

Generative AI and Job Quality in an Aging Workforce: Evidence from Australia

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1. Introduction

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- GenAI adoption has accelerated rapidly, *The State of AI* survey estimates that the share of organisations regularly using GenAI in at least one business function rose from 33% in 2023 to 79% in 2025 (Singla et al., 2025)
- GenAI can *automate* tasks previously performed by workers and/or *augment* workers' capabilities to perform these tasks (Acemoglu & Restrepo, 2019; Eloundou et al., 2024)
- Task-based exposure measures reveal substantial differences across occupations and worker groups, with occupations exposed to a specific combination of automation and augmentation (Gmyrek et al., 2023, 2025; Jobs and Skills Australia, 2025)
- Exposure and preparedness hence likely to vary by age: 75% of white-collar workers aged 58 and over report using AI, compared with 90% of workers aged 27–42 (Jobs and Skills Australia, 2025)
- In an ageing labour market, it is therefore critical to identify whether older workers are concentrated in jobs with different forms of GenAI exposure

Why Job Quality and Training Matter

- Exposure measures identify the tasks GenAI could affect, but not the conditions under which those tasks are performed: two occupations with similar exposure may differ in pay, security, voice and discretion
- These job-quality conditions shape workers' bargaining power and capacity to adapt to technological change (Bustillo et al., 2011; Bryson et al., 2013; Iskander & Lowe, 2013)
- Training is a core organisational response to changing skill requirements. But older workers receive less employer-funded training, often because they are perceived as less adaptable or too close to retirement (Posthuma & Campion, 2009; Canduela et al., 2012)
- Older women face additional barriers to training, skill recognition and job mobility (Lössbroek & Radl, 2019; Hamilton & Zettna, 2024)
- **This study examines GenAI exposure alongside job quality and skill investment, focusing on older workers**

Research Questions

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 - Which workers hold these types of work?
3. **Is skill investment aligned with exposure to GenAI?**

2. Methods

Data and Measures

- We merged HILDA Survey (Wave 24) with Jobs and Skills Australia AI Exposure Dataset at the four-digit ANZSCO code level.
- Active sample composed of 8,073 employed workers
- Each worker is assigned two exposure scores:
 - **Automation exposure:** GenAI could perform tasks in place of the worker
 - **Augmentation exposure:** GenAI could assist the worker in performing tasks
- **Five job-quality dimensions:** material job quality, work intensity, perceived security, skill and discretion, and voice
- **Training:** any work-related training in the previous 12 months; among those who trained, the number of courses, their average duration (hours), and whether the training provided new skills or aimed to improve skills used in the current job
- Age measured continuously, quadratically and as 55 and over; gender examined alongside age at every stage

Analytical Strategy

Stage 1: Exposure by age

- Survey-weighted linear and quadratic regressions
- Continuous age or a binary indicator for 55 and over

Stage 2: Latent Profile Analysis $f(\mathbf{y}_i) = \sum_{k=1}^K \pi_k f_k(\mathbf{y}_i \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma})$

- Seven standardised indicators: two exposure scores and five job-quality dimensions.
- One to seven profiles compared on parsimony, classification quality and interpretability

Stage 3: Who holds each type of job? $\Pr(C_i = k) = \frac{\exp(\mathbf{x}_i' \boldsymbol{\gamma}_k)}{\sum_{j=1}^K \exp(\mathbf{x}_i' \boldsymbol{\gamma}_j)}$

- $\mathbf{x}_i$: age, gender, education, tenure, partnership, dependent children, health limitation, metropolitan residence and state; relative risk ratios

Stage 4: Is skill investment aligned with exposure? $\Pr(T_i = 1) = \frac{\exp(\mathbf{z}_i' \boldsymbol{\delta})}{1 + \exp(\mathbf{z}_i' \boldsymbol{\delta})}$

- T_i : any work-related training in the past 12 months
- $\mathbf{z}_i$: automation and augmentation exposure scores or job profile interacted with age 55+, each with the Stage 3 controls; odds ratios
- Among workers who trained, we also look at new skills, improved skills, and the number and average duration of courses

3. Results

Table 1. Generative AI Exposure by Age

Table 1. Generative-AI exposure by age

	Automation	Augmentation
Age (continuous variable)		
Age	0.0008*** (0.0002)	0.0006*** (0.0001)
Age 55 and over (binary variable)		
55 and over	0.009 (0.005)	−0.006 (0.003)
Age (quadratic specification)		
Age	0.0055*** (0.0009)	0.0081*** (0.0006)
Age squared	−5.60E ^{−05} *** (1.09E ^{−05})	−8.98E ^{−05} *** (6.50E ^{−06})
Turning point (years)	49.3	45.1
Women	0.041*** (0.004)	0.020*** (0.002)
N	8,073	8,073

Source: Authors’ calculations using HILDA (wave 24) and JSA (2025). Notes: Survey weights applied. Turning points are computed from $-\beta_1/(2\beta_2)$. *p < .10, **p < .05, ***p < .01.

Table 1. Exposure Across Working Life

- Workers aged 55 and over are not significantly more exposed than workers under 55
- The quadratic models reveal an inverted-U relationship: automation exposure peaks at approximately 49.3 years; augmentation exposure peaks earlier, at approximately 45.1 years
- Gender differences are more pronounced than age differences: women's jobs are significantly more exposed to GenAI on both dimensions

Table 2. Job Type Profiles

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LPA classes	Main occupation groups	Main industries	Automation	Augmentation	Material Job Quality	Voice	Skill and discretion	Perceived Security	Work Intensity (reversed)	Share
Low exposure – Moderate JQ	Laborers (33%), community and personal service workers (27%)	Construction (17%), health care and social assistance (16%)	-1.17	-1.66	-0.39	-0.24	-0.43	-0.28	0.29	0.19
Augmentation-exposed – High JQ	Professionals (44%), managers (24%)	Health care and social assistance (28%), education and training (17%)	-0.21	0.27	0.37	0.41	0.44	0.29	-0.32	0.44
Average-exposure – Low JQ	Sales workers (29%), community and personal service workers (24%)	Retail trade (27%), health care and social assistance (19%)	-0.15	-0.10	-1.15	-0.73	-0.85	-0.64	0.59	0.13
High-exposure – Mixed JQ	Clerical and administrative workers (44%), professionals (38%)	Professional, scientific and technical services (15%), financial and insurance services (13%)	1.41	0.88	0.21	-0.24	-0.12	-0.13	0.14	0.24

Source: Authors’ calculations using HILDA (wave 24) and JSA (2025). *Notes:* Survey weights applied. Values are standardized across the estimation sample, so zero is the sample mean, positive values indicate levels above the sample mean and negative values indicate levels below the sample mean. Work intensity is reverse-coded, with higher values indicating lower intensity. The two most common occupations and industries in each profile are shown.

Table 2. Exposure Is Not a Proxy for Job Quality

- The analysis identifies four distinct combinations of GenAI exposure and job quality:
 - **Low exposure–Moderate JQ** (19%)
 - **Augmentation-exposed–High JQ** (44%): strongest voice, skill and discretion, material job quality, and perceived security
 - **Average-exposure–Low JQ** (13%): lowest scores on four job-quality dimensions
 - **High-exposure–Mixed JQ** (24%): material job quality above average, but voice, skill and discretion, and perceived security below average
- Similar exposure levels can therefore coexist with substantially different employment conditions

Table 4. Multinomial Logit of Job Profile Membership

Table 4. Multinomial logit of job profile membership (relative risk ratios)

	Low exposure Moderate JQ	– Average-exposure Low JQ	– High-exposure Mixed JQ	–
<i>(reference category: Augmentation-exposed – High JQ)</i>				
Aged 55 and over	1.458*** (0.170)	1.498** (0.250)	1.497*** (0.157)	
Women	0.434*** (0.038)	1.301** (0.164)	1.197** (0.091)	
Tenure (years)	0.947*** (0.006)	0.894*** (0.013)	0.971*** (0.004)	
Education (ref. Year 12 or below)				
Certificate or diploma	0.722*** (0.075)	0.593*** (0.075)	0.877 (0.108)	
<u>Bachelor</u> degree	0.130*** (0.019)	0.342*** (0.063)	0.575*** (0.071)	
Postgraduate degree	0.070*** (0.013)	0.222*** (0.044)	0.388*** (0.049)	
Partnered	0.617*** (0.059)	0.481*** (0.066)	1.214** (0.113)	
Dependent children	0.998 (0.038)	0.975 (0.052)	0.930** (0.031)	
Health limitation	1.127 (0.128)	1.063 (0.185)	0.962 (0.095)	
Metropolitan	0.765*** (0.070)	1.535*** (0.181)	1.632*** (0.147)	
State controls	Yes	Yes	Yes	
Observations	8,053			

Source: Authors’ calculations using HILDA (wave 24) and JSA (2025). *Notes:* Survey weights applied. Relative risk ratios from multinomial logistic regression. Ratios above 1 indicate a higher relative likelihood of membership in a given profile and ratios below 1 a lower relative likelihood. * p < .10, ** p < .05, *** p < .01.

Table 4. Age and Gender Predict Profile Membership

- Considering the reference category Augmentation-exposed-High JQ work, relative to workers under 55, older workers are approximately 46 to 50% more likely to hold each of the other three profiles
- Compared with men, women are 30.1% more likely to hold Average-exposure-Low JQ work and 19.7% more likely to hold High-exposure-Mixed JQ work

Table 5. Work-Related Training by Profile, Age and Gender

Table 5. Work-related training by job profile, age and gender

	Odds ratios			Coefficients	
	Trained	New skills	Improved skills	Courses	Hours
Job profile (reference: Augmentation-exposed – High JQ)					
Low exposure – Moderate JQ	0.678*** (0.072)	0.652** (0.115)	0.758 (0.140)	−0.290 (0.546)	0.124 (0.254)
Average-exposure – Low JQ	0.824 (0.114)	0.695 (0.179)	0.470*** (0.110)	−0.848* (0.465)	−0.469 (0.302)
High-exposure – Mixed JQ	0.512*** (0.047)	0.814 (0.136)	0.735* (0.121)	−0.562 (0.359)	−0.322 (0.213)
Age					
Aged 55 and over	1.058 (0.136)	0.770 (0.154)	0.560*** (0.112)	−0.547 (0.440)	−0.232 (0.257)
Job profile × age					
Low exposure × 55 and over	1.086 (0.218)	0.825 (0.273)	1.189 (0.385)	2.199** (1.068)	−0.524 (0.427)
Average-exposure × 55 and over	0.645* (0.169)	0.617 (0.280)	2.319** (0.966)	0.041 (0.883)	−0.792 (0.491)
High-exposure × 55 and over	0.965 (0.184)	0.918 (0.310)	1.160 (0.377)	1.606* (0.863)	−0.244 (0.455)
Gender					
Women	1.419*** (0.088)	1.129 (0.136)	1.066 (0.124)	0.914*** (0.254)	−0.765*** (0.157)
Observations	8,053	2,946	2,948	2,938	2,932

Source: Authors' calculations using HILDA (wave 24) and JSA (2025). Notes: Survey weights applied. Full results available in Supplementary Materials S4. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 5. Is Training Aligned with GenAI Exposure?

- Relative to the augmentation-exposed profile, the odds of having trained among workers under 55 are 0.51 in High-exposure–Mixed JQ work. The jobs in which GenAI has most scope to substitute for tasks are therefore those in which workers are least likely to have trained
- Age is not significant for training participation. Among workers who trained, the odds that the training improved their existing skills are 0.56 for older workers, in three of the four profiles
- Older workers are less likely to hold the augmentation-exposed profile, which has the highest training incidence. When they do access training, the fact that they are less likely to improve their skills compounds this disadvantage
- Current patterns of skill investment appear better suited to supporting workers in already advantaged jobs than those facing the greatest risks of task substitution

4. Discussion and Conclusion

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Findings and limitations

- GenAI exposure and job quality do not vary along a single gradient: similar levels of automation exposure coexist with very different employment conditions, so exposure is not a sufficient proxy for risk or opportunity
- Workers aged 55 and over are not more exposed to GenAI. Their disadvantage is associated with their distribution across job types, with a lower likelihood of holding augmentation-exposed, high job-quality work
- Training is positively associated with augmentation exposure and negatively with automation exposure: jobs with the greatest scope for task substitution have the lowest training incidence
- Gender differences exceed age differences at every stage, suggesting that age and gender segmentation may compound for older women
- GenAI exposure is a useful lens to explore the potential impacts of this new technology but remains limited. Future research will need to explore adoption data.

Implications

- Assessments of GenAI's labour-market effects should account for job quality alongside task exposure
- Skill investment is currently weakest where substitution potential is highest, pointing to a case for targeting training towards these occupations and towards older workers
- Consistent with evidence on worker voice and technological change (Bryson et al., 2013; O'Brady & Doellgast, 2021), low voice in the most exposed jobs may limit workers' capacity to shape implementation

Thank you for your attention.
Any questions?

Appendix

A1. Measuring Job Quality

Dimension	Components
Material job quality	Log weekly earnings, permanent employment, employer tenure and full-time hours
Work intensity	Work pace, effort, time pressure and whether work is more stressful than expected
Perceived security	Secure future, employer viability and perceived likelihood of retaining the job
Skill and discretion	Variety, use of skills, learning new skills and taking initiative
Voice	Influence at work, union membership and collective or enterprise agreement coverage

Note: Components are standardised and averaged within each dimension