support for educators, flexible program design, and a well-functioning ecosystem of formal and informal learning pathways.

Finding 21: The role of industry, including its engagement with the education and training sector, will be vital

Industry-led training is an important source of dynamism in the skills system, including training provided to businesses, students and individual technology users.

Greater collaboration and coordination between the technology industry – and industry more broadly – and the tertiary education and training sector will also be vital in ensuring the relevance and responsiveness of education and training in fast-evolving industries and job types.

While ad hoc engagement introduces some level of dynamism, more structured and coordinated engagement can enable dynamism with greater scale and sustainability.

Finding 22: The capability, capacity and currency of educators and trainers will be vital in ensuring high-quality and relevant learning experiences.

Educators and trainers will need to be equipped to manage the implications of Gen AI for learning, teaching and assessment, and for current industry practice in their field.

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Glossary

Term	Definition
ABS	Australian Bureau of Statistics
AI	Artificial intelligence refers to a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment.
Agentic AI	Agentic artificial intelligence refers to AI that is capable of accomplishing multi-step tasks in pursuit of a high-level goal with little or no human oversight.
Adaptation	Adaptation facilitates deeper, ongoing changes to how work is undertaken, as technology is further harnessed into new production processes *or* leads to labour being reinstated to new tasks. These actions result in new or additional outputs, representing an expansion of the conceptual 'production possibility frontier'.
ANZSCO	Australian and New Zealand Standard Classification of Occupations
AQF	Australian Qualifications Framework
Augmentation	Augmentation refers to a situation where workers use technology to enhance their capabilities – typically to accomplish more, with greater accuracy and speed.
Automation	Automation refers to a situation where Gen AI acquits tasks or produces outputs. Automated processes produce outputs previously completed by humans.
Cultural load	Cultural load is the additional workload that Aboriginal and Torres Strait Islander people and other cultural minorities experience in the workplace.
DEWR	Department of Employment and Workplace Relations
DISR	Department of Industry, Science and Resources
Exposure scores	Estimates of exposure give an indication of how technologies could be applied, including the extent to which tasks could be either augmented or automated.
FSO	Future Skills Organisation
GAN	A Generative Adversarial Network is a deep learning architecture that trains two neural networks to compete against each other to generate more authentic data from a given training dataset.
Gen AI	Generative artificial intelligence is a subset of artificial intelligence, typically based on deep learning neural networks, that use generative models to produce text, images, videos, or other data.
HILDA	Household, Income and Labour Dynamics in Australia
ICT	Information and Communication Technology
ILO	International Labor Organisation
IT	Information Technology
IVI	Internet Vacancy Index
JSA	Jobs and Skills Australia

OECD	Organisation for Economic Co-operation and Development
OSCA	Occupation Standard Classification for Australia
PC	Productivity Commission
PLIDA	Person Level Integrated Data Asset
RBTC	Routine-biased technological change refers to a situation where technologies tend to substitute for human labour in routine tasks while increasing demand for non-routine tasks.
SBTC	Skill-biased technological change refers to a situation where technologies tend to be more complementary to workers at a particular skill level.
Transformers	A transformer model is a neural network derived from Vaswani et al. that tracks relationships in sequential data to learn context and meaning, in order to transform an input sequence into an output sequence.
VET	Vocational Education and Training