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NEW ZEALAND

SELECTED ISSUES

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July 23, 2026

Approved By
Asia and Pacific Department

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CONTENTS

AI AND NEW ZEALAND'S PRODUCTIVITY CHALLENGE: EXPOSURE, ADOPTION, AND POLICY PRIORITIES[1]

Artificial intelligence (AI) could help address New Zealand's long-standing productivity challenge, but the size of the gains is uncertain and depends on structural conditions. About 60 percent of workers in New Zealand are in occupations exposed to AI, with roughly half well-positioned to benefit and half—about one-third of all workers—at risk of displacement. Early evidence shows that AI is already diffusing across the economy—AI use is relatively high by advanced-economy standards, and demand for AI-related skills is rising, driven overwhelmingly by within-sector deepening in professional, technical, and finance activities. New Zealand ranks among the best-prepared economies globally on the IMF AI Preparedness Index, with strengths in regulation and digital infrastructure, but low R&D intensity is its main structural weakness. While estimating the impacts of a new technology on long-term productivity and growth is inherently uncertain, a task-based model suggests AI could raise annual productivity growth in New Zealand by 0.1 to 0.4 percentage point over the next decade. The size of these effects depends on the strength of complementarity, the capacity of capital markets to finance adoption and whether AI delivers economy-wide net productivity gains. Realizing this potential would require continued structural reform—deeper capital markets, stronger competition, and stronger R&D incentives—alongside support for worker reallocation.

A. Introduction

1. **Artificial intelligence (AI) holds the promise of boosting growth and productivity globally—by automating tasks previously performed by humans, accelerating scientific discovery, and raising the efficiency of capital**. As a general-purpose technology, its reach is unusually broad: unlike earlier waves of automation, which fell mainly on routine manual and clerical work, AI extends to cognitive and analytical tasks and so touches high-skill, white-collar occupations long thought to be insulated from technological change (Cazzaniga and others 2024). At the same time, AI adoption may reshape labor markets, as firms and governments deploy the technology and substitute tools for workers in producing output. While the long-run effect on employment could be positive—with new tasks and occupations emerging as others disappear—the short-run adjustment can be disruptive, particularly in economies that face large structural challenges, where productivity has been sluggish, and where workers have historically found it difficult to reallocate across the labor market.

2. **New Zealand's labor productivity growth has been weak for much of the past decade, and its level remains below that of most advanced economies**. The economy's small scale, distance from global markets, and thin capital markets have historically presented challenges for its economic performance. Product markets are relatively concentrated—a small number of large

[1] Prepared by Marina M. Tavares (RES). Jaden Jonghyuk Kim (RES) provided research assistance. This paper was presented to the New Zealand authorities during the mission in June 2026, and the author thank the authorities for comments during the presentation. The author also thank Yan Carrière-Swallow (APD) for comments and suggestions.

players dominate sectors such as groceries, retail banking, and building materials, several of which have been examined in Commerce Commission market studies—raising the question of whether weak competition, a key spur to technology adoption, has contributed to the sluggish productivity trend. Financing options are limited as well: young, high-growth firms ("gazelles") emerge at a lower rate than in peer economies and face financing constraints, while business R&D is low across sectors (Petrescu 2025). Capital markets remain shallower than advanced economy peers and household balance sheets are dominated by housing, which can constrain external finance and pose a barrier to technology adoption, particularly for small and medium-sized enterprises (SMEs).[2] In July 2025, the government released New Zealand's first national AI strategy, which takes an adoption-focused, light-touch approach (MBIE 2025). Against this backdrop, this paper assesses New Zealand's exposure to AI, the extent to which AI is already diffusing across the economy, and the conditions under which adoption could translate into durable productivity gains.

3. New Zealand's workforce is about as exposed to AI as other advanced economies, with exposure concentrated among higher-income and female workers. This paper uses occupational exposure and complementarity measures mapped to Stats NZ 2023 Census employment, and applies the exposure and complementarity framework of Cazzaniga and others (2024). We estimate that about 60 percent of workers are in high-exposure occupations—broadly in line with Australia, the United Kingdom, and the United States—split roughly evenly between roles well-positioned to benefit from AI and roles at risk of displacement. The latter—around one-third of all workers, in high-exposure, low-complementarity occupations—are disproportionately female and concentrated in the middle of the income distribution. Exposure rises steadily across the income distribution, though the potential for AI to complement—rather than replace—workers is strongest in the upper-middle of the distribution.

4. Based on available metrics, AI is already diffusing across the New Zealand economy, and its footprint is rising.[3] AI use is relatively high by advanced-economy standards, though below frontier adopters. Evidence from online job postings, applying the methodology of Jaumotte and others (2026), shows demand for AI-related skills rising, driven overwhelmingly by within-sector deepening rather than by shifts in the sectoral composition of the economy. Demand is concentrated in professional, technical, and finance occupations. Notably, the information sector plays a smaller role in AI-skill demand in New Zealand than in other advanced economies-a striking difference, given that in most economies information is the leading sector in both AI adoption and

[2] Capital-market depth affects firms through several channels—access to external and growth finance, the cost of capital, financing for intangible and innovation investment, the ability of young firms to scale, the reallocation of capital to its most productive uses, and the availability of equity and venture financing. Together with distance from global markets, which can slow the diffusion of ideas, these frictions leave New Zealand's ability to adopt and absorb new technologies partly contingent on lifting capital intensity.

[3] New Zealand lacked an official firm-level survey of technology adoption over this period. Stats NZ's Business Operations Survey, which historically included alternating modules on information and communications technology and on innovation, was paused for 2024 and 2025, having last been run in 2023. A successor Survey of Business Operations—delivered jointly by the Ministry of Business, Innovation and Employment and Stats NZ—is planned for 2026 and will include questions on the use and impact of AI (Statistics New Zealand 2026).

AI creation. Consistent with this, job postings are tilted toward AI-user skills rather than AI-developer skills, and the share requiring both is rising.

5. **AI could support higher productivity, but the size of the gains is uncertain and hinges on structural conditions**. New Zealand ranks among the best-prepared economies globally on the IMF AI Preparedness Index, with particular strengths in regulation and digital infrastructure; low R&D spending per unit of GDP is the main structural soft spot. We apply the task-based model of Rockall, Tavares, and Pizzinelli (2025) to New Zealand, and find that AI could raise annual productivity growth by 0.1 to 0.4 percentage point over the next decade, equivalent to output roughly 6 to 15 percent higher after a decade. The magnitude of the gain depends on the strength of complementarity, the depth of capital markets, and whether AI delivers economy-wide productivity gains. Continued structural reform—particularly to deepen capital markets, strengthen competition, and raise incentives for innovation and R&D—would help convert New Zealand's preparedness into realized productivity growth.

6. **This paper contributes to a small but growing literature on the economic impact of AI in New Zealand**. Its contribution is threefold. First, it is among the few studies to estimate New Zealand workers' exposure to AI (Ball 2026; see also New Zealand Treasury 2024). Relative to the Reserve Bank's occupation-level exposure scores—constructed using large language models—this paper applies the Felten, Raj, and Seamans (2021) exposure measure together with the Pizzinelli and others (2023) complementarity framework, which enables transparent cross-country comparison and distinguishes roles that AI is likely to augment from those it is likely to displace. Second, it is the first to analyze the forces driving the adoption of AI-related skills in New Zealand using online job-postings data. Third, it is the first to develop scenario analysis quantifying the potential impact of AI on New Zealand's productivity and growth.

7. **The paper is organized as follows**. Section II examines New Zealand's exposure to AI. Section III studies AI adoption, through both AI usage and the demand for AI-related skills in the labor market. Section IV assesses New Zealand's AI preparedness and quantifies the potential impact of AI on productivity and growth across scenarios. Section V concludes.

B. Labor Market Exposure to AI: Opportunities and Risks

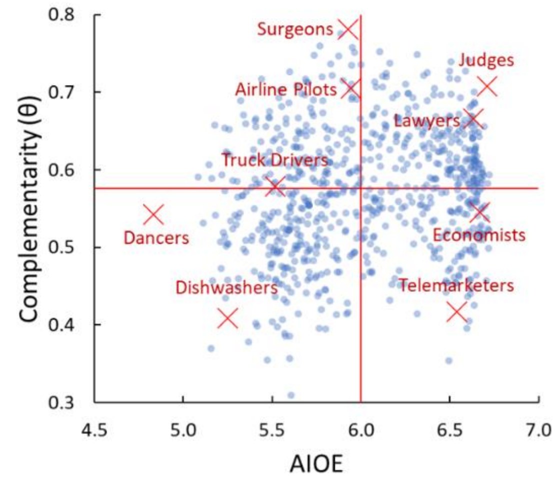
Conceptual Framework: Replacement Risk Versus Augmentation Potential

8. **The analysis distinguishes an occupation's exposure to AI from the likelihood that AI complements rather than replaces the worker**. Exposure follows Felten, Raj, and Seamans (2021, 2023) and measures the degree of overlap between AI applications and the human abilities required in an occupation. Exposure alone is agnostic about whether AI substitutes for or augments labor. To capture this distinction, this paper applies the complementarity methodology of Pizzinelli and others (2023), which draws on the "work context" and "skills" modules of Occupational Information Network (O*NET), a U.S. Department of Labor database of standardized occupational descriptors (National Center for O*NET Development, n.d.) and groups job characteristics into six dimensions: communication, responsibility, physical conditions, criticality, routine, and required skills. A high

complementarity score indicates that societal, ethical, or practical considerations make unsupervised use of AI less likely, so that AI is more apt to raise a worker's productivity than to displace them.

9. Combining the two measures yields three occupational groups that anchor the rest of the analysis. High-exposure, high-complementarity (HEHC) occupations—such as judges, whose work is highly exposed to AI but shielded by societal norms—are positioned to gain from AI-driven productivity (Figure 1). High-exposure, low-complementarity (HELC) occupations—such as many clerical roles—face a greater risk of displacement. Low-exposure (LE) occupations have limited scope for AI application in either direction. The thresholds are defined relative to median values, so the categories describe relative rather than absolute exposure.

Figure 1. Conceptual Diagram of AI Exposure (AIOE) and Complementarity (θ)



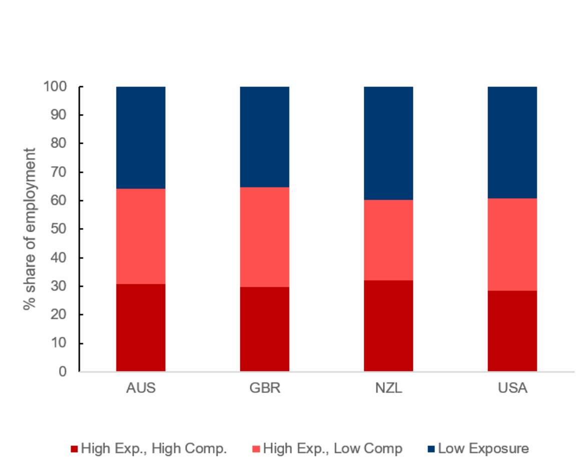
Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); and IMF staff calculations.

Note: Red reference lines denote the median of AIOE and complementarity.

New Zealand in Cross-Country Perspective

10. About 40 percent of workers globally, and around 60 percent in advanced economies, are in high-exposure occupations. In the average advanced economy, some 27 percent of employment is in HEHC occupations and about 33 percent in HELC occupations; the corresponding shares are 16 and 24 percent in emerging market economies and 8 and 18 percent in low-income countries (Cazzaniga and others 2024). Advanced economies are therefore both more exposed to near-term labor-market disruption-owing to their concentration of cognitive-intensive roles-and better placed to capture AI's productivity benefits.

Figure 2. Employment Shares by AI Exposure and Complementarity, Selected Advanced Economies



Sources: Stats NZ 2023 Census; Cazzaniga and others (2024); Felten, Raj, and Seamans (2021) AIOE via ISCO-08 mapping; and IMF staff calculations.

Note: HEHC = high-exposure, high-complementarity; HELC = high-exposure, low-complementarity; LE =

11. We estimate New Zealand's exposure by applying international AI exposure and complementarity measures to the country's occupational structure. The exposure and complementarity scores are defined at the level of international (ISCO-08) occupation codes, following Felten, Raj, and Seamans (2021) and Pizzinelli and others (2023). We map these scores to

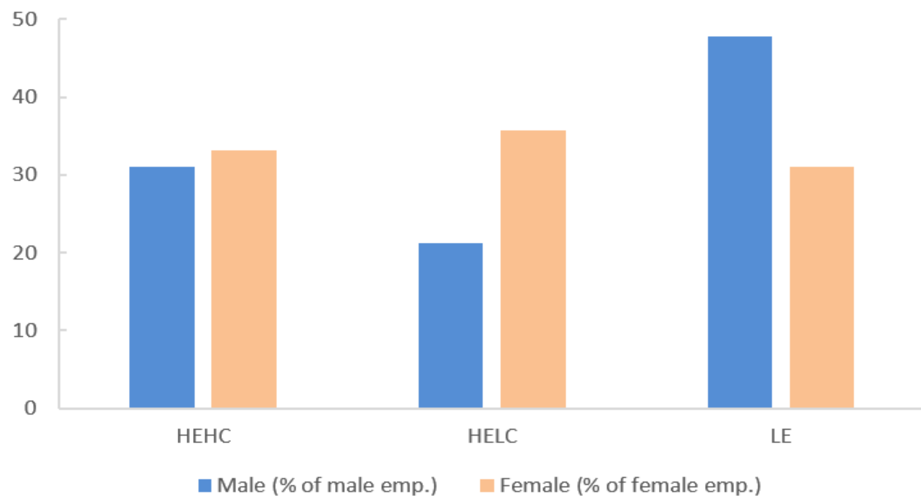
New Zealand employment using the official Australian Bureau of Statistics concordance from ANZSCO to ISCO-08 (at the four-digit unit-group level), applied to 2023 Census occupational employment counts (Stats NZ table WRK_010), to obtain the share of employment in each exposure-complementarity category. Two assumptions are worth noting. First, applying scores constructed on other countries' occupational data to New Zealand assumes that the task content of a given occupation is broadly comparable across advanced economies. Second, the two classifications are not perfectly aligned-for example, ANZSCO has no direct counterpart to ISCO-08's Technicians and Associate Professionals major group, and ISCO-08 none for ANZSCO's Community and Personal Service Workers-so a small number of occupations are matched imperfectly. The full concordance and further methodological detail are provided in Annex I.

12. New Zealand's exposure profile is broadly in line with other advanced economies. About 60 percent of workers are in high-exposure occupations, with 33 percent in high-complementarity roles (well-positioned to benefit) and 27 percent in low-complementarity roles (at greater risk of displacement) (Figure 2). The shares across the HEHC, HELC, and LE categories are close to those of Australia, the United Kingdom, and the United States. This similarity reflects a comparable economic structure, with a large share of employment in professional, managerial, and service occupations. It implies that New Zealand faces a similar mix of opportunity and risk as its advanced-economy peers.

Exposure Across Gender and the Income Distribution

13. Women are more exposed to AI than men, consistent with the cross-country pattern, but face both greater risk and greater opportunity. Based on Stats NZ 2023 Census employment, a larger share of women than men work in high-exposure occupations, and the pattern reflects the composition of female employment. Women’s concentration in professional and technical occupations—cognitive-intensive roles in which AI is more likely to augment than replace—underpins their higher share of high-exposure, high-complementarity (HEHC) employment (33.2 percent of female versus 31.0 percent of male employment) (Figure 3). At the same time, women are heavily represented in clerical and back-office roles, the archetypal high-exposure, low-complementarity (HELC) occupations, which accounts for the larger gender gap on the displacement-risk side (35.8 percent of female versus 21.2 percent of male employment). Men, by contrast, are more concentrated in low-exposure occupations (47.8 percent, versus 31.0 percent of women)—typically manual and physically oriented roles that are less amenable to AI. Because women’s higher exposure spans both high- and low-complementarity roles, they face elevated displacement risk in some occupations alongside stronger augmentation potential in others. This dual exposure mirrors the cross-country evidence of Cazzaniga and others (2025), who document that women are at once more likely to benefit from AI and more vulnerable to displacement, with low-earning women in substitution-prone jobs the most at risk.

Figure 3. AI Exposure by Gender in New Zealand
(Percent of Own-Gender Employment)



Sources: Stats NZ 2023 Census; Felten and others (2021) AIOE via ISCO-08 mapping; and IMF staff calculations.

Note: Bars show shares of own-gender employment in each exposure category.

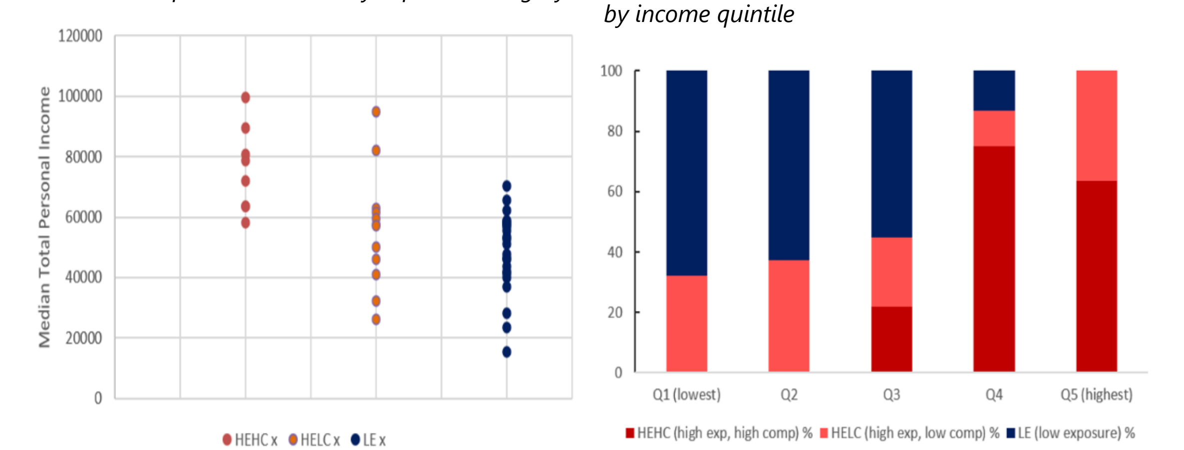
14. Exposure rises steadily with income, while the potential for complementarity is concentrated in the upper middle of the distribution. Leveraging data on occupational median total personal income and sorting them, the estimates show that the share of employment in high-exposure occupations increases from the lowest to the highest income quintile: the bottom quintiles are dominated by low-exposure occupations, whereas the top two quintiles are heavily high-exposure (Figure 4). Within high-exposure employment, the highest-income workers are increasingly concentrated in high-complementarity roles—though complementarity dips somewhat at the very top of the distribution, reflecting the classification of many ICT, business, and human-resources professionals as high-exposure, low-complementarity. These results should be read as indicative rather than precise: the analysis assigns earnings at the occupation level—relying on median income by occupation rather than individual-level microdata—and so can mask important within-occupation heterogeneity in earnings.

15. Taken together, the exposure evidence points to material transition risks alongside upside potential to boost labor productivity. Roughly one-third of New Zealand workers are in HELC occupations facing the highest displacement risk, and these workers are disproportionately female and concentrated in the middle of the income distribution. At the same time, the concentration of high-complementarity employment among higher earners indicates substantial scope for AI to raise productivity where it augments skilled workers. The net effect on employment and incomes would depend on the pace of adoption, the extent of productivity gains, and workers' ability to move into complementary roles.

Figure 4. AI Exposure Across the Income Distribution in New Zealand

Panel 1: median personal income by exposure category

Panel 2: composition of employment (HEHC / HELC / LE) by income quintile



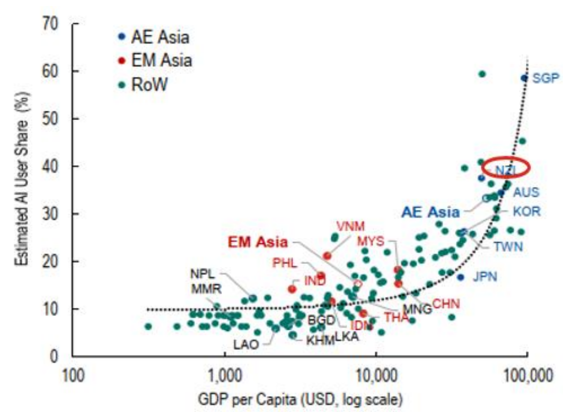
Sources: Stats NZ 2023 Census (WRK_010/WRK_011); Pizzinelli and others (2023); and IMF staff calculations.

Note: Quintiles are ranked by total personal income. HEHC = high-exposure, high-complementarity; HELC = high-exposure, low-complementarity; LE = low-exposure.

C. Early Evidence of AI Diffusion in the New Zealand Economy

16. Exposure measures describe the potential for adoption; the next question is whether AI is actually being adopted. In the absence of official statistics on AI adoption, this paper combines two sources of timely, third-party evidence to gauge diffusion. First, we use cross-country estimates of the share of the working-age population actively using AI tools, derived from usage data on devices running Microsoft software (Misra and others 2025). Second, we draw on real-time demand for AI-related skills from a commercial database of online job postings (Lightcast), described further below. Both suggest that AI is already spreading through the New Zealand economy, though from a modest base and unevenly across sectors. AI use is relatively high, but global adoption remains uneven.

Figure 5. AI Use and GDP per Capita



Sources: Misra and others (2025); IMF APD Regional Economic Outlook (Forthcoming); and IMF staff calculations.

Note: AI-user share estimated from device-level use of AI tools over 2025. Values for regional groups are averages.

17. New Zealand shows relatively high AI use among advanced economies. Estimates for 2025 put the share of the working-age population actively using AI tools at around 40 percent-toward the upper end of advanced economies, above the level implied by its income alone, but below leaders such as Singapore, at around 60 percent (Misra and others 2025) (Figure 5).[4] Higher AI use could support productivity gains if adoption broadens across firms and sectors. Because adoption is highly uneven across economies—and, within economies, across firms—it also carries the risk of widening productivity gaps between frontier and lagging firms —a particular concern in New Zealand, where better-managed and larger frontier firms make more effective use of new technology and where the productivity gap to laggard firms is already wide (Winter and others 2025).

Demand for AI-Related Skills is Rising

18. Online job postings provide a granular, timely measure of employers' demand for AI-related skills. The Lightcast job postings data record the occupation and job title, the specific skills requested, the industry and employer. Job postings have become a popular data source for measuring labour-market dynamics,[5] owing to their rich detail and high frequency. The data are assembled by aggregating and de-duplicating advertisements from tens of thousands of online sources, and they therefore capture only vacancies advertised online: positions placed solely in print (for example, newspaper classifieds), filled by word of mouth, or filled through internal promotion are not observed, and the series measures new postings—a flow proxy for labour demand—rather than the stock of employment. As discussed in Jaumotte and others (2026) and in the OECD's benchmarking work (Tsvetkova and others 2024), online postings also tend to be biased toward higher-skill occupations, and their coverage and representativeness for New Zealand have not been independently validated by the provider; Annex II assesses this directly for New Zealand. Following Jaumotte and others (2026), among skills, AI-related skills are classified into developer skills (used to build and maintain AI systems), user skills (used to apply AI tools in business processes), and hybrid postings requiring both. This taxonomy makes it possible to separate the creation of AI capabilities from the application of AI tools across the wider economy. Table 1 illustrates examples of job postings and their most important skills.

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[4] These estimates are indicative: they are based on Microsoft usage data and so do not capture AI use through other providers' tools, and they do not distinguish whether AI is used for work or for personal purposes. A final caveat is that the coverage of Microsoft software differs across countries, so cross-country comparisons should be treated with some caution.

[5] Lightcast (formerly Burning Glass) job-postings data have been used widely to study labour demand, skill requirements, and the labour-market effects of technological change—see, for example, Acemoglu and others (2022), Hershbein and Kahn (2018), and Deming and Noray (2020) for the United States. The World Bank has drawn on the same data to study the labour-demand effects of generative AI, finding that postings for occupations more vulnerable to AI substitution declined relative to less-vulnerable ones following the release of ChatGPT (Liu, Yu, and Wang 2025).

Table 1. New Zealand: Examples of Occupations, Job Titles, and Skills Derived from Job Postings Data

ISCO-08 Occupation (4-digit)	Example job titles	Top skills in postings (6)
2512 Software Developers	Software Engineer; Data Engineer	Software Engineering; Software Development; Python*; SQL*; Amazon Web Services (AWS)*; Agile Methodology
3251 Dental Assistants & Therapists	Dental Hygienist; Dental Assistant	Dental Hygiene; Dentistry; Preventive Care; Medical History Documentation; Periodontology; Velscope*
3314 Statistical, Mathematical & Related Associate Professionals	Data Analyst; BI Analyst	Data Analysis; SQL*; Python*; Tableau*; Power BI*; Data Visualization
5230 Cashiers & Ticket Clerks	Cashier; Front-of-House Cashier	Customer Service; Point of Sale; Cash Register; Communication; Sales; Greeting Customers

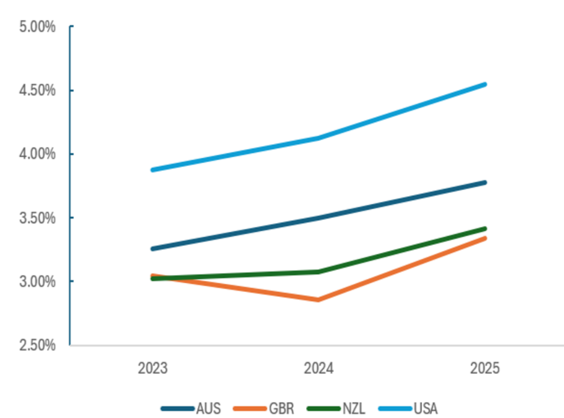
Sources: Jaumotte and others (2026); Lightcast; and IMF staff calculations.

Note: Skills marked with an asterisk are newly emerging skills.

19. Demand for AI-related skills is rising in New Zealand and among many Advanced Economies. The share of job postings requiring AI-related skills in New Zealand has increased from 3 percent in 2023 to 3.4 percent in 2025 (+0.4 percentage point). New Zealand's level is broadly in line with peers such as Australia and the United Kingdom and below the United States, which leads among the economies examined and experienced an increase in AI skills demand by 0.7 p.p. over this period (Figure 6).

Figure 6. AI Skills Demand over 2023–25

(Percent of Job Postings)



Sources: Jaumotte and others (2026); Lightcast; and IMF staff calculations.

Note: Share of job postings with AI skills.

20. The composition of demand also differs between the United States and New Zealand. In the United States, AI adoption is led by the information sector, whereas in New Zealand it is concentrated in professional, technical, and finance activities (Figure 7, panel 1). In the United States, 20 percent of job postings in the information sector required AI skills in 2025, up from close to 15 percent in 2023. In New Zealand, by contrast, fewer than 15 percent of information-sector postings required an AI skill in both 2023 and 2025—indicating lower adoption within the sector, not merely a smaller information sector. Professional services are a key source of

AI-skill demand in both countries, with close to 15 percent of postings requiring AI skills; finance follows, where in 2025 almost 12 percent of postings require AI skills.

21. The increase in New Zealand's AI-skill demand has been driven by a handful of high-skill service sectors. Ranking sectors by their contribution to the within-sector deepening of AI-skill demand, professional and technical services stand out by a wide margin, followed by finance and insurance and real estate (Figure 7, panel 2). These sectors employ a large share of high-exposure, high-complementarity workers, suggesting that AI adoption in New Zealand is concentrated precisely in the segment best placed to benefit from augmentation.

Adoption is Driven by Within-Sector Deepening

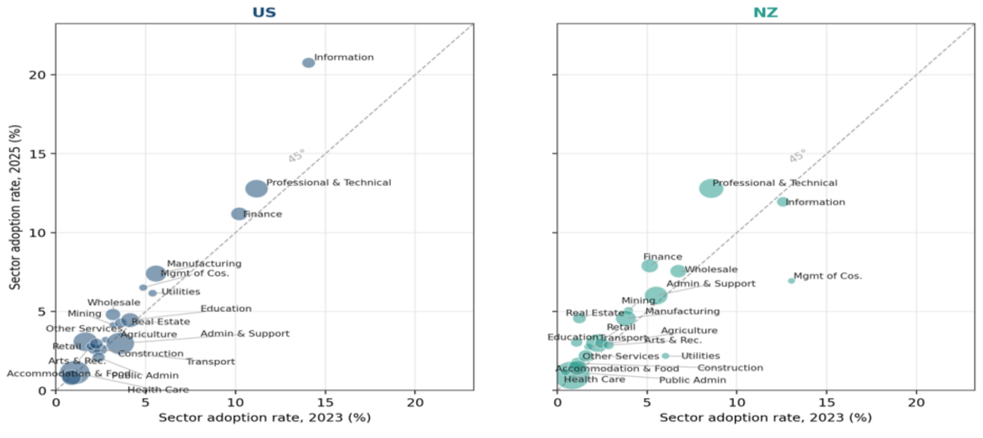
22. Rising AI-skill demand reflects deeper adoption within sectors rather than a shift toward AI-intensive sectors. We use shift-share analysis to decompose the 2023–25 change in AI-related skill demand into a within-sector component (existing sectors adopting AI more intensively) and a between-sector component (the economy's composition shifting toward AI-intensive sectors). Because the decomposition requires each posting to be assigned to an industry, it is computed on the subset of postings that carry sectoral information—a more restricted sample than the full series in Figure 6—so the magnitudes here are not directly comparable to the overall change in AI-skill demand shown there[6]. In New Zealand, the within-sector component contributes about +1.06 percentage points and the between-sector component about +0.13 percentage points, for a net change of roughly +1.19 percentage points. The comparable figures for the United States are +0.74, −0.03, and +0.71 percentage points, respectively. New Zealand's larger net increase is therefore driven overwhelmingly by within-sector deepening—above all in professional and technical services—rather than by structural change in the composition of employment.

23. Demand in New Zealand is tilted toward applying AI rather than building it, and the share of postings requiring both is rising. Decomposing AI-related postings into developer-only, user-only, and hybrid ("both") categories shows that New Zealand is more user-tilted than the United States. In New Zealand, the developer-only share has edged up from about 17 percent to 21 percent between 2022 and 2026, while the hybrid share has risen from about 24 percent to 34 percent; the remainder is user-only. The rising hybrid share suggests that employers increasingly value workers who can both apply and adapt AI tools—pointing to the importance of broad-based AI-user skills across the workforce, not only specialist AI-developer capabilities.

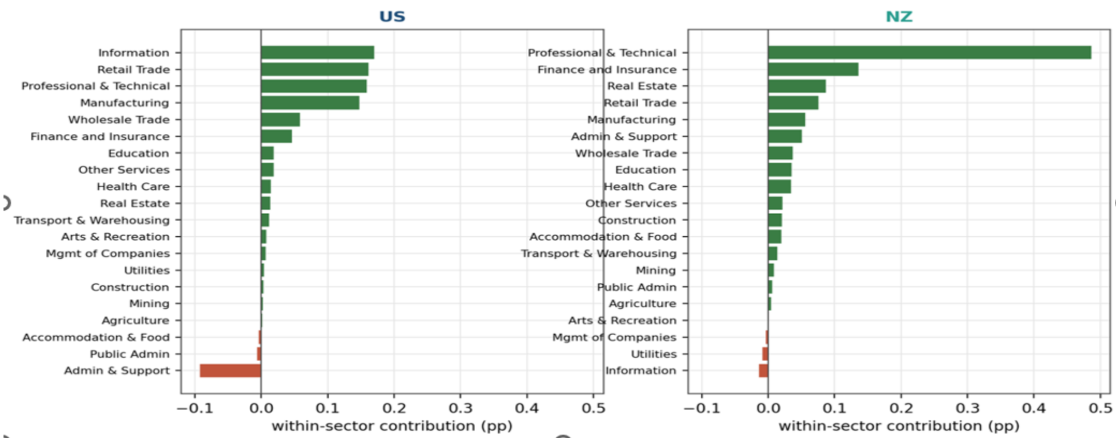
[6] We assessed the representativeness of the industry-classified posting sample by comparing each sector's share of classified New Zealand postings with its share of employment, proxied by Stats NZ Linked Employer-Employee Data (LEED) filled jobs for 2024. The largest discrepancy is in health care and social assistance, which accounts for close to 28 percent of classified postings but only about 12 percent of filled jobs. This gap should not impact the decomposition, because health care records a very low AI-skill intensity—around 0.8–1.0 percent over 2023–25, as low as or below the unclassified postings that are dropped from the sample, and well below both the classified-sector average and the professional and technical services that account for most of the within-sector component.

Figure 7. Sectors Driving Within-Sector AI-Adoption Deepening, 2023–25

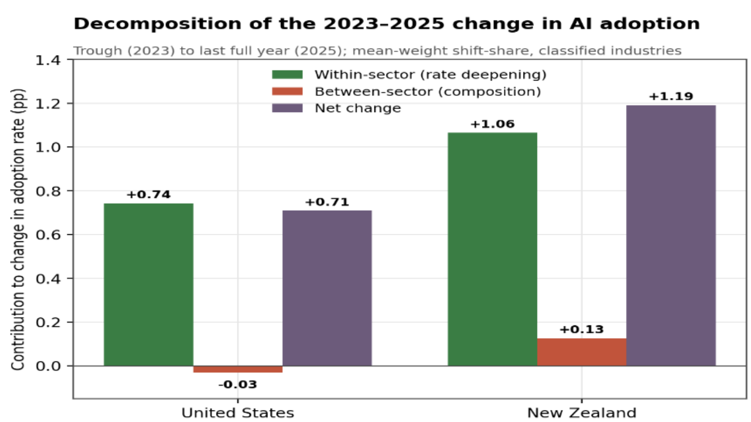
Panel 1: Sector-level AI adoption, 2023 vs 2025 (above 45 line = sector deepened)
Bubble size = average share of postings, classified industries



Panel 2: Sectors drove within-sector AI-adoption deepening, 2023-2025.



Panel 3: Sectors drove within-sector AI-adoption deepening, 2023-2025.



Sources: Jaumotte and others (2026); Lightcast; and IMF staff calculations.

Note: In panel 1, bubble size proportional to average share of postings; classified industries only. In panel 2, bars show each sector's within-sector contribution to the change in AI-skill demand. Panel 3, Mean-weighted shift-share; classified industries only. Trough (2023) to last full year (2025).

D. Can AI Translate into Productivity Gains?

24. Whether AI will generate broad productivity gains in New Zealand will depend on exposure, preparedness, and adoption. This section first assesses New Zealand's AI preparedness, then uses a task-based model to illustrate the range of possible productivity outcomes under scenarios tailored to New Zealand's structural features.

AI Preparedness: Strong Overall, with R&D the Soft Spot

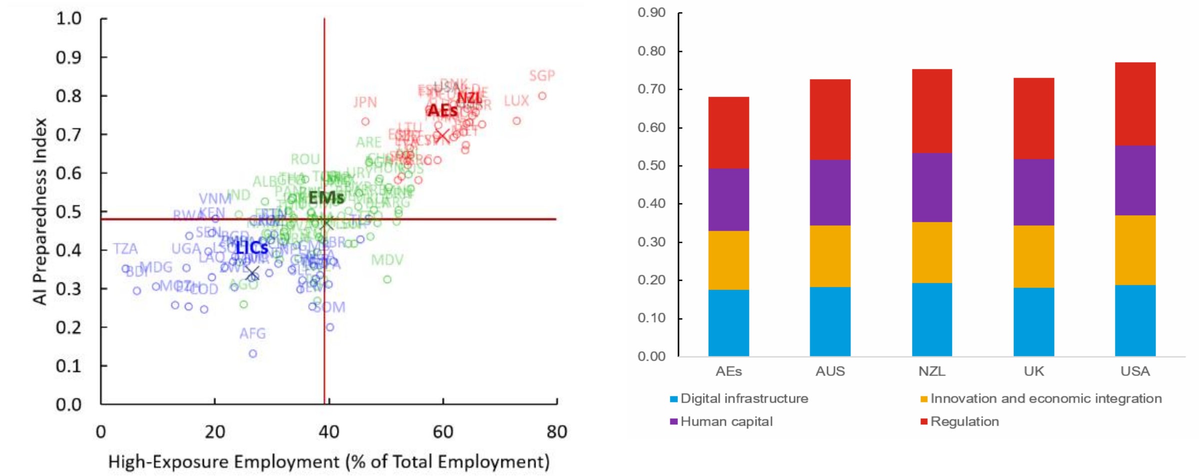
25. New Zealand ranks among the economies best prepared to capture AI gains globally. The IMF AI Preparedness Index (AIPI) developed by Cazzaniga and others (2024) is designed to measure countries' ability to adopt AI broadly—across economic sectors and segments of society. This distinguishes it from indices with different aims: for example, Stanford HAI's Global AI Vibrancy ranking (Stanford HAI 2024) gauges the strength of national AI ecosystems—research, investment, patents, and models—and thus a country's capacity to produce AI, while the Oxford Insights Government AI Readiness Index (Oxford Insights 2024) assesses how ready governments are to deploy AI in public services. The AIPI measures readiness across four dimensions: digital infrastructure, innovation and economic integration, human capital and labor-market policies, and regulation and ethics (Figure 8, panel 1). Higher-income economies—including advanced economies and some emerging markets—are generally better prepared than low-income countries. New Zealand ranks among the top 10 economies globally on the overall index, reflecting strong institutional foundations.

26. New Zealand's strengths are uneven across the four pillars, and low R&D intensity is the main structural weakness. The country leads on regulation and ethics (0.879) and on digital infrastructure (0.775), but scores lower on human capital (0.725) and, especially, on innovation and economic integration (0.635) (Figure 8, panel 2). Business R&D spending—a key input to the innovation pillar—is well below peer advanced economies (Petrescu 2025). The contrast with the top-ranked economy is instructive. Singapore leads the global index with an overall score of about 0.80, against roughly 0.75 for New Zealand (Cazzaniga and others 2024; IMF AI Preparedness Index dashboard). New Zealand's standing is anchored by its world-leading regulation and ethics pillar; the gap with Singapore instead reflects the pillars where New Zealand is weakest—innovation and economic integration and human capital—which draw on R&D, STEM skills, and global economic integration, and where a hub economy such as Singapore excels. Because AI's productivity benefits depend not only on adopting existing tools but also on adapting and extending them, a persistent R&D gap could limit New Zealand's ability to move from AI use toward AI-driven innovation tailored to the country's specific needs. More broadly, because AI and its applications are evolving rapidly, a high preparedness ranking is most valuable if it is used to keep frameworks adaptable and agile—regularly revisiting regulation, skills policies, and adoption supports as the technology and the global environment change—rather than treated as a fixed advantage.

Figure 8. AI Preparedness

Panel 1: Scatter of AIPI against high-exposure employment

Panel 2: AI Preparedness Index and Its Four Components, Selected Economies



Sources: Cazzaniga and others (2024) and IMF staff calculations.

Note: AIPI covers digital infrastructure, innovation and economic integration, human capital and labor-market policies, and regulation and ethics.

A Model-Based View of AI's Productivity Impact

27. To quantify the potential aggregate effects, staff use a task-based general-equilibrium model calibrated to New Zealand. The framework of Rockall, Tavares, and Pizzinelli (2025)—building on Moll, Rachel, and Restrepo (2022) and Drozd, Taschereau-Dumouchel, and Tavares (2023)—features agents that differ in labor productivity and asset holdings, and occupations that differ in AI exposure and complementarity. AI affects the economy through four channels: labor displacement (tasks shift from labor to capital, reducing labor income); complementarity (value added and labor demand shift toward AI-complementary occupations); productivity gains (a broad-based boost to output that can offset labor-income losses); and capital income (higher returns to capital raise capital income, which accrues disproportionately to higher-wealth households).

28. The main mechanism in the model is that firms choose which tasks to automate given prevailing factor prices. Facing a wage and a rental rate of capital, the firm assigns each task to whichever factor is cheaper, automating tasks up to a cutoff and leaving the remainder to labor. As AI lowers the effective cost of performing exposed tasks with capital, the automation cutoff shifts, reallocating tasks from labor to capital while raising overall productivity.[7] The distributional outcome depends on where along the income distribution exposure and complementarity fall and on how

[7] The model assumes full employment. Workers whose tasks are displaced by capital effectively supply fewer units of labor, placing downward pressure on wages. The net effect on an individual worker depends on whether the wage gains generated by higher productivity are sufficient to offset the income losses associated with the displacement of the tasks they previously performed.

strongly AI complements the workers whose tasks are not automated. A detailed treatment is provided in Rockall, Tavares, and Pizzinelli (2025).

29. While uncertainty about long-term impacts is large, three scenarios tailored to New Zealand illustrate the range of possible productivity and output outcomes. Across the scenarios, AI raises annual productivity growth by between 0.1 and 0.4 percentage point over the next decade. In every scenario, the impact on output exceeds the impact on total factor productivity (TFP), and this wedge reflects capital deepening: by raising the return to capital, AI induces additional investment, so that output rises by more than the direct gain in TFP. The scenarios share the same complementarity structure but differ in how AI raises productivity and how far capital can deepen:

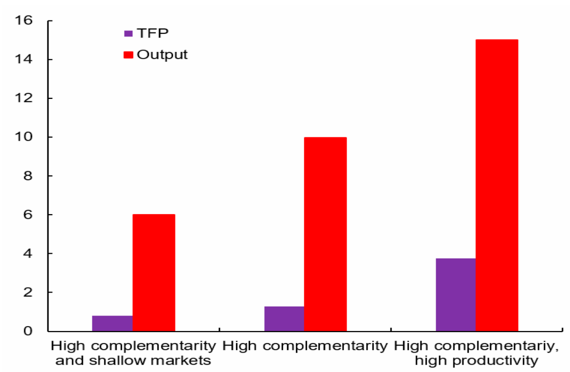
- **High complementarity with a shallow credit market**. AI strongly augments exposed high-income workers, but New Zealand's structural constraint—limited scope for domestic capital deepening—means AI lifts productivity mainly through use rather than through domestic investment. This is the most conservative case, raising annual productivity growth by about 0.1 percentage point, which contributes to the level of output being around 6 percent higher after roughly a decade.

- **High complementarity.** The same strong complementarity, but with capital markets able to deepen so that AI generates capital deepening as well. Productivity growth rises by an intermediate amount of about 0.13 percentage points, contributing to lifting output by around 10 percent after a decade—gains that are largely embodied in capital rather than in broad-based total factor productivity.

- **High complementarity with high productivity**. In addition to strong complementarity and capital deepening, AI delivers economy-wide TFP gains that raise baseline productivity for all workers—including those in HELC and low-exposure occupations. This most optimistic case yields the largest gains, raising annual productivity growth by about 0.4 percentage point—a cumulative TFP gain of roughly 4 percent—and lifting output by around 15 percent after a decade.

30. The scenarios illustrate both the upside and the deep uncertainty around AI's productivity effects. The spread across scenarios—from about 0.1 to 0.4 percentage point of additional annual productivity growth, or roughly 6 to 15 percent of output over a decade—underscores that the magnitude of any gain is highly sensitive to whether capital markets can deepen and whether AI delivers

Figure 9. Impact of AI on TFP and Output in New Zealand



Sources: Rockall, Tavares, and Pizzinelli (2025) and IMF staff calculations.

Note: Steady-state comparison approximately 10 years after adoption. Scenarios are illustrative and depend on calibration assumptions.

broad-based productivity improvements. The results also carry the standard caveats of steady-state model comparisons: they abstract from adjustment costs and transition dynamics, depend on calibration choices, and should be interpreted as illustrative scenarios rather than as forecasts. Consistent with the exposure evidence, stronger complementarity tends to raise labor-income inequality even as it lifts output, so distributional outcomes would depend heavily on redistributive and other fiscal policies.

31. A further caveat is that the model is a closed-economy framework, whereas New Zealand is a small, open economy. This distinction matters in at least three ways. First, the model links AI's capital-income gains to domestically held capital, yet New Zealand residents hold a large share of their savings abroad—through vehicles such as the New Zealand Superannuation Fund and KiwiSaver funds, which invest heavily in global equities. New Zealand savers could therefore capture part of the rise in global capital returns and technology-firm valuations that AI adoption generates, even without a commensurate increase in domestic investment—a channel the closed-economy model does not capture. Second, openness interacts with the capital-market depth that separates the scenarios: access to foreign savings could relax the domestic capital-deepening constraint underlying the most conservative scenario, while foreign ownership of domestic capital could send some AI-related capital-income gains abroad. Third, because much of New Zealand's capital—and the technology embodied in it—is imported, AI is likely to reach the economy largely through imported hardware, software, and cloud services; realizing that potential would nonetheless depend on domestic business investment and capability-building, given the country's relatively low capital intensity, including in the intangible and digital capital most complementary to AI (Winter and others 2025). On balance, New Zealand's international investment position could make the gains from AI less dependent on domestic capital deepening than the closed-economy scenarios imply, though the direction and magnitude of these effects are uncertain and would merit dedicated open-economy analysis.

E. Conclusion

32. New Zealand has substantial potential in benefiting from AI, but capturing it will not be automatic. The economy’s exposure to AI is broadly in line with that of other advanced economies; AI use is relatively high; job-postings evidence points to rising and accelerating adoption; and preparedness ranks among the best in the world. Under favorable conditions, including properly managed impact on labor displacement, the model simulations suggest AI could raise output materially over the coming decade. These findings support a constructive view of AI as a potential boost to New Zealand’s productivity growth.

33. At the same time, the transition carries material labor-market risks that would need to be managed. Around one-third of workers are in occupations at high risk of disruption, and these workers are disproportionately women and concentrated in the middle of the income distribution. The employment impact would depend on reallocation—whether productivity gains generate new labor demand and whether affected workers can transition into complementary roles. Active labor-market policies, accessible retraining and lifelong-learning systems, and broad diffusion of AI-user skills across the workforce would help workers adapt, while adequate social protection would cushion those facing longer transitions.

34. Structural bottlenecks could slow diffusion and limit the aggregate payoff, making continued structural reform central to the AI agenda. Low R&D intensity, high and volatile electricity prices, shallow capital markets, and barriers to firm entry and scale-up all risk slowing the spread of AI from frontier firms and sectors to the wider economy. Continued structural reform would help convert preparedness into realized productivity gains. Priorities would include deepening capital markets to support the reallocation of resources toward productive, AI-adopting firms; strengthening competition to ensure that AI-driven gains are widely diffused rather than captured by incumbents; and strengthening incentives for innovation and business R&D to move New Zealand from AI use toward AI-driven solution tailored to the country's need. Competition matters for diffusion in particular, since it raises firms' incentives to adopt new technologies, speeds the reallocation of resources toward more productive firms, and helps successful firms scale. Because AI's distributional effects depend on complementarity and on the ownership of capital, redistributive and fiscal policies would ultimately shape how broadly its benefits are shared.

35. On balance, AI offers New Zealand a plausible opportunity to lift productivity, provided adoption broadens and structural constraints ease. The country's strong preparedness and rising adoption are encouraging, but the future gains documented here are contingent rather than assured. Realizing them would require complementary structural reform, support for worker reallocation, and attention to the distributional consequences of a technology whose benefits, absent policy, would tend to accrue to those already best placed to capture them. And because both the technology and the global environment in which AI is used will keep evolving, that opportunity will be captured only if New Zealand's preparedness and policies continue to adapt.

Annex I. Methodology: Mapping AI Exposure to New Zealand's Occupational Structure

1. **We estimate New Zealand's exposure to artificial intelligence by applying international AI exposure and complementarity measures to the country's occupational structure.** The exposure and complementarity scores are defined at the level of International Standard Classification of Occupations (ISCO-08) unit groups, following Felten, Raj, and Seamans (2021) and Pizzinelli and others (2023). We map these scores to New Zealand employment using the official Australian Bureau of Statistics (ABS) concordance from the Australian and New Zealand Standard Classification of Occupations (ANZSCO) to ISCO-08, applied to 2023 Census occupational employment counts (Stats NZ table WRK_010), to obtain the share of employment in each exposure–complementarity category.

2. **Each occupation is assigned to one of three categories** based on its AIOE score (AI Occupational Exposure) and theta score (complementarity), relative to their cross-occupation medians (AIOE median = 6.00; theta median = 0.576). High exposure, high complementarity (HEHC) occupations are those with AIOE at or above the median and theta at or above the median: workers in these occupations are more likely to benefit from AI as a complement to their tasks. High exposure, low complementarity (HELC) occupations have AIOE at or above the median but theta below the median: workers face greater risk of task substitution. Low exposure (LE) occupations have AIOE below the median, indicating limited direct AI exposure regardless of complementarity.

3. **Two assumptions are worth noting**. First, applying scores constructed on other countries' occupational data to New Zealand assumes that the task content of a given occupation is broadly comparable across advanced economies—an assumption that is standard in the cross-country literature but may not hold perfectly at the margin. Second, ANZSCO and ISCO-08 are not perfectly aligned: for example, ANZSCO has no direct counterpart to ISCO-08's Technicians and Associate Professionals major group, and ISCO-08 has no equivalent for ANZSCO's Community and Personal Service Workers major group. A small number of sub-major groups are therefore matched to the closest ISCO-08 equivalent, as detailed in Table AI.1 below.

4. **Three specific mapping choices merit disclosure**. Farmers and Farm Managers (ANZSCO 12) are mapped to ISCO-08 6100 (Market-oriented skilled agricultural workers) rather than ISCO-08 1300 (Production and specialized services managers), reflecting the agricultural rather than managerial nature of this group's tasks. Hospitality, Retail and Service Managers (ANZSCO 14) are assigned to the low exposure category despite their ISCO-08 1400 score falling above the AIOE median, on the grounds that this group's task content is predominantly operational and customer-facing rather than information-processing in nature. Other Technicians and Trades Workers (ANZSCO 39) are mapped to ISCO-08 7200 (Metal, machinery and related trades workers) rather than ISCO-08 3100, reflecting their predominantly manual trades character.

5. **Employment counts are drawn from the 2023 New Zealand Census of Population and Dwellings** (Stats NZ, dataset WRK_010: Occupation, ethnicity, age, and gender for the employed

census usually resident population count aged 15 years and over). The reference population is all employed usually resident persons aged 15 and over, totaling approximately 2.62 million. Median income by occupation is drawn from Stats NZ dataset WRK_011; values are averages of available age and gender sub-cells at the national level, as aggregate-level cells are subject to random rounding for confidentiality. Income quintiles are constructed at the occupation sub-major level using these median income values weighted by employment counts.

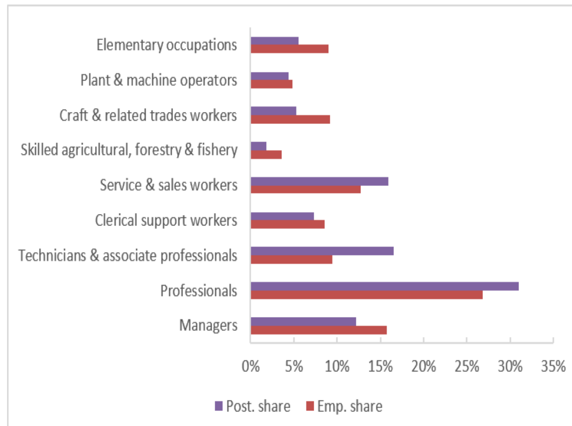
Table 1. New Zealand: Occupational Classification and Category Mapping

Major group (ANZSCO)	Sub-major group (ANZSCO)	ISCO-08 code	ISCO-08 label	AI exposure classification
Managers	Chief Executives, General Managers and Legislators	1100	Chief executives, senior officials and legislators	HEHC
Managers	Farmers and Farm Managers	6100	Market-oriented skilled agricultural workers	LE
Managers	Specialist Managers	1200	Administrative and commercial managers	HEHC
Managers	Hospitality, Retail and Service Managers	1400	Hospitality, retail and other services managers	LE
Professionals	Arts and Media Professionals	2600	Legal, social and cultural professionals	HEHC
Professionals	Business, Human Resource and Marketing Professionals	2400	Business and administration professionals	HELC
Professionals	Design, Engineering, Science and Transport Professionals	2100	Science and engineering professionals	HEHC
Professionals	Education Professionals	2300	Teaching professionals	HEHC
Professionals	Health Professionals	2200	Health professionals	HEHC
Professionals	ICT Professionals	2500	Information and communications technology professionals	HELC
Professionals	Legal, Social and Welfare Professionals	2600	Legal, social and cultural professionals	HEHC
Technicians and Trades Workers	Engineering, ICT and Science Technicians	3100	Science and engineering associate professionals	HEHC
Technicians and Trades Workers	Automotive and Engineering Trades Workers	7200	Metal, machinery and related trades workers	LE
Technicians and Trades Workers	Construction Trades Workers	7100	Building and related trades workers (excluding electricians)	LE
Technicians and Trades Workers	Electrotechnology and Telecommunications Trades Workers	7400	Electrical and electronics trades workers	LE
Technicians and Trades Workers	Food Trades Workers	7500	Food processing, woodworking, garment and other craft and related trades workers	LE
Technicians and Trades Workers	Skilled Animal and Horticultural Workers	6100	Market-oriented skilled agricultural workers	LE
Technicians and Trades Workers	Other Technicians and Trades Workers	7200	Metal, machinery and related trades workers	LE
Community and Personal Service Workers	Health and Welfare Support Workers	3200	Health associate professionals	LE
Community and Personal Service Workers	Carers and Aides	5300	Personal care workers	LE
Community and Personal Service Workers	Hospitality Workers	5100	Personal services workers	LE
Community and Personal Service Workers	Protective Service Workers	5400	Protective services workers	LE
Community and Personal Service Workers	Sports and Personal Service Workers	5100	Personal services workers	LE
Clerical and Administrative Workers	Office Managers and Program Administrators	3300	Business and administration associate professionals	HELC
Clerical and Administrative Workers	Personal Assistants and Secretaries	4100	General and keyboard clerks	HELC
Clerical and Administrative Workers	General Clerical Workers	4100	General and keyboard clerks	HELC
Clerical and Administrative Workers	Inquiry Clerks and Receptionists	4200	Customer services clerks	HELC
Clerical and Administrative Workers	Numerical Clerks	4300	Numerical and material recording clerks	HELC
Clerical and Administrative Workers	Clerical and Office Support Workers	4400	Other clerical support workers	HELC
Clerical and Administrative Workers	Other Clerical and Administrative Workers	4400	Other clerical support workers	HELC
Sales Workers	Sales Representatives and Agents	3300	Business and administration associate professionals	HELC
Sales Workers	Sales Assistants and Salespersons	5200	Sales workers	HELC
Sales Workers	Sales Support Workers	5200	Sales workers	HELC
Machinery Operators and Drivers	Machine and Stationary Plant Operators	8100	Stationary plant and machine operators	LE
Machinery Operators and Drivers	Mobile Plant Operators	8300	Drivers and mobile plant operators	LE
Machinery Operators and Drivers	Road and Rail Drivers	8300	Drivers and mobile plant operators	LE
Machinery Operators and Drivers	Storepersons	9300	Labourers in mining, construction, manufacturing and transport	LE
Labourers	Cleaners and Laundry Workers	9100	Cleaners and helpers	LE
Labourers	Construction and Mining Labourers	9300	Labourers in mining, construction, manufacturing and transport	LE
Labourers	Factory Process Workers	9300	Labourers in mining, construction, manufacturing and transport	LE
Labourers	Farm, Forestry and Garden Workers	9200	Agricultural, forestry and fishery labourers	LE
Labourers	Food Preparation Assistants	9400	Food preparation assistants	LE
Labourers	Other Labourers	9600	Refuse workers and other elementary workers	LE

Annex II. Lightcast Data Benchmarking

1. Benchmarking the New Zealand job-postings panel against Census employment confirms the pattern documented in the international literature. As noted in Jaumotte and others (2026) and in the OECD's benchmarking work (Tsvetkova and others 2024), online job postings tend to be weighted toward higher-skill, office-based occupations. Comparing the occupational composition of 2023 postings with 2023 Census employment (Stats NZ), on a common ISCO-08 classification, reproduces exactly this pattern: professionals are the largest occupational group in both postings and employment, the broad shape of the two distributions is similar, and the differences are concentrated where the literature would predict. Postings are taken for the Census reference year, and armed forces and unclassified records are excluded; because postings are ISCO-coded while New Zealand employment is published on ANZSCO, the Census counts are crosswalked to ISCO-08, with the assignments documented in the accompanying workbook.

Figure 1. Representativeness of Job Postings in New Zealand



Sources: Stats NZ Census 2023, Lightcast and IMF staff calculations

Note: ISCO-08 major groups

2. Relative to employment, the postings are tilted toward professional, technical, and customer-facing occupations, consistent with the international evidence (Figure A.1). Professionals account for 31.0 percent of postings against 26.8 percent of employment, and technicians and associate professionals for 16.5 against 9.4 percent—reflecting information-technology and business-support roles that are advertised online at high rates—while service and sales workers are also somewhat over-weighted. Craft and trades, elementary, skilled agricultural, and clerical occupations carry smaller shares of postings than of employment. This is the same skew toward higher-skill occupations found for comparable advanced economies.

3. Such differences are expected, because job postings measure a flow of advertised vacancies rather than the stock of employment. Occupations differ in how frequently they turn over, and those with higher separation and hiring rates generate more postings per job than long-tenure occupations; their share of postings would exceed their share of employment even if online advertising were fully comprehensive. A gap between posting and employment shares therefore reflects differences in occupational turnover and in the propensity to advertise online, and is not, in itself, evidence of under-coverage. The lower posting share of managers, for instance, partly reflects owner-operators and working proprietors—who seldom advertise—together with the crosswalk's placement of owner-operator farmers in skilled agricultural occupations.

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