

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

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Abstract

This study examines how exposure to generative artificial intelligence (GenAI) interacts with job quality in the Australian labor market to understand how this technology will impact older workers. It applies latent profile analysis and regression models to original data obtained by merging two nationally representative datasets. Four job profiles were identified, defined by augmentation and automation exposure and five dimensions of job quality. Exposure and job quality did not vary along a single gradient, with high automation exposure present across both high and low quality profiles. Skill investment aligned more closely with augmentation exposure because training concentrated among workers already in secure, autonomous and well paid jobs. Older workers' training disadvantage operated through sorting across profiles rather than through differential treatment within them, although a direct disadvantage remained in training content. Understanding exposure through job quality highlights the likely consequences of GenAI in organizations for already vulnerable workers.

Key words: Job quality, Digital technology, Older workers, Training, Occupational skill requirements, Workforce

1. Introduction

As generative artificial intelligence (GenAI) transforms the nature of work in organizations, urgent questions are being raised about its impact on job design and workplace inclusion, and about appropriate governance and regulatory responses. Adoption has been rapid, with the share of executives reporting regular use of GenAI in at least one business function rising from 33 per cent in 2023 to 79 per cent in 2025 (Singla et al., 2025), yet the consequences of its integration remain contested, polarized between the prospect of displacing workers and that of augmenting their work. We have yet to understand how these disparate potential effects are distributed across jobs, or what this means for different groups of workers as this diffusion occurs in ageing labor markets. This paper is the first to examine GenAI exposure alongside job quality using nationally representative data, with a focus on how older workers, an already vulnerable group, are likely to be impacted.

A growing strand of research examines occupational exposure to GenAI by treating occupations as bundles of tasks affected differently by the technology. This task-based literature argues that technological change affects labor demand by displacing workers from existing tasks while creating new tasks in which labor retains a comparative advantage (Acemoglu & Restrepo, 2019; Autor et al., 2003). Applying this logic to GenAI, Eloundou et al. (2024) assessed whether large language models could perform specific occupational tasks or substantially reduce the time workers require to complete them. The International Labour Organization (ILO) subsequently translated task-level assessments into occupation-level measures that distinguish between automation exposure and augmentation exposure (Gmyrek et al., 2023, 2025). Jobs and Skills Australia (2025) has adapted this framework to the Australian labor market, producing exposure measures at the four-digit Australian and New Zealand Standard Classification of Occupations (ANZSCO) level. These measures reveal substantial variation in exposure across occupations and worker cohorts. Most occupations face a combined exposure to augmentation and automation, with women being more exposed to both. Further survey evidence shows that older workers may face greater barriers to adoption and digital access with 75 per cent of white-collar workers aged 58 and over using AI, compared with 90 per cent of those aged 27–42 (Jobs and Skills Australia, 2025).

Automation and augmentation exposure measures allow us to understand the potential consequences of GenAI on individual tasks, but fall short of capturing the characteristics of the jobs that these tasks belong to. Two occupations with similar task-exposure to GenAI may differ substantially in conditions of the job (e.g., pay, hours or access to union representation). These conditions are likely to interact with GenAI exposure risk to produce different outcomes for workers. Examining exposure to GenAI in combination with job quality is therefore crucial to understand the actual implications of exposure in

workplaces and for workers. Job quality is a multidimensional concept referring to job attributes (such as earnings, employment security, work intensity, and worker voice) that contribute to the wellbeing of workers, built on the premise that pay alone does not suffice to understand the conditions of employment (Bustillo et al., 2011). If workers in exposed jobs also experience limited discretion, weak collective representation and restricted access to training, then technological change is likely to reproduce existing inequalities rather than disturb them.

The emergence of new tasks because of GenAI, and whether workers are allocated and able to complete them, depends on how firms organize production and invest in workers' skills (Acemoglu & Restrepo, 2019). Training is a core organizational response to changing skill requirements, and whether skill investment is directed towards jobs where GenAI substitutes for tasks or towards those where it complements them has consequences for vulnerable groups. Access to workplace training is already unevenly distributed by age, with older workers less likely to have participated in or been offered training by employers (Canduela et al., 2012; Davies et al., 2017). In Australia, workers aged 55 and over comprise close to 20 per cent of the labor force (Australian Bureau of Statistics, 2026), and older workers, particularly older women, face barriers to job mobility and skill recognition (Hamilton & Zettna, 2024). Segmentation operates within occupations and industries as well as across them, structuring access to higher-quality jobs in ways that compound over the working life.

This study examines how GenAI exposure interacts with the quality of jobs within the Australian labor market to determine the likely implications of exposure for different groups of workers, with a focus on older workers in particular. Three questions guide the analysis. First, how is exposure to GenAI distributed across the workforce by age? Second, how do automation and augmentation exposure combine with the material and non-material dimensions of job quality, do these combinations form distinct types of work, and which workers hold them? Third, is skill investment aligned with exposure? The analysis merges Wave 24 of the Household, Income and Labour Dynamics in Australia (HILDA) Survey to the Jobs and Skills Australia AI Exposure Dataset (2025) at the four-digit ANZSCO level. Latent profile analysis identifies job types defined jointly by exposure and by five dimensions of job quality, multinomial logistic regression establishes which workers hold them, and models of training participation and content test whether skill investment is aligned with exposure. Systematically in this analysis, we further investigate how these patterns differ by gender.

This paper extends the conceptual literature on the impacts of GenAI by developing an approach that analyzes exposure and job quality simultaneously, and applies it to produce new empirical evidence on the Australian workforce. First, exposure and job quality do not vary along a single gradient. Four job profiles emerge from the analysis, and the profile most exposed to automation offers pay above the workforce average alongside below-average voice, skill and discretion, and perceived security.

Automation exposure therefore cannot be read as a proxy for disadvantage, nor augmentation exposure as a proxy for opportunity, and the consequences of the technology depend on the conditions of the jobs in which exposure occurs. Second, skill investment aligned more closely with augmentation than automation exposure, so the jobs in which GenAI has most scope to substitute for tasks were those in which workers were least likely to have trained recently. Third, older workers were less likely than workers under 55 to hold the augmentation-exposed profile. They were not less likely than younger workers to have trained overall, but potential disadvantage in skill investment operated through their position in the labor market. When they did train, the training was less likely to have improved their existing skills, in three of the four profiles. Fourth, gender differences were larger than age differences at every stage. Women's jobs were more exposed to both automation and augmentation, and women were over-represented in the profile with the lowest voice and discretion and in the most exposed profile.

2. Conceptual Background

This section presents the conceptual background used in the analysis, namely job quality, the training and skill investment literature for older workers, and exposure to GenAI. Women are over-represented in lower-paid occupations and industries and are more likely to be in precarious employment, which means that exposure is not equally distributed between men and women. Age and gender also intersect, as older women face barriers to job mobility, skills recognition (Hamilton & Zettna, 2024) and re-employment following job loss (Australian Human Rights Commission, 2016) and the effects of technological change on women do not operate independently from existing social and labor-market inequalities (Wajcman, 2010). This conceptual background therefore incorporates findings on gender.

2.1. Job quality

Job quality is operationalized in various ways across the literature, but rests on the common premise that pay does not sufficiently capture the conditions under which work is performed, and that a fuller account requires attention to the multiple job attributes that contribute to worker wellbeing (Bustillo et al., 2011). This concept is closely aligned with the ILO decent work agenda, which specifies employment opportunity, remuneration, security, and social dialogue as constitutive elements of decent work (Anker et al., 2003; ILO, 1999).

Measurement frameworks differ in the dimensions that constitute job quality, drawing on a common pool of attributes (Cazes et al., 2015; Green et al., 2013). Earnings and working hours capture the material terms of employment, while contractual status distinguishes the security associated with ongoing employment from the greater uncertainty commonly attached to casual or other non-standard

employment (Kalleberg, 2011). Job quality also depends on work intensity, defined by the pace and volume of work demanded (Green, 2004), and on the opportunities workers have to use their skills and exercise discretion over how their work is performed (Green, 2006). Security encompasses both contractual arrangements and workers' perceived likelihood of losing their jobs. These dimensions do not necessarily overlap with each other, and subjective insecurity can adversely affect wellbeing even where contractual status appears relatively secure (Gallie et al., 2017). Worker voice and representation constitute a further dimension because they shape the terms on which other employment conditions are negotiated and can moderate the effects of organizational change on workers' wellbeing (Bryson et al., 2013; Holman, 2013). Job quality is therefore understood as a multidimensional concept that captures both the economic rewards of employment and the qualitative, structural and institutional conditions under which work is organized and experienced.

Consideration of job quality is essential to understand how workers and organizations navigate change, including technological change. Iskander & Lowe (2013) show that workers draw on skill and discretion to reshape work practices, and that this capacity constitutes a form of bargaining power independent of external institutions. Bryson et al. (2013) also find that organizational change raises job-related anxiety among workers not covered by collective bargaining, but not among those whose union is involved in introducing it, and that consultation in the absence of formal bargaining institutions is insufficient to alter the outcome. In jobs where discretion over how work is performed and collective representation are low, workers have little scope to shape how a new technology enters their work. Consideration of job quality should therefore be central to analyses of the differential impact of GenAI exposure between occupations.

Job quality is unevenly distributed across the workforce. It varies with age, and the direction of that variation depends on institutional setting. Using European Labour Force Survey, Arranz et al. (2019) find that older workers report higher non-wage job quality than younger workers, and that more coordinated and centralized wage bargaining, stricter employment protection and vocationally oriented training systems favor the job quality of older workers over younger ones. Job quality also varies by gender, with women concentrated in occupations and industries that score lower on several dimensions, and occupations with balanced shares of men and women record better job quality on most dimensions than either male-dominated or female-dominated occupations (Eurofound, 2020).

2.2. Older workers, technology and training

The proliferation of GenAI in organizations raises concerns for older workers' job quality. Our understanding of its impacts is still nascent, but older workers are already estimated to be experiencing significant task reconfiguration (OECD, 2023). Decades of research indicates that older workers are

disadvantaged by technological change, usually because of age-based stereotypes about their ability to adapt to new technologies, and presumptions that their proximity to retirement reduces their capacity or willingness to invest in training (Posthuma & Campion, 2009). Workers aged 55 and over also report less access to employer-funded training than their younger colleagues (Eurofound, 2025).

The introduction of workplace computers in the early twenty-first century provides a useful parallel. Older workers used computers relatively less, which was explained by their proximity to retirement more than age-related capacity for skill acquisition. As workers approached retirement, the shorter period over which they could benefit from new skills reduced both worker and organizational incentives to invest in training. Nevertheless, most workers acquired computer skills when their jobs required them, including those out of formal education for many years (Friedberg 2003). Lower technology use among older workers is therefore not evidence of lower ability to upskill, but may reflect the low perceived returns to investing in new skills. Age and gender intersect in shaping who receives training. Drawing on linked employer-employee data from nine European countries, Lössbroek & Radl (2019) find that older men and women participate in training at comparable rates, but that older women more often pay for formal programs themselves. Managerial ageism operates primarily against older women, excluding them from training opportunities available to comparable male colleagues. Training therefore differs in how it is funded and what it consists of, not only in how much of it workers receive.

Decisions about training are also shaped by age-based assumptions about adaptability and technological competence. Expectations that older workers are approaching retirement, and therefore are no longer worth investing in, operate alongside persistent ‘ideal worker’ norms that privilege workers perceived as continuously productive, adaptable and physically capable, characteristics commonly associated with younger male workers. Older workers are viewed as ‘on their way out’ and less cognitively or physically capable than younger workers, irrespective of their abilities, performance or intended retirement timing (Hamilton et al., 2026). Handley & Outer (2021:2392) refer to this as the ‘grey ceiling’. The relevant issue is therefore not simply workers’ chronological age or actual remaining years of employment, but how their adaptability and proximity to retirement are perceived by managers, organizations and the workers themselves. When these perceptions restrict access to learning, age inequalities in technological skills risk becoming self-reinforcing.

Poor organizational investment in training can disrupt older workers’ participation in paid employment. In workplaces where technological change has been introduced, but are not facilitated to upskill, older workers are more likely to retire early in response to technological change (Casas & Román, 2023). Conversely, Friedberg (2003) found that workplace computer use was associated with later retirement and Picchio & van Ours (2013) found that firm-provided training significantly improved older workers’

subsequent employment prospects. This evidence suggests that whether older workers face disadvantage in adapting to GenAI depends on the jobs they hold, alongside investment in training.

2.3. Exposure to GenAI

Research on occupational exposure to artificial intelligence has emerged rapidly over the past decade. Early research explored whether machine-learning systems could perform particular work tasks, drawing on the task descriptions in O*NET, the occupational database maintained by the United States Department of Labor (Brynjolfsson et al. 2018). Felten et al. (2021) assessed whether advances in specific AI applications aligned with the abilities required in different occupations. These studies established an approach to measuring AI exposure from the content of work without needing data on adoption, which is difficult to measure while organizations are still adjusting to the technology. After the release of large language models, studies assessed whether GenAI could perform specific tasks, assist with them, or neither (Eloundou et al. 2023; Gmyrek et al., 2023). This research led to a distinction between automation exposure defined as GenAI performing tasks in place of workers, and augmentation exposure, defined as GenAI assisting them.

In Australia, the Jobs and Skills Australia (2025) Generative AI Capacity Study finds that augmentation generally outweighs automation. Automation potential is concentrated in routine roles, particularly clerical work, and many clerical tasks unaffected by previous waves of automation could now be undertaken by GenAI. Administrative roles, entry-level workers and occupations dominated by women are more exposed to automation, and older workers face disproportionate risk because of labor market segmentation and digital access gaps. Pizzinelli et al. (2023) further analyze human complementarity which can be defined as the extent to which an occupation depends on interpersonal interaction, judgment, discretion or physical presence that GenAI cannot substitute. They find that across six countries women and highly educated workers face greater occupational exposure at both high and low complementarity, and that workers in the upper part of the earnings distribution are more likely to hold occupations combining high exposure with high complementarity. A study from UN Women & LinkedIn (2025) finds that women are disproportionately exposed to GenAI disruption but may also benefit from growing demand for human-centred skills and skills-based hiring.

3. Data and Measures

3.1. Data

The analysis uses Wave 24 of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a nationally representative longitudinal household study that has followed Australian residents annually since 2001. This dataset contains rich data on economic and personal well-being, and family

life, job characteristics including perceptions of work (Department of Social Services et al. 2025). The analysis sample comprises respondents who were employed at the time of interview, aged 18 or over, and whose occupation could be matched to the exposure measures described below, and who were non-missing on the variables of interest¹. Occupation is recorded using the four-digit Australian and New Zealand Standard Classification of Occupations (ANZSCO). This yields a sample of 8,073 workers. Sample sizes vary slightly across models depending on the covariates included.

3.2. Measures

3.2.1. *Exposure to GenAI*

Following the framework developed by Gmyrek et al. (2023), this study uses two measures of exposure to GenAI: (1) Exposure to automation (i.e., a job is exposed because GenAI can perform its tasks in place of the worker); (2) Exposure to augmentation (i.e., a job is exposed because GenAI can support the worker in performing them). Both indicators are constructed from descriptions of occupations, which is more reliable at present — as discussed earlier, adoption at the organizational level remains poorly documented and is changing rapidly. Another advantage for this study is that both indicators have been produced for Australian occupations. Jobs and Skills Australia (2025) applied this framework to the Australian labor market as part of its Generative AI Capacity Study, publishing automation and augmentation exposure scores at the four-digit ANZSCO level. The four-digit unit group is the most disaggregated level of the classification and distinguishes 357 occupations (JSA, 2025). Exposure varies substantially within broader occupational categories, so matching at a more aggregated level would conceal much of the variation the measures capture. Because the restricted HILDA data contains the 4-digit level disaggregation, each respondent was assigned the exposure scores of their four-digit occupation.

3.2.2. *Job quality*

Following the framework described in section 2.1., we measure job quality across five dimensions. Two principles of job quality measurement guide the measures used here. First, job quality indicators should not combine the conditions a job provides with the outcomes those conditions produce. Bustillo et al. (2011) note that some indices combine job components with possible outcomes, notably job satisfaction, which makes the resulting measure difficult to interpret. This study therefore treats self-reported information on what a job requires or provides as a subjective condition, while satisfaction with the job

¹ 99.8% of working-age observations from HILDA were matched to the JSA database

is treated as an outcome and excluded from the measurement of job quality. Second, certain conditions identified as important to worker wellbeing, particularly work intensity and time pressure, are absent from many established indicators and should be measured explicitly. Voice is also retained as a separate dimension, given its role in shaping how organizations respond to change. The five dimensions are constructed as follows.²

- *Material job quality* combines the logarithm of weekly earnings in the main job, permanent employment status, tenure with the current employer, and full-time hours.
- *Work intensity* combines items on the pace of work, the effort it requires, time pressure, and whether the job is more stressful than expected.
- *Perceived security* combines agreement that the job has a secure future, that the employer will remain in business, and the respondent's estimated chance of retaining their job over the coming year.
- *Skill and discretion* combines four items on whether the job provides variety, uses the worker's skills and abilities, requires learning new skills, and requires taking initiative.
- *Voice* combines self-reported influence over what happens at work, trade union membership, and coverage by a collective or enterprise agreement.

Each dimension score is constructed by standardizing its components and taking their mean, so that components can be interpreted using the same scale. Descriptive statistics of the job quality dimensions and underlying indicators are presented in Supplementary Materials S1.

3.2.3. *Individual characteristics*

The analysis also draws on a set of individual and job characteristics used in the models described below. Age is the main demographic characteristic interest. It is included in most models as a binary indicator distinguishing workers aged 55, and some of the analysis as a continuous variable and with a quadratic term. Gender is included as a binary variable. The multinomial logistic and logistic models control for highest educational attainment (Year 12 or below, certificate or diploma, bachelor degree, postgraduate qualification), tenure with the current employer, partnership status, presence of a long-

² There is no consensus in the literature on whether training is a measure of job quality in itself. Arranz et al. (2019) include employer-funded training in their skills and training dimension, while the index of Muñoz de Bustillo et al. (2011) does not include it as a distinct component. The HILDA measure reports whether a worker trained in the past year, which is take-up rather than a characteristic of what the employer provides. We therefore analyse training separately as an outcome.

term health condition or disability that limits work, residence in a major metropolitan area, and state or territory of residence.

Training is included as an indicator of the skill investment associated with different jobs, and is measured in two parts. All employed respondents are asked whether they undertook any work-related training in the previous twelve months. Those who did are asked four further questions: how many courses they undertook, their average duration in hours, whether the training provided new skills, and whether its purpose was to improve skills used in their current job. Each of these is analyzed separately among the subpopulation of workers who trained.

4. Analytic strategy

The analysis proceeds in four stages.

The first stage describes how exposure to GenAI is distributed by age. For each exposure measure, we estimate survey-weighted linear regressions of the form

$$E_i = \alpha + \beta_1 X_i + \varepsilon_i \text{ [Eq. 1]}$$

where E_i is either the automation or the augmentation exposure score assigned to worker i on the basis of their four-digit occupation. The following specifications are estimated separately for each measure: a continuous age variable; a binary indicator for workers aged 55 and over, a quadratic term for age, which allows exposure to follow a non-linear shape across the working life.

The second stage creates a typology of GenAI exposure and job quality. We use Latent Profile Analysis (LPA), which models the observed distribution of job characteristics as a mixture of latent subgroups. Blustein et al. (2020) and Hasselhorn et al. (2020) use the same approach to identify configurations of precarious work and of job quality in later working life. The model treats the observed distribution of variables as a combination of K underlying distributions, one for each profile

$$f(y_i) = \sum_{k=1}^K \pi_k f_k(y_i | \mu_k, \Sigma) \text{ [Eq. 2]}$$

where K is the number of profiles, π_k is the share of workers in profile k , and f_k is a multivariate normal density with profile-specific means μ_k . Error variances Σ are constrained to be equal across profiles, so that profiles differ in the level of each indicator rather than in its dispersion. The model is estimated on seven standardized indicators, the two exposure scores and the five job quality dimensions, by maximum likelihood with twenty random starting values. Solutions from one to seven profiles are compared on the Bayesian and sample-size-adjusted Bayesian information criteria, entropy, the size of

the smallest profile, and interpretability (Supplementary Materials S2). Each worker is assigned to the profile for which their posterior probability is highest.

The third stage uses a multinomial logit to establish the sociodemographic characteristics of workers in each GenAI-Job Quality profiles, as described in Equation 3:

$$\Pr(C_i = k) = \frac{\exp(x_i' \gamma_k)}{\sum_{j=1}^K \exp(x_i' \gamma_j)} \text{ [Eq. 3]}$$

where C_i is the profile to which worker i is assigned and x_i contains age, gender and the controls described in Section 3.2.3.

In the fourth stage, we examine whether training is distributed in line with exposure. We first model the probability of having trained on the two standardized exposure scores as described in equation 4:

$$\Pr(T_i = 1) = \frac{1}{1 + e^{-(\delta_0 + \delta_1 \text{Auto}_i + \delta_2 \text{Aug}_i + x_i' \theta)}} \text{ [Eq. 4]}$$

where T_i indicates any work-related training in the previous twelve months, Auto_i and Aug_i are the standardized automation and augmentation exposure scores, and x_i contains age, gender and the controls described above. The coefficients of interest are δ_1 and δ_2 . The same outcome is then modelled on job profile interacted with the age indicator, and the specification is applied among workers who trained to the number of courses undertaken, their average duration, and whether the training provided new skills or improved existing ones.

Coefficients from the multinomial logistic models are reported as relative risk ratios, and from the logistic models as odds ratios. Values greater than 1 indicate a higher likelihood of being in the outcome category relative to the reference category, while values below 1 indicate a lower likelihood. Gender is examined alongside age as a key demographic at every stage.

5. Results

5.1. Exposure and job quality across the workforce

Table 1. Generative-AI exposure by age

	Automation	Augmentation
Age (continuous variable)		
Age	0.0008***	0.0006***

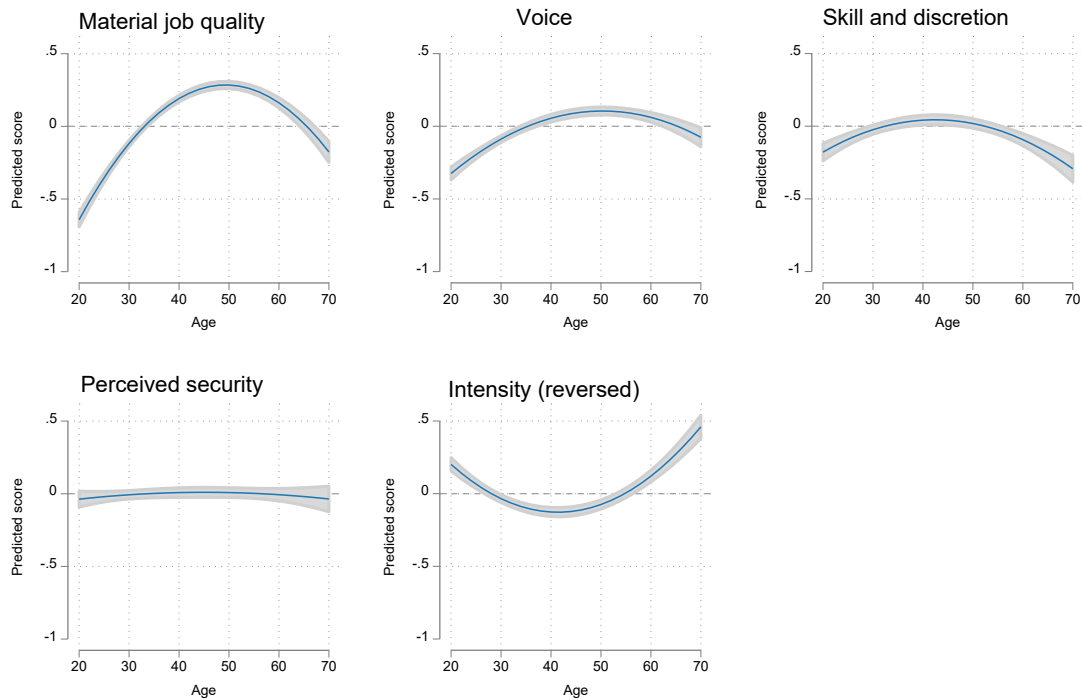
	(0.0002)	(0.0001)
Age 55 and over (binary variable)		
55 and over	0.009 (0.005)	-0.006 (0.003)
Age (quadratic specification)		
Age	0.0055*** (0.0009)	0.0081*** (0.0006)
Age squared	-5.60E ⁻⁰⁵ *** (1.09E ⁻⁰⁵)	-8.98E ⁻⁰⁵ *** (6.50E ⁻⁰⁶)
Turning point (years)	49.3	45.1
Gender (binary variable)		
Women	0.041*** (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 reports differences in GenAI exposure by age and gender. Age is positively associated with both dimensions in the linear specification, each additional year being associated with a 0.0008 increase in automation exposure and a 0.0006 increase in augmentation exposure (significant at the 1% level). Comparing workers aged 55 and over with those under 55 however highlights a different picture with older workers not significantly more exposed to automation or augmentation, with a negative sign for the latter. The difference between the two specifications suggests that this relationship is not linear. Adding a quadratic term indeed shows a significant negative squared coefficient on both dimensions, which means that exposure rises during early and mid-career stages and declines later, following and inverted-U shape and peaking at 49.3 years for automation and 45.1 for augmentation.

Gender differences are relatively more visible. Women are more exposed than men on both dimensions with women more exposed to automation by a magnitude of 0.041 to augmentation by a magnitude of 0.020 (both significant at the 1% level). Women's jobs are therefore more exposed to GenAI overall.

Figure 1. Distribution of job quality by age



Source: Authors' calculations using HILDA (wave 24) and JSA (2025). *Notes:* Survey weights applied. Predicted values from separate regressions of each dimension on age and age squared; shading shows 95% confidence intervals. Dimensions are standardized across the estimation sample, so zero is the sample mean and higher values indicate better job quality. Work intensity is reverse-coded.

Figure 1 shows the standardized score of each job quality dimension by age and Supplementary Material S1 shows the descriptive statistics. A dimension value of zero is the sample mean, and higher values denote better job quality for a given dimension. Work intensity is reverse-coded with higher values denoting less demanding work. S1 shows that older workers scored above the workforce mean on material job quality (0.21) and voice (0.15), and below it on skill and discretion (−0.11), and similar scores for perceived security. The values in Figure 1 are predicted levels at each age, computed from survey-weighted regressions of each dimension on age and age squared. Material job quality, voice, and skill and discretion followed an inverted-U shape. Material job quality peaked at around 49 and returned to the mean in the mid-sixties. Voice followed a similar shape and peaked at around 50. Skill and discretion turned earlier and more weakly with a peak around 42 and declined more steeply after that age compared to the other two dimensions. Work intensity followed a U-shape, suggesting that jobs are least demanding at the two ends of the working life and most demanding around 41. Perceived security showed no particular age pattern.

Appendix A1 shows the predicted levels of job quality by age and gender and shows that both groups overall follow the same shape and values, except for material job quality where men have a much higher

level of job quality than women, widening at younger ages and only moderately narrowing at older ages.

5.2. GenAI Exposure and Job Quality typology

Latent profile models were estimated for one to seven profiles, and the four-profile solution was retained on the basis of parsimony, classification quality and interpretability following Hasselhorn et al. (2020).³

³ The different information criteria did not reach a minimum in the set of tested models, which is common in job quality typologies (Hasselhorn et al. 2020). The choice of the 4-class solution was therefore chosen as it strikes the balance between precision and parsimony, this solution had the smaller information criteria while having no group(s) with less than 10% of the sample.

Table 2. Job type profiles

LPA classes	Main groups	occupationMain industries	Automati on	Augment ation	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 reports the mean scores of each job profile on the seven indicators, expressed as standardized z-scores, and the main occupational and industry composition of each type.

The first job profile, Low-exposure – Moderate Job Quality (JQ), accounts for 19 per cent of employment. It has the lowest scores on both exposure dimensions, 1.17 standard deviations below the workforce mean for automation and 1.66 below for augmentation. It is the most occupationally heterogeneous of the four, with 33 per cent of laborers, 27 per cent of community and personal service workers, and is concentrated in construction (17 per cent) and health care and social assistance (16 per cent). Job quality is below average on four of the five dimensions, particularly skill and discretion (−0.43) and material job quality (−0.39), while work is somewhat less demanding than average (0.29). Augmentation exposure is 0.49 standard deviations below automation exposure in this job type, suggesting that these jobs stand further from the assistive capacity of GenAI than from its displacing risk.

The second job profile, Augmentation-exposed – High JQ, is the largest and accounts for 44 per cent of employment. Professionals and managers constitute 68 per cent of the profile, and health care and social assistance (28 per cent) and education and training (17 per cent) account for almost half of its employment. Automation exposure is slightly below the workforce mean (−0.21) while augmentation exposure is above it (0.27), making this the only job profile in which the relative assistive capacity of GenAI exceeds its displacing risk. It has the highest score of any profile on four dimensions of job quality, with skill and discretion at 0.44 standard deviations above the mean, voice at 0.41, material job quality at 0.37 and perceived security at 0.29. Half of its workers are covered by a collective or enterprise agreement, which is the highest of the four profiles and reflects high collective agreement coverage of the healthcare and education industries (Australian Bureau of Statistics 2024). It is also the most demanding profile of work (−0.32), a combination of high job quality and high work intensity that has been documented among older workers in previous research (see for instance Stiller, Ebener and Hasselhorn 2023).

The third job profile, Average-exposure – Low JQ, accounts for 13 per cent of employment. Its exposure scores are close to the workforce mean on both dimensions (−0.15 and −0.10). It is composed mostly of sales workers (29 per cent) and community and personal service workers (24 per cent), and is concentrated in retail trade (27 per cent). It has the lowest score of any profile on four dimensions of job quality by a substantial margin: material job quality is 1.15 standard deviations below the mean, skill and discretion 0.85 below, voice 0.73 below and perceived security 0.64 below. The exception is work intensity, since it is relatively less intense than the other profiles (0.59).

The fourth job profile, high-exposure administrative work of mixed job quality, accounts for 24 per cent of employment. It has the highest automation exposure, 1.41 standard deviations above the workforce mean, and the highest augmentation exposure at 0.88. Clerical and administrative workers make up 44 per cent of the profile and professionals 38 per cent, likely reflecting office-based information work spanning clerical and business-professional roles. It is the only job profile in which professional, scientific and technical services (15 per cent) and financial and insurance services (13 per cent) are the leading industries. Material job quality is above the workforce mean (0.21) and work is slightly less demanding than average (0.14), while voice (−0.24), skill and discretion (−0.12) and perceived security (−0.13) are relatively lower than average.

These profiles indicate that exposure to GenAI and job quality do not vary along a single gradient. The second and third job types are almost indistinguishable in their automation exposure, differing by 0.06 standard deviations, yet they are separated by 1.52 standard deviations on material job quality, 1.29 on skill and discretion, 1.14 on voice and 0.93 on perceived security. Work intensity is the only dimension on which service work scores higher, and it does so because the work is less demanding, by 0.91 standard deviations. Similar exposure to automation is therefore compatible with very different employment conditions. The fourth job type has the highest exposure on both dimensions, but material job quality is above the workforce mean while voice, skill and discretion and perceived security fall below it. The jobs most exposed to GenAI are therefore not the most disadvantaged in material terms. They are jobs that offer adequate pay and security of contract and hours, but in which workers have comparatively little say over how their work is done and comparatively limited scope to navigate technological change. Whether exposure to GenAI translates into disadvantage may depend less on the material terms of employment than on these non-material dimensions of job quality, which shape workers' capacity to respond to changes in how their work is organized.

5.3. Socio-demographic characteristics of the four job profiles

Table 3. Worker characteristics in the four job profiles

Job profile	Aged 55 or older (%)	Mean age	Women (%)	Mean tenure (years)	Mean number of dependent children	Bachelor's degree or higher (%)	Metropolitan area (%)
Low exposure – Moderate JQ	19.6	38.6	32.2	5.4	1.18	13.2	64.3
Augmentation-exposed – High JQ	17.6	41.7	53.6	8.1	1.35	58.9	75.6

Average-exposure – Low JQ	14.1	35.6	59.7	3.4	0.94	34.8	80.0
High-exposure – Mixed JQ	19.9	41.9	57.0	6.6	1.23	45.8	81.4
All workers	17.9	40.4	51.1	6.6	1.24	44.0	75.4

Source: Authors' calculations using HILDA (wave 24) and JSA (2025). *Notes:* Survey weights applied.

Table 3 shows the socio-demographic characteristics of workers in each of the four job profiles. Workers aged 55 and over accounted for between 14.1 and 19.9 per cent of the profiles, against a workforce share of 17.9 per cent. The youngest was Average-exposure – Low JQ, with a mean age of 35.6 years and the smallest share of older workers (14.1 per cent). Older workers were most present in Low exposure – Moderate JQ (19.6 per cent) and High-exposure – Mixed JQ (19.9 per cent), which sit at opposite ends of the exposure distribution. Women were 32.2 per cent of the low-exposure profile and 59.7 per cent of the average-exposure profile, a spread of 28 percentage points against a workforce share of 51.1 per cent, and were also over-represented in the high-exposure profile (57.0 per cent). Average tenure was from 8.1 years in Augmentation-exposed – High JQ down to 3.4 years in the average-exposure profile, a wider gap than their mean ages would suggest. Degree holding followed a similar order, from 13.2 per cent in the low-exposure profile to 58.9 per cent in the augmentation-exposed profile, with the high-exposure profile in between at 45.8 per cent, consistent with professionals making up 38 per cent of it. The high-exposure profile was also the most metropolitan (81.4 per cent) and the low-exposure profile the least (64.3 per cent).

Next, we use a multinomial logistic model to establish which of these characteristics are independently associated with profile membership (i.e., how do each of these characteristics correlate with class membership when other factors are accounted for). The results are presented in Table 4, expressed in relative risk ratios with Augmentation-exposed-High JQ as the reference profile. Workers aged 55 and over were more likely than younger workers to hold each of the other three profiles, by between 45.8 and 49.8 per cent, significant at the 5 per cent level for Average-exposure – Low JQ and 1 percent for the two other profiles. Older workers were therefore significantly less likely to hold the augmentation-exposed-High JQ profile. Women were 56.6 per cent less likely to hold Low exposure – Moderate JQ profile by respectively 30.1 and 19.7 per cent more likely to hold Average-exposure – Low JQ work and High-exposure – Mixed JQ work. Education is strongly correlated with class membership with workers holding a degree less likely to be in the three other categories than Augmentation-exposed-High JQ, similarly to tenure. The number of dependent children was significantly lower only in the High Exposure-Mixed JQ profile and health limitation was not significant overall.

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)	
Bachelor 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. * $p < .10$, ** $p < .05$, *** $p < .01$.

5.4. Training and exposure

This section analyzes the extent to which current training take-up and characteristics are aligned with exposure. To do so, we first model the probability of having trained on automation and augmentation exposure, then on job profiles and finally, we analyze characteristics of the training received among workers who trained.

The relationship between the two forms of exposure and training had opposite signs as shown in Supplementary Materials S3. A one SD increase in automation exposure was associated with odds of 0.71 of participating in a training in the past year whereas a one SD increase in augmentation exposure was associated with odds of 1.16, both significant at the 1% level.

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 shows the same pattern across the four profiles. Relative to the augmentation-exposed profile, the odds of having trained among workers under 55 were 0.51 in High-exposure – Mixed JQ work and 0.68 in Low exposure – Moderate JQ work, both significant at the 1 per cent level, while Average-exposure – Low JQ work did not differ significantly. The profile with the highest automation exposure was therefore the one with the smallest relative likelihood of training take-up. Age was not significant, indicating this pattern held for workers below and above 55 years old. The interaction term between age and profiles was significant in only one case, average-exposure work, where odds for older workers were 0.65 those of their younger counterparts. Among workers who trained, the odds that the training had improved their existing skills were 0.56 for older workers, significant at the 1 per cent level. The estimate for new skill acquisition also pointed at older workers having a smaller likelihood but not significant. Women had 1.42 times the odds of having trained relative to men, and among those who trained they undertook 0.9 more courses while spending 0.8 fewer hours on each, all significant at the 1 per cent level. The content of their training did not differ from men on either measure.

Older workers were less likely to hold the augmentation-exposed profile, which also has the highest training incidence, placing their location in the labor market at a disadvantage. When they did access training, the fact that they were less likely to improve their skills compounded this disadvantage.

6. Discussion and conclusion

Using an original dataset that links measures of occupational exposure to job and workforce characteristics, this paper examined how exposure to GenAI interacts with job quality, focusing particularly on the experiences of older workers. We find that exposure did not map onto job quality along a single gradient. Jobs with similar levels of exposure were associated with very different employment conditions, and the profile most exposed overall had above-average pay, contractual security and hours. This challenges existing approaches of exposure to GenAI that tend to treat automation as a straightforward indicator of the risk of job loss and augmentation as a proxy for opportunities for workers. Four latent job profiles emerged from the LPA: (1) low-exposure (both augmentation and automation) work of moderate job quality held largely by labourers and community and personal service workers in construction and health care; (2) augmentation-exposed professional work of high job quality held by professionals and managers concentrated in health care and education; (3) average-exposure service work of low job quality held by sales and personal service workers in retail; and (4) high-exposure office-based information work of mixed job quality held by clerical and administrative workers alongside professionals in business and financial services. The fact that clerical and administrative work is the most exposed to automation is in line with previous research. Routine, codifiable work has long been the most susceptible to technological substitution (Acemoglu & Restrepo, 2019; Autor et al., 2003), including GenAI (Eloundou et al., 2024; Gmyrek et al., 2023, 2025, JSA 2025). Understanding exposure alongside job quality nevertheless reveals what this exposure means for workers and organizations. Jobs in the High Exposure-Mixed JQ profile paid comparatively well and offered secure contracts and hours, suggesting that the vulnerability they carry is not material precarity but the absence of voice and discretion through which workers might shape how the technology enters their work (Bryson et al., 2013; Iskander & Lowe, 2013). As this technological change transforms organizations, these findings highlight the need to consider not only what work is being performed, but also the conditions of this work – including who performs it.

Age did not predict exposure in the way that debate about older workers and technology would suggest. Workers aged 55 and over were not significantly more exposed to either automation or augmentation, with exposure instead rising through early and mid-career and declining thereafter. The disadvantage older workers faced operated through where they sat in the labor market rather than through exposure. They were significantly less likely to hold augmentation-exposed professional work. This echoes

research on age-based segmentation showing older workers face barriers to career progression and to the recognition of their skills within organisations (Hamilton & Zettina, 2024).

One aim of this paper was to establish whether the jobs most exposed to GenAI were also those in which workers could receive skills to adapt to it. We found that training participation was positively associated with augmentation exposure and negatively associated with automation exposure. The same pattern held across profiles, with the odds of having trained in the high exposure profile lower than those of augmentation-exposed professional work. The jobs in which GenAI has most scope to substitute for tasks were therefore those in which workers were least likely to have trained. Older workers were not less likely than younger workers to have trained, which is notable given established findings that they receive less employer-funded training (Canduela et al., 2012). This may reflect how training is measured in this study, which captures any work-related training in the previous twelve months rather than employer-funded provision specifically. Among those who did train, however, the odds that the training had improved skills used in their current job were lower for older workers in three of the four profiles. Combined with their under-representation in augmentation-exposed work, this points to a disadvantage arising from the jobs older workers hold and from the training available in them.

This paper contributes to the literature in two ways. First, it extends research on GenAI and its impact on work in organizations, by combining task-based measures with job quality. Task-based measures establish what GenAI can do to the tasks that make up an occupation, but say little about the conditions under which those tasks are performed (Eloundou et al., 2024), and in the literature, automation has tended to be equated with risk and augmentation with opportunity (Gmyrek et al., 2023, 2025). Our results challenge this assumption by arguing that the consequences of GenAI are shaped not by exposure alone, but by how exposure intersects with existing patterns of labor market segmentation and job quality in complex ways. It is this combination of job quality and exposure that distributes the risks and opportunities associated with GenAI across the labor market and organizations. Second, the paper contributes to research on workplace aging. Research shows that older workers' vulnerability to technological change is due to stereotypes about adaptability and assumptions that proximity to retirement reduces the returns to skill investment (Friedberg, 2003; Posthuma & Campion, 2009). Older workers also receive less employer-provided training than younger colleagues (Canduela et al., 2012; Eurofound, 2025). Our results only partly echo these findings and highlight a more structural mechanism operating through labor market segmentation. Older workers were not significantly more exposed to GenAI on either dimension, but they were less likely to hold the augmentation-exposed profile once sociodemographic variables were accounted for. The disadvantage therefore operated through the sorting of older workers across jobs and this segmentation shapes both exposure and job

quality. Addressing stereotypes about older workers' adaptability, while necessary, does not suffice to address a disadvantage that operates through the allocation of jobs. Gender segmentation operates alongside this mechanism. Women were more exposed to GenAI on both dimensions and they were over-represented in the average-exposure profile, which had the lowest voice and skill and discretion of the four, and in the high-exposure profile, consistent with their concentration in clerical and service work. For older women, whose barriers to mobility and re-employment are already documented (Hamilton & Zettna, 2024), the two forms of segmentation are likely to compound.

These findings have implications for organizational approaches to the adoption of GenAI, particularly on voice and training. Workers in high-exposure office-based information work face the greatest exposure with the least capacity to shape how GenAI enters their jobs, which leaves implementation to be determined by managerial priorities and by whether the technology reduces costs. Given existing research that union involvement in shaping technology implementation is associated with more mutually beneficial outcomes (Bryson et al., 2013; O'Brady & Doellgast, 2021), the implementation of GenAI in these jobs is likely to be a more stressful and disempowering experience for employees. Recent studies on GenAI similarly emphasize the importance of worker and union participation in technology governance and implementation (Agnolin & Gonzalez-Rostani, 2026; Budhwar et al., 2023; Kochan et al., 2024). These findings point to the value of strengthening consultation and participation mechanisms to ensure that workers have opportunities to influence decisions about how GenAI affects the organization of their work. They also underscore the need for effective employer training provisions. For older workers especially, access to training on GenAI that supports ongoing skill development will be crucial for adapting to organizational change.

Finally, our findings also raise policy questions about the adequacy of training systems and the regulation of GenAI at work. Current patterns of skill investment appear better suited to supporting workers in already advantaged jobs than to assisting those facing the greatest risks of task substitution. If the objective of policy is to enable workers to adapt to technological change and reduce the potential for displacement, greater investment may be required in the jobs currently receiving the least training. Policymakers seeking to support adaptation to GenAI may therefore need to focus not only on expanding training provision, but also on ensuring that access to high-quality, skill-enhancing training reaches workers in the occupations most exposed to technological change. More broadly, as Bailey (2022, p. 546) summarized, "Government must hold firms responsible for the technologies they deploy." At the time of writing, regulatory responses to the use of GenAI in workplaces are newly emerging, such as the European Union's *AI Act*, which has moved to closely limit the use of AI tools for the recruitment and management of workers (Artificial Intelligence Act, 2024). Building in this direction, our findings suggest that the governance of GenAI in organizations must extend beyond

managing the risk of job displacement to ensure workers have both a voice in implementation processes, as well as access to the training needed to adapt to this major technological change.

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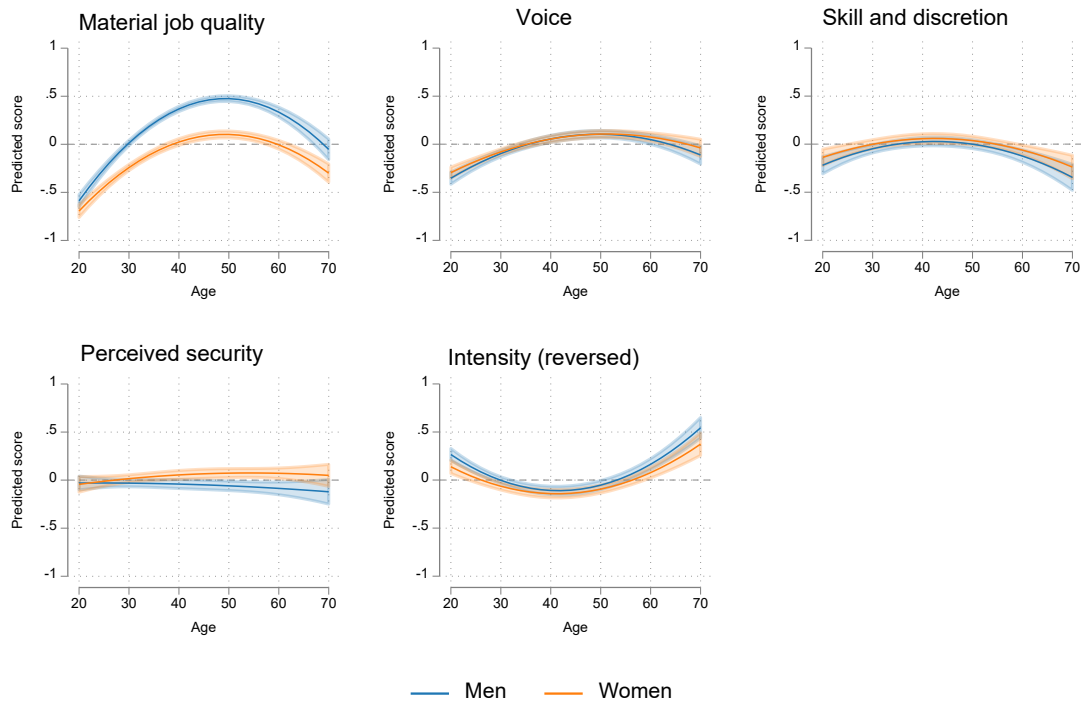
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Appendix

A1. Job quality by age and gender



Source: Authors' calculations using HILDA (wave 24) and JSA (2025). *Notes:* Survey weights applied. Predicted values from separate regressions of each dimension on age and age squared; shading shows 95% confidence intervals. Dimensions are standardized across the estimation sample, so zero is the sample mean and higher values indicate better job quality. Work intensity is reverse-coded.

Online Supplementary Material

S1. Descriptive statistics

	All workers		Under 55		55 and over	
	Mean	SE	Mean	SE	Mean	SE
<i>Material job quality</i>						
Log weekly earnings, main job	7.246	0.011	7.253	0.012	7.213	0.023
Permanent or ongoing contract	0.740	0.007	0.736	0.007	0.755	0.014
Tenure with current employer (years)	6.632	0.112	5.290	0.103	12.787	0.361
Full-time (35 or more hours)	0.704	0.007	0.717	0.008	0.643	0.014
<i>Voice</i>						
Say over what happens at work	3.950	0.026	3.958	0.029	3.915	0.051
Trade union member	0.219	0.007	0.202	0.007	0.299	0.015
Collective or enterprise agreement	0.395	0.008	0.381	0.009	0.459	0.015
<i>Skill and discretion</i>						
Job provides variety	4.642	0.024	4.657	0.027	4.575	0.051
Job uses skills and abilities	5.300	0.021	5.290	0.024	5.347	0.044
Job requires learning new skills	4.686	0.025	4.761	0.028	4.342	0.058
Job requires taking initiative	5.410	0.022	5.425	0.025	5.341	0.045
<i>Perceived security</i>						
Job has a secure future	5.085	0.025	5.094	0.028	5.042	0.052
Employer will remain in business	5.918	0.023	5.912	0.026	5.945	0.044
Perceived chance of keeping job (%)	90.404	0.276	90.456	0.304	90.167	0.662
<i>Work intensity</i>						
Works at very high speed	4.961	0.025	5.041	0.028	4.593	0.052
Job requires working hard	4.723	0.024	4.750	0.028	4.597	0.050
Not enough time to do everything	4.076	0.029	4.106	0.033	3.938	0.062
Job is more stressful than expected	3.509	0.024	3.546	0.027	3.339	0.052
Work stress affects health	2.687	0.024	2.716	0.027	2.553	0.050
<i>Job quality dimensions (standardized)</i>						
Material job quality	-0.008	0.015	-0.056	0.017	0.208	0.034
Voice	-0.015	0.016	-0.052	0.018	0.153	0.033
Skill and discretion	-0.025	0.016	-0.007	0.018	-0.111	0.031
Perceived security	-0.041	0.016	-0.038	0.018	-0.052	0.035
Work intensity, reversed	0.024	0.016	-0.010	0.018	0.183	0.032
<i>GenAI exposure (standardized)</i>						
Automation exposure	-0.001	0.015	-0.012	0.017	0.048	0.033
Augmentation exposure	-0.001	0.015	0.010	0.017	-0.055	0.031
<i>Individual characteristics</i>						

Woman	0.511	0.006	0.510	0.007	0.516	0.013
Partnered	0.647	0.008	0.633	0.009	0.712	0.015
Dependent children	1.237	0.020	1.057	0.023	2.067	0.040
Health condition limiting work	0.173	0.006	0.151	0.006	0.271	0.014
Metropolitan area	0.754	0.008	0.764	0.008	0.707	0.016
Education						
Year 12 or below	0.261	0.007	0.264	0.008	0.247	0.014
Certificate or diploma	0.299	0.007	0.276	0.007	0.405	0.016
Bachelor degree	0.244	0.007	0.263	0.008	0.157	0.013
Postgraduate degree	0.196	0.007	0.197	0.008	0.191	0.012
State or territory						
New South Wales	0.310	0.010	0.313	0.011	0.299	0.016
Victoria	0.257	0.009	0.257	0.010	0.259	0.016
Queensland	0.206	0.009	0.203	0.010	0.220	0.018
South Australia	0.067	0.004	0.067	0.005	0.064	0.007
Western Australia	0.104	0.006	0.104	0.007	0.106	0.010
Tasmania	0.024	0.002	0.023	0.003	0.028	0.004
Northern Territory	0.009	0.002	0.009	0.003	0.009	0.004
Australian Capital Territory	0.022	0.003	0.024	0.003	0.015	0.004
Observations	8,073					

Source: Authors' calculations using HILDA (wave 24) and JSA (2025). *Notes:* Survey weights applied. Work intensity is reverse-coded. Standardized dimension and exposure scores are expressed in standard deviations of the estimation sample. Observations are the estimation sample.

S2. Latent profile analysis model comparison

k (Number of profiles)	Parameters	Log- likelihood	AIC	BIC	SABIC	Entropy	Smallest class (%)
1	14	−80,182.1	160,392.3	160,490.2	160,445.7	n.a.	100.0
2	22	−77,121.6	154,287.1	154,441.0	154,371.1	0.859	22.4
3	30	−75,163.6	150,387.1	150,597.0	150,501.7	0.863	20.1
4	38	−74,164.4	148,404.8	148,670.7	148,550.0	0.829	11.5
5	46	−73,355.3	146,802.6	147,124.5	146,978.3	0.834	9.4
6	54	−72,772.5	145,653.1	146,030.9	145,859.3	0.812	9.9
7	62	−72,412.9	144,949.9	145,383.6	145,186.6	0.822	8.5

Source: Authors' calculations using HILDA (wave 24) and JSA (2025). *Notes:* Latent profile models were estimated on the estimation sample by maximum likelihood on seven indicators (i.e., automation exposure, augmentation exposure and the five job quality dimensions) with twenty random starting values. AIC refers to Akaike's information criterion, BIC to Bayesian information criterion, and SABIC to its sample-size-adjusted form.

S3. Logistic regression of training participation on continuous exposure scores

	Trained in previous 12 months
Automation exposure	0.709*** (0.035)
Augmentation exposure	1.157*** (0.057)
Aged 55 and over	1.013 (0.096)
Women	1.504*** (0.094)
Tenure (years)	1.003 (0.004)
Certificate or diploma	1.226** (0.114)
Bachelor degree	1.571*** (0.171)
Postgraduate degree	1.756*** (0.195)
Partnered	1.130 (0.085)
Dependent children	0.955* (0.024)
Health condition limiting work	1.322*** (0.111)
Metropolitan area	0.900 (0.069)
<i>State or territory (reference: New South Wales)</i>	
Victoria	1.053 (0.099)
Queensland	1.307*** (0.135)
South Australia	1.395*** (0.163)
Western Australia	1.145 (0.130)
Tasmania	1.098 (0.194)
Northern Territory	1.780** (0.522)
Australian Capital Territory	0.671*

	(0.146)
Observations	8,053

Source: Authors' calculations using HILDA (wave 24) and JSA (2025). *Notes:* Survey weights applied. Odds ratios reported. Education is relative to Year 12 or below. Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

S4. Work-related training by job profile (full table)

	(1)	(2)	(3)	(4)	(5)
	<i>Trained</i>	<i>Courses</i>	<i>Hours</i>	<i>New skills</i>	<i>Improved skills</i>
	<i>Logit</i>	<i>OLS</i>	<i>OLS</i>	<i>Logit</i>	<i>Logit</i>
<i>Job profile (reference: Augmentation-exposed – High JQ)</i>					
Low exposure – Moderate JQ	–0.388*** (0.105)	–0.290 (0.546)	0.124 (0.254)	–0.428** (0.176)	–0.278 (0.185)
Average-exposure – Low JQ	–0.194 (0.139)	–0.848* (0.465)	–0.469 (0.302)	–0.363 (0.258)	–0.755*** (0.233)
High-exposure – Mixed JQ	–0.669*** (0.092)	–0.562 (0.359)	–0.322 (0.213)	–0.206 (0.167)	–0.308* (0.165)
<i>Age</i>					
Aged 55 and over	0.056 (0.129)	–0.547 (0.440)	–0.232 (0.257)	–0.261 (0.199)	–0.579*** (0.200)
<i>Job profile × aged 55 and over</i>					
Low exposure × 55 and over	0.083 (0.201)	2.199** (1.068)	–0.524 (0.427)	–0.192 (0.331)	0.173 (0.324)
Average-exposure × 55 and over	–0.438* (0.262)	0.041 (0.883)	–0.792 (0.491)	–0.482 (0.453)	0.841** (0.416)
High-exposure × 55 and over	–0.036 (0.191)	1.606* (0.863)	–0.244 (0.455)	–0.086 (0.338)	0.149 (0.325)
Women	0.350*** (0.062)	0.914*** (0.254)	–0.765*** (0.157)	0.122 (0.120)	0.064 (0.117)
Tenure (years)	–0.001 (0.004)	0.056*** (0.019)	–0.016* (0.009)	–0.032*** (0.007)	–0.001 (0.007)
Certificate or diploma	0.213** (0.092)	0.956*** (0.293)	0.328* (0.194)	–0.163 (0.177)	0.130 (0.184)
Bachelor degree	0.407*** (0.108)	0.869*** (0.312)	0.081 (0.234)	–0.006 (0.190)	0.366* (0.205)
Postgraduate degree	0.493*** (0.110)	1.686*** (0.487)	0.064 (0.231)	0.191 (0.179)	0.310 (0.208)
Partnered	0.107 (0.073)	0.068 (0.326)	0.085 (0.163)	0.160 (0.133)	0.170 (0.131)
Dependent children	–0.043* (0.026)	0.042 (0.099)	0.124** (0.063)	–0.161*** (0.054)	–0.069 (0.051)
Health condition limiting work	0.269*** (0.083)	0.905** (0.382)	–0.122 (0.209)	–0.230* (0.138)	–0.127 (0.146)
Metropolitan area	–0.117	–0.833***	–0.109	0.323***	–0.216*

	(0.075)	(0.322)	(0.168)	(0.125)	(0.125)
<i>State or territory (reference: New South Wales)</i>					
Victoria	0.044 (0.095)	−0.396 (0.338)	0.004 (0.192)	−0.407*** (0.138)	−0.072 (0.142)
Queensland	0.253** (0.104)	−0.882** (0.415)	0.383* (0.224)	−0.504*** (0.177)	−0.246 (0.173)
South Australia	0.329*** (0.116)	0.292 (0.485)	0.357 (0.274)	−0.120 (0.190)	0.166 (0.199)
Western Australia	0.138 (0.112)	0.211 (0.467)	0.410 (0.263)	−0.423** (0.176)	0.145 (0.182)
Tasmania	0.118 (0.179)	−2.060*** (0.607)	0.173 (0.295)	−0.257 (0.276)	0.254 (0.306)
Northern Territory	0.546* (0.288)	−1.893** (0.926)	0.683 (0.607)	−0.313 (0.567)	0.328 (0.718)
Australian Capital Territory	−0.431** (0.212)	−0.123 (0.917)	0.157 (0.403)	−0.028 (0.374)	−0.191 (0.292)
Constant	−0.853*** (0.131)	3.592*** (0.434)	5.566*** (0.270)	1.555*** (0.255)	1.082*** (0.269)
Observations	8,053	2,938	2,932	2,946	2,948

Source: Authors' calculations using HILDA (wave 24) and JSA (2025). *Notes:* Survey weights applied. Columns 1, 4 and 5 are logistic and columns 2 and 3 linear, all reported as coefficients. Columns 2 to 5 are estimated among workers who trained. Education is relative to Year 12 or below. Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.