

Predicting Employment Outcomes of Australian Information Technology Graduates Using Machine Learning

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ABSTRACT: Graduate employment outcomes in information technology are an important issue for Australian higher education because growth in digital work has translated unevenly into immediate professional employment for new graduates. This study predicts aggregate employment outcomes for Australian Computing and Information Systems graduates using the latest publicly available national evidence. A longitudinal panel was constructed from Quality Indicators for Learning and Teaching Graduate Outcomes Survey data covering multiple undergraduate study areas. Full-time employment, overall employment, participation and median salary were modelled using regularised regression with study-area-specific time effects and an indicator for changes in survey definitions, while random forest and gradient boosting models provided time-block validation benchmarks. Results show weakening immediate full-time employment alongside rising graduate salaries and continuing demand across major ICT occupations. Forecasts indicate continued competitive entry to full-time professional work over the medium term while median graduate salary increases. The findings highlight a persistent disconnect between occupational demand and graduate transition outcomes, with implications for industry engagement, work-integrated learning, authentic assessment, career development and data-informed employability support in Australian higher education.

Key words: employment forecasting; graduate employability; higher education; information technology; machine learning

INTRODUCTION

Graduate employability is central to higher education quality, curriculum design and student decision making, yet it cannot be reduced to a single skills measure or to whether a graduate is employed shortly after completing a degree. Contemporary research conceptualises employability as a multidimensional outcome shaped by human and social capital, individual attributes, professional identity, context and access to opportunity (Clarke, 2018; Römgens, Scoupe, & Beausaert, 2020; Tomlinson, 2017). This distinction is particularly important in information technology, where graduates enter a heterogeneous professional environment that includes software development, systems analysis, cyber security, data infrastructure, cloud computing and related digital occupations. Employers seek disciplinary competence, but they also value communication, adaptability, collaboration and professional judgement (Herbert et al., 2020; Succi & Canovi, 2020). An informative analysis of computing graduate outcomes therefore needs

to separate growth in the wider ICT workforce from the short-term transition into professional employment experienced by new graduates.

Australia provides a strong national evidence base through the Quality Indicators for Learning and Teaching program. The Graduate Outcomes Survey measures employment, salary, further study and skills utilisation approximately four to six months after course completion. The 2025 GOS National Report, released in 2026, contains more than 120,000 graduate responses and reports outcomes by study area, providing a consistent basis for longitudinal analysis (Social Research Centre, 2026b). Within this framework, Computing and Information Systems represents the principal study area corresponding to the broad field of Information Technology and includes Computer Science, Information Systems and related qualifications. These national data allow us to study transition from computing education into professional work using outcomes (not perceptions of employability) as opposed to only perceptions. Australian research shows similarly that graduate outcomes are influenced by educational experiences, work-integrated learning and career development activities rather than disciplinary knowledge or general economic conditions alone (Jackson & Rowe, 2023; Jackson et al., 2024).

Recently national results have been mixed. Full-time employment of Computing and Information Systems undergraduates in 2019 was 75.9%; 72.1% in 2020; 67.9% in 2021; 76.6% in 2022; 74.4% in 2023; 67.8% in 2024 and 65.3% in 2025. Median salary has increased more recently from AUD 65,500 in 2021 to AUD 80,000 in 2025 (Social Research Centre, 2023, 2025, 2026b). The 2025 figure should be interpreted with care because GOS changed the labour force definition in that year. In their report for 2025 they state “this change put upward pressure on full-time employment rates among undergraduates and downward pressure on participation” which means that it is not possible to compare directly with earlier years (Social Research Centre, 2026b). The present study therefore represents the methodological change explicitly in the forecasting model rather than treating the series as fully homogeneous.

The industry context complicates the picture even further. Jobs and Skills Australia reported approximately 203,200 Software and Applications Programmers in February 2026, together with substantial employment in ICT Business and Systems Analysis and in Database, Systems Administration and ICT Security occupations (Jobs and Skills Australia, 2026). Cyber security has also been identified as an area of sustained and evolving skills demand in Australia (Jobs and Skills Australia, 2025). These indicators demonstrate continuing demand for digital capability, but they do not imply that new graduates enter professional roles

without friction. Graduate transitions are influenced by prior experience, career resources, work-integrated learning, professional networks and the ability to communicate capability to employers (Jackson, 2024; Jackson & Bridgstock, 2021; Jackson & Dean, 2023). The relevant question is therefore not whether the Australian ICT sector remains important, but whether employment outcomes for recent computing graduates are likely to improve at the same rate as demand within established occupations.

Previous machine-learning employability studies commonly predict individual graduate status, institutional outcomes or post-internship employability using classification or cross-sectional predictors, including Australian doctoral-graduate research (Aviso et al., 2021; Haque et al., 2024; Kahlik & Saleh Al-Hababi, 2024; Mewburn et al., 2020). The present study differs in its target, evidence base and evaluation design: it forecasts national annual study-area aggregates rather than individual employment probabilities; it uses the latest comparable five-year QILT panel with Computing and Information Systems as the focal field; it evaluates four outcomes against nonlinear benchmarks with held-out calendar years; and it interprets graduate trends alongside independently reported ICT occupational levels. The contribution is thus an application of established regularised regression and ensemble methods to transparent, time-ordered Australian educational planning. The study asks how computing graduate outcomes have developed, how the competing approaches perform in genuinely subsequent years, and what conditional 2027–2031 trajectories imply. Its contribution is empirical and methodological rather than a claim to invent a new machine-learning algorithm or extend employability theory.

METHODOLOGY

The study adopted a secondary quantitative design using publicly available Australian data. The primary source was the Quality Indicators for Learning and Teaching Graduate Outcomes Survey. The study area tables provide the annual observations for 21 undergraduate study areas from 2021 to 2025 (Social Research Centre, 2023, 2025, 2026b). For each study area and year, the panel records full-time employment, overall employment, participation and median annual salary, producing 105 field-year observations. Earlier Computing and Information Systems results for 2019 and 2020 were retained only for descriptive historical context and were not required to define the principal 2021 to 2025 modelling panel. The 2025 Employer Satisfaction Survey provided complementary evidence on employer assessments of Information Technology graduate capability (Social Research Centre, 2026a). Current occupational indicators were obtained from Jobs and Skills

Australia profiles available in 2026 (Jobs and Skills Australia, 2026). Table 1 summarises the role of each source in the analysis.

The focal study area is 'Computing and information systems', the corresponding QILT undergraduate category for the broad field of Information Technology. Its 2025 national observations were 65.3% full-time employment, 79.2% overall employment, 88.7% participation and AUD 80,000 median full-time salary (Social Research Centre, 2026b). Of full-time-employed graduates in this area, 75.8% worked in managerial or professional occupations. The 2025 Employer Satisfaction Survey provides complementary employer ratings of technical, adaptive, foundation, collaborative and employability capability (Social Research Centre, 2026a). These ratings and Jobs and Skills Australia occupational profiles are used solely to contextualise forecasts. The observation and prediction units remain QILT study-area-year records; the results therefore refer to aggregate rates and medians, never to a particular graduate's probability of securing work.

Four outcomes were modelled separately: full-time employment, overall employment and labour-force participation (all expressed as percentages), and nominal median full-time salary (Australian dollars). The ridge model included a common time trend, one-hot study-area effects, interactions between each study area and year, and an indicator for the 2025 change in QILT labour-force definitions. Time was counted from 2021. The ridge regularisation penalty constrained differences between field-specific trends (Sarker, 2021). Features were standardised inside each training fold. Computing and Information Systems predictions were generated directly by supplying that study-area label and each forecast year to the trained model, with the 2025 regime indicator active. The other 20 fields informed estimation but were not averaged into the reported forecasts. The 2025 definition indicator is informative as a sensitivity adjustment, although a single post-change year is insufficient to identify a lasting definition effect separately from wider conditions (Social Research Centre, 2026b).

Ridge regression was evaluated against random forest and gradient boosting using nested, time-ordered validation (Bergmeir et al., 2018; Cerqueira et al., 2020). In the outer tests, the model predicted 2024 after fitting on 2021–2023, and predicted 2025 after fitting on 2021–2024. For each ridge training period, the regularisation penalty was selected from 42 logarithmically spaced settings between 0.01 and 10,000 by expanding-window, one-year-ahead validation within the training years. The earlier fold trained on 2021–2022 and tested 2023; the later fold trained on 2021–2023 and tested 2024, when that year was eligible. All preprocessing and tuning were confined to the respective training data. The random forest used 300 trees and a minimum leaf size of two (Probst et al., 2019);

gradient boosting used 200 estimators, depth two and a learning rate of 0.03. Every model received the same predictors. Performance was measured as mean absolute error (MAE), expressed in percentage points for rates and Australian dollars for salary. The final ridge models were tuned chronologically and fitted to all 105 field-year observations, with outcome-specific penalties of 89.376, 63.808, 63.808 and 4.307, respectively. The 2027–2031 planning horizon extends two to six years beyond the final observed year, materially beyond the one-year validation tests.

To communicate forecast uncertainty, exploratory empirical error envelopes were calculated from the 90th percentile of absolute ridge prediction errors across all 21 fields in the independent 2024 and 2025 holdouts. Their width increases with the square root of the number of years beyond 2025; rates are restricted to 0–100% and salaries to non-negative values. Because only two one-year holdouts inform these ranges, they are indicative sensitivity bands rather than statistically calibrated 90% prediction intervals. Structural or policy changes could produce outcomes outside them. The full errors, tuning settings and forecasts are provided in the executable Colab notebook.

The five-year panel pools 21 fields to stabilise estimation, yet each field contributes only five annual observations, and inter-field similarities do not create additional independent calendar years. Thus the 2024 and 2025 holdouts provide tests of one-year prediction rather than direct tests of 2027–2031 accuracy. The 2027 start was selected to show a medium-term planning scenario, with the six-year distance to 2031 explicitly acknowledged. The empirical error ranges reflect pooled study-area errors and an assumed expansion with horizon, while the 2025 classification change and future economic conditions introduce further uncertainty. As future QILT releases become available, the appropriate evaluation is rolling re-estimation and comparison of forecast distributions with subsequently observed outcomes.

The outcomes also differ in how they should be read. Full-time and overall employment rates depend on the survey-defined reference population, and participation is affected by the labour-force classification applied to respondents. The salary outcome is a median among eligible full-time-employed respondents, so an increase can reflect changes in the composition of employed graduates as well as wage growth. An aggregate rise in salary therefore cannot establish that each computing graduate experiences a higher wage. The panel treats each published field-year estimate equally because comparable response-count weights and sampling variances for every outcome were not supplied in the modelling data. As a result, model errors describe discrepancies between reported aggregate estimates and predicted aggregates, not uncertainty arising from the Graduate

Outcomes Survey sampling process itself. A future extension using official survey standard errors, response denominators and additional years would separate sampling uncertainty from model and structural uncertainty more convincingly.

Table 1. Public Australian datasets used here

Source	Population or unit	Variables used
QILT GOS 2021 to 2025	21 undergraduate study areas; 105 field-year observations	Full-time employment, overall employment, participation, median salary
QILT GOS historical tables	Computing and Information Systems, 2019 to 2020	Historical employment trajectory
QILT ESS 2025	Employers of Australian higher education graduates	Foundation, adaptive, collaborative, technical and employability ratings
Jobs and Skills Australia 2026	Core Australian ICT occupations	Employment level, annual growth, median weekly earnings

RESULTS AND DISCUSSION

Figure 1 presents the observed short-term employment trajectory for Australian Computing and Information Systems undergraduates. Full-time employment was 75.9% in 2019, 67.9% in 2021, 76.6% in 2022, 74.4% in 2023, 67.8% in 2024 and 65.3% in 2025. Overall employment was 82.9% in 2019 and 79.2% in 2025. The drop between the same-definition years 2022 and 2024 indicates weaker immediate full-time transitions following the post-pandemic peak. QILT's 2025 revised labour-force definition placed upward pressure on full-time employment and downward pressure on participation (Social Research Centre, 2026b). Consequently, the full extent of the 2024–2025 difference cannot be isolated as a labour-market change; the 2025 observation is shown as a methodological discontinuity rather than as strictly like-for-like evidence.

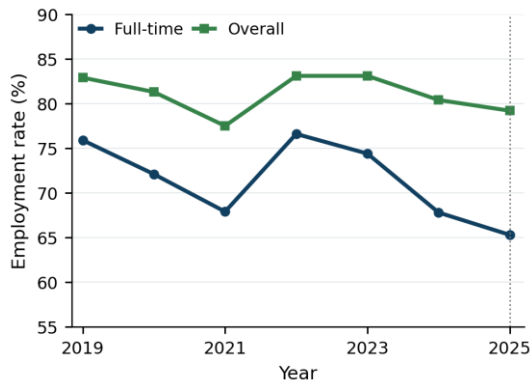


Figure 1. Observed Computing graduate employment, 2019–2025

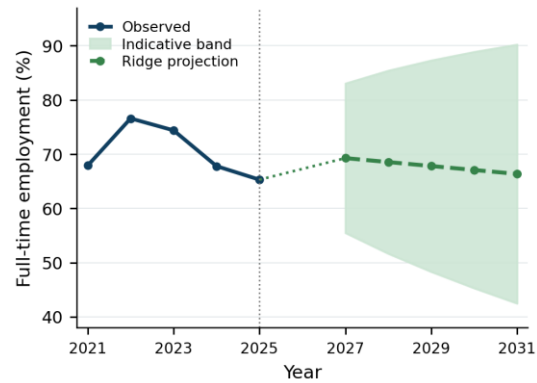


Figure 2. Full-time employment forecast and indicative envelope, 2027–2031

The national series distinguishes the short post-graduation transition from the established occupational labour market. Computing and Information Systems graduates in 2025 recorded a comparatively modest full-time employment rate alongside a relatively high median salary and a substantial proportion employed in managerial or professional roles (Social Research Centre, 2026b). This contrast is consistent with heterogeneous transitions, where opportunities and returns differ across graduates and job types (Clarke, 2018; Donald et al., 2019; Tomlinson, 2017). These aggregated indicators do not establish which individuals experienced delays, nor identify employers' recruitment mechanisms.

Figure 2 reports a revised, strictly time-validated ridge projection for the focal QILT category: 69.3% full-time employment in 2027, 68.5% in 2028, 67.8% in 2029, 67.1% in 2030 and 66.4% in 2031. The central estimate for 2027 is higher than the 2025 observation of 65.3%, yet it falls by roughly 2.9 percentage points from 2027 to 2031. Across that same stretch, the approximate 90% uncertainty band widens, shifting from 55.5–83.1% in 2027 to 42.5–90.2% by 2031. This comparatively wide band is important for interpretation: the direction and magnitude of long-horizon change cannot be determined with reliability from the point estimate alone, especially when economic conditions, AI adoption, and recruitment patterns differ. The extrapolation characterizes a conditional national study-area rate, not the future stock of Australian ICT jobs. A further sensitivity analysis re-estimated the ridge model using only 2021–2024, which also omits the year that introduced the revised GOS labour-force definition. In the excluded-year specification, full-time employment is projected at 72.3% for 2027 and 70.9% for 2031, compared with 69.3% and 66.4% when all five years are included. The corresponding overall-employment projections for 2031 are 79.2% and 78.0%, respectively, and the 2031 nominal salary estimates are approximately AUD 99,830 and AUD 100,196. These results indicate that the employment outlook depends materially on whether 2025

is included. Because excluding the year removes information about real labour-market changes while also reflecting the survey redefinition, the comparison identifies model sensitivity rather than isolating a definitional effect.

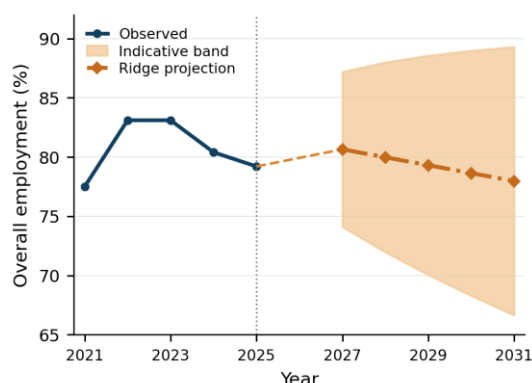


Figure 3. Overall employment forecast and indicative envelope, 2027–2031

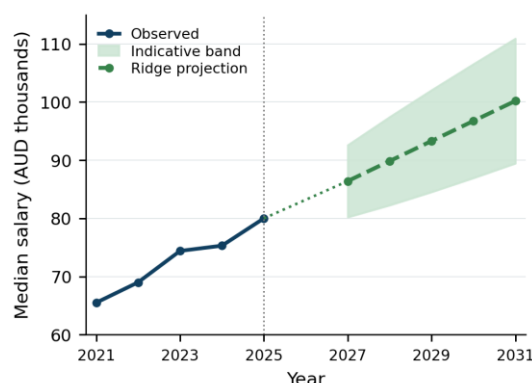


Figure 4. Nominal salary forecast and indicative envelope, 2027–2031

Overall employment remains comparatively stable in the revised projection (Figure 3): 80.6% in 2027, 80.0% in 2028, 79.3% in 2029, 78.6% in 2030 and 78.0% in 2031. The 2031 approximate 90% envelope spans 66.6–89.3%, illustrating substantial uncertainty even when the fitted trend is modest. Overall employment covers a broader set of labour-market arrangements than full-time work; it should not be treated as a direct indicator of graduate job quality, professional alignment or secure career progression (Römgens et al., 2020; Small et al., 2018). The model also projects labour-force participation at 90.2% (indicative range 82.3–98.1%) in 2027 and 89.4% (75.7–100.0%) in 2031.

The observed median annual salary for full-time-employed Computing and Information Systems undergraduates rose from AUD 65,500 in 2021 to AUD 80,000 in 2025 (Social Research Centre, 2023, 2025, 2026b). The time-validated ridge model projects nominal medians of AUD 86,407 in 2027, AUD 89,854 in 2028, AUD 93,301 in 2029, AUD 96,749 in 2030 and AUD 100,196 in 2031 (Figure 4). Its indicative 2031 error envelope is approximately AUD 89,457–110,935. Salary and employment-rate forecasts describe different aggregate quantities and therefore can follow different trends without implying any causal trade-off. These amounts are nominal, with no forecast inflation adjustment, and the sample of graduates earning full-time salaries may change in composition.

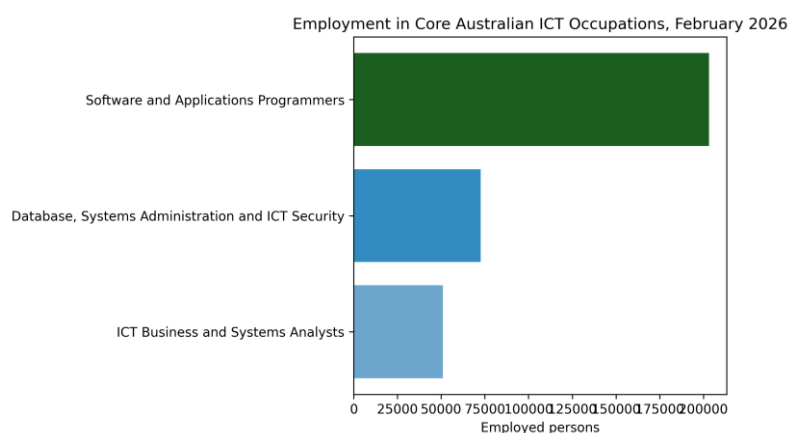


Figure 5. Employment in core Australian ICT occupations, February 2026

Jobs and Skills Australia provides a contemporaneous but distinct perspective (Figure 5). Its February 2026 occupational profiles reported approximately 203,200 Software and Applications Programmers, 51,000 ICT Business and Systems Analysts, and 72,600 people in Database, Systems Administration and ICT Security occupations (Jobs and Skills Australia, 2026). These are stocks of workers at different career stages, whereas QILT measures graduates about four to six months after completion. Their juxtaposition documents concurrent occupational scale and more variable entry outcomes; it establishes neither a causal explanation of changes in graduate employment nor a direct predictor in the fitted panel. Different timing, populations and measurement methods limit quantitative comparison.

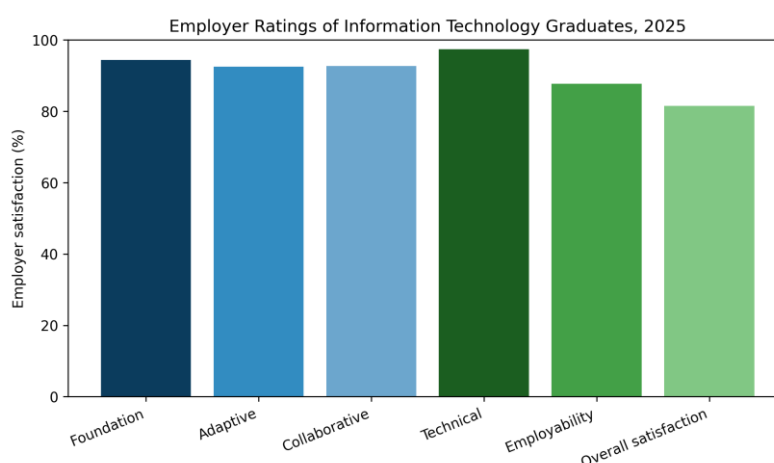


Figure 6. Employer satisfaction ratings of Information Technology graduates, 2025

Table 2. Computing and Information Systems ridge forecasts with indicative empirical error envelopes, 2027–2031

Year	Full-time employment % (range)	Median salary AUD (range)
2027	69.3 (55.5–83.1)	86,407 (80,207–92,607)
2028	68.5 (51.7–85.4)	89,854 (82,260–97,448)

Year	Full-time employment % (range)	Median salary AUD (range)
2029	67.8 (48.3–87.3)	93,301 (84,533–102,070)
2030	67.1 (45.3–88.9)	96,749 (86,945–106,552)
2031	66.4 (42.5–90.2)	100,196 (89,457–110,935)

Table 2 reports full-time employment and nominal salary projections with the associated indicative empirical error envelopes. The overall employment projection is presented in Figure 3, while all four forecast series, including participation, and the underlying validation results are available in the accompanying Colab notebook. The other 20 study areas contribute information when the models are fitted, but the published estimates refer exclusively to Computing and Information Systems. The breadth of the empirical envelopes supports interpretation as planning scenarios requiring annual updates, rather than precise future outcomes or causal claims.

The out-of-time results, displayed in Figure 7 and Table 3, give MAE for every target, model and held-out year. For full-time employment, ridge errors were 6.669 percentage points in 2024 and 2.476 in 2025, compared with 6.086 and 3.130 for random forest and 5.678 and 4.201 for gradient boosting. For overall employment the ridge errors were 3.100 and 1.463 points; for participation, 0.883 and 4.408 points; and for salary, AUD 2,647 and AUD 1,547. Rankings differ between years and targets. Tree ensembles provided useful short-horizon comparators, while ridge offered an explicit extrapolating temporal structure. The small number of holdout years and the 2025 definition change limit the strength of any model-superiority claim.

The fuller model comparison highlights why performance needs to be examined outcome by outcome. For overall employment in 2024, gradient boosting recorded 2.291 percentage points of MAE, compared with 2.586 for random forest and 3.100 for ridge; in 2025, ridge recorded the smallest error at 1.463 points. Participation presents an especially important caution: the 2024 ridge error was 0.883 points but the 2025 error was 4.408 points, in the year when QILT introduced its revised labour-force definition. For salary, ridge performed better than the two ensemble benchmarks in both holdouts, with errors of approximately AUD 2,647 and AUD 1,547. These results support the use of multiple benchmarks and separate error reporting for each target. They do not demonstrate that the chosen functional form remains superior several years after the last observation, and they provide only limited information about the frequency with which any longer-horizon uncertainty band will contain future observations.

Table 3. Out-of-time mean absolute error (percentage points; AUD for salary), 2024 and 2025

Outcome	Model	2024	2025
Full-time employment	Ridge	6.669	2.476
Full-time employment	Random Forest	6.086	3.130
Full-time employment	Gradient Boosting	5.678	4.201
Overall employment	Ridge	3.100	1.463
Overall employment	Random Forest	2.586	1.921
Overall employment	Gradient Boosting	2.291	2.369
Participation	Ridge	0.883	4.408
Participation	Random Forest	0.687	4.122
Participation	Gradient Boosting	0.881	4.039
Median salary	Ridge	2,647	1,547
Median salary	Random Forest	4,431	3,809
Median salary	Gradient Boosting	4,515	3,617

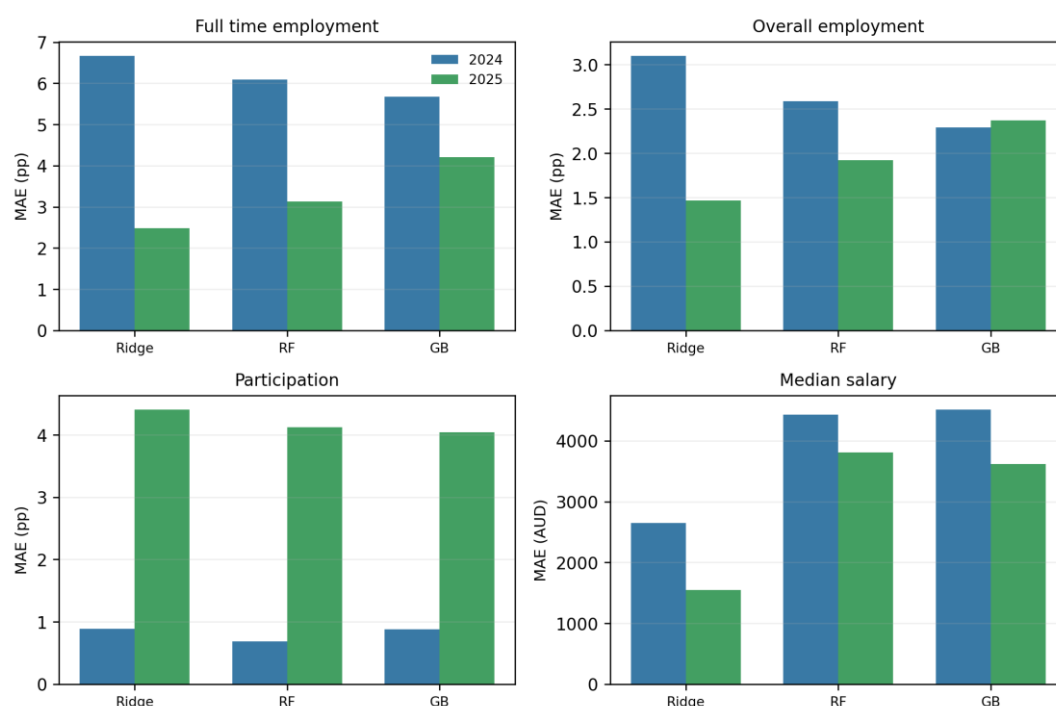


Figure 7. Time-block validation for four outcomes: model mean absolute errors, 2024 and 2025

The 2025 Employer Satisfaction Survey reports strong technical, foundation, adaptive and collaborative ratings for Information Technology graduates, with somewhat lower overall satisfaction and employability ratings (Social Research Centre, 2026a). Such differences support the practical relevance of authentic teamwork, professional communication and work-integrated learning, as suggested by prior employability research (Jackson, 2020, 2024; Jackson & Dean, 2023; Succi & Canovi, 2020). They are contextual observations from a distinct sample, not variables in the forecasting model and not evidence that particular teaching interventions caused the observed changes in national employment rates.

The implications differ by level of action. For institutional policy, regular QILT monitoring can inform career-support priorities while distinguishing employment

rates, salary and participation and documenting definition changes. For curriculum practice, work-integrated learning, authentic team projects, technical communication, professional portfolios and feedback from employers warrant local evaluation (Howard, Dasore, Haque, Kuttala, & Al Zein, 2026; Jackson et al., 2024; Jackson & O'Connor, 2026; Oliver & Jorre de St Jorre, 2018). AI-supported conceptual learning can also be evaluated separately from employment effects (Howard, Dasore, Haque, Kuttala, Al Zein, & Dhungana, 2026). The national panel provides a rationale for evaluating such practices, rather than measuring their causal effects. For further research, longer QILT panels and linked institution- or graduate-level data could support subgroup analysis, improved interval calibration and direct tests of factors influencing graduate transitions. Any individual-level analytics would require suitable safeguards and transparent human oversight (Barredo Arrieta et al., 2020; Lundberg et al., 2020).

The study has several important limitations. Its 105 field-year observations represent only five annual time points across 21 study areas, limiting estimation of study-area slopes and longer-horizon reliability. The 2022 post-pandemic recovery, followed by the 2025 labour-force-definition change, may distort trends; the sole revised-definition year cannot separate definitional and economic effects. Chronological evaluation reduces information leakage, yet the two one-year holdouts offer limited evidence for projections to 2031. Approximate error envelopes are exploratory sensitivity ranges based on observed short-horizon errors and an assumed increase with forecast lead time, rather than calibrated long-horizon prediction intervals. Aggregate rates cannot be interpreted as individual employment probabilities, and employer satisfaction and ICT occupation profiles refer to different populations. The salary series is nominal and excludes inflation adjustments. The forecasts should therefore be updated annually and interpreted as conditional scenarios for institutional planning rather than deterministic or causal estimates.

CONCLUSION

This study analysed national QILT Computing and Information Systems graduate outcomes for 2021–2025 using regularised linear regression and nonlinear benchmarks with chronological validation. In the revised conditional scenario, full-time employment is approximately 69.3% in 2027 and 66.4% in 2031, while nominal median salary rises from about AUD 86,407 to AUD 100,196. An all-target validation table and widening empirical error envelopes make the model's substantial uncertainty visible. The contrast between weaker immediate graduate entry and substantial established ICT employment is descriptive rather than causal. These findings support evidence-informed employability monitoring, targeted

career development and curriculum evaluation, with further longitudinal evidence needed to assess mechanisms and the reliability of medium-term projections.

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