THE UNIVERSITY OF SYDNEY

The Wired Belt

Where AI Could Reshape Australian Politics

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Acknowledgement of Country

We recognise and pay respect to the Elders and communities- past, present, and emerging- of the lands that the University of Sydney's campuses stand on. For thousands of years they have shared and exchanged knowledges across innumerable generations for the benefit of all.

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Executive summary

Artificial intelligence is usually framed as an economic and technological issue. This report argues that it may also become a major force reshaping Australian politics.

Previous waves of economic disruption were concentrated in regional, industrial and resource-dependent communities. AI is likely to have a different geography. Its effects may fall most heavily on educated, professionally employed and digitally intensive metropolitan electorates – the communities that form Australia's emerging "wired belt".

To identify these communities, the report constructs an AI Exposure Index for all 150 federal electorates. The index combines three established measures of occupational exposure to AI and weights them according to each electorate's specific occupational composition. It measures exposure to AI-driven automation, augmentation and task redesign; it is not a forecast of net job losses.

The political consequences of AI will not depend solely on whether jobs disappear. They may emerge through fewer graduate positions, flatter career pathways, greater insecurity, slower wage growth and reduced professional autonomy. These changes could weaken the expectation that education, expertise and professional work will provide economic mobility and security.

The central political issue is therefore not simply how many jobs AI may eliminate, but whether voters continue to believe that education and professional employment will deliver opportunity and advancement. If that belief significantly weakens across Australia's wired belt, political change will accelerate rapidly.

Key findings

AI exposure is overwhelmingly metropolitan. The average inner-metropolitan electorate records an index score of 68.8, compared with 32.8 for the average rural electorate. All 30 of the most exposed seats are metropolitan: 24 inner-metropolitan and six outer-metropolitan.

The most exposed seats sit at the heart of Australia's knowledge economy. Bradfield, Wentworth, Warringah, Bennelong, Sydney and Kooyong are among the highest-ranked electorates, reflecting their concentration of professional, administrative, analytical and digitally intensive employment.

These communities combine economic advantage with higher levels of mortgage stress. In the 30 most exposed seats, 44.1 per cent of residents hold a bachelor's degree or above, median weekly household income averages $2,266 and mortgage stress averages 17.1 per cent. In the 30 least-exposed seats, the equivalent figures are 13.4 per cent, $1,396 and 11.6 per cent.

Labor, the Liberals and the Teals are on the political front line. Labor holds 19 of the 30 most exposed seats and 47 of the top 60. Six of the top 30 are held by Teal-aligned MPs – four independents and two members of Community Strong Australia – while the Liberals hold four and the Greens one.

The wired belt is already politically volatile. Across the 2019, 2022 and 2025 Federal elections, the most AI-exposed seats in New South Wales, Victoria and Queensland changed representation at about 3.2 times the rate of other seats in those states and accounted for 48.6 per cent of all recorded seat changes.

AI exposure runs in the opposite direction to One Nation's current support. A recent national poll conducted by RedBridge Group found One Nation support was strongest in lower AI-exposed rural and provincial electorates and weakest in highly AI-exposed inner-metropolitan seats. AI may therefore create a second political front alongside the economic grievances already reshaping regional Australian politics.

The Wired Belt: *Where AI Could Reshape Australian Politics*

The next jobs shock in Australian politics may not begin in the coal towns, factory belts or irrigation districts. It may begin in professional suburbs—from Bennelong, Berowra and Chisholm to Griffith, Menzies and Mitchell—where expectations of education, home ownership and secure white-collar work still underpin much of the political centre.

Few subjects at present generate as much speculation, or as much anxiety, as the impact of artificial intelligence (AI) on jobs.

Quantifying that impact has become something of a cottage industry in its own right, though the headline estimates describe different phenomena. The World Economic Forum's *Future of Jobs Report 2025*, drawing on a survey of more than 1,000 employers across 55 economies, projects labour-market churn equivalent to 22 per cent of current jobs by 2030 (World Economic Forum, 2025). CEDA (2015) estimated that almost five million Australian jobs - about 40 per cent of the workforce - faced a high probability of computerisation within 10 to 15 years. McKinsey (2024) estimates that up to 1.3 million workers, or around 9 per cent of the Australian workforce, may need to move into different occupations by 2030. Pearson (2025) estimates that 26 per cent of Australian employment is at high risk of automation and puts the potential annual transition cost at $104 billion.

By contrast, recent analysis by the Department of Employment and Workplace Relations (DEWR) finds no evidence to date of broad labour-market upheaval from AI, although employment, hours worked and job advertisements have grown more slowly in highly exposed occupations than in less-exposed ones since the release of ChatGPT on 30 November 2022.[1]

These numbers do not measure the same thing, and debate too often collapses into a contest between extremes: claims that whole occupations will vanish almost overnight, and reassurances that, because mass unemployment has not yet arrived, there is little to worry about. The more plausible reality is what Molly Kinder (2026) calls the *messy middle*[2]: many jobs survive, but parts of them are stripped away, recombined or handed to machines, with the sharpest effects falling on particular occupations, sectors and career stages.[3]

[1] DEWR's Office of the Chief Economist found that, between November 2022 and April 2026, employment in Australia's most AI-exposed occupational quintile grew by 5.6 per cent, compared with 9.5 per cent in the least-exposed quintile. The report treats this as a modest and suggestive gap, not evidence of large-scale displacement. Employment among 20–24-year-olds grew slightly faster than employment among workers aged 25 and over during the same period, in contrast to the youth-specific declines reported by Brynjolfsson, Chandar and Chen (2025) in the United States (Department of Employment and Workplace Relations, 2026).

[2] This "messy middle" has a strong foundation in the economics of technological change. The task-based literature shows that new technologies generally alter the bundle of tasks within occupations before they eliminate occupations altogether. They substitute for workers in some activities, complement them in others, and can create new tasks and roles even as existing ones disappear (Autor, Levy and Murnane, 2003; Acemoglu and Restrepo, 2019). The political question is therefore not simply how many jobs vanish, but whose tasks, bargaining power, career progression and income are altered along the way.

[3] Using high-frequency US payroll data, Brynjolfsson, Chandar and Chen (2025) estimate that employment among workers aged 22–25 in the most AI-exposed occupations declined by 16 per cent relative to the counterfactual after controlling for firm-level shocks. In a separate descriptive comparison, employment among software developers aged 22–25 was nearly 20 per cent below its late-2022 peak by September 2025. Declines were concentrated in occupations where AI is used more for automation than augmentation. IMF analysis of global vacancy data points in a similar direction: vacancies demanding AI skills offer higher wages, but the diffusion of those skills is associated with weaker employment in highly exposed, low-complementarity occupations, posing particular challenges for younger workers (Jaumotte et al., 2026).

Image: Unsplash

Whatever the precise scale, one thing is clear: a labour-market shock of this kind will have consequences far beyond the labour market. When the economic ground beneath a community shifts, its politics tends to shift with it. Voters in a town, suburb or city rarely change their votes en masse; they tend to do so only when the work that defines a place stops paying, disappears or no longer offers the next generation a plausible future.[4] That dynamic has helped reshape rural and provincial politics over the past two decades. It is also why the rise of an AI economy could become a political story as much as an economic one.

The political effects will depend heavily on where the jobs disruption lands. Earlier waves of labour-market change – the long decline of agricultural employment, deindustrialisation and the wind-down of carbon-intensive industries – were concentrated in regional communities. The next wave may have a different geography.

A recent study by Digital Planet at Tufts University (Chakravorti, Filipovic and Adisa, 2026), *Will Wired Belts Become the New Rust Belts?*, describes an emerging US "wired belt" as the new "rust belt": not the shuttered factory towns of the old Midwest industrial heartland, but the educated, digitally intensive metropolitan labour markets where routine cognitive work is concentrated.[5] If AI changes the value of professional, administrative and analytical work, this wired belt is where the economic disruption will be felt first, and most sharply, which raises an important political question: where on the political map is Australia's wired belt?

[4] The connection between technological disruption and electoral change is not merely analogical. Frey, Berger and Chen (2018) found that US labour markets more exposed to industrial robots recorded significantly greater support for Donald Trump in 2016. Anelli, Colantone and Stanig (2021), examining 13 Western European countries, similarly found that individuals more vulnerable to robot adoption were more likely to support the radical right. These studies demonstrate that geographically and occupationally concentrated technological exposure can translate into political realignment.

[5] Chakravorti, Filipovic and Adisa's (2026) analysis, covering 784 US occupations, finds that exposure is concentrated not only in the largest coastal metropolitan areas but also in smaller, highly educated labour markets. University centres such as Durham–Chapel Hill, Boulder, Ithaca, Madison and Ann Arbor rank among the 25 most exposed local economies. A companion Brookings analysis (Muro, Jones and Methkupally, 2026) found that 62 of the 100 most AI-exposed US counties voted Democratic in the 2024 presidential election, suggesting that highly educated areas on the moderate-to-progressive side of US politics are also disproportionately exposed.

Mapping the Australian “wired belt”: *an AI Exposure Index for all 150 federal electorates*

Using the latest available Census data and the 2024 federal electoral redistribution, we constructed an AI Exposure Index for each of Australia’s 150 federal electorates. The occupation-based index measures the extent to which each electorate’s specific employment profile is concentrated in work that may be affected by AI.

To reduce dependence on any single methodology, it combines three complementary measures:

1. **Jobs and Skills Australia’s (2025) generative-AI automation exposure scores**, which estimate the potential for generative AI to automate tasks within Australian occupations;
2. **the International Labour Organization’s global index of occupational exposure to generative AI** (Gmyrek et al., 2025); and
3. **the AI Occupational Exposure measure developed by Felten, Raj and Seamans (2021),** which captures broader occupational exposure to advances in artificial intelligence.

Figure 1: AI Exposure by Electorate

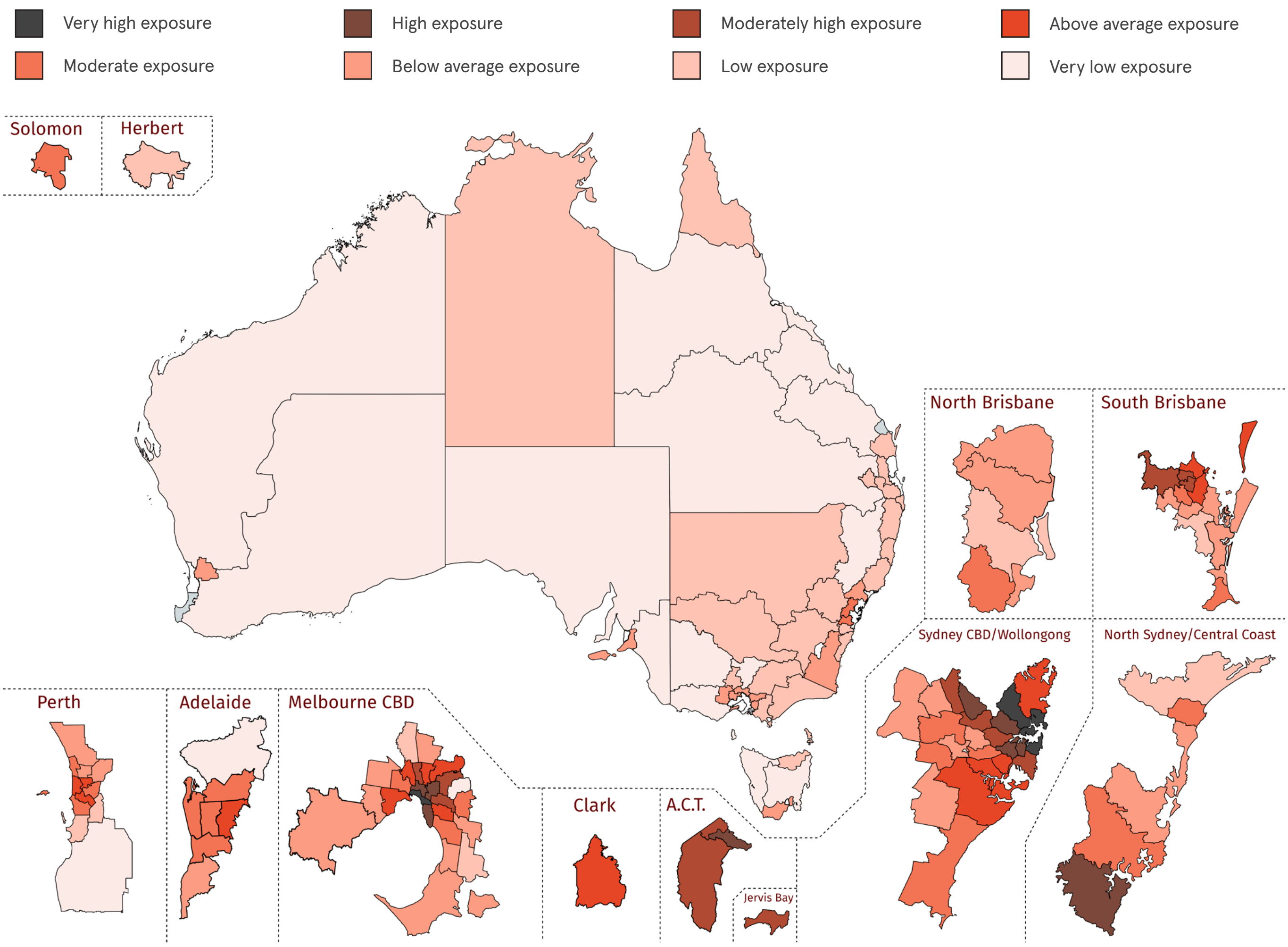


Image: Thought Catalogue, Unsplash

The political risk does not require mass unemployment

We matched these exposure scores to 474 occupational categories and then weighted them according to the actual occupational composition of each electorate.[6] Using ABS data, we identified the number of workers employed in each category within every electorate. This means that an electorate's score reflects not simply whether highly exposed occupations are present, but the proportion of its employed population working in those specific occupations. The three resulting electorate-level measures were standardised, given equal weight and combined into a single index, which was then transformed onto a 50-centred scale on which 25 points represent one standard deviation. Higher scores indicate a greater concentration of employment in occupations potentially exposed to AI-driven task transformation or automation; they do not represent forecasts of job losses.

The electorate estimates use occupational data from the 2021 Census mapped onto the federal boundaries established by the 2024 redistribution. Current member and party labels are recorded as at the date of publication. Appendix 1 divides the 150 electorates into five quintiles of 30 seats each and presents the rankings alongside a range of demographic, economic and socio-economic indicators.

An important caveat is that the Index measures exposure to AI-driven task change, not net job loss. A high-exposure seat may experience automation, augmentation, work redesign or the creation of new roles. The political risk does not require mass unemployment. It may arise if AI changes the terms on which people enter, progress through and feel secure within professional and administrative careers, through fewer graduate openings, more contingent work, flatter career ladders, slower wage growth, reduced autonomy and a suspicion that gains are flowing to others. Regional experience suggests that such pressures can weaken established political loyalties well before a full-scale employment crisis emerges.

The Index highlights three themes with direct implications for Australian politics.

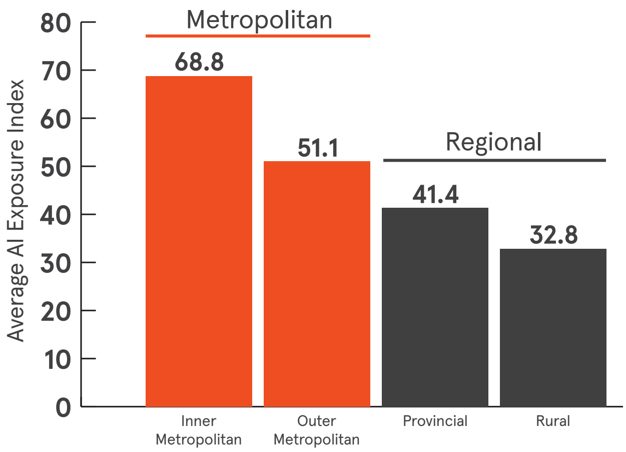
[6] Because the three exposure measures use different occupational classifications and levels of aggregation, their scores were first cross-walked to a common ANZSCO framework (four-digit occupation unit group level). Appendix 2 provides a detailed summary of the methodology used to construct the AI Exposure Index.

1. The most exposed electorates: *metropolitan, professional, younger, more diverse, and more mortgage exposed*

The clearest pattern in the data is geographic. AI exposure is highest in inner-metropolitan electorates, declines through the outer suburbs, and falls further across provincial and rural Australia.

Figure 2: Australia's most AI-exposed seats are metropolitan

Average AI Exposure Index by electorate type, 150 federal electorates (2024 boundaries)



The gap is significant. The average inner-metropolitan seat scores 68.8 on the index, compared with 32.8 for the average rural electorate. And at the very top, the pattern is absolute.

Table 1 lists the 30 seats most exposed to AI-driven task change, all of which are metropolitan: 24 inner metropolitan and six outer metropolitan electorates, with not a single provincial or rural electorate among them.

These 30 seats constitute Australia's wired belt. They are educated, digitally intensive and mortgage-exposed electorates in which analysts, administrators, finance professionals, marketers, programmers, writers, consultants, public servants and other graduate professionals are concentrated.

The 30 most exposed electorates are also younger, higher-income, more highly educated, more likely to include residents born overseas, more professionally concentrated and more mortgage stressed than any other quintile. Figures 3–7 show the relationships between AI exposure and age, overseas birth, mortgage affordability pressure, education and household income.

This combination matters politically: voters in Australia's wired belt carry high housing costs and strong expectations of economic mobility. If AI begins to unsettle professional and office work, these characteristics could intensify demands for a credible policy response and contribute to political volatility across the established urban moderate voting bloc of Australia's major capital cities.

Figure 3: More AI-Exposed Electorates Tend to Have Younger Populations

AI Exposure Index vs median age of residents, across all 150 Federal electorates

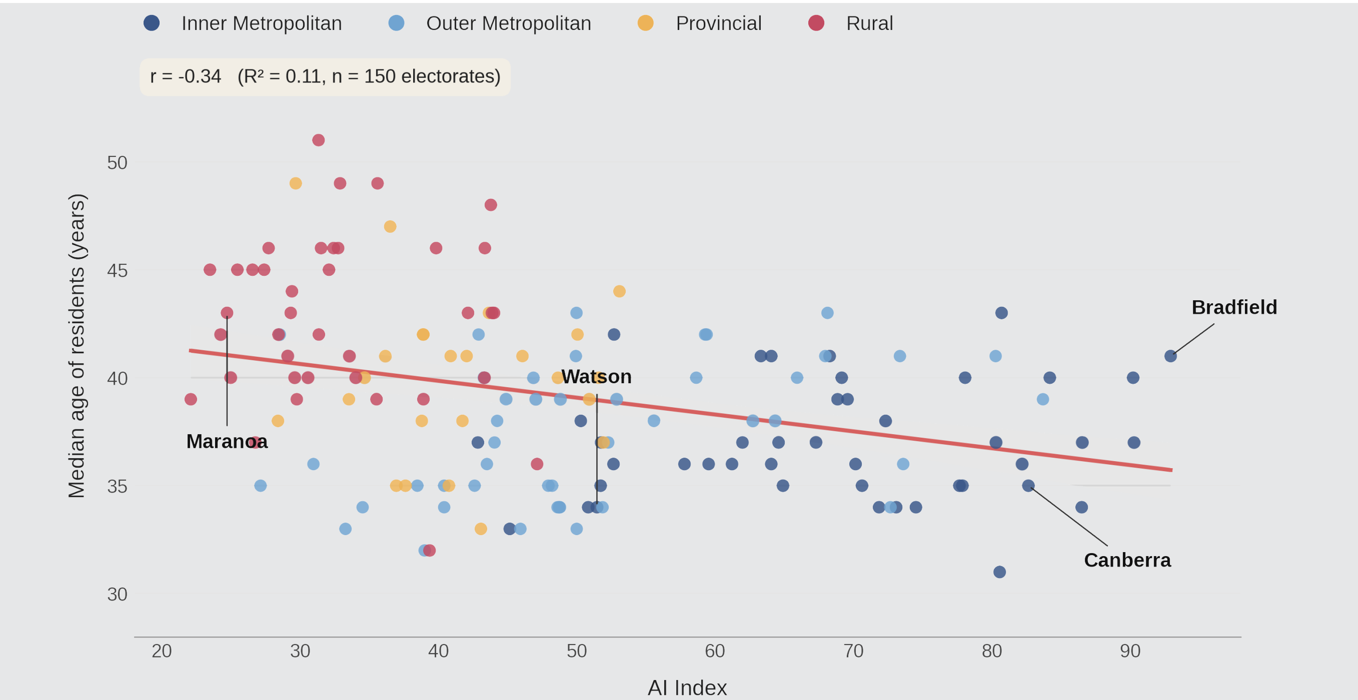


Table 1: The 30 federal electorates most exposed to AI-driven task change

Rank	Electorate	State	Classification	Member	Party	Index
1	Bradfield	NSW	Inner Metro	Nicolette Boele	IND (TEAL)	92.9
2	Wentworth	NSW	Inner Metro	Allegra Spender	CSA (TEAL)	90.3
3	Warringah	NSW	Inner Metro	Zali Steggall	CSA (TEAL)	90.2
4	Bennelong	NSW	Inner Metro	Jerome Laxale	ALP	86.5
5	Sydney	NSW	Inner Metro	Tanya Plibersek	ALP	86.5
6	Kooyong	VIC	Inner Metro	Monique Ryan	IND (TEAL)	84.2
7	Mitchell	NSW	Outer Metro	Alex Hawke	LIB	83.7
8	Canberra	ACT	Inner Metro	Alicia Payne	ALP	82.6
9	Macnamara	VIC	Inner Metro	Josh Burns	ALP	82.2
10	Goldstein	VIC	Inner Metro	Tim Wilson	LIB	80.7
11	Melbourne	VIC	Inner Metro	Sarah Witty	ALP	80.6
12	Grayndler	NSW	Inner Metro	Anthony Albanese	ALP	80.3
13	Berowra	NSW	Outer Metro	Julian Leeser	LIB	80.3
14	Chisholm	VIC	Inner Metro	Carina Garland	ALP	78.1
15	Parramatta	NSW	Inner Metro	Andrew Charlton	ALP	77.9
16	Reid	NSW	Inner Metro	Sally Sitou	ALP	77.7
17	Brisbane	QLD	Inner Metro	Madonna Jarrett	ALP	74.5
18	Ryan	QLD	Outer Metro	Elizabeth Watson-Brown	GRN	73.6
19	Menzies	VIC	Outer Metro	Gabriel Ng	ALP	73.4
20	Griffith	QLD	Inner Metro	Renee Coffey	ALP	73.1
21	Greenway	NSW	Outer Metro	Michelle Rowland	ALP	72.7
22	Bean	ACT	Inner Metro	David Smith	ALP	72.3
23	Fenner	ACT	Inner Metro	Andrew Leigh	ALP	71.8
24	Wills	VIC	Inner Metro	Peter Khalil	ALP	70.6
25	Kingsford Smith	NSW	Inner Metro	Matt Thistlethwaite	ALP	70.1
26	Maribyrnong	VIC	Inner Metro	Jo Briskey	ALP	69.6
27	Banks	NSW	Inner Metro	Zhi Soon	ALP	69.1
28	Curtin	WA	Inner Metro	Kate Chaney	IND (TEAL)	68.8
29	Cook	NSW	Inner Metro	Simon Kennedy	LIB	68.3
30	Mackellar	NSW	Outer Metro	Sophie Scamps	IND (TEAL)	68.1

Figure 4: More AI-Exposed Electorates Tend to Have Larger Overseas-Born Populations

AI Exposure Index vs share of residents born overseas, across all 150 Federal electorates

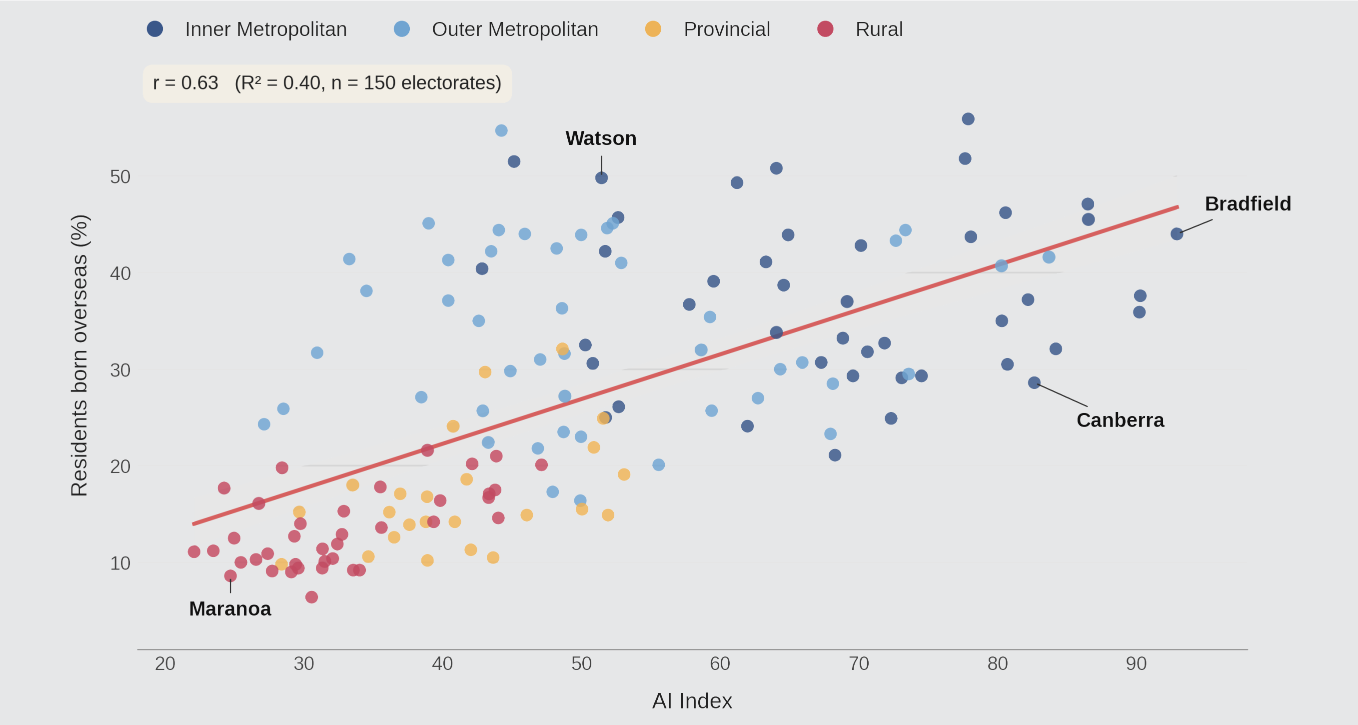


Figure 5: More AI-Exposed Electorates Also Face Greater Mortgage Stress

AI Exposure Index vs share of mortgage holders in mortgage stress, across all 150 Federal electorates

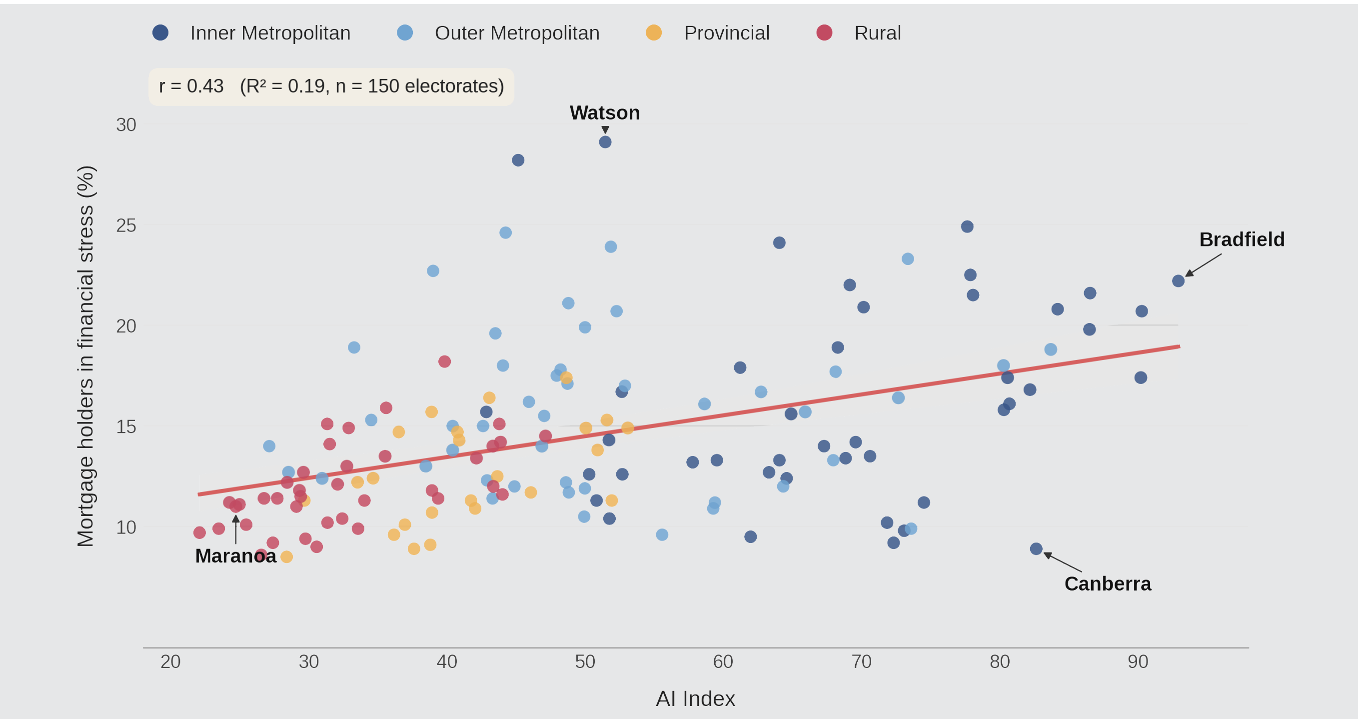


Figure 6: More AI-Exposed Electorates Have More University-Educated Residents

AI Exposure Index vs share of residents with a bachelor's degree or above, across all 150 Federal electorates

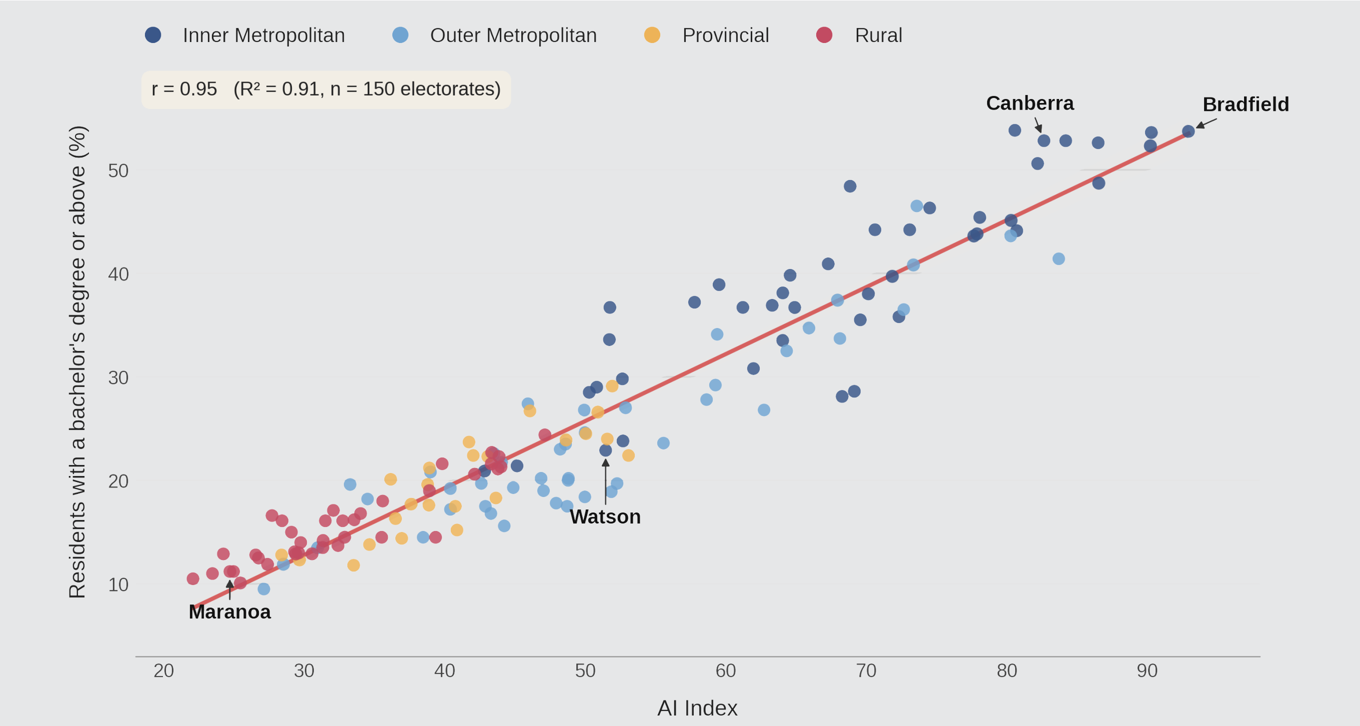


Figure 7: More AI-Exposed Electorates Have Higher Household Incomes

AI Exposure Index vs median weekly household income, across all 150 Federal electorates

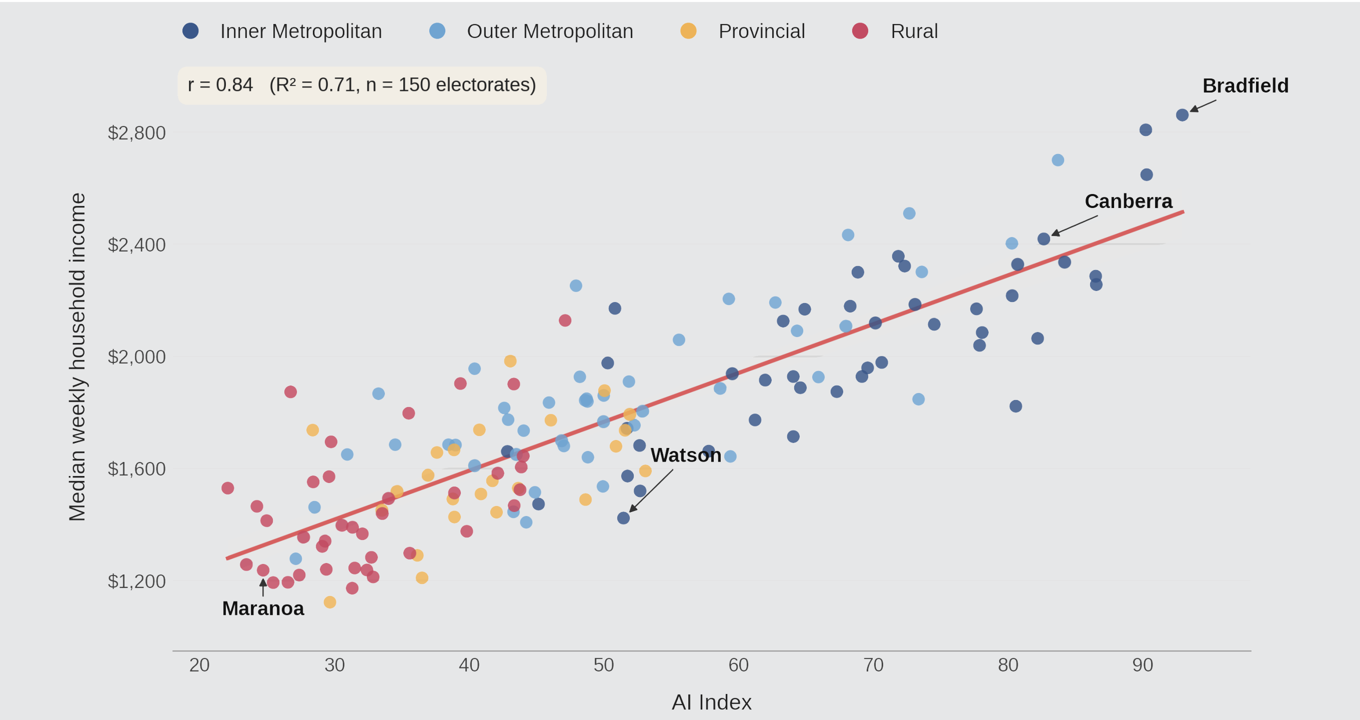


Table 2: The most AI-exposed seats are also younger, better-educated and more mortgage-stressed

Average demographic and socio-economic indicators by AI Exposure quintile, 150 federal electorates

Quintile	Average AI Exposure Index	Average median age	Average born overseas	Median weekly household income	Average share mwith a bachelor's degree or above	Average share employed as managers and professionals[7]	Average mortgage affordability pressure[8]
Quintile 1 (Seats ranked 1-30)	77.7	37.5	37.0%	$2,266	44.1%	33.3%	17.1%
Quintile 2 (Seats ranked 31-60)	58.2	38.2	33.8%	$1,843	31.0%	23.7%	15.1%
Quintile 3 (Seats ranked 61-90)	46.7	38.6	28.2%	$1,735	22.0%	18.5%	15.4%
Quintile 4 (Seats ranked 91-120)	38.7	38.7	21.3%	$1,593	18.1%	16.8%	13.3%
Quintile 5 (Seats ranked 121-150)	28.7	42.5	14.3%	$1,396	13.4%	15.3%	11.6%

Note: Values are unweighted means across the 30 electorates in each quintile.

Table 2 summarises the socio-economic profile of each quintile and highlights the differences between the wired belt electorates and the electorates least exposed to AI-driven task change.

Australia's wired belt communities have enjoyed strong and sustained economic growth for several decades. However, should AI-driven job disruption begin in earnest, Australia's wired belt is likely to face a form of economic upheaval these communities have not experienced for decades, and for which they possess neither a familiar political language nor an established political response. The pattern extends beyond the top quintile: of the 60 most exposed electorates, 39 are inner-metropolitan and 17 are outer-metropolitan. In other words, 56 of the top 60 electorates are metropolitan, while only four are provincial and none is rural.

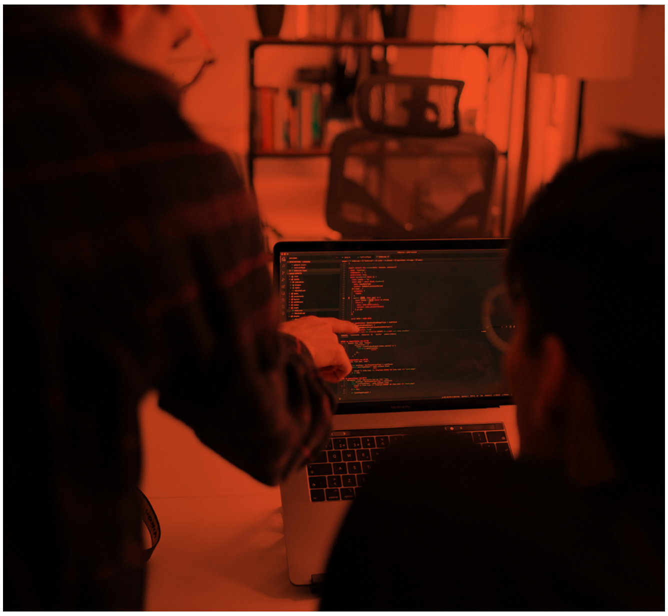


Image: Unsplash

[7] "Average managers and professionals" is measured as the proportion of employed persons aged 15 years and over in each electorate whose primary job in the week before Census Night was classified under the Australian and New Zealand Standard Classification of Occupations (ANZSCO) as either Major Group 1, Managers, or Major Group 2, Professionals. Managers are defined as workers who plan, organise, direct, control, coordinate or review the operations of organisations or organisational units. Professionals perform analytical, conceptual or creative tasks through the application of theoretical knowledge and experience. The measure therefore captures the occupational composition of an electorate's employed population, rather than residents' educational qualifications or formal workplace seniority.

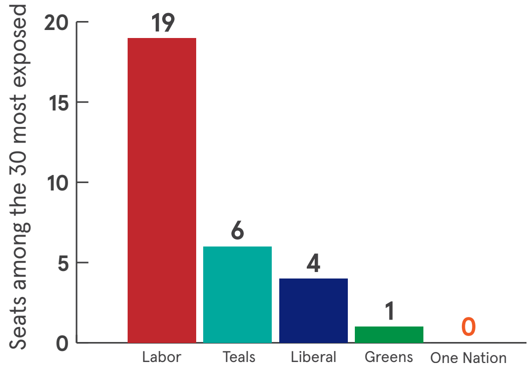
[8] "Average mortgage affordability pressure" is measured using the Australian Bureau of Statistics' 2021 Census Mortgage Affordability Indicator (MAID): the proportion of occupied private dwellings owned with a mortgage, or purchased under a shared-equity scheme, in which mortgage repayments exceed 30 per cent of imputed household income. The ABS warns that the use of imputed incomes may overstate the proportion of affected households and that exceeding the 30 per cent threshold does not necessarily indicate financial stress.

2. The political holders:
Labor, Liberals and the Teals are on the front line

The thirty most-exposed electorates are a roll-call of heartland seats for the established urban moderate voting bloc of the Labor Party, the Liberal Party and the Teals.

Figure 8: Who holds the seats most exposed to AI disruption?

Party holding each of the 30 most AI-exposed federal electorates



Source: Authors' AI Exposure Index; current members, 2024 electoral boundaries.

Labor holds 19 of the 30 most AI-exposed seats, including the Prime Minister's seat of Grayndler at number 12. Six are held by Teal-aligned MPs: the Community Strong Australia members for Wentworth and Warringah, and the independents for Bradfield, Kooyong, Curtin and Mackellar. The Liberals hold four - Mitchell, Goldstein, Berowra and Cook - and the Greens hold Ryan. One Nation holds none. Across the top 60 seats, Labor holds 47, the Coalition five, teal-aligned MPs six, the Greens one and Andrew Wilkie holds Clark as an independent. Labor therefore holds 78 per cent of the 60 most AI-exposed seats.

As Figure 9 shows, once the nine Labor-held rural seats (Braddon, Eden-Monaro, Gilmore, Hunter, Leichhardt, Lingiari, Lyons, McEwen and Richmond) and the three Labor-held ACT seats (Canberra, Bean and Fenner) are excluded, a clear pattern emerges across the 82 remaining urban and provincial Labor-held electorates: AI job risk is highest in those seats with lower union representation[9] and a higher proportion of workers in professional and managerial occupations. Conversely, it is lowest in those Labor held seats with higher union representation and a correspondingly larger share of workers who are not professionals or managers.

Figure 9: AI Exposure Index, unionisation and professional employment across Labor-held urban and provincial seats

In these 82 electorates, higher AI exposure coincides with lower union representation and a larger professional-managerial workforce.

[9] Unionisation is modelled, not directly observed, at electorate level: industry-level union membership rates (ABS, 2024) were weighted by each electorate's employment in each industry and summed. It captures unionisation arising from an electorate's industry mix, but assumes a constant union membership rate within each industry across electorates.


Image: Jaykumar bherwani,Unsplash

Given the central role of trade unions in shaping Labor's policy platform, this emerging division – between the more unionised, working-class Labor seats and the less unionised, professional-class seats – has the potential to add considerable complexity to Labor's task in responding to the impact of AI on Australian jobs. Tertiary-educated, middle-class professionals have long formed a significant portion of the Federal Labor voting base, yet they have little formal standing within the Party's trade-union-based governance model. In a budgetary context of limited fiscal capacity, the positive correlation between AI job risk and professional and managerial employment, set against the negative correlation between AI job risk and unionisation, may deepen this subtle economic discontinuity between Labor's voting base and its stakeholder hierarchy.

The wired belt is also unusually politically volatile. Across the 2019, 2022 and 2025 federal elections, the 26 Quintile 1 seats located in New South Wales, Victoria and Queensland recorded changes of representation at about 3.2 times the rate of the other seats in those states. Although they comprised around 23 per cent of the electorates, they accounted for 48.6 per cent of recorded seat changes.[10] This does not show that AI exposure caused the volatility. It does show that many of the electorates most exposed to future AI disruption are already politically competitive and open to change.

Any AI jobs shock would therefore run through metropolitan electorates that have provided much of the moderate ballast in federal politics. Debate over graduate employment, retraining, wage growth, productivity gains and the distribution of AI's benefits is likely to become increasingly important in these seats. The parties and independents that develop credible responses will be better placed to retain the support of AI-exposed voters. In the coming decades, the careers of many federal MPs in east-coast capital city electorates may sink or swim on the tides of the AI jobs policy debate.

How the broader political contest will play out, and what part each political party will play, is impossible to forecast. However, the experience of the extreme political disruption currently playing out in regional Australia (see the recent Farrer by-election[11]) suggests that once the economic disruption begins, it will lead to a significant shift in the voting patterns of directly impacted workers, and the political orientation of new (and existing) political parties or networks of independents. In other words, in this scenario, political change in Australia will only accelerate for the foreseeable future.

[10] Of the 30 Quintile 1 seats in the AI Exposure Index, 26 are located in New South Wales, Victoria and Queensland, which together comprise 115 electorates under the boundaries used for the 2025 federal election. Across the 2019, 2022 and 2025 elections, these 26 seats recorded 18 of the 37 changes of representation in the three states, or 48.6 per cent. This equates to 0.69 changes per Quintile 1 seat, compared with 0.21 among the remaining 89 electorates—a rate approximately 3.2 times as high. Changes are defined consistently with the Australian Electoral Commission's "seats that changed hands" tables, comparing the party or independent status of the successful candidate with the result of the preceding general election. The analysis therefore excludes changes arising solely from electoral redistributions or intervening by-elections.

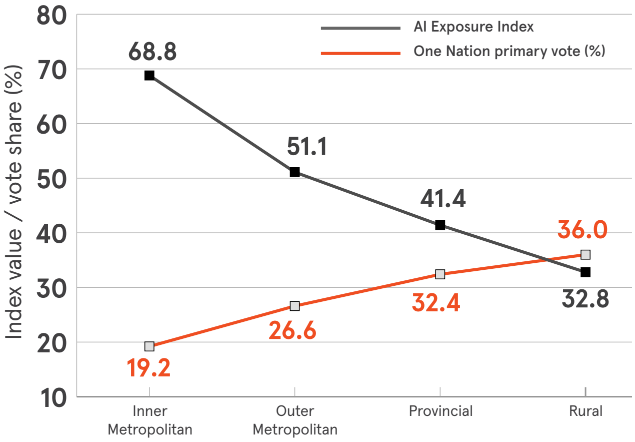
[11] The by-election, held on 9 May 2026, followed Sussan Ley's resignation after she lost a Liberal party-room leadership spill to Angus Taylor. One Nation's David Farley won outright — the party's first lower-house victory in its thirty-year history — defeating independent Michelle Milthorpe by 58–42 on a two-candidate-preferred basis, a larger margin than Ley had managed against the same opponent barely a year earlier. The Liberal primary vote collapsed by around 30 percentage points. The contest turned on local grievances — Murray–Darling water management, regional cost of living, healthcare access — rather than AI, but it remains the clearest available illustration of how quickly a seat considered safe for eighty years can break from the major parties once its underlying economic bargain is seen to have failed (Beaumont, 2026).

3. The inverse: *AI exposure and One Nation support currently occupy different political geographies*

A national RedBridge Group and Accent Research poll conducted from 29 April to 14 May 2026 found higher One Nation support in less urban seat types, which also have lower average scores on the AI Exposure Index. In the poll's seat-type estimates, exposure falls from inner metropolitan to outer metropolitan, provincial and rural seats, while One Nation's primary vote rises. Figures 10 points to a dual geography of political pressure: AI exposure in metropolitan Australia and anti-establishment pressure in regional Australia.

Figure 10: The AI fault line runs opposite to the One Nation vote

AI exposure falls and One Nation's primary vote rises as seats become less urban



Source: AI Exposure Index; RedBridge Group and Accent Research poll conducted from 29 April to 14 May 2026

In the poll, One Nation recorded a primary vote of about 19 per cent in inner-metropolitan seats and 36 per cent in rural seats. The combined Labor and Coalition vote moved in the opposite direction, holding up best in the most AI-exposed metropolitan seats and declining as AI exposure fell.

This inverse pattern has two implications. First, the metropolitan seats currently least receptive to One Nation are among those most exposed to AI-driven changes in work. As a result. their present political moderation should not be mistaken for immunity from political disruption: a different urban economic shock could produce a different form of political realignment.

Second, lower average AI exposure in provincial and rural electorates means that the AI jobs debate is unlikely to displace other issues shaping national politics. Immigration, climate, water, tax, services and the cost of living will continue to generate political conflict, particularly where regional and metropolitan interests diverge. The age gradient in the data, higher exposure in younger electorates and lower exposure in older ones, also suggests that AI will intersect with, rather than replace, existing generational and geographic fault lines. The higher proportion of overseas-born voters in AI-exposed electorates may also introduce an additional layer of complexity into contemporary immigration policy debates.

Table 3: Primary vote and AI exposure by seat type

Classification	Seats	Avg AI Exposure	Labor	Coalition	One Nation	Greens	Ind.
Inner Metropolitan	43	**68.8**	32.7	22.6	**19.2**	13.5	7.5
Outer Metropolitan	45	**51.1**	34.6	21.1	**26.6**	10.4	1.7
Provincial	24	**41.4**	30.1	20.8	**32.4**	9.8	0.8
Rural	38	**32.8**	22.9	22.2	**36.0**	7.6	3.2

Source: RedBridge Group and Accent Research poll, fieldwork 29 April-14 May 2026. Teal-aligned candidates are included in the "Ind." column.

Image: Compagnons, Unsplash

What happens if AI-driven disruption intensifies?

The AI Exposure Index maps Australia's emerging wired belt and identifies the parties and parliamentarians most exposed to its politics.

It cannot predict how individual electorates will respond. Much will depend on whether Labor, the Liberals and the Teal-aligned independents can offer credible answers on skills, entry-level work, career progression, remuneration and the distribution of AI-driven productivity gains.

However, what we can say with some confidence is that as the pace of AI-led job disruption lands in these highly exposed seats, the rate of political change in Australia will quicken — a pattern consistent with research showing that geographically concentrated economic decline is a meaningful driver of political rupture (Rodríguez-Pose, 2018).

This is because, for the first time, all four categories of federal electorates — inner metropolitan, outer metropolitan, provincial and rural — could face serious labour-market disruption simultaneously. Australian politics has not experienced such broad-based economic disruption since the Second World War. If metropolitan electorates experience sustained insecurity at the same time that provincial and rural communities remain under pressure, political competition is likely to become more fragmented and volatile. The major political brands are likely to survive, but who they represent and how they represent them could shift considerably, and the emergence of new political forces will only accelerate.

That is the structural significance of an AI shock: it does not replace the old disruptions — de-agrarianisation, deindustrialisation, decarbonisation, each of which has already left its mark on the Nationals' and the Coalition's regional base (Brett, 2020) — but lands on top of them. It effectively opens a second front in precisely the seats the first never reached, much as the "China shock" of import competition hardened political realignment in the parts of the US manufacturing belt it hit hardest (Autor et al., 2020). Because AI is diffusing faster than earlier industrial transitions, this political front could open sooner, and move quicker.

As the experience in regional Australia shows us, none of this acceleration in political change requires mass job losses or high unemployment. All it needs is for voters in exposed communities to no longer believe that their education will lead to real career opportunities or that their work will provide genuine economic security. Once that bargain no longer holds, then recent experience suggests that all political bets are off.[12]

Many Australians are already feeling whiplashed by the rate of political change in Australian federal politics. The conclusion from this analysis of AI-exposed electorates is that when it comes to political change in Australia, it is very possible that you ain't seen nothing yet.

[12] This accords with Kurer's (2020) influential study of the "declining middle", which finds that political backlash is often driven less by outright economic hardship than by perceived downward movement in the occupational and social hierarchy. For Australia's wired belt, the politically consequential moment may therefore arrive not when professional employment disappears, but when education, expertise and hard work no longer appear to deliver the status, autonomy and security voters expected.

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Appendix 1: *Data by Quintile*

Quintile 1 — Seats ranked 1–30 (most AI-exposed)

Rank	State	Electorate	Classification	Member	Party	Index	Median age	Born over-seas	Bachelor degree & above	Managers and Pro-fessionals	Mortgage stress
1	NSW	Bradfield	Inner Metropolitan	Nicolette Boele	IND	92.9	41	44.0%	53.7%	37.9%	22.2%
2	NSW	Wentworth	Inner Metropolitan	Allegra Spender	CSA	90.3	37	37.6%	53.6%	43.0%	20.7%
3	NSW	Warringah	Inner Metropolitan	Zali Steggall	CSA	90.2	40	35.9%	52.3%	41.8%	17.4%
4	NSW	Bennelong	Inner Metropolitan	Jerome Laxale	ALP	86.5	37	45.5%	48.7%	34.8%	21.6%
5	NSW	Sydney	Inner Metropolitan	Tanya Plibersek	ALP	86.5	34	47.1%	52.6%	39.3%	19.8%
6	VIC	Kooyong	Inner Metropolitan	Monique Ryan	IND	84.2	40	32.1%	52.8%	37.4%	20.8%
7	NSW	Mitchell	Outer Metropolitan	Alex Hawke	LIB	83.7	39	41.6%	41.4%	32.7%	18.8%
8	ACT	Canberra	Inner Metropolitan	Alicia Payne	ALP	82.6	35	28.6%	52.8%	38.5%	8.9%
9	VIC	Macnamara	Inner Metropolitan	Josh Burns	ALP	82.2	36	37.2%	50.6%	39.1%	16.8%
10	VIC	Goldstein	Inner Metropolitan	Tim Wilson	LIB	80.7	43	30.5%	44.1%	34.6%	16.1%
11	VIC	Melbourne	Inner Metropolitan	Sarah Witty	ALP	80.6	31	46.2%	53.8%	37.7%	17.4%
12	NSW	Grayndler	Inner Metropolitan	Anthony Albanese	ALP	80.3	37	35.0%	45.1%	36.0%	15.8%
13	NSW	Berowra	Outer Metropolitan	Julian Leeser	LIB	80.3	41	40.7%	43.6%	32.1%	18.0%
14	VIC	Chisholm	Inner Metropolitan	Carina Garland	ALP	78.1	40	43.7%	45.4%	30.5%	21.5%
15	NSW	Parramatta	Inner Metropolitan	Andrew Charlton	ALP	77.9	35	55.9%	43.8%	27.0%	22.5%
16	NSW	Reid	Inner Metropolitan	Sally Sitou	ALP	77.7	35	51.8%	43.6%	29.8%	24.9%
17	QLD	Brisbane	Inner Metropolitan	Madonna Jarrett	ALP	74.5	34	29.3%	46.3%	36.9%	11.2%
18	QLD	Ryan	Outer Metropolitan	Elizabeth Watson-Brown	GRN	73.6	36	29.5%	46.5%	34.5%	9.9%
19	VIC	Menzies	Outer Metropolitan	Gabriel Ng	ALP	73.4	41	44.4%	40.8%	27.6%	23.3%
20	QLD	Griffith	Inner Metropolitan	Renee Coffey	ALP	73.1	34	29.1%	44.2%	35.8%	9.8%
21	NSW	Greenway	Outer Metropolitan	Michelle Rowland	ALP	72.7	34	43.3%	36.5%	27.8%	16.4%
22	ACT	Bean	Inner Metropolitan	David Smith	ALP	72.3	38	24.9%	35.8%	29.6%	9.2%
23	ACT	Fenner	Inner Metropolitan	Andrew Leigh	ALP	71.8	34	32.7%	39.7%	30.6%	10.2%
24	VIC	Wills	Inner Metropolitan	Peter Khalil	ALP	70.6	35	31.8%	44.2%	33.3%	13.5%
25	NSW	Kingsford Smith	Inner Metropolitan	Matt Thistlethwaite	ALP	70.1	36	42.8%	38.0%	28.2%	20.9%
26	VIC	Maribyrnong	Inner Metropolitan	Jo Briskey	ALP	69.6	39	29.3%	35.5%	28.8%	14.2%
27	NSW	Banks	Inner Metropolitan	Zhi Soon	ALP	69.1	40	37.0%	28.6%	21.5%	22.0%
28	WA	Curtin	Inner Metropolitan	Kate Chaney	IND	68.8	39	33.2%	48.4%	35.6%	13.4%
29	NSW	Cook	Inner Metropolitan	Simon Kennedy	LIB	68.3	41	21.1%	28.1%	26.8%	18.9%
30	NSW	Mackellar	Outer Metropolitan	Sophie Scamps	IND	68.1	43	28.5%	33.7%	29.5%	17.7%

Quintile 2 — Seats ranked 31–60

Rank	State	Electorate	Classification	Member	Party	Index	Median age	Born over-seas	Bachelor degree & above	Managers and Pro-fessionals	Mortgage stress
31	VIC	Jagajaga	Outer Metropolitan	Kate Thwaites	ALP	68.0	41	23.3%	37.4%	29.8%	13.3%
32	VIC	Cooper	Inner Metropolitan	Ged Kearney	ALP	67.3	37	30.7%	40.9%	31.3%	14.0%
33	VIC	Deakin	Outer Metropolitan	Matt Gregg	ALP	65.9	40	30.7%	34.7%	26.7%	15.7%
34	VIC	Gellibrand	Inner Metropolitan	Tim Watts	ALP	64.9	35	43.9%	36.7%	26.0%	15.6%
35	WA	Perth	Inner Metropolitan	Patrick Gorman	ALP	64.6	37	38.7%	39.8%	31.3%	12.4%
36	QLD	Bonner	Outer Metropolitan	Kara Cook	ALP	64.3	38	30.0%	32.5%	27.1%	12.0%
37	SA	Sturt	Inner Metropolitan	Claire Clutterham	ALP	64.1	41	33.8%	38.1%	26.9%	13.3%
38	NSW	Barton	Inner Metropolitan	Ash Ambihaipahar	ALP	64.0	36	50.8%	33.5%	21.5%	24.1%
39	WA	Tangney	Inner Metropolitan	Sam Lim	ALP	63.3	41	41.1%	36.9%	27.4%	12.7%
40	NSW	Hughes	Outer Metropolitan	David Moncrieff	ALP	62.7	38	27.0%	26.8%	23.2%	16.7%
41	QLD	Lilley	Inner Metropolitan	Anika Wells	ALP	62.0	37	24.1%	30.8%	26.2%	9.5%
42	VIC	Hotham	Inner Metropolitan	Clare O'Neil	ALP	61.2	36	49.3%	36.7%	23.8%	17.9%
43	QLD	Moreton	Inner Metropolitan	Julie-Ann Campbell	ALP	59.5	36	39.1%	38.9%	26.5%	13.3%
44	SA	Boothby	Outer Metropolitan	Louise Miller-Frost	ALP	59.4	42	25.7%	34.1%	25.7%	11.2%
45	WA	Moore	Outer Metropolitan	Tom French	ALP	59.3	42	35.4%	29.2%	26.3%	10.9%
46	VIC	Aston	Outer Metropolitan	Mary Doyle	ALP	58.6	40	32.0%	27.8%	22.5%	16.1%
47	SA	Adelaide	Inner Metropolitan	Steve Georganas	ALP	57.8	36	36.7%	37.2%	25.9%	13.2%
48	QLD	Dickson	Outer Metropolitan	Ali France	ALP	55.6	38	20.1%	23.6%	22.8%	9.6%
49	NSW	Robertson	Provincial	Gordon Reid	ALP	53.1	44	19.1%	22.4%	20.6%	14.9%
50	VIC	Isaacs	Outer Metropolitan	Mark Dreyfus	ALP	52.9	39	41.0%	27.0%	21.3%	17.0%
51	SA	Hindmarsh	Inner Metropolitan	Mark Butler	ALP	52.7	42	26.1%	23.8%	20.4%	12.6%
52	VIC	Fraser	Inner Metropolitan	Daniel Mulino	ALP	52.6	36	45.7%	29.8%	21.0%	16.7%
53	NSW	McMahon	Outer Metropolitan	Chris Bowen	ALP	52.3	37	45.1%	19.7%	14.1%	20.7%
54	NSW	Newcastle	Provincial	Sharon Claydon	ALP	51.9	37	14.9%	29.1%	25.2%	11.3%
55	NSW	Werriwa	Outer Metropolitan	Anne Stanley	ALP	51.9	34	44.6%	18.9%	15.0%	23.9%
56	TAS	Clark	Inner Metropolitan	Andrew Wilkie	IND	51.7	37	25.0%	36.7%	23.2%	10.4%
57	WA	Swan	Inner Metropolitan	Zaneta Mascarenhas	ALP	51.7	35	42.2%	33.6%	23.6%	14.3%
58	QLD	McPherson	Provincial	Leon Rebello	LNP	51.6	40	24.9%	24.0%	22.1%	15.3%
59	NSW	Watson	Inner Metropolitan	Tony Burke	ALP	51.4	34	49.8%	22.9%	12.7%	29.1%
60	NSW	Cunningham	Provincial	Alison Byrnes	ALP	50.9	39	21.9%	26.6%	21.4%	13.8%

Quintile 3 — Seats ranked 61–90

Rank	State	Electorate	Classification	Member	Party	Index	Median age	Born over-seas	Bachelor degree & above	Managers and Pro-fessionals	Mortgage stress
61	NT	Solomon	Inner Metropolitan	Luke Gosling	ALP	50.8	34	30.6%	29.0%	24.5%	11.3%
62	WA	Fremantle	Inner Metropolitan	Josh Wilson	ALP	50.3	38	32.5%	28.5%	25.0%	12.6%
63	NSW	Macquarie	Provincial	Susan Templeman	ALP	50.0	42	15.5%	24.5%	21.8%	14.9%
64	NSW	Chifley	Outer Metropolitan	Ed Husic	ALP	50.0	33	43.9%	24.6%	15.0%	19.9%
65	QLD	Bowman	Outer Metropolitan	Henry Pike	LNP	50.0	43	23.0%	18.4%	18.5%	11.9%
66	TAS	Franklin	Outer Metropolitan	Julie Collins	ALP	49.9	41	16.4%	26.8%	21.1%	10.5%
67	QLD	Petrie	Outer Metropolitan	Emma Comer	ALP	48.8	39	27.2%	20.2%	18.2%	11.7%
68	NSW	Macarthur	Outer Metropolitan	Mike Freelander	ALP	48.8	34	31.6%	20.0%	16.2%	21.1%
69	NSW	Lindsay	Outer Metropolitan	Melissa McIntosh	LIB	48.7	34	23.5%	17.5%	16.8%	17.1%
70	QLD	Moncrieff	Provincial	Angie Bell	LNP	48.6	40	32.1%	23.9%	19.2%	17.4%
71	QLD	Oxley	Outer Metropolitan	Milton Dick	ALP	48.6	34	36.3%	23.5%	18.9%	12.2%
72	VIC	Gorton	Outer Metropolitan	Alice Jordan-Baird	ALP	48.2	35	42.5%	23.0%	16.9%	17.8%
73	NSW	Hume	Outer Metropolitan	Angus Taylor	LIB	47.9	35	17.3%	17.8%	20.3%	17.5%
74	VIC	McEwen	Rural	Rob Mitchell	ALP	47.1	36	20.1%	24.4%	22.0%	14.5%
75	QLD	Fadden	Outer Metropolitan	Cameron Caldwell	LNP	47.0	39	31.0%	19.0%	18.1%	15.5%
76	VIC	Dunkley	Outer Metropolitan	Jodie Belyea	ALP	46.9	40	21.8%	20.2%	19.8%	14.0%
77	VIC	Corangamite	Provincial	Libby Coker	ALP	46.1	41	14.9%	26.7%	21.9%	11.7%
78	VIC	Lalor	Outer Metropolitan	Joanne Ryan	ALP	45.9	33	44.0%	27.4%	16.9%	16.2%
79	NSW	Blaxland	Inner Metropolitan	Jason Clare	ALP	45.1	33	51.5%	21.4%	11.7%	28.2%
80	SA	Makin	Outer Metropolitan	Tony Zappia	ALP	44.9	39	29.8%	19.3%	16.5%	12.0%
81	NSW	Fowler	Outer Metropolitan	Dai Le	IND	44.2	38	54.7%	15.6%	10.7%	24.6%
82	VIC	Bruce	Outer Metropolitan	Julian Hill	ALP	44.0	37	44.4%	21.7%	16.5%	18.0%
83	NSW	Eden-Monaro	Rural	Kristy McBain	ALP	44.0	43	14.6%	21.3%	20.2%	11.6%
84	QLD	Fairfax	Rural	Ted O'Brien	LNP	43.9	43	21.0%	22.3%	19.4%	14.2%
85	VIC	Flinders	Rural	Zoe McKenzie	LIB	43.8	48	17.5%	21.1%	18.9%	15.1%
86	NSW	Shortland	Provincial	Pat Conroy	ALP	43.6	43	10.5%	18.3%	17.6%	12.5%
87	VIC	Scullin	Outer Metropolitan	Andrew Giles	ALP	43.5	36	42.2%	22.6%	15.5%	19.6%
88	SA	Mayo	Rural	Rebekha Sharkie	CA	43.3	46	17.1%	22.7%	20.9%	12.0%
89	VIC	Casey	Rural	Aaron Violi	LIB	43.3	40	16.7%	21.6%	21.1%	14.0%
90	SA	Kingston	Outer Metropolitan	Amanda Rishworth	ALP	43.3	40	22.4%	16.8%	16.2%	11.4%

Quintile 4 — Seats ranked 91–120

Rank	State	Electorate	Classification	Member	Party	Index	Median age	Born over-seas	Bachelor degree & above	Managers and Pro-fessionals	Mortgage stress
91	VIC	La Trobe	Provincial	Jason Wood	LIB	43.1	33	29.7%	22.3%	19.7%	16.4%
92	WA	Bullwinkel	Outer Metropolitan	Trish Cook	ALP	42.9	42	25.7%	17.5%	18.0%	12.3%
93	WA	Cowan	Inner Metropolitan	Anne Aly	ALP	42.8	37	40.4%	20.9%	17.2%	15.7%
94	WA	Hasluck	Outer Metropolitan	Tania Lawrence	ALP	42.6	35	35.0%	19.7%	17.5%	15.0%
95	QLD	Fisher	Rural	Andrew Wallace	LNP	42.1	43	20.2%	20.6%	18.4%	13.4%
96	VIC	Ballarat	Provincial	Catherine King	ALP	42.0	41	11.3%	22.4%	19.6%	10.9%
97	VIC	Corio	Provincial	Richard Marles	ALP	41.7	38	18.6%	23.7%	19.6%	11.3%
98	NSW	Dobell	Provincial	Emma McBride	ALP	40.9	41	14.2%	15.2%	15.7%	14.3%
99	VIC	Hawke	Provincial	Sam Rae	ALP	40.7	35	24.1%	17.5%	15.4%	14.7%
100	QLD	Rankin	Outer Metropolitan	Jim Chalmers	ALP	40.4	34	37.1%	19.2%	14.8%	15.0%
101	WA	Pearce	Outer Metropolitan	Tracey Roberts	ALP	40.4	35	41.3%	17.2%	17.9%	13.8%
102	NSW	Richmond	Rural	Justine Elliot	ALP	39.8	46	16.4%	21.6%	18.4%	18.2%
103	NT	Lingiari	Rural	Marion Scrymgour	ALP	39.3	32	14.2%	14.5%	16.9%	11.4%
104	VIC	Calwell	Outer Metropolitan	Basem Abdo	ALP	39.0	32	45.1%	20.8%	13.6%	22.7%
105	VIC	Bendigo	Provincial	Lisa Chesters	ALP	38.9	42	10.2%	21.2%	19.1%	10.7%
106	QLD	Leichhardt	Rural	Matt Smith	ALP	38.9	39	21.6%	19.0%	18.3%	11.8%
107	NSW	Whitlam	Provincial	Carol Berry	ALP	38.9	42	16.8%	17.6%	16.6%	15.7%
108	QLD	Groom	Provincial	Garth Hamilton	LNP	38.8	38	14.2%	19.6%	18.3%	9.1%
109	QLD	Forde	Outer Metropolitan	Rowan Holzberger	ALP	38.5	35	27.1%	14.5%	14.9%	13.0%
110	QLD	Herbert	Provincial	Phillip Thompson	LNP	37.6	35	13.9%	17.7%	17.5%	8.9%
111	QLD	Blair	Provincial	Shayne Neumann	ALP	36.9	35	17.1%	14.4%	14.8%	10.1%
112	NSW	Cowper	Provincial	Pat Conaghan	NAT	36.5	47	12.6%	16.3%	15.2%	14.7%
113	TAS	Bass	Provincial	Jess Teesdale	ALP	36.2	41	15.2%	20.1%	17.3%	9.6%
114	NSW	Gilmore	Rural	Fiona Phillips	ALP	35.6	49	13.6%	18.0%	15.2%	15.9%
115	QLD	Wright	Rural	Scott Buchholz	LNP	35.5	39	17.8%	14.5%	16.6%	13.5%
116	NSW	Paterson	Provincial	Meryl Swanson	ALP	34.6	40	10.6%	13.8%	14.3%	12.4%
117	WA	Burt	Outer Metropolitan	Matt Keogh	ALP	34.5	34	38.1%	18.2%	14.4%	15.3%
118	NSW	Calare	Rural	Andrew Gee	IND	34.0	40	9.2%	16.8%	17.5%	11.3%
119	NSW	Riverina	Rural	Michael McCormack	NAT	33.5	41	9.2%	16.2%	19.4%	9.9%
120	QLD	Longman	Provincial	Terry Young	LNP	33.5	39	18.0%	11.8%	12.3%	12.2%

Quintile 5 — Seats ranked 121–150 (least AI-exposed)

Rank	State	Electorate	Classification	Member	Party	Index	Median age	Born over-seas	Bachelor degree & above	Managers and Pro-fessionals	Mortgage stress
121	VIC	Holt	Outer Metropolitan	Cassandra Fernando	ALP	33.3	33	41.4%	19.6%	14.6%	18.9%
122	QLD	Wide Bay	Rural	Llew O'Brien	LNP	32.9	49	15.3%	14.5%	13.3%	14.9%
123	VIC	Monash	Rural	Mary Aldred	LIB	32.7	46	12.9%	16.1%	16.5%	13.0%
124	VIC	Gippsland	Rural	Darren Chester	NAT	32.4	46	11.9%	13.7%	14.9%	10.4%
125	VIC	Indi	Rural	Helen Haines	IND	32.1	45	10.4%	17.1%	18.4%	12.1%
126	NSW	Page	Rural	Kevin Hogan	NAT	31.5	46	10.1%	16.1%	15.3%	14.1%
127	NSW	Farrer	Rural	David Farley	ONP	31.3	42	11.4%	14.2%	17.9%	10.2%
128	NSW	Lyne	Rural	Alison Penfold	NAT	31.3	51	9.4%	13.5%	13.4%	15.1%
129	WA	Brand	Outer Metropolitan	Madeleine King	ALP	30.9	36	31.7%	13.5%	13.4%	12.4%
130	NSW	Parkes	Rural	Jamie Chaffey	NAT	30.6	40	6.4%	12.9%	17.8%	9.0%
131	QLD	Dawson	Rural	Andrew Willcox	LNP	29.7	39	14.0%	14.0%	16.0%	9.4%
132	QLD	Hinkler	Provincial	David Batt	LNP	29.7	49	15.2%	12.3%	11.8%	11.3%
133	NSW	Hunter	Rural	Daniel Repacholi	ALP	29.6	40	9.4%	13.0%	13.6%	12.7%
134	TAS	Lyons	Rural	Rebecca White	ALP	29.4	44	9.8%	12.9%	14.1%	11.5%
135	VIC	Nicholls	Rural	Sam Birrell	NAT	29.3	43	12.7%	13.1%	16.5%	11.8%
136	NSW	New England	Rural	Barnaby Joyce	ONP	29.1	41	9.0%	15.0%	17.0%	11.0%
137	WA	Canning	Outer Metropolitan	Andrew Hastie	LIB	28.5	42	25.9%	11.9%	12.8%	12.7%
138	WA	Forrest	Rural	Ben Small	LIB	28.4	42	19.8%	16.1%	16.1%	12.2%
139	QLD	Capricornia	Provincial	Michelle Landry	LNP	28.4	38	9.8%	12.8%	14.7%	8.5%
140	VIC	Wannon	Rural	Dan Tehan	LIB	27.7	46	9.1%	16.6%	19.4%	11.4%
141	VIC	Mallee	Rural	Anne Webster	NAT	27.4	45	10.9%	11.9%	17.3%	9.2%
142	SA	Spence	Outer Metropolitan	Matt Burnell	ALP	27.1	35	24.3%	9.5%	10.6%	14.0%
143	WA	Durack	Rural	Melissa Price	LIB	26.7	37	16.1%	12.5%	16.5%	11.4%
144	TAS	Braddon	Rural	Anne Urquhart	ALP	26.5	45	10.3%	12.8%	14.0%	8.6%
145	SA	Grey	Rural	Tom Venning	LIB	25.5	45	10.0%	10.1%	15.2%	10.1%
146	QLD	Kennedy	Rural	Bob Katter	KAP	25.0	40	12.5%	11.2%	14.6%	11.1%
147	QLD	Maranoa	Rural	David Littleproud	LNP	24.7	43	8.6%	11.2%	16.7%	11.0%
148	WA	O'Connor	Rural	Rick Wilson	LIB	24.2	42	17.7%	12.9%	17.1%	11.2%
149	SA	Barker	Rural	Tony Pasin	LIB	23.5	45	11.2%	11.0%	16.1%	9.9%
150	QLD	Flynn	Rural	Colin Boyce	LNP	22.1	39	11.1%	10.5%	14.4%	9.7%

Appendix 2: *Construction of the AI Exposure Index*

Overview

The AI Exposure Index measures how concentrated employment in each of Australia's 150 federal electorates is in occupations potentially exposed to artificial intelligence. It is an index of occupational exposure to AI-driven task change, not a forecast of job losses: a high score may indicate greater potential for automation, augmentation or job redesign within existing occupations.

The Index combines three established measures of occupational exposure:

1. Jobs and Skills Australia's (JSA) generative-AI automation exposure scores
2. the International Labour Organization's (ILO) global index of occupational exposure to generative AI
3. the AI Occupational Exposure (AIOE) measure developed by Felten, Raj and Seamans

Using multiple measures reduces dependence on the assumptions, classifications or methodology of any single source. The three capture related but distinct dimensions: generative-AI task automation, broader generative-AI exposure, and exposure to AI advances more generally.

Notation. *Throughout this appendix, i indexes occupations, j indexes the 150 electorates, and s indexes the three source measures (JSA, ILO, AIOE).*

Occupational employment data

Electorate employment profiles are based on occupational data from the 2021 Census of Population and Housing. Employed residents were classified across 474 categories under the Australian and New Zealand Standard Classification of Occupations (ANZSCO) four-digit occupation unit group (including relevant "not further defined" categories).

For each electorate, occupational counts were converted into shares of matched employment: an occupation accounting for 10 per cent of an electorate's employed residents therefore carries ten times the weight of one accounting for 1 per cent. The Index reflects each electorate's employment composition, not merely the presence of particular occupations.

Because Census data classify residents by place of usual residence, the Index describes the occupational profile of people living in each electorate rather than jobs located within its boundaries — appropriate for electorate-level analysis, since residents vote where they live regardless of where they work.

Occupational crosswalks

The three source measures use different occupational classifications and levels of detail; before electorate-level calculations, each was mapped to a common set of 474 occupational categories, all with valid JSA, ILO and AIOE scores, so the same occupation set underlies all three measures. Where a source reported exposure at a broader level than the Census classification, its score was assigned to each corresponding category, and this crosswalk was applied consistently across all 150 electorates.

This crosswalk is nevertheless a potential source of measurement error: classifications may group together workers who perform materially different tasks, and titles do not always correspond exactly across sources. The assigned scores should therefore be read as estimates of average exposure within occupational categories, not precise measures for every worker within them.

Electorate-level weighting

A separate electorate exposure score was calculated for each source measure, weighting occupational exposure scores by each occupation's share of matched employment. For electorate j and source measure s, the calculation was:

$$E_{js} = \sum_{i=1}^{474} w_{ij} X_{is} \qquad (1)$$

where i = 1, ..., 474 indexes occupations, j = 1, ..., 150 indexes federal electorates, $s \in \{JSA,\ ILO,\ AIOE\}$ indexes the three source measures, and Ejs is electorate j's exposure score under source measure s.

An electorate therefore receives a high exposure score only where a substantial share of residents work in highly exposed occupations; a small number of such workers cannot by itself produce a high score.

Occupations were not weighted by earnings, hours worked, employment status or economic output — each employed resident received the same weight. The Index therefore measures the concentration of potentially exposed workers, not the value of income or production potentially affected.

Standardisation

The three source measures use different scales and cannot be directly averaged. Each electorate-level measure was therefore converted to a standardised score (z-score) across the 150 electorates. For source s, the standardised score for electorate j is:

$$Z_{js} = \frac{E_{js} - \mu_s}{\sigma_s} \qquad (2)$$

where μs and σs are, respectively, the mean and standard deviation of source measure s across the 150 electorates.

A z-score of zero indicates the national electorate average; positive scores indicate above-average exposure and negative scores below-average exposure. A score of +1, for example, is one standard deviation above the electorate average on that measure. Standardisation places the three measures on a common scale while preserving electorates' relative position within each.

Aggregation and index transformation

The three standardised scores were assigned equal weight and averaged:

$$C_j = \frac{Z_{j,JSA} + Z_{j,ILO} + Z_{j,AIOE}}{3} \qquad (3)$$

where Cj is electorate j's composite standardised exposure score. Equal weighting was adopted because no source has a sufficiently stronger theoretical or empirical claim to authority than the others, and it limits any single measure's influence over the final rankings.

The composite score was then transformed into the published Index:

$$AEI_j = 50 + 25C_j \qquad (4)$$

where $AEIj$ is the published AI Exposure Index score for electorate j. On this scale, 50 represents the average electorate, a score of 75 represents exposure one standard deviation above average, and a score of 25 represents exposure one standard deviation below average. As such, its values are also relative rather than absolute — a score of 80 does not mean 80 per cent of jobs will be automated, or that an electorate scoring 80 is twice as exposed as one scoring 40, only that its profile is substantially more AI-exposed than average.

Treatment of the 2024 electoral redistribution

Occupational data originate from the 2021 Census but are reported on the 2024 electoral boundaries, using Mesh Block geography to map counts between the two. Units falling wholly within a 2024 electorate were assigned directly; units crossing a boundary were apportioned by population weight, with fractional allocations preserving the full employment count, then aggregated into an estimated profile for each of the 150 divisions.

This produces estimates for the current map but cannot capture occupational change since 2021, particularly in rapidly growing electorates — the Index should be read as an estimate on the 2024 boundaries using the most recent complete Census data, not a direct measurement of the 2026 workforce.

Quintiles and rankings

Electorates were ranked from highest to lowest by Index score, then divided into five equal groups of 30 electorates:

Quintile	Ranks	Description
1	1–30	Most AI-exposed
2	31–60	
3	61–90	
4	91–120	
5	121–150	Least AI-exposed

These are descriptive groupings, not substantively distinct categories: quintile boundaries do not mark a threshold at which an electorate becomes "AI exposed," and electorates near a boundary may have similar scores despite appearing in different groups. Rankings warrant similar caution, since small differences in Index scores can produce rank differences that look more substantial than the underlying variation.

Interpretation and limitations

The Index measures potential exposure arising from each electorate's occupational composition — not actual local AI adoption, employer investment, organisational readiness, worker capability, or occupations' and industries' capacity to adapt.

Occupations comprise multiple tasks, and AI may affect only some; workers within an occupation may also perform materially different work. Occupational exposure should not be read as the probability that an occupation, job or worker will disappear.

Exposure may also produce different consequences: AI may substitute for tasks previously performed by workers in some occupations, or complement workers, increase productivity, or reallocate responsibilities in others; the component measures cannot perfectly distinguish substitution, augmentation and job redesign.

The Index does not estimate the creation of new tasks, occupations or jobs: it measures exposure within the existing occupational structure, not the net employment effects of artificial intelligence.

Finally, the Index is relative to the 150 electorates, the 2021 occupational data, and the three exposure measures used to construct it. Its purpose is to identify the geographic concentration of potentially AI-exposed work and support systematic comparison between electorates — not to forecast the timing, magnitude or net employment consequences of artificial intelligence.

Artificial intelligence is usually framed as an economic and technological issue. This report argues that it may also become a major force reshaping Australian politics.

Previous waves of economic disruption were concentrated in regional, industrial and resource-dependent communities.

AI is likely to have a different geography. Its effects may fall most heavily on educated, professionally employed and digitally intensive metropolitan electorates – the communities that form Australia's emerging "wired belt".

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