

PREDICTING EMPLOYMENT OUTCOMES OF AUSTRALIAN INFORMATION TECHNOLOGY GRADUATES USING MACHINE LEARNING

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ABSTRACT

Graduate employment outcomes in information technology have become a major issue for Australian higher education because the strong growth in digital work is not necessarily translating into immediate professional employment for new graduates. In this study, we present a machine learning prediction of the overall employment outcomes for Australian Computing and Information Systems graduates based on the latest publicly available national evidence. We constructed a longitudinal panel from Quality Indicators for Learning and Teaching Graduate Outcomes Survey data of multiple undergraduate study areas over the last few years. We also modelled full time employment, overall employment, participation and median salary using regularised regression with study area specific time effects and an indicator that accounts for changes in survey definitions. Random forest and gradient boosting models were used as prediction models for time block validation. The results show a weakening in immediate full-time employment among Computing and Information Systems graduates in the face of an expanding graduate salary base and continued demand for the most demanding ICT fields. Our forecasts indicate that competitive entry is likely to remain on a strong footing in the medium term and that the graduate salary improves. These results demonstrate an ongoing disconnect between demand for jobs and graduate transition outcomes, and this has implications for industry engagement, work integrated learning, authentic assessment, career development and data informed employability support in Australian higher education.

Keywords: graduate employability, information technology, machine learning, higher education, employment forecasting, Australia

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; Römgers, 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, Rothwell, Glover, & Lambert, 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, 2026a). 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 make it possible to examine the transition from computing education into professional work using observed outcomes rather than relying only on perceptions of employability. Australian research similarly shows that graduate outcomes are shaped by educational experiences, work-integrated learning and career development activities, not solely by disciplinary knowledge or general economic conditions (Jackson & Rowe, 2023; Jackson, Lambert, Sibson, Bridgstock, & Tofa, 2024).

Recent national results reveal a mixed trajectory. Full time employment among Computing and Information Systems undergraduates was 75.9% in 2019, 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. Over the more recent period, median salary increased from AUD 65,500 in 2021 to AUD 80,000 in 2025 (Social Research Centre, 2023, 2025, 2026a). Interpretation of the 2025 figure requires care because the GOS introduced a revised labour force definition in that year. The 2025 report notes that this change placed upward pressure on undergraduate full-time employment rates and downward pressure on participation, which limits direct comparability with earlier observations (Social Research Centre, 2026a). 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 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.

This study addresses a gap between descriptive reporting of graduate outcomes and forward-looking analysis of the Australian computing graduate transition. It constructs a multi-year, multi-field higher education panel and applies machine learning models to estimate future aggregate outcomes beyond the latest observed GOS year. Machine learning has increasingly been used in employability research, including graduate employment classification, post-internship employability prediction, institutional-attribute modelling and analysis of non-academic employment opportunities for Australian doctoral graduates (Aviso et al., 2021; Haque, Quek, Ting, Goh, & Hasan, 2024; Kahlik & Saleh Al-Hababi, 2024; Mewburn, Grant, Suominen, & Kizimchuk, 2020). The study addresses three questions: how have Australian Computing and Information Systems graduate outcomes changed in recent years; which predictive approach is most appropriate for time ordered forecasting with a short aggregate panel; and what trajectory is indicated for full-time employment, overall employment and median salary from 2027 to 2031? The contribution is a reproducible educational analytics framework that combines national graduate outcomes, model validation and contemporary ICT occupation evidence while avoiding the assumption that industry growth translates directly into equivalent graduate employment gains.

METHODS

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. Published study area tables were collated to obtain annual observations for 21 undergraduate study areas from 2021 to 2025 (Social Research Centre, 2023, 2025, 2026a). 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, 2026b). 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 was Computing and Information Systems, which corresponds to the broad Information Technology field in QILT reporting. In 2025, the observed values were 65.3% full-time employment, 79.2% overall employment, 88.7% participation and a median full-time salary of AUD 80,000 (Social Research Centre, 2026a). QILT also reported that 75.8% of Computing and Information Systems undergraduates employed full-time were working in managerial or professional occupations. Employer Satisfaction Survey results were used as complementary indicators of work readiness through employer ratings of foundation, adaptive, collaborative, technical and employability skills (Social Research Centre, 2026b). These measures were not treated as interchangeable with employment status. This distinction follows contemporary employability scholarship, which argues that realised employment is only one manifestation of a broader capability that also depends on context and opportunity (Clarke, 2018; Small, Shacklock, & Marchant, 2018). Jobs and Skills Australia indicators were likewise used for contextual interpretation rather than as graduate-level labels or causal predictors.

For forecasting, study area was represented through one-hot encoded categorical effects. A time variable measured years since 2021 and was interacted with each study area indicator so that each field could follow a distinct temporal trajectory. Regularisation was used to constrain unstable field-specific slopes toward the overall pattern. A binary indicator identified 2025 and future observations under the revised GOS labour force definition. Separate ridge regression models were fitted for full-time employment, overall employment, participation and median salary, with the regularisation penalty selected from a logarithmically spaced grid by cross validation. Ridge regression was chosen as the principal forecasting model because its regularised parametric structure can extrapolate beyond the observed time range, whereas tree-based ensembles primarily partition combinations already represented in the training data. The modelling choice was therefore determined by the forward forecasting objective rather than by in sample goodness of fit alone, consistent with the principle that algorithm selection should reflect the intended predictive task (Sarker, 2021).

Random forest and gradient boosting regressors were retained as nonlinear predictive benchmarks. Random forest performance is sensitive to tuning choices such as the number of trees and minimum node size, so fixed reproducible settings were used and performance was evaluated out-of-time (Probst, Wright, & Boulesteix, 2019). To reduce temporal leakage, the study did not rely on a conventional random train test split. Instead, time-block validation trained each model on observations preceding the holdout year and evaluated predictions separately for 2024 and 2025. Mean absolute error was the principal metric because it can be interpreted directly in percentage points for employment rates. After validation, the ridge model was refitted to all 105 observations and used to generate the principal 2027 to 2031 forecasts. These forecasts are conditional model estimates rather than official QILT or Jobs and Skills Australia projections. Their purpose is to provide an evidence-based baseline for higher education planning and to identify the direction and magnitude of risk implied by the observed national series.

Table 1. Public Australian datasets used in the analysis

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 of Australian Computing and Information Systems undergraduates from 2019 to 2025. Full time employment declined from 75.9% in 2019 to 67.9% in 2021, recovered to 76.6% in 2022 during the post-pandemic employment rebound, and then fell to 74.4% in 2023, 67.8% in 2024 and 65.3% in 2025. Overall employment followed the same broad direction but was less volatile, decreasing from 82.9% in 2019 to 79.2% in 2025. The 2025 observation is marked separately because QILT changed the labour force definition in that year. As the revised definition placed upward pressure on reported undergraduate full-time employment, the 2025 decline cannot be explained simply as an artefact of a stricter definition (Social Research Centre, 2026a). The series therefore provides evidence of a genuine weakening in immediate full-time employment outcomes, although the magnitude of the change should be interpreted cautiously because the definition break prevents perfect year-to-year comparability.

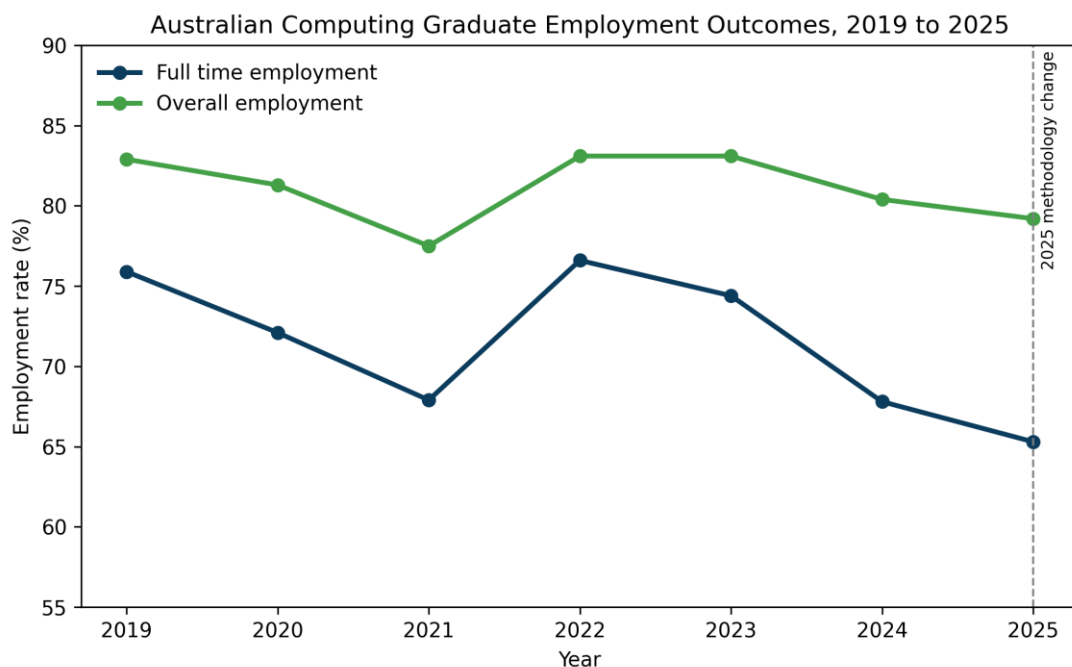


Figure 1. Australian Computing graduate employment outcomes, 2019 to 2025

The employment series demonstrates why aggregate ICT demand and graduate transition outcomes should be analysed separately. In 2025, Computing and Information Systems recorded a comparatively modest full-time employment rate while maintaining an above average median salary and a high proportion of full-time employed graduates in managerial or professional occupations (Social

Research Centre, 2026a). This combination suggests a segmented transition rather than a uniformly weak employment market. Graduates who secure appropriate professional positions appear to receive relatively strong returns, while a sizeable share of the cohort requires longer to obtain full-time work. Such a pattern is consistent with employability research that emphasises the role of professional identity, experience, social resources and access to opportunity in converting educational achievement into employment outcomes (Clarke, 2018; Donald, Baruch, & Ashleigh, 2019; Tomlinson, 2017).

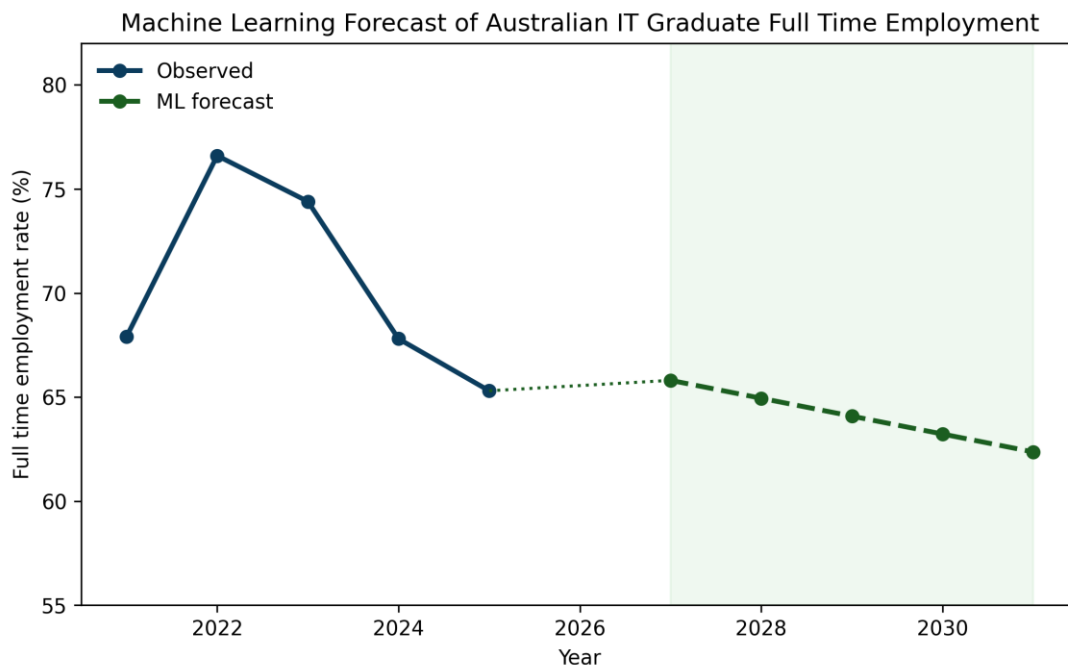


Figure 2. Machine learning forecast of Australian IT graduate full-time employment, 2027 to 2031

Figure 2 presents the principal ridge forecast for full-time employment from 2027 onward. Following the observed 65.3% rate in 2025, the model estimates 65.8% in 2027, 64.9% in 2028, 64.1% in 2029, 63.2% in 2030 and 62.4% in 2031. The dotted bridge between the latest observed value and 2027 indicates that 2026 is not included in the principal reporting horizon. The forecast represents continuation of the recent Computing and Information Systems trajectory after regularisation across all 21 study areas; it should not be interpreted as a forecast that total Australian ICT employment will contract. Graduate full-time employment is affected by entry-level competition, further study, recruitment practices, prior work experience and the timing of transitions into professional roles as well as by total occupational demand. Previous research similarly shows that work-integrated learning, co-curricular activity and paid work experience can influence graduate outcomes independently of disciplinary study alone (Jackson & Bridgstock, 2021; Jackson & Rowe, 2023).

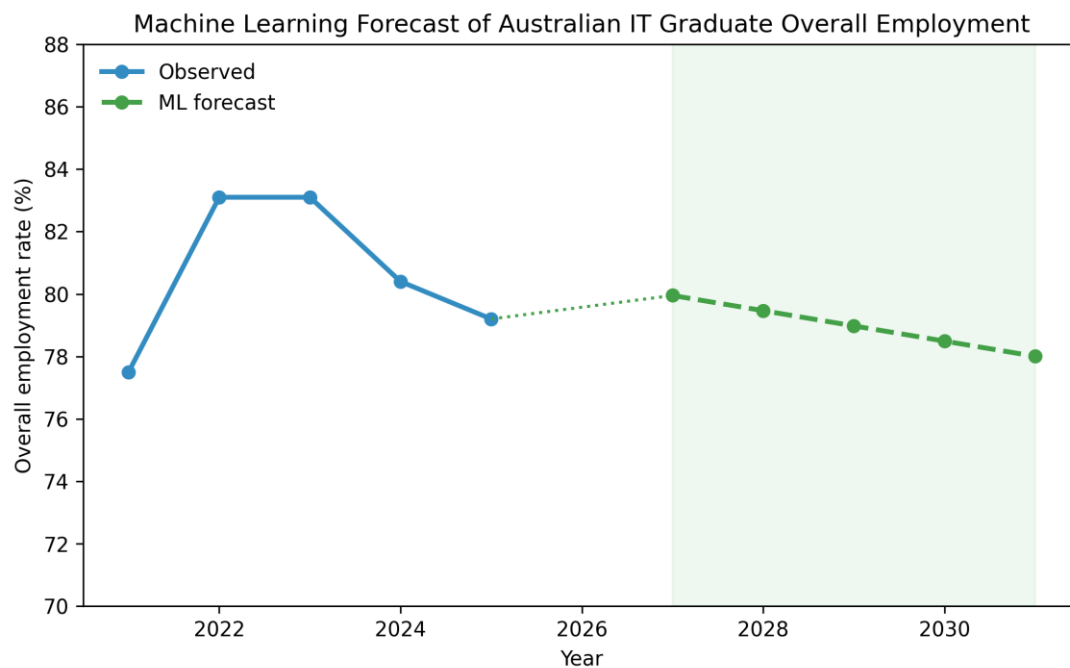


Figure 3. Machine learning forecast of Australian IT graduate overall employment, 2027 to 2031

Overall employment is forecast to remain more stable than full-time employment. Figure 3 indicates an overall employment rate of 80.0% in 2027, followed by 79.5% in 2028, 79.0% in 2029, 78.5% in 2030 and 78.0% in 2031. The smaller decline relative to full-time employment suggests that part time, casual and transitional work may continue to form an important part of early career outcomes. For higher education, this distinction matters because the binary condition of being employed does not establish whether the position is stable, professional, appropriately skilled or aligned with the graduate's qualification. The result is consistent with multidimensional accounts of employability that separate individual capability from the quality and context of realised employment (Römgers et al., 2020; Small et al., 2018).

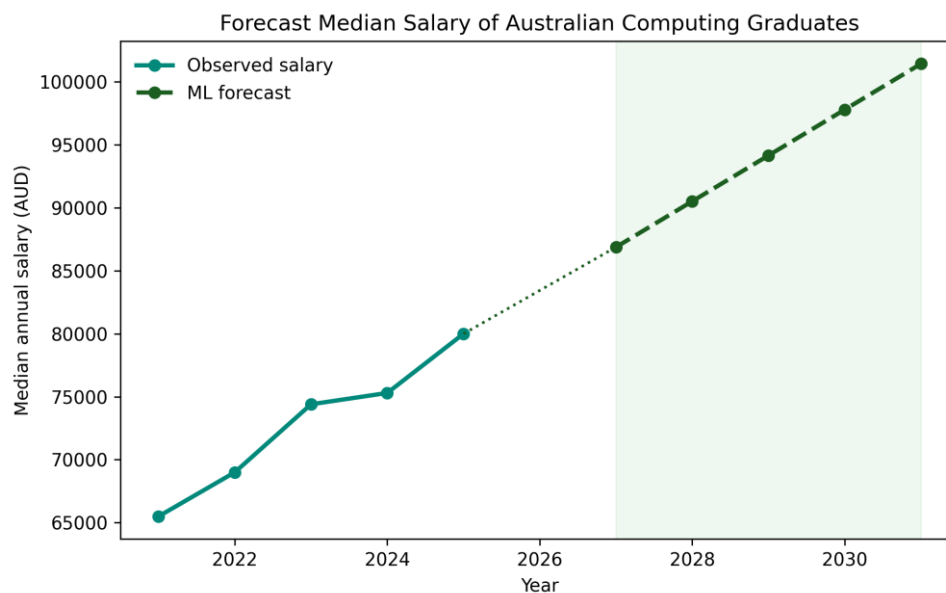


Figure 4. Forecast median salary of Australian Computing graduates, 2027 to 2031

Salary follows a different trajectory. Figure 4 shows that the median salary for Computing and Information Systems graduates increased from AUD 65,500 in 2021 to AUD 69,000 in 2022, AUD 74,400 in 2023, AUD 75,300 in 2024 and AUD 80,000 in 2025 (Social Research Centre, 2023, 2025, 2026a). The model forecasts approximately AUD 86,900 in 2027, AUD 90,500 in 2028, AUD 94,200 in

2029, AUD 97,800 in 2030 and AUD 101,400 in 2031. Rising salary alongside softer employment rates is not inherently contradictory. It can occur when demand remains strong for skilled professional roles while access to those roles becomes more selective at graduate entry. This interpretation is consistent with the 2025 GOS pattern, in which Computing and Information Systems combined a comparatively modest full-time employment rate with an above average graduate salary (Social Research Centre, 2026a). The salary forecast should nevertheless be read as a nominal trend estimate; the model does not adjust future values for inflation.

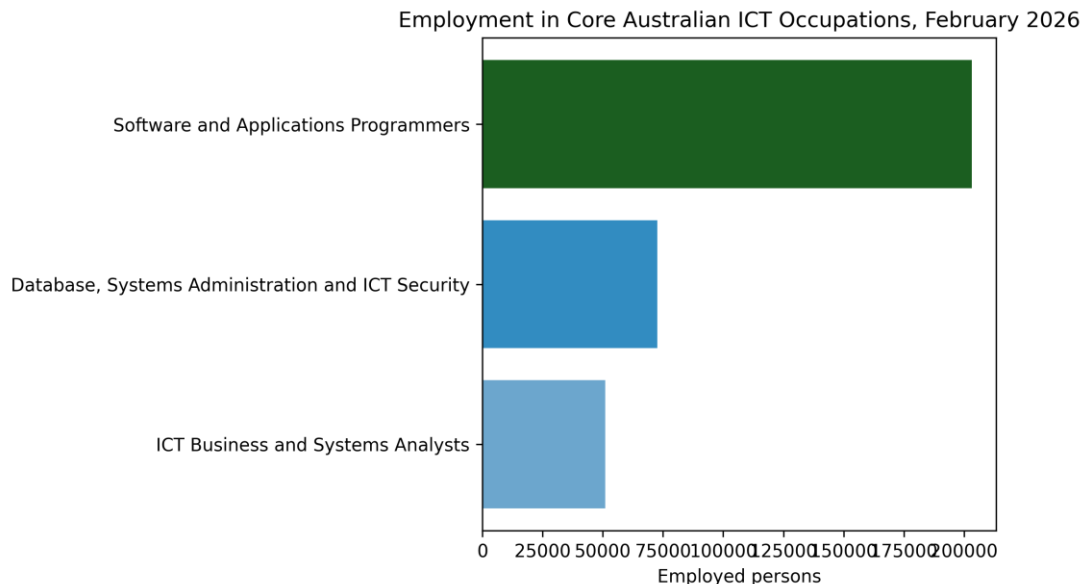


Figure 5. Employment in core Australian ICT occupations, February 2026

Current industry indicators provide an external check on this interpretation. Figure 5 shows that Software and Applications Programmers accounted for approximately 203,200 employed persons in the February 2026 Jobs and Skills Australia profile and recorded annual employment growth of about 13,700. ICT Business and Systems Analysts accounted for approximately 51,000 workers, while Database, Systems Administration and ICT Security occupations accounted for approximately 72,600 (Jobs and Skills Australia, 2026). Jobs and Skills Australia has also identified cyber security as an area of sustained and changing skills demand (Jobs and Skills Australia, 2025). These indicators are consistent with continued expansion in important ICT occupations even while immediate graduate employment outcomes have weakened. They therefore reinforce the distinction between demand within the established ICT workforce and the conditions faced by graduates attempting to enter that workforce.

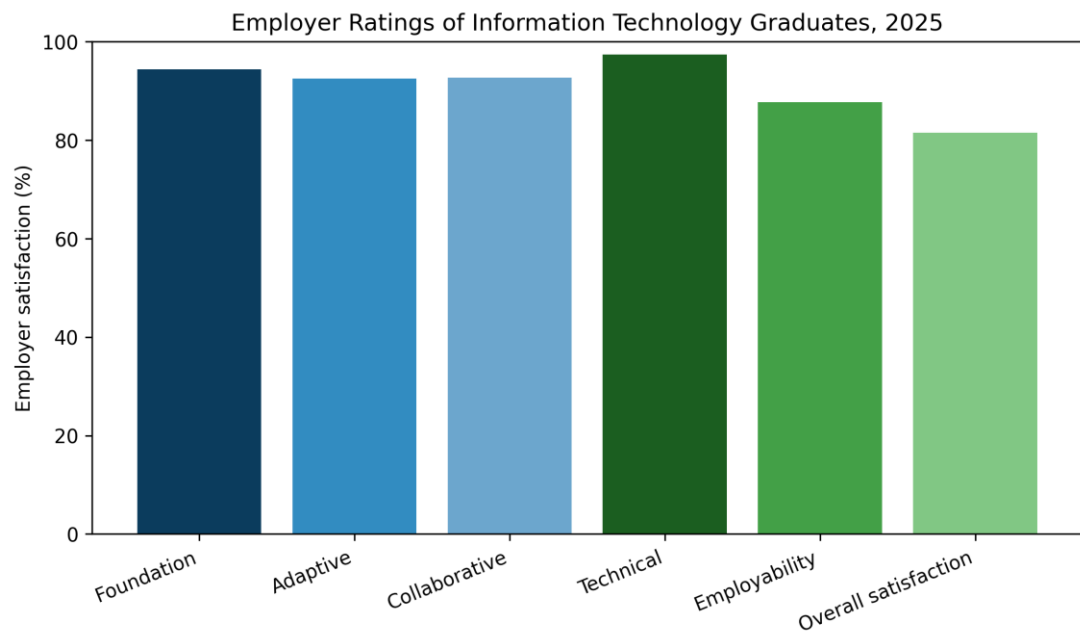


Figure 6. Employer ratings of Information Technology graduates, 2025

Table 2. Machine learning forecasts for Australian Computing graduates, 2027 to 2031

Year	Full time employment (%)	Median salary (AUD)
2027	65.8	86,881
2028	64.9	90,520
2029	64.1	94,160
2030	63.2	97,799
2031	62.4	101,439

Table 2 summarises the principal forecast horizon. The most important result is not evidence that Information Technology qualifications are losing value, but evidence of a persistent separation between graduate entry outcomes and the strength of established ICT occupations. The model forecasts a gradual reduction in immediate full-time employment from 65.8% in 2027 to 62.4% in 2031 while median salary continues to increase. One plausible interpretation is that employers continue to compete for experienced software, security and systems capability while maintaining demanding thresholds for entry-level recruitment. The public data cannot test that mechanism directly, so it should be treated as an interpretation rather than a causal conclusion. For universities, the practical implication is that positive occupation growth should not be assumed to guarantee an easy transition into full-time professional work. Recent Australian research similarly indicates that work-based learning, mentoring and structured employability development can strengthen graduate outcomes and students' capacity to convert educational achievement into employment (Jackson, 2024; Jackson et al., 2024; Jackson & O'Connor, 2026).

The validation results support the use of regularised regression for forward projection while also demonstrating the uncertainty of the forecasting problem. Figure 7 compares ridge regression, random forest and gradient boosting under time-block holdouts. For 2024, gradient boosting achieved the lowest mean absolute error at approximately 5.68 percentage points, followed by random forest at 6.17 and ridge at 10.00. In the 2025 holdout, random forest performed best at approximately 3.09 points, ridge at 3.31 and gradient boosting at 4.27. The tree models were therefore competitive for prediction within or near the observed range. Ridge was nevertheless retained for the 2027 to 2031 forecasts because its regularised field-specific temporal structure supports controlled extrapolation, whereas tree ensembles do not naturally extend linear or monotonic trends beyond the values represented during training. The mixed

validation ranking also cautions against presenting any single model as decisively superior. Rather, it shows the importance of out-of-time testing and of matching model choice to the intended forecasting task (Probst et al., 2019; Sarker, 2021).

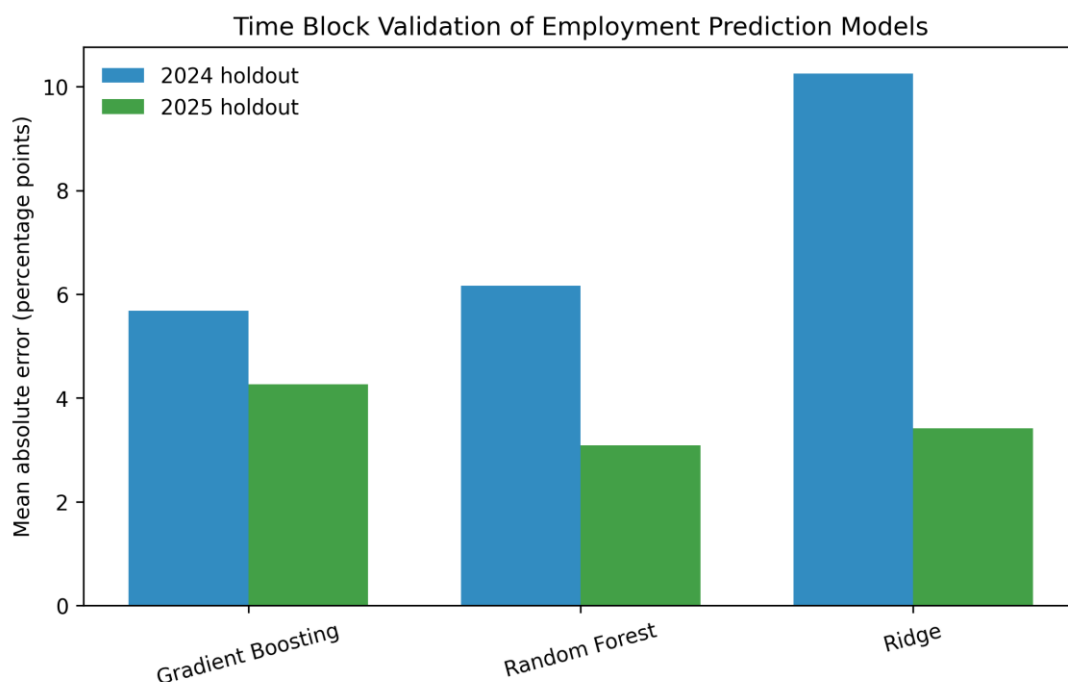


Figure 7. Time block validation of employment prediction models

Employer evidence helps clarify which elements of graduate transition are more directly open to educational intervention. In the 2025 Employer Satisfaction Survey, Information Technology graduates received strong ratings for technical, foundation, adaptive and collaborative skills, while employer ratings of employability and overall satisfaction were lower than the technical skills rating (Social Research Centre, 2026b). This pattern suggests that disciplinary competence remains essential but may not be sufficient for a smooth transition into professional work. Research comparing employer and student perceptions likewise shows strong employer emphasis on transferable and interpersonal capabilities (Succi & Canovi, 2020). Australian work-integrated learning research further indicates that workplace, project and international experiences can strengthen employability when they are deliberately designed and connected to reflection, feedback and professional practice (Hains-Wesson & Ji, 2020; Jackson, 2020, 2024; Jackson & Dean, 2023). For computing curricula, this supports authentic team projects, communication with non-technical stakeholders, portfolio development and repeated exposure to industry-style problem solving alongside technical learning.

The findings also have implications for educational technology and curriculum analytics. Higher education providers can use digital learning environments not only to monitor academic progress but also to make the development of professional capability more visible. Digital portfolios, authentic project repositories, competency maps, work-integrated learning records and structured reflective evidence can document how students apply disciplinary knowledge in contexts that resemble professional practice. Contemporary research recommends making graduate attributes explicit in curriculum and assessment and distributing employability development across the student experience rather than treating it as an intervention immediately before graduation (Oliver & Jorre de St Jorre, 2018; Jackson et al., 2024; Jackson & Meek, 2021; Jackson & O'Connor, 2026). At an institutional level, aggregate graduate outcome trends could be combined with curriculum and participation indicators to identify cohorts or subject areas that warrant additional career development support. Any predictive system used for consequential educational decisions would require transparent governance, validation and human oversight; explainable artificial intelligence research provides established methods for examining model behaviour and feature contributions (Barredo Arrieta et al., 2020; Lundberg et al., 2020).

Several limitations qualify the forecasts. First, the modelling dataset consists of aggregated study area observations rather than individual graduate records. The results therefore forecast national field level outcomes and cannot be interpreted as individual probabilities of employment. This differs materially from studies that train classifiers on graduate-level administrative or tracer data (Haque et al., 2024; Kahlík & Saleh Al-Hababi, 2024). Second, the core panel covers only five years and includes both the exceptional post-pandemic recovery of 2022 and the methodological break introduced in 2025. The structural indicator addresses the known definition change but cannot fully restore comparability, particularly because only one observed year is available under the revised definition (Social Research Centre, 2026a). Third, the linear extrapolation underlying the ridge forecasts is sensitive to structural changes. Economic conditions, migration settings, artificial intelligence adoption, recruitment practices and changes in course composition could all alter outcomes after 2025. Fourth, the Jobs and Skills Australia indicators describe the wider ICT workforce and are used only for contextual interpretation, not as causal predictors of graduate employment. Fifth, the salary forecasts are nominal and do not model inflation. The 2027 to 2031 estimates should therefore be interpreted as an evidence-based baseline scenario and updated when new GOS observations become available.

CONCLUSION

This study used the latest public Australian evidence available in August 2026 to examine and forecast employment outcomes for Information Technology graduates. The national series shows that short-term full-time employment among Computing and Information Systems graduates declined from its 2022 peak of 76.6% to 65.3% in 2025, while median salary increased to AUD 80,000 (Social Research Centre, 2026a). A regularised panel model forecasts full-time employment of approximately 65.8% in 2027 and 62.4% in 2031, while nominal median salary is projected to exceed AUD 100,000 by 2031. These estimates coexist with substantial employment and recent growth in major Australian ICT occupations (Jobs and Skills Australia, 2026). The evidence therefore does not indicate declining relevance of Information Technology qualifications. Instead, it points to a more difficult and potentially more selective transition from study into full-time professional work. For higher education, the response should focus on authentic industry engagement, work-integrated learning, professional portfolios, communication capability and transparent use of graduate outcome analytics, consistent with Australian evidence on employability development and graduate transition (Jackson, 2024; Jackson & O'Connor, 2026; Jackson & Rowe, 2023). The forecasting framework is reproducible, but its value depends on regular updating and cautious interpretation as new QILT data become available.

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