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RESEARCH ARTICLE

AI ADOPTION IN AUSTRALIA'S HEALTH CARE AND SOCIAL ASSISTANCE INDUSTRY: AN EXPLORATORY QUANTITATIVE ANALYSIS OF ABS SECONDARY DATA

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Abstract

This article profiles reported artificial intelligence (AI) use among Australian businesses in the Health Care and Social Assistance industry using secondary data from the Australian Bureau of Statistics (ABS). It compares the sector with the national business estimate and other industry divisions, then fits a small exploratory regression using the ABS's published industry-level rates. In 2024–25, 17% of businesses in Health Care and Social Assistance reported using AI, compared with 12% nationally. The sector ranked fifth among 17 industry divisions and reported a 49% innovation-active rate, three percentage points above the national rate. Across the 17 divisions, a one percentage-point higher innovation-active rate was associated with a 0.33 percentage-point higher AI-use rate in an unweighted ordinary least squares model ($R^2 = 0.130$, $p = 0.156$). The model's fitted value for the health division was 14.5%, compared with the observed 17%. This difference is descriptive: the ABS data are rounded industry aggregates and do not identify clinical AI, implementation intensity, patient outcomes, or a health-sector-specific causal effect. The findings provide a concise baseline for business and policy discussion and highlight the need for measures of adoption stage, governance, workforce readiness, and evaluated outcomes.

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Introduction:-

Artificial intelligence (AI) is increasingly discussed as a source of administrative efficiency, decision support, and new service capability. In health care, potential uses include documentation assistance, image analysis, workflow planning, and support for clinical or operational decisions. These applications differ in risk, data requirements, and the degree of human oversight they need. A business that reports some AI use may be testing a general-purpose tool for office work, while another may have integrated a specialised system into a clinical workflow. A single adoption percentage cannot distinguish these situations.Australian evidence on business adoption is expanding. The Australian Bureau of Statistics (ABS) Business Characteristics Survey (BCS) offers an official measure of whether businesses report using selected information and communication technologies, with results by industry. In 2024–25,

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the ABS reported AI use in 17% of businesses in the Health Care and Social Assistance industry, against 12% across Australian businesses. The question measures reported use and is not designed to measure its intensity or extent (Australian Bureau of Statistics 2026a, 2026b; Siddiqui et al. 2013).

This study develops a focused quantitative profile of that sector. It addresses three questions: (1) how does reported AI use in Health Care and Social Assistance compare with the national estimate and other industries? (2) how does the sector's innovation-active rate compare with the national rate? and (3) what does a simple cross-industry regression suggest about the association between innovation activity and reported AI use, and where does the health sector sit relative to that benchmark?

The contribution is deliberately bounded. The analysis uses the ABS industry division as published. It does not treat the division as equivalent to hospitals, medical practices, or clinical AI. The regression uses the 17 industry divisions as observations and provides a descriptive benchmark only. This design allows a modest statistical model while avoiding claims that cannot be supported by one aggregated health-sector observation.

The distinction between the health system and the businesses counted in the survey is important. Health and social assistance organisations range from large hospitals and residential-care providers to small practices and community-service operators. Their technologies may support clinical work, administration, scheduling, client communication, or internal planning. The ABS industry estimate groups these businesses and asks only whether AI was used in the business. It therefore gives a useful measure of sectoral reach, but it cannot show which activities account for that reach or how adoption is distributed between small and large providers.

This distinction also motivates the article's business focus. Health organisations must balance service needs, workforce constraints, data stewardship, and accountability. An adoption rate can identify where AI has entered business operations, but it cannot establish whether a tool is clinically appropriate, safe, cost-effective, or beneficial to patients. Separating these questions helps policy makers and managers avoid treating a prevalence statistic as an impact estimate.

The article offers three contributions. It places the health and social assistance estimate within the national and inter-industry distribution, compares AI use with the ABS innovation-active measure, and uses a transparent linear model to benchmark the health division against the 16 other industries. The model is intentionally small because the published table contains one health-sector observation and no business-level records. The paper then translates the descriptive findings into a short agenda for better measurement and responsible adoption.

A further reason to examine this sector is that the commercial and public-service dimensions of health technology are closely connected. Many providers operate under tight workforce and budget constraints, while also handling sensitive information and delivering services where errors can have serious consequences. AI adoption is therefore an organisational decision involving expected operational value, data readiness, staff capability, and governance. The same technology may be suitable for one administrative task but inappropriate for another clinical or client-facing task. Industry-level evidence cannot resolve these decisions, but it can establish a baseline and identify questions that more detailed research should answer.

The paper proceeds from prevalence to comparison and then interpretation. It first summarises the national and industry estimates, then uses innovation activity as a limited cross-industry correlate of AI use. Results are interpreted as descriptive evidence about reported business uptake. This framing avoids inferring performance from adoption and keeps the statistical model aligned with the available secondary data.

Background and conceptual framing:-

Organisational technology adoption depends on interacting technological, organisational, and environmental conditions. The technology–organisation–environment perspective emphasises factors such as infrastructure, leadership, organisational capability, skills, available resources, and external pressures (Tornatzky and Fleischer 1990). These conditions are particularly relevant in health and social assistance, where organisations differ widely in size, service model, data maturity, and regulatory exposure.

The adoption of AI in health also requires governance that accounts for safety, accountability, human rights, privacy, and equity. The World Health Organization's guidance outlines principles for responsible AI in health, while the Australian Government's review of safe and responsible AI in health care considers how existing legal and regulatory

arrangements apply to AI-enabled systems (World Health Organization 2021; Australian Government Department of Health, Disability and Ageing 2025). These sources concern responsible implementation; they do not imply that the ABS adoption percentage represents clinical deployment.Adoption should also be distinguished from realised benefit. General-purpose technologies often require complementary investments in data, processes, skills, and organisational change before measurable productivity gains emerge (Brynjolfsson et al. 2021). Firm-level research likewise finds that AI adoption varies with complementary assets and other firm characteristics (OECD 2025). The present analysis therefore treats innovation activity as a contextual indicator rather than as a proxy for productivity or care quality.

Australian business surveys use different sampling frames and thresholds for AI adoption. The Reserve Bank of Australia, for example, reports survey evidence about AI use among firms and notes that much reported adoption remains limited or experimental (Fernando et al. 2025). Such findings reinforce the importance of separating initial use from operational integration. They are not pooled with the ABS percentages here because the data sources do not measure an identical construct or population.

Data and Methods:-

Data source and scope:-

The primary dataset is the ABS publication Characteristics of Australian Business, 2024–25 financial year, based on the BCS. The BCS covers employing businesses in the Australian economy, subject to scope exclusions. The 2024–25 release is the first under a redeveloped biennial framework combining innovation and digital activity content (Australian Bureau of Statistics 2026a, 2026b).

The focal category is the ANZSIC industry division Health Care and Social Assistance. It is a broad business-industry category, not a hospital-only or clinical-technology category. The AI-use variable is the percentage of businesses within each industry that indicated AI use from a list of ICTs used in the business. The ABS notes that this question is not designed to capture intensity or extent of use. Businesses could select more than one technology. The innovation-active variable is the share of businesses that introduced an innovation, had innovation in development, or abandoned innovation activity during the reference period (Australian Bureau of Statistics 2026a).

The national trend compares the ABS figures of 1% in 2021–22 and 12% in 2024–25. The cross-industry analysis uses AI-use and innovation-active rates for all 17 published industry divisions in 2024–25. Industry percentages are rounded to whole numbers. All industry-level calculations give each division equal weight; consequently, the unweighted mean of industry rates is not the national business-weighted rate.

Descriptive analysis:-

The analysis reports the national change in percentage points, the sector's difference from national AI use, the difference in innovation-active shares, and the sector's rank among 17 industries. It also summarises the unweighted mean, median, and range of industry AI-use percentages. These summaries describe the published rates and do not incorporate survey-level standard errors.

Exploratory regression:-

To provide a simple model-based comparison, the 17 industry observations are fitted using ordinary least squares (OLS):-

$$\mathrm{AI}_i = \beta_0 + \beta_1 \mathrm{Innovation}_i + \varepsilon_i,$$

where AI_i is the published percentage of businesses reporting AI use in industry i, and $\mathrm{Innovation}_i$ is the percentage classified as innovation-active. Each industry is equally weighted. The model estimates a cross-industry association, not a causal effect. The fitted value for Health Care and Social Assistance is calculated by substituting its 49% innovation-active rate into the estimated line. The observed-minus-fitted value is reported as a residual for descriptive benchmarking.

Pearson correlation and its conventional two-sided p-value summarise the linear association. Spearman rank correlation is included as a simple check on whether the industry ordering is similar. Because the sample consists of only 17 rounded aggregate observations, and no design-based standard errors are available in the published industry table, p-values are exploratory and should not be interpreted as formal ABS survey inference. The accompanying R script reproduces the regression and summary calculations from the provided CSV file.

Ethics and data management:-
The analysis uses published aggregate statistics and contains no person-level, patient-level, or identifiable records. It does not estimate individual clinical risk or assess the safety or effectiveness of any AI system. Source links, definitions, units, and limitations are recorded in the accompanying Excel workbook.

Results:-

National and health-sector adoption rates:-
Reported business AI use increased from 1% in 2021–22 to 12% in 2024–25, an 11 percentage-point change. In the latest cross-section, 17% of Health Care and Social Assistance businesses reported AI use. This is five percentage points above the national rate, or approximately 1.42 times the national percentage. The difference is descriptive and no claim of statistical significance is made because the published table does not provide the standard errors required for such a comparison.

The health division had a 49% innovation-active rate, three percentage points above the 46% national rate. It ranked fifth in AI use among the 17 industry divisions. Information Media and Telecommunications had the highest rate (38%), followed by Professional, Scientific and Technical Services and Financial and Insurance Services (both 24%), and Mining (18%). The range across industries was 1% to 38%; the unweighted mean was 13.6% and the median was 12% (Table 1).

The distribution is uneven: the leading industry rate of 38% is more than twice the health division rate, while several industries reported single-digit use. The 17% health estimate is thus relatively high, but it sits in a sectoral landscape where adoption differs substantially. This spread supports using an industry benchmark rather than interpreting the national average as a common baseline for all businesses. At the same time, the high-performing sectors may differ in workforce composition, digital infrastructure, business size, and the kinds of tasks for which AI is useful. These industry comparisons describe the pattern; they do not identify why it exists. The use of data-science and prediction in health-related area was well established since long (Dhungana 2022; Dhungana and Ghimire 2021; Ahmad et al. 2015; Mishra et al. 2017)

The 11 percentage-point national increase between the two ABS reference years is also sizeable in relative terms, but the starting value was low. Expressing the change as a percentage-point difference is therefore clearer than presenting a growth multiple, which would magnify a small baseline. The two observations indicate diffusion over time, although they do not show whether growth was steady, concentrated in particular business sizes, or associated with deeper integration.

AI use and innovation activity by industry, 2024–25:-

Industry division	AI use (%)	Innovation-active (%)
Information Media and Telecommunications	38	57
Professional, Scientific and Technical Services	24	44
Financial and Insurance Services	24	49
Mining	18	37
Health Care and Social Assistance	**17**	**49**
Arts and Recreation Services	16	58
Electricity, Gas, Water and Waste Services	15	40
Wholesale Trade	14	58
Administrative and Support Services	12	36
Rental, Hiring and Real Estate Services	11	38
Manufacturing	9	55
Retail Trade	9	59
Other Services	9	49
Construction	6	36
Accommodation and Food Services	5	55
Agriculture, Forestry and Fishing	3	37
Transport, Postal and Warehousing	1	28

Note: ABS business percentages are rounded to whole numbers. Innovation-active includes businesses with introduced, in-development, or abandoned innovation activity. Health Care and Social Assistance is a broad industry

division. Source: ABS (2026).Reported AI use by industry. The red bar identifies the focal Health Care and Social Assistance division. Source: ABS (2026).The health division's position is notable but not exceptional in the distribution. Nine of the 17 industry divisions reported AI-use rates at or above the 12% national estimate, and eight were below it. Health Care and Social Assistance, at 17%, was five percentage points above the unweighted industry median of 12% and about 3.4 points above the unweighted industry mean of 13.6%. These comparisons give the sector a clear place in the cross-industry pattern, but the mean and median treat each division equally and are not estimates of the average Australian business.

Innovation activity provides a second point of comparison. The health division's 49% innovation-active rate was three percentage points above the national rate of 46% and equal to the median across the 17 industry divisions. This suggests that the health division combines above-national reported AI use with a middle-of-the-distribution innovation-active share. The two indicators measure different things: one records reported use of AI, while the other includes innovation introduced, in development, or abandoned. Their proximity should not be interpreted as evidence that one directly produces the other.

Cross-industry regression benchmark:-

The OLS model estimated a slope of 0.332 (standard error 0.222), indicating that a one percentage-point higher innovation-active share was associated with a 0.33 percentage-point higher reported AI-use rate across industries. The model explained 13.0% of the unweighted between-industry variation ($R^2 = 0.130$). The corresponding Pearson correlation was $r = 0.360$ ($p = 0.156$). Spearman rank correlation was $\rho = 0.287$ ($p = 0.265$). Neither association met a conventional 5% significance threshold. The conventional 95% confidence interval for the OLS slope was approximately -0.142 to 0.806, which includes zero and is consistent with substantial uncertainty about the direction and size of the linear association.

At the health division's innovation-active share of 49%, the fitted AI-use rate was 14.5%. The observed rate was 17%, giving an observed-minus-fitted residual of about +2.5 percentage points. This indicates that the health division's published rate sits modestly above the line fitted across industry divisions. It does not mean that innovation activity caused the difference, that health businesses outperform, or that AI improved care. The small aggregate sample and rounded values make the benchmark sensitive to individual industries and measurement error.

The model's explanatory power is limited. An R^2 of 0.130 means that the fitted linear relation accounts for about 13% of the unweighted variation in the published industry rates in this sample. It does not mean innovation explains 13% of AI adoption within health businesses. The slope interval also cautions against reading the positive point estimate as a stable relationship. A larger or more detailed dataset could yield a different coefficient, particularly if it separated health sub-industries or weighted estimates by business counts.

The rank-based result points in the same broad direction as the OLS estimate, but it is also small and uncertain. Agreement in sign across the two summaries is a useful descriptive check; it does not solve the limitations created by 17 observations, tied rounded values, and unequal sector sizes. These results are best understood as a signal for future measurement rather than a test of a health-sector adoption theory.

Taken together, the descriptive and model-based results tell a consistent but limited story. AI use in the health division is above the national rate and somewhat above the value predicted by a simple industry-wide line, while the overall association between innovation activity and AI use remains imprecise. This pattern is compatible with the view that innovation capability can accompany technology adoption, but it also shows that the relationship is not deterministic. Health organisations may face specific incentives to adopt digital tools alongside additional constraints around privacy, procurement, workforce acceptance, and safety. The available aggregate data do not allow those explanations to be separated.

For readers comparing sectors, the model's modest explanatory power is as relevant as its positive coefficient. Innovation activity alone leaves most between-industry variation unaccounted for in this small sample. Future statistical work could add business size and digital capability, use several survey waves, and report uncertainty that reflects the ABS sample design. Such extensions would help determine whether the observed health-sector position persists once industry composition and sampling variation are considered'

Exploratory OLS model and health-sector benchmark:-

Model statistic	Estimate
Industry divisions (n)	17
Slope: AI-use percentage points per innovation-active percentage point	0.332
Standard error of slope	0.222
R^2	0.130
Two-sided slope test (p)	0.156
Health observed AI-use rate (%)	17.0
Health fitted AI-use rate (%)	14.5
Health observed-minus-fitted residual (percentage points)	+2.5

Note: OLS gives equal weight to each published industry division. The test is an exploratory industry-level association and is not design-based ABS inference. The fitted value is a cross-industry benchmark, not a health-sector forecast.

Discussion:-

The ABS estimates indicate that reported AI use is more common in Health Care and Social Assistance than across businesses nationally, but the measure is broad. The 17% estimate could include administrative, communication, or operational applications as well as specialised health technologies. It does not identify whether businesses use AI in diagnosis, clinical decision-making, patient monitoring, rostering, documentation, or non-clinical work. It also does not reveal how frequently a tool is used, which staff use it, or whether it has been integrated into routine service delivery.

The sector's 49% innovation-active share provides a useful organisational context. Health and social assistance businesses report slightly greater innovation activity than the national business average, while AI use is also above the national rate. Across industries, however, the relationship between these measures is positive but statistically imprecise. Some industries combine high innovation activity with lower AI-use rates, demonstrating that innovation status alone cannot explain technology adoption. Data infrastructure, procurement capacity, workforce capability, workflow fit, privacy constraints, and governance may also matter, but the aggregate ABS table cannot test these mechanisms.

The fitted benchmark places the health division about 2.5 percentage points above the OLS line. This modest residual is useful as a descriptive signal for follow-up, not as an effect estimate. With only one health-sector observation, the data cannot support a health-only regression or establish the contribution of health-specific characteristics. A better next-stage study would use repeated observations over time or business-level data, with separate categories for hospitals, medical services, residential care, and social assistance where disclosure and data availability permit.

What the sector estimate can and cannot tell us:-

The 17% figure should be read as evidence that some businesses in the broad division report AI use, not as a count of AI-enabled clinical services. It may include general office tools and administrative applications, as well as specialised systems. The ABS does not provide an application breakdown in this table. A higher rate than the national average therefore indicates relative prevalence, but it cannot tell whether AI is more deeply embedded in health operations or whether the applications are more consequential than those in other industries.

This measurement distinction matters for business decisions. An organisation may begin with low-risk functions such as drafting internal material or summarising non-sensitive records, then consider higher-stakes workflows only after assessing information security, human oversight, and operational fit. Those stages should be measured separately. If surveys count all use as one category, trial use and routine deployment are combined, and managers cannot compare adoption maturity across organisations.

The industry-level regression also should not be used to rank organisations or predict outcomes for a particular provider. It assigns equal weight to each industry division and uses innovation activity as a single contextual variable. It leaves out business size, ownership, workforce mix, service type, digital infrastructure, procurement capacity, data quality, and region. The residual for Health Care and Social Assistance simply describes its position relative to this limited line. It is not evidence that the sector has a hidden adoption advantage.

For health service managers, the results support a staged approach to adoption. Organisations can identify a bounded administrative or service problem, assess the data and workflow requirements, involve clinicians and consumers where relevant, and evaluate safety, privacy, equity, and operational impact before scaling. The Australian Government's review of health AI regulation and WHO's principles make clear that governance and accountability are central to safe deployment (Australian Government Department of Health, Disability and Ageing 2025; World Health Organization 2021). The ABS measure can help establish sector prevalence, but it should be paired with implementation and outcome indicators before leaders infer organisational or care benefits.

Practical implications:-

Three implications follow from the descriptive evidence. First, national reporting should distinguish any AI use from pilot activity, regular use, workflow integration, and high-impact clinical deployment. These are materially different adoption stages. Second, future surveys should report health subsectors and business size where feasible, because large health organisations and small community providers may have very different resources and risk profiles. Third, evaluation should connect adoption to defined outcomes such as administrative time, service access, staff workload, safety events, patient experience, or equity, using suitable comparison designs.

These recommendations do not assume that greater adoption is inherently better. Appropriate use depends on the task, the quality of the evidence, the ability to monitor system performance, and the availability of human review. In health settings, safe adoption requires accountability for decisions and clear processes for identifying and responding to errors.

A practical evaluation should begin before implementation. Managers can state the intended use, identify who remains accountable, document what data the system processes, and specify how users will check its outputs. A pilot can then be assessed against a baseline and a small number of service-relevant measures. Depending on the application, these may include staff time, administrative backlogs, appointment access, documentation quality, error rates, or user experience. These operational measures should be kept distinct from clinical effectiveness or patient safety outcomes, which require appropriate evaluation designs and expertise.

Workforce participation is also central. Staff who use or are affected by a system can identify workflow disruptions, missing context, and failure modes that may not be apparent in a procurement review. Training should cover the intended purpose of the tool, limitations of its outputs, data handling, escalation routes, and the circumstances in which staff should override or stop using it. In settings involving clinical decisions, AI outputs should not displace professional accountability.

At the policy level, repeated and comparable survey measures could distinguish initial experimentation from regular use and integrated deployment. Reporting by business size and health sub-industry would help identify where support is most needed. Linked but privacy-preserving evaluations could then test whether adoption changes operational or care outcomes. Such evidence would help decision makers distinguish technology diffusion from demonstrated value.

Limitations:-

This analysis has several important limits. First, the unit of analysis is an industry division, not an individual business. The regression therefore estimates an ecological association and cannot support firm-level interpretation. Second, the health category combines Health Care and Social Assistance businesses. Results cannot be attributed specifically to hospitals, general practices, residential aged care, allied health, or social services.

Third, the ABS AI-use item measures whether a business reported use, not adoption intensity, purpose, expenditure, governance maturity, or outcomes. It does not tell us whether use was clinical or administrative. Fourth, the industry percentages are rounded to whole numbers. With only 17 divisions, rounding and influential industries can affect both correlations and regression estimates. The p-values are conventional exploratory tests and are not adjusted for ABS sampling design or survey weights.

Fifth, the analysis is cross-sectional for the industry comparison. The national 2021–22 and 2024–25 values provide two reference points but not a continuous time series. Finally, no patient-level outcomes, operational performance measures, or firm-level covariates are available in the tables used here. The results therefore cannot establish AI's effects on productivity, service quality, clinical safety, or patient outcomes.

Conclusion:-

In 2024–25, 17% of Australian businesses in Health Care and Social Assistance reported using AI, five percentage points above the 12% national estimate. The division's innovation-active share was 49%, compared with 46% nationally, and the division ranked fifth in AI use among the 17 industries. A modest OLS model found a positive but statistically inconclusive cross-industry association between innovation activity and AI use. The health division's observed rate was about 2.5 percentage points above its fitted cross-industry benchmark.

These findings offer a useful baseline for business and policy discussions, but they do not measure clinical deployment or care outcomes. Stronger evidence will require more detailed, repeated, and health-subsector-specific measures of adoption, supported by evaluations of safety, effectiveness, equity, workforce effects, and organisational value.

Data availability:-

The 17 industry observations used in this article are included in data.csv. The Excel workbook contains the source metadata, definitions, descriptive calculations, and OLS benchmark. The script analysis.R reproduces the statistical summaries and regression using base R.

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