Feature Article

MEASURING FIRM-LEVEL ARTIFICIAL INTELLIGENCE USE AND ITS EFFECTS ON FIRM PERFORMANCE AND EMPLOYMENT IN SINGAPORE

OVERVIEW

Artificial Intelligence (AI) is expected to transform firms and labour markets, and lead to productivity growth. However, measuring its economic effects remains difficult as firm-level AI use is rarely observed directly. Addressing this measurement gap is important as policymakers need evidence on how AI is being adopted, which firms are using it, and whether adoption is associated with tangible benefits for workers and firms, as they design AI-related policies.

This study develops a firm-level measure of AI use in Singapore using data from online job postings. The constructed measure is then linked to firm-level administrative data to enable the characteristics of AI-using firms to be analysed and the impact of firms' AI use on their performance and employment to be empirically estimated. Job postings provide a useful source of information as AI-related hiring reveals a firm's demand for AI capabilities.

Using the dataset created, the study examines three questions. First, how do firms use AI alongside other digital technologies? Second, what types of firms are more likely to use AI? Third, does AI use improve firm performance and change their workforce composition?

FINDINGS

Finding 1:

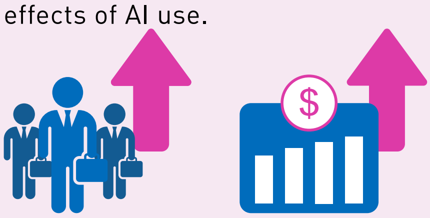
AI use is not a stand-alone leap for firms. Instead, it tends to build on the prior efforts of firms to adopt foundational and complementary digital technologies.

Finding 2:

Firms in digital- and data-intensive sectors/clusters (i.e., information & communications, electronics, professional services and finance & insurance) are more likely to use AI. Larger firms are also more likely to use AI, even after accounting for their sector and age.

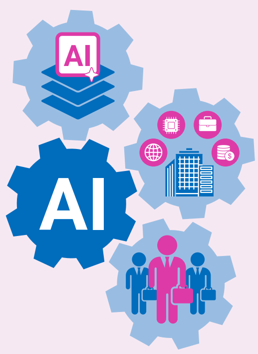
Finding 3:

Initial AI use is associated with an increase in firms' revenue and total employment, and these gains continue to rise as AI capabilities deepen. This result could reflect the potential scale and/or innovation effects of AI use.



POLICY TAKEAWAY

These findings suggest three policy lessons to help firms and workers realise economic benefits from AI. First, it is important for firms to strengthen their foundational digital capabilities as this could aid in their AI adoption. Second, support for AI use should be differentiated by sector and firm size. This may entail identifying sector-specific AI use cases with larger returns, or the provision of support to smaller firms that may lack internal capabilities to effectively integrate AI. Third, workforce policy should focus on job transformation and worker training to help workers move toward AI-complementary tasks even as some tasks become automated.



EXECUTIVE SUMMARY

- This study develops a firm-level measure of Artificial Intelligence (AI) use in Singapore based on data from online job postings. Linking the constructed measure to firm-level administrative data, the study then analyses the characteristics of AI-using firms and empirically estimates the impact of firms' AI use on their performance and employment.

- The main findings of the study are as follows. First, using network analysis, the study finds that AI use is not a stand-alone leap for firms. Instead, it tends to build on the prior efforts of firms to adopt foundational and complementary digital technologies.

- Second, using a liner probability model, the study finds that firms in digital- and data-intensive sectors/clusters (i.e., information & communications, electronics, professional services and finance & insurance) are more likely to use AI. Larger firms are also more likely to use AI, even after accounting for their sector and age.

- Third, using a combination of matched staggered difference-in-differences and fixed effects regressions, the study finds that:

  - Initial AI use is associated with an increase in firms' revenue and total employment, and these gains continue to rise as AI capabilities deepen. This result could reflect the potential scale and/or innovation effects of AI use (e.g., AI reduces costs and/or enables the creation of new products, thus allowing firms to expand output). At the same time, the increase in firm-level employment suggests that any worker separations that may occur at the firm are outweighed by new hiring. It may also be the case that AI tends to automate specific tasks rather than entire jobs, thus allowing workers to focus on the remaining and/or new complementary tasks.

  - Firms do not see a statistically significant increase in their productivity and profit within four years of first AI adoption. This could be because the full benefits of AI may only materialise after complementary investments are made, similar to the experience of earlier transformative technologies such as the internet.

  - Employment effects of firms' AI use differ across worker types. Initial gains are found to be concentrated among local higher-earners and mid-career workers, as well as skilled foreign professionals. However, as firms deepen their AI capabilities, the local employment gains broaden across wage and age groups.

- Fourth, heterogeneity analyses show that the impact of firms' AI use varies across sector and firm size. For example, firms in the finance & insurance, wholesale trade and information & communications sectors, as well as micro and medium firms, see larger gains in revenue on average.

- As the study analyses firms' AI use up to 2024, the estimates should be seen as reflecting the early impact of AI diffusion, and would not capture the effects of more recent advances in AI capabilities (e.g., agentic AI) as well as broader enterprise adoption. Future studies could analyse the effects of the different AI use cases that firms are implementing using more recent data that better capture the advances in AI technology and new patterns of adoption.

The views expressed in this paper are solely those of the author and do not necessarily reflect those of the Ministry of Trade and Industry or the Government of Singapore.[1]

1 The author would like to thank Ms Yong Yik Wei, Dr Andy Feng, Dr Tan Di Song, Dr Christopher Saw, the Digital Industry Singapore Office, and the Research and Statistics Unit in the Infocomm Media Development Authority for their useful suggestions and comments. All remaining errors belong to the author.

INTRODUCTION

Artificial Intelligence (AI) is expected to transform firms and labour markets, and lead to productivity growth. However, measuring its economic effects remains difficult as firm-level AI use is rarely observed directly. Administrative datasets provide broad coverage but typically do not record whether a firm uses AI. On the other hand, surveys can capture direct information on AI adoption but have limitations, such as delayed responses and challenges in ensuring consistent understanding of AI and measuring its usage intensity, especially as AI capabilities are advancing rapidly. Addressing this measurement gap is important as policymakers need evidence on how AI is being adopted, which firms are using it, and whether adoption is associated with tangible benefits for workers and firms, as they design AI-related policies.

This study develops a firm-level measure of AI use in Singapore using data from online job postings. The constructed measure is then linked to firm-level administrative data to enable the characteristics of AI-using firms to be analysed and the impact of firms' AI use on their performance and employment to be empirically estimated. Job postings provide a useful source of information as AI-related hiring reveals a firm's demand for AI capabilities.

Using the dataset created, the study examines three questions. First, how do firms use AI alongside other digital technologies? Second, what types of firms are more likely to use AI? Third, does AI use improve firm performance and change their workforce composition?

LITERATURE REVIEW

The literature offers three lessons for studying firm-level AI use.

First, AI adoption depends on firms' characteristics and capabilities. Studies (e.g., Bonney, et al. (2024), Calvino et al. (2022) and Calvino et al. (2023)) show that AI adopters tended to be larger, more productive, more digitalised and concentrated in the information & communications technology and professional services sectors. They also show that firms were more likely to adopt new technologies during the COVID-19 pandemic (e.g., analytics, cloud, digital commerce and collaborative software) when they already had pre-existing digital capabilities.

Second, AI can improve firm performance, but timing matters. Evidence from AI-related hiring and innovation (e.g., Babina et al. (2024) and Alderucci et al. (2020)) suggests positive associations with sales, employment, market value, productivity and wages, possibly through product innovation. However, these effects may emerge only in the longer term (e.g., five to eight years) after firms have made complementary intangible investments (e.g., new processes, human capital, business models).

This lag is consistent with the concept of "Productivity J-curve" (Brynjolfsson et al. (2021)), which states that transformative technologies can initially depress measured productivity as firms incur adjustment costs upfront, before gains materialise after organisational changes are implemented. Recent evidence on industrial AI by McElheran et al. (2025) similarly finds that short-term productivity and profit losses may precede longer-term gains.

Third, AI's employment effects depend on task reallocation (Acemoglu and Restrepo (2019)). AI may automate some tasks while increasing the demand for workers that are performing complementary and/or newly-created tasks.[2] Survey and job-posting evidence (e.g., Bonney et al. (2024) and Liu and Webber (2026)) suggest that AI-using firms did not reduce overall hiring but could have shifted hiring towards certain occupations. For Singapore, it is important to study the impact of AI use on different groups of workers because many resident workers are in occupations highly exposed to AI (Khan (2024)), with half in high-complementarity occupations (e.g., managers, science and engineering, health and legal professionals) and half in low-complementarity occupations (e.g., clerical support workers).[3]

This study brings these strands together using Singapore firm-level data. A measure of firms' AI use is first constructed using data from online job postings and then combined with firm-level administrative data. Using the dataset created, the study examines how firms are using AI, what types of firms are more likely to use AI, and whether AI use improves firm performance and shifts workforce composition.

2 *AI may also change job content. For instance, Autor and Thompson (2025) show that task automation may raise the expertise requirements of jobs, thus reducing the relative supply of workers who qualify for the jobs. As a result, wages rise while employment falls.*

3 *High-complementarity occupations are those in which AI is more likely to complement human labour in performing the tasks in the occupation, while low-complementarity occupations are those with greater scope for AI to substitute tasks in the occupation that are currently performed by human labour.*

CONCEPTUAL FRAMEWORK

AI can affect firms through three channels: task reallocation, innovation and scale effects. These channels operate at the same time and may have different implications for firm outcomes.

i. Task Reallocation

Task reallocation occurs when AI changes how tasks within a job are performed. AI may substitute for labour in tasks where it is more cost-effective, such as drafting text or classifying documents. Firms may therefore reduce demand for workers in jobs made up largely of tasks that AI can automate.

However, task-level substitution need not translate into job-level displacement. As AI automates some tasks, workers may shift toward the remaining and/or new complementary tasks, such as those requiring human judgement or relationship management. AI can therefore augment workers and raise demand for jobs with complementary task content. The skills required in such jobs would also change. For example, if AI takes over basic bookkeeping, accounting workers may need to focus more on problem solving and judgement.

ii. Innovation

The innovation effect arises when AI enables firms to develop new or improved products and services. AI may also support faster research and development. If these allow firms to enter new markets or expand demand, revenue and employment may rise. Profit may also increase if the new products generate margins that exceed investment and adjustment costs.

iii. Scale

As firms invest in AI and implement complementary organisational changes, they may see improvements in operational efficiency and cost reductions. If demand is sufficiently elastic, lower prices (due to reduced costs) will allow firms to expand output. As firms expand production, they will need more workers, even if they use fewer workers per unit of output (e.g., due to AI automation). This channel leads to higher revenue and employment. However, the impact on profit and labour productivity may be ambiguous, especially in the short term, as firms may face large investment costs upfront while labour productivity improvements may only materialise with a lag.[4]

In the long term, as firms improve their organisational processes and redesign and/or create new jobs to leverage AI effectively, these investments could translate into stronger total factor productivity and labour productivity growth.

DATA

This study uses MyCareersFuture job postings data from 2018 to 2024 to identify AI-using firms in Singapore. Firms are identified as AI-using if they post at least one AI-related job posting on MyCareersFuture during this period. AI-related job postings are postings with job descriptions that contain at least one match against a validated AI vocabulary list.[5,6]

4 *Investment costs related to AI include AI software investments, data infrastructure, workflow redesign, and worker training. Investment costs are not observed in the data used for our empirical study.*

5 *The AI vocabulary list is based on OECD (2025) and accounts for generative AI and pre-generative AI technologies. While there are studies in the literature (Hosseini and Lichtinger (2025)) that apply a large language model classifier on job postings that have first been identified through AI keyword matching to determine whether firms are AI-using, such an approach introduces additional model dependence and is less transparent.*

6 *Employment agencies are excluded as they may be hiring on behalf of other firms on MyCareersFuture.*

A key assumption underpinning this measure is that AI-related hiring reveals a firm's demand for AI capabilities. Specifically, a firm will post an AI-related vacancy when it expects the worker hired to generate economic value, which could come about because the worker complements existing AI capital or helps the firm to build new AI capabilities. Even if no AI-related hiring is observed in subsequent years, firms may continue to build and maintain their AI capabilities.

It should be noted that this measure is not intended to capture every form of AI use. By construct, it likely focuses on firms that are making internal investments in AI capabilities through new AI-related hiring, instead of firms using (i) off-the-shelf AI tools, (ii) external vendors to provide customised AI solutions, or (iii) existing employees to develop AI capabilities without new AI-related hiring. Another caveat is that the measure may classify a firm as AI-using even if a posted vacancy is not filled. Nonetheless, while the measure does not comprehensively cover all forms of AI use, it provides a timely and scalable[7] indicator of revealed AI capability-building at the firm-level when direct measures (e.g., administrative and survey data) are limited.

Subject to the caveats above, the measure can be used to study the *extensive* margin of AI use (i.e., firms using AI for the first time). Apart from this, an AI intensity measure – based on the cumulative maximum number of <u>annual</u> AI-related job postings across time[8] – is also constructed and used to study the *intensive* margin of AI use. The cumulative maximum is preferred to a simple annual count because AI capabilities may accumulate and persist over time.[9] It is also preferred to a cumulative sum[10] of annual AI-related postings over time as subsequent postings may reflect replacement hiring rather than an increase in capabilities.

After identifying firms' AI use based on the job postings data, the AI-use indicator constructed for all firms that posted vacancies on MyCareersFuture over the study period is linked to firm entity and financial data[11], local employment and wage data, foreign employment data, as well as firm-level government grant data from government administrative sources. The merged dataset allows firm outcomes such as revenue, profits and labour productivity (i.e., value-added per worker, VAPW[12]), as well as firm-level employment outcomes such as total employment, local employment by wage and age bands, and foreign employment by pass types to be studied.

Based on this approach, around 8 per cent (1,555 firms) of all firms in the dataset are identified as AI-using.[13]

IDENTIFYING AI-USING FIRMS AND HOW THEY USE AI

i. Methodology

To study how firms are using AI, the AI vocabulary used to identify AI-related job postings is further classified into five use cases: customer engagement, analytics & insights, process automation & operational efficiency, product innovation & enhancement, and generative AI.[14] At the same time, firms' use of other digital technologies (i.e., advanced digital technologies, business software, cybersecurity, data analytics, digital commerce, and digital workplace) is also identified.[15] A network analysis is then conducted on firms' adoption of the various AI use cases and other digital technologies as of 2024.

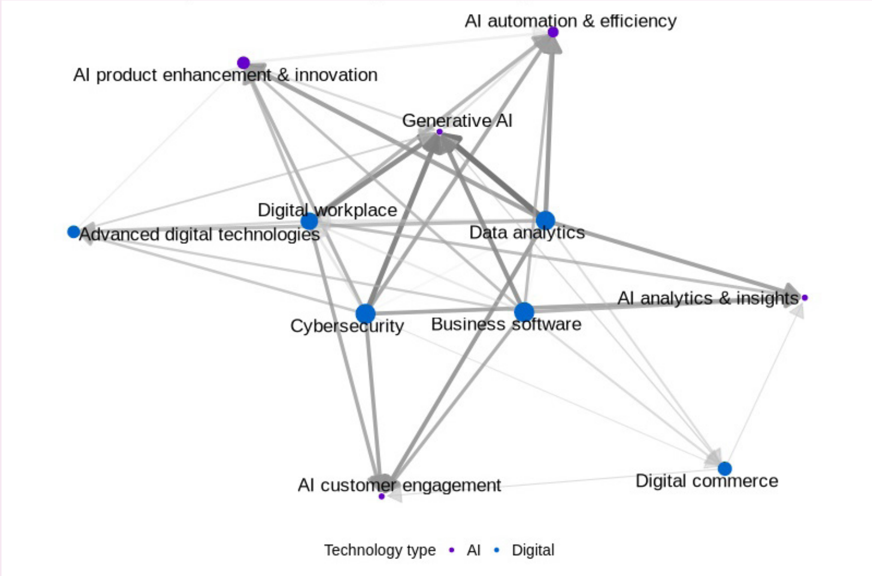
ii. Results

The network analysis shows that other digital technologies not only complement AI technologies but also tend to be adopted before the AI technologies (evidenced by the arrows pointing from the other digital technologies to AI use cases in Exhibit 1). Furthermore, certain digital technologies, including cybersecurity, digital workplace, data analytics and business software, act as foundational capabilities leading to multiple AI use cases.

7 *This indicator can be consistently constructed across firms and years using widely-available job postings data.*
8 *The cumulative maximum refers to the maximum number of annual job postings across time.*
9 *A firm that hires several AI workers in one year may continue to benefit from those workers (e.g., workers are retained, or from the AI processes they built, or from the complementary assets they created), even if the firm posts fewer AI-related jobs in subsequent years.*
10 *The cumulative sum refers to the total sum of annual job postings over time.*
11 *Financial data was not available for all firms as some firms (e.g., solvent exempt private companies) are exempt from filing financial statements with the Accounting and Corporate Regulatory Authority (ACRA). As firms may define different fiscal years (FY) for reporting, ACRA data was used only if the period from start to end of the FY is 12 months, with the data attributed to the calendar year where majority of the period fell. Data denominated in other currencies was converted to the Singapore dollar (SGD) using the annual average Bloomberg exchange rate.*
12 *VAPW is proxied using the sum of profit and wages divided by total employees*
13 *Firms in the dataset are those with job postings on MyCareersFuture (excluding employment agencies) and available firm entity and employment data. Financial data is available only for a subset of these firms.*
14 *The AI keywords are classified using a large language model, with the output further refined by human inspection. Some generic AI keywords may not be classified into any of the use case categories (e.g., artificial intelligence, deep learning, adaptive boosting).*
15 *The keywords for the other digital technologies reference the technologies in Calvino, et al. (2023), and are classified using a large language model.*

This suggests that firms do not adopt AI technologies in isolation. Instead, AI appears to be the next layer of a digital stack that firms progressively build. These findings are consistent with international evidence that firms are more likely to adopt new technologies when they already have existing complementary technologies in place.[16]

Exhibit 1. Network analysis on AI and digital technologies



Note: Each node corresponds to a technology or use case. An edge (line) between two nodes is drawn if the technologies co-occur (i.e., there are firms that use both technologies). Each edge is directed and weighted based on conditional probabilities of occurrence. An arrow is directed from node B to A if it is more likely that technology A is present when B is also present rather than vice versa (i.e., $P(A|B) > P(B|A)$), and the conditional probability exceeds 0.4. The size of the node is proportional to the number of outward arrows.

CHARACTERISTICS OF AI-USING FIRMS

i. Methodology

To examine which firm characteristics are associated with AI use, a cross-sectional linear probability model using the latest data as of 2024 is estimated:

$$AI\ use_i = \beta_1 sector_i + \beta_2 size_i + \beta_3 age_i + \epsilon_i \tag{1}$$

The dependent variable $AI\ use_i$ is an indicator for whether firm i is identified as AI-using.[17] The explanatory variables include the sector ($sector_i$), employment size ($size_i$), and age (age_i) of firm i.[18,19]

ii. Results

The findings from the analysis are as follows.

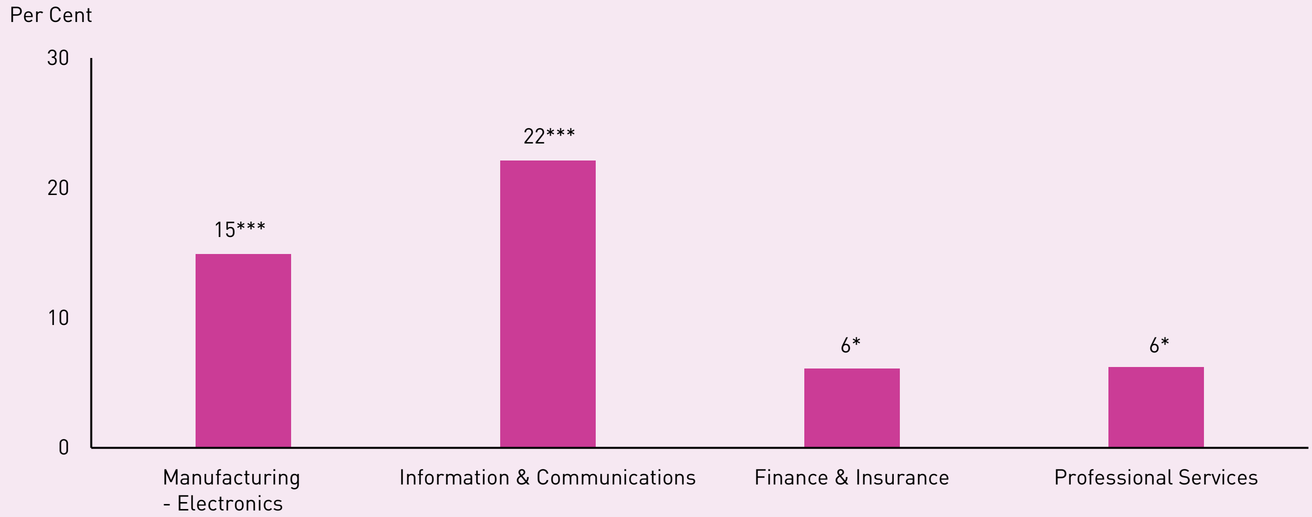
First, AI-using firms are more likely to be from the information & communications, electronics, professional services and finance & insurance sector/cluster (Exhibit 2.1, full results in Annex A). Specifically, information & communications and electronics firms in the base employment size (i.e., 1-10 workers) and age (i.e., <6 years) category have a predicted AI-use probability of 22 per cent and 15 per cent respectively. These sectors share a common feature of being digital- and data-intensive. For example, electronics manufacturing often involves advanced production technologies, making it more feasible for firms to integrate AI for predictive maintenance and quality control.

16 This finding also motivates the inclusion of a lagged digital-use indicator in the empirical specification used to estimate the causal impact of AI use on firm performance and employment.
17 Using AI intensity as the dependent variable yields similar findings.
18 The intercept is omitted from the regression specification. All sectors are included and the omitted base categories for size and age are micro firms (1-10 workers) and young firms (age 0-5 years) respectively.
19 Robustness checks were conducted using revenue size (instead of employment size) for the smaller sample of firms with available financial data and results are similar. Other robustness checks carried out include using different age and size bands, and results are similar.

Second, larger firms are more likely to use AI (Exhibit 2.2). This relationship holds even after accounting for sector and age. In particular, large firms with >250 workers are 39 percentage-points (pp) more likely to use AI compared to micro firms in the same sector and age category. This pattern is consistent with larger firms having more financial resources, data and managerial capacity to invest in AI-related capital and skills.

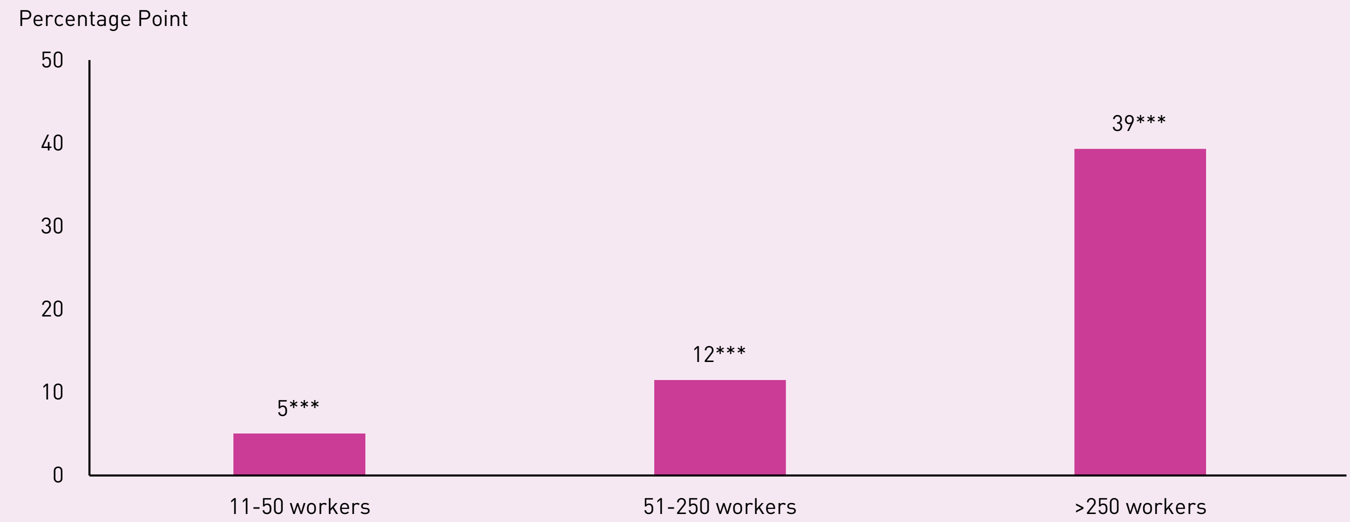
Third, firm age has no statistically significant relationship with the likelihood of AI use. This suggests that AI use is not confined to either younger firms or older incumbents. Instead, AI use appears more closely related to sector and firm size.

Exhibit 2.1. Likelihood of firm AI use for selected sectors



Note: *** p<0.01, ** p<0.05, * p<0.1. All sectors included in regression; only sectors with statistically significant results are shown.

Exhibit 2.2. Likelihood of firm AI use by employment size



Note: *** p<0.01, ** p<0.05, * p<0.1. The base category is firms with 1-10 workers.

IMPACT OF AI USE ON FIRM OUTCOMES AND EMPLOYMENT

i. Methodology

To estimate the causal effect of AI use on firm outcomes and employment, AI-using firms are compared with matched non-AI-using firms. Specifically, coarsened exact matching is employed to ensure that non-AI-using firms (control firms) are comparable to AI-using firms (treated firms) before their first year of AI use.[20] The first year of AI use defines the firm's treatment cohort.[21]

Extensive-margin effects of AI use

At the extensive margin, firm outcomes are estimated using a staggered difference-in-differences regression specification[22]:

$$ln(Y_{it} + 1) = \sum_{c=2019}^{2024} \sum_{b=-3}^{5} \beta_{c,t}\, AI\ use\ cohort_i^c \times event\ time_t^b \times treated_i + X_{it-1} + FE + \varepsilon_{it} \quad (2)$$

Y_{it} is a firm-level outcome for firm i in year t; $AI\ use\ cohort_i^c$ denotes if and when the firm is first flagged as an AI-using firm (i.e., treatment cohort) from year 2019 to 2024[23], $event\ time_t^b$ is measured relative to the cohort's year of treatment ($t = 0$), with the year before serving as the base reference period and hence omitted ($t = -1$), and $treated_i$ indicates whether the firm is an AI-using firm. Lagged controls X_{it-1} include the cumulative amount of government digitalisation or productivity grants[24] received by the firm and a digital-use indicator for whether the firm had ever used digital technologies by that period. Fixed effects FE include firm, year, cohort, firm-cohort, cohort-year, sector-year and sector-cohort effects. Standard errors are clustered at the firm-cohort level. The cohort-specific event-time coefficients $\beta_{c,t}$ are averaged across cohorts to estimate average treatment effects at each event time.

To interpret $\beta_{c,t}$ as the causal effect of AI use, it is important to address the issue of selection bias. This refers to the concern that firms choosing to adopt AI may differ from non-AI-using firms in ways that also predict their subsequent outcomes. In this study, several research design choices help to mitigate this concern. First, matching improves comparability between non-AI-using firms and AI-using firms before treatment. Second, the fixed effects variables in the regression help to absorb time-invariant firm differences, macro and sector-specific time shocks, as well as cohort-specific dynamics. Third, lagged controls for receipt of digitalisation and productivity government grants, and for digital use, in the regression help to account for support received by firms and their digital transformation that may be correlated with both firms' AI use and subsequent outcomes.

Together, these design choices help reduce selection bias but they do not by themselves rule it out. As an additional validity check, the pre-treatment outcomes of matched treated and control firms are examined to assess whether they exhibit parallel trends. This is important as it undergirds the assumption that in the absence of AI use, the treated firms would have followed similar outcome paths as the control firms. To test for parallel trends, the outcomes of the treated and control firms before the first AI use of the former are compared, and all outcomes are found to exhibit parallel trends up to three years before first AI use.[25]

Nonetheless, the estimates should still be interpreted with appropriate caution. As highlighted earlier, the measure of AI use adopted in this study captures firms' revealed demand for AI capability, and not their direct usage or successful implementation of AI. It also more likely identifies firms making internal investments in AI capabilities through new AI-related hiring, instead of firms using off-the-shelf AI tools, external vendors providing customised AI solutions, or existing employees to develop AI capabilities. As such, results are best interpreted as the effects associated with internal AI capability-building, rather than all possible AI uses.

20 *Pre-matching, AI-using firms are more likely to use digital technologies, have greater revenue, profit, average local wages and employment. Matching variables used include sector, digital use, age, total and local employment, average local wages and government grants. Post-matching, there is an improvement in pre-treatment similarities for both the matching variables and variables not used for matching.*

21 *Cohort refers to the first year of AI use for treated firms. Firms in cohort t are matched to control firms using data in year t-1. Control firms may be matched in multiple years to the corresponding cohorts of treated firms. Observations for control firms that are matched to multiple cohorts are replicated and stacked with the corresponding event time assigned and matching weights applied.*

22 *A staggered difference-in-differences specification is used as there is heterogeneous treatment timing (i.e., different cohorts).*

23 *As firm-level data is available for years 2018 to 2024, only cohorts treated from year 2019 to 2024 are studied as data in year t-1 is required for matching.*

24 *Only government grants that are likely confounders (i.e., Productivity Solutions Grant, Market Readiness Assistance, Capability Development Grant, Enterprise Development Grant) are included.*

25 *This is a common check conducted by researchers estimating difference-in-differences regressions. It is not possible to directly test for parallel trends post-treatment as treated firms can never be observed in their non-treated state (i.e., an unobserved counterfactual).*

Intensive-margin effects of AI use

At the intensive margin, outcomes are examined using a fixed effects regression specification:

$$ln(Y_{it} + 1) = \beta_1 AI\ intensity_{it\text{-}1} + X_{it\text{-}1} + FE + \varepsilon_{it} \qquad (3)$$

Here, $AI\ intensity_{it\text{-}1}$ is the lagged cumulative maximum number of annual AI-related job postings.[26,27] The other variables are as defined in equation (1).

This regression specification examines whether firms that deepen AI capabilities, proxied by more intensive AI-related hiring, experience larger changes in outcomes.

Heterogeneity analysis

Lastly, heterogeneity analysis by sector and pre-treatment revenue size is conducted using the following regression specification:

$$ln(Y_{it} + 1) = \sum_k \beta_k AI\ using_{it\text{-}1} \times category_i^k + X_{it\text{-}1} + FE + \varepsilon_{it} \qquad (4)$$

Here, $AI\ using_{it\text{-}1}$ indicates whether the firm had ever used AI by t-1, and $category_i^k$ denotes the firm's sector or pre-treatment revenue size. The other variables are as defined in equation (1).

ii. Results

Effects of AI use on total employment and financial outcomes

At the extensive margin, AI use is associated with an increase in total employment and revenue. In particular, initial AI use is associated with an increase in total employment and revenue of 4 per cent and 7 per cent respectively in the year of adoption (i.e., $t = 0$), and 8 per cent and 16 per cent respectively one year post-adoption (Exhibit 3, full results in Annex B and C).[28] This could reflect the potential scale and/or innovation effects of AI use. For example, AI may enable firms to improve operational efficiency and increase their output, and/or support the creation of new or better products and services, which may in turn help them enter new markets.

At the intensive margin, the results show that firms continue to expand as they deepen their AI capabilities. A 1 per cent increase in AI intensity is associated with a 0.24 per cent increase in total employment and a 0.22 per cent increase in revenue. It should be noted that while the findings show net employment gains at the firm-level from AI use, there may still be worker separations occurring at the firm, although these are more than offset by new hiring.

On the other hand, there is no evidence of statistically significant gains in profit and VAPW at the firm-level over the immediate four-year post-adoption period.[29] This is consistent with the productivity J-curve interpretation, which suggests that the benefits of AI may fully materialise only after complementary investments and organisational redesign have been implemented. Specifically, firms incur investment and adjustment costs in the short term, not just in terms of their investments in AI software and data infrastructure, but also investments in complementary areas such as workflow redesign, experimentation and worker training. However, measured profit and productivity gains may emerge only after these complementary investments and adjustments are completed and embedded in firms' processes.

26 A staggered difference-in-differences specification for the intensive margin analysis is not adopted as AI intensity is not static and may change over time.

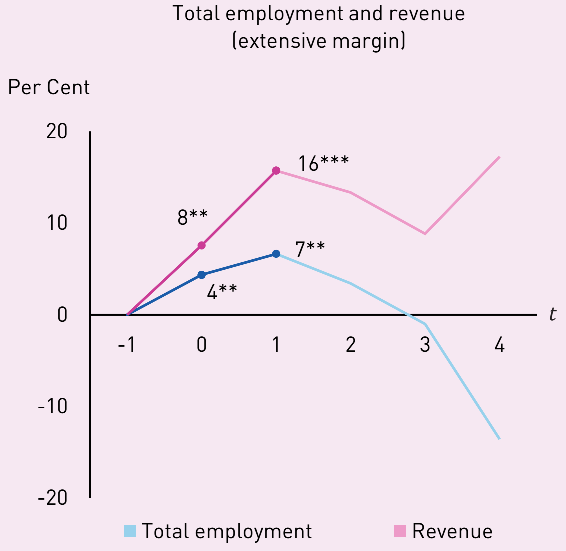
27 Robustness checks were conducted using alternative measures of AI intensity (i.e., cumulative sum of the number of annual AI-related job postings). Robustness checks were also conducted to check if there was selection into treatment intensity by limiting the sample to treated firms with at most three AI-related job postings in the initial year of AI use (based on AI intensity distribution plots). Lastly, robustness checks were conducted to limit the sample to exclude growth firms (>20 per cent employment Compound Annual Growth Rate (CAGR) over three years for firms with >10 workers, or absolute growth of >3.3 workers over three years for firms with <10 workers), to ensure that the findings are driven by AI use instead of other unobserved firm characteristics (e.g., innovativeness of growth firms). Results of all the robustness checks are in line with the main results.

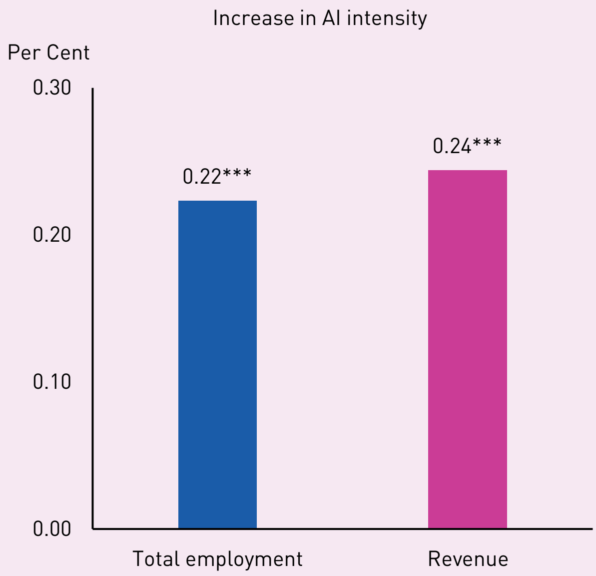
28 Results by AI-using cohorts from 2019 to 2024 were generally positive in year of adoption, although their statistical significance may vary. Exceptions are the 2021 cohort, where revenue was negative but not statistically significant, and the 2023 cohort, where total employment was negative albeit not statistically significant. As the 2023 cohort coincided with the emergence of generative AI technologies, first-time adopting firms could be in more experimental phase without viable AI use cases, leading to noisier estimates.

29 Firms' AI use also does not have a statistically significant impact on average local wages over the four-year post-adoption period.

Beyond these quantitative findings, Singapore firms that embarked on AI transformation under IMDA's Digital Leaders Programme have also reported business improvements from their AI use cases. The two firms showcased in Box 1 below – iHub Solutions and Nanyang Inc – provide concrete examples of how AI use can lead to improvements in firms' outcomes, including revenue and profit, when AI adoption is accompanied by complementary digital investments and workflow redesign.

Exhibit 3. Impact of AI use on total employment and revenue





Note: *** p<0.01, ** p<0.05, * p<0.1. Results that are statistically significant at the 5% level are in solid colours and labelled. Regression for revenue is conducted using the smaller sample of firms with revenue data.

BOX 1. BUSINESS GAINS FROM AI ADOPTION

Examples of Singapore firms that have embarked on AI transformation under IMDA's Digital Leaders Programme

iHub Solutions

Headquartered in Singapore with operations in Malaysia, Hong Kong, the Philippines and Thailand, iHub Solutions is a leading third-party logistics provider offering e-commerce fulfilment, warehousing, last-mile delivery and software integration through its proprietary platforms.

The company's transformation was born from a need to solve margin-sensitive operations and heavy reliance on manual, paper-based coordination. As e-commerce demand surged, iHub recognised the need for digitalisation.

Supported by IMDA's Digital Leaders Programme, iHub redesigned its core workflows by integrating advanced technologies anchored on a robust digital foundation of reliable data into its Virtual Logistics System (VLS) platform. This allowed iHub to deploy an advance digital tracking system to monitor the real-time movement of all works and assets.

iHub subsequently enhanced its VLS platform with a GenAI-powered Virtual Assistant for business intelligence. By translating natural language queries into SQL commands, it enabled non-technical staff to access insights instantly without relying on data specialists. iHub also deployed AI-driven route optimisation, using live orders, customer locations, historical data and Google OR-Tools to assign routes dynamically.

Since launching its VLS Virtual Assistant platform in 2024, iHub has achieved a **20 per cent revenue increase** and **30 per cent profit lift**. Route planning dropped from **15 minutes to 3 minutes**, cutting cycle times by **80 per cent**, while warehouse tracking improved accuracy and reduced losses.

Crucially, iHub's digital transition focused heavily on inclusive workforce upskilling. Rather than let technology replace headcount, their human-centric approach systematically eliminated mundane, tedious tasks and elevated the know-how of their ground staff to use the new digital tools to help them do their work faster and more accurately. In a powerful testament to this inclusive design, a 74-year-old warehouse assistant successfully picked up the new platform, embracing the technology as an effective everyday "teammate" on the warehouse floor.

Nanyang Inc

Since 1965, Nanyang Inc has evolved from a tentage provider to a trusted full-service logistics provider for events ranging from weddings to large-scale exhibitions. As Singapore's event industry grew more competitive, and client expectations for speed and precision soared, the company recognised that its future differentiator would be the intelligent use of digitalisation and AI.

Nanyang Inc's back-office operations faced severe bottlenecks due to their reliance on different silo platforms even as customer demands increased. The lack of integration led to extended response times for complex quotes, high human error rates in inventory tracking, and constrained scalability.

To resolve these hurdles, the company first experimented with a GenAI-powered chatbot to handle web enquiries, which successfully saved the team 82 per cent of the time previously spent on manual responses. Building on this success, Nanyang Inc worked with a tech vendor to develop AutomateAI, a unified platform powered by Google's Vertex AI and BigQuery. This platform fundamentally redesigned their workflow with the use of AI agents to automatically parse natural language customer requests, verify inventory availability, and instantly generate quotations and invoices.

Workforce Transformation and Upskilling

A critical component of this journey was workforce upskilling and the strategic shift of human capital. Nanyang Inc used AI to absorb routine data-entry and system-coordination tasks. This empowered its workers to focus on more complex activities, such as complicated corporate sales, strategic client advisory, and on-site safety management.

The impact of this digital transformation was immediate, delivering a **67 per cent reduction in order processing time**, **850 man-hours saved monthly**, **65 per cent higher customer retention**, and a **257 per cent return on investment** within the first year.

Effects of AI use on local employment by wage and age

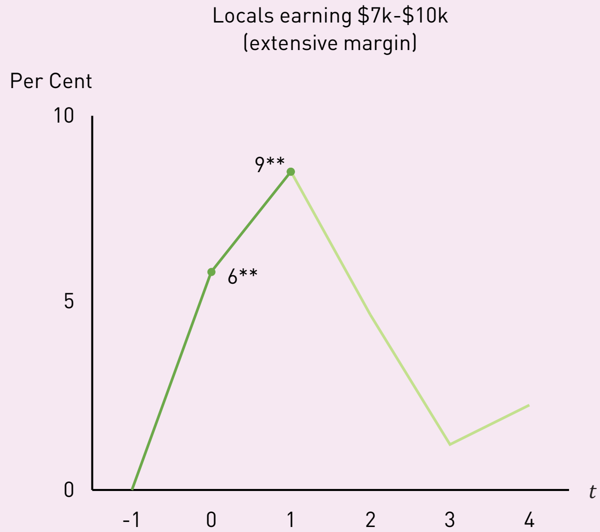
Local employment results by wage and age bands suggest that the initial employment gains from AI use are concentrated among workers who likely have a larger share of AI-complementary tasks or are more adaptable to redesigned workflows.

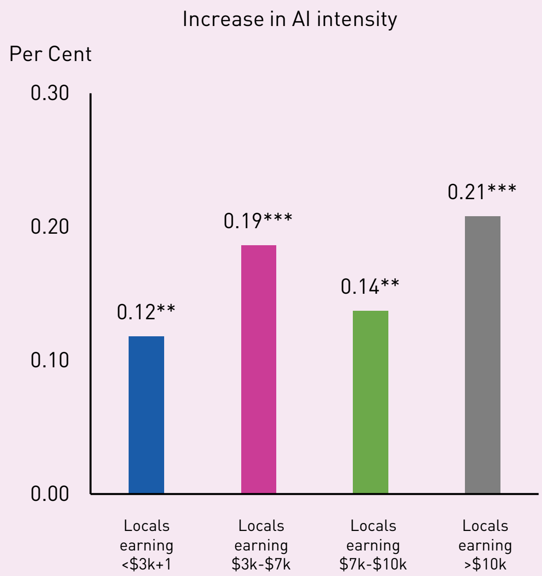
At the extensive margin, employment gains are concentrated among local higher-earners, particularly those with monthly wages of S$7,000 to S$10,000, and among local mid-career workers aged 35 to 44 (Exhibits 4 and 5, full results in Annex B). No statistically significant employment effect is observed for the other wage and age bands. Foreign employment results by pass types show that initial AI use increases the employment of higher-income and higher-skilled Employment Pass holders, with no statistically significant effect for the other pass types.

These findings are consistent with the task reallocation channel. Higher-income workers are more likely to perform multiple tasks: analytical, managerial, technical, or client-facing. While AI may automate some routine tasks of their jobs, these workers may be well positioned to shift their effort towards the remaining tasks that are complementary to AI, such as judgement and relationship management. Mid-career workers may similarly benefit from a combination of accumulated experience and adaptability. They may have enough firm- or occupation-specific knowledge to apply AI effectively, while remaining flexible enough to adapt to redesigned workflows. In some cases, firms may supplement their workforce capabilities with targeted hiring from abroad, particularly where specialised technical skills or expertise are scarce.

However, the intensive margin analysis shows that as firms deepen their AI capabilities, employment gains broaden across wage and age bands. Specifically, local employment rises across all wage bands and for a broader group of workers aged 25 to 54 as AI intensity increases (Exhibits 4 and 5, full results in Annex C). This may reflect scale effects as AI-using firms expand overall hiring. It may also reflect worker adaptation: when AI becomes embedded in firms' processes, a broader group of workers may undergo skills training or may reorganise around AI-enabled workflows.

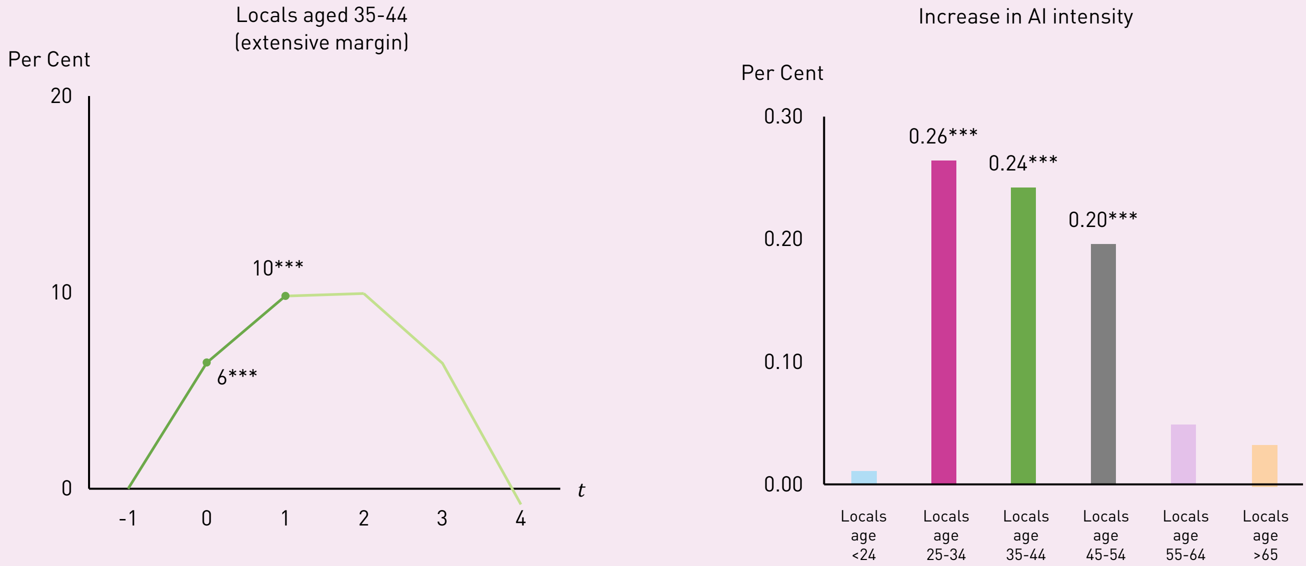
Exhibit 4. Impact of AI use on local employment by wage





Note: *** p<0.01, ** p<0.05, * p<0.1. Results that are statistically significant at the 5% level are in solid colours and labelled.

Exhibit 5. Impact of AI use on local employment by age



Note: *** p<0.01, ** p<0.05, * p<0.1. Results that are statistically significant at the 5% level are in solid colours and labelled.

Impact of AI use by sector[30]

The heterogeneity analysis shows that the effects of AI use vary across sectors.

Among the sectors analysed, AI-using firms in finance & insurance, wholesale trade and information & communications experience larger revenue gains compared to the other sectors (Exhibit 6, full results in Annex D).

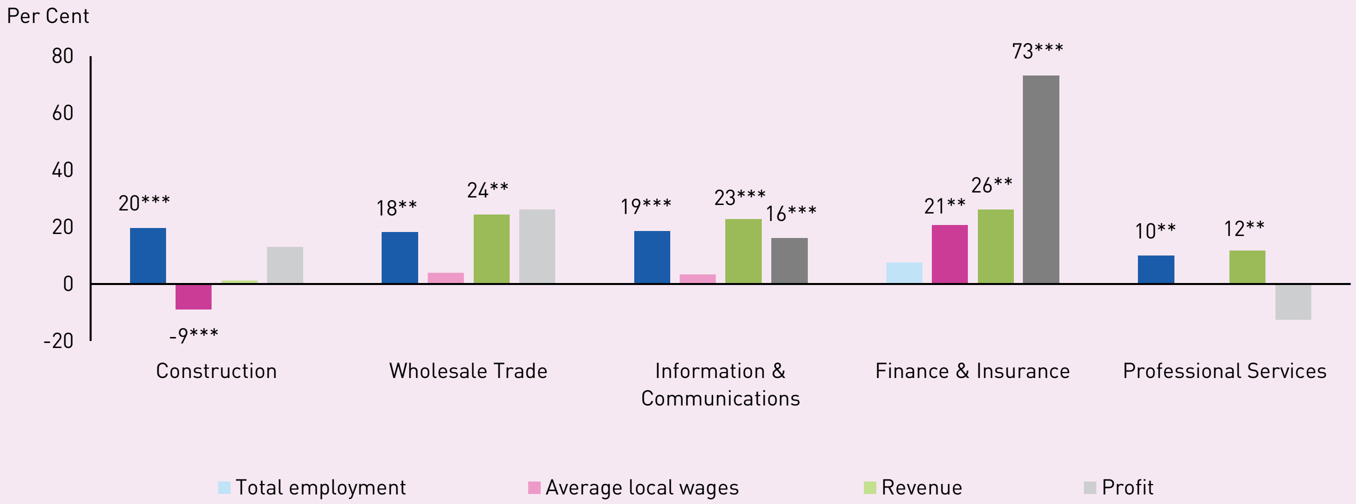
By sectors, AI-using firms in finance & insurance experience the largest increases in revenue and profit among the sectors analysed. AI may be especially valuable in the finance & insurance sector, as it can support the development of new or enhanced products and services, streamline operations or reduce operational costs (e.g., personalised investment products, fraud detection, credit risk scoring). AI-using firms in the sector also see increases in average local wages, as they may shift their workforce composition towards higher-income workers who may generate greater productivity gains with AI.

Meanwhile, AI-using firms in wholesale trade experience increases in revenue and total employment. This may be due to AI improving their ability to conduct demand forecasting, inventory planning and logistics optimisation, thereby resulting in firm expansion.

At the same time, information & communications firms show improvements in revenue, profit and total employment from AI use. This is consistent with AI supporting the development of new or enhanced products and services, personalised customer engagement and improved task efficiency. As markets expand with AI use, firms in this sector may increase their overall worker demand.

30 Results for sectors not discussed in this section are not statistically significant or at risk of spurious statistical significance due to low sample size.

Exhibit 6. Impact of AI use by selected sector



Note: *** p<0.01, ** p<0.05, * p<0.1. Results that are statistically significant at the 5% level are in solid colours and labelled. Sectors with low sample size (i.e., less than 30 AI-using firms) or results that are not statistically significant are not shown.

Impact of AI use by firm size

Heterogeneity analysis by firm size suggests that micro, small and medium firms see benefits from AI use (Exhibit 7, full results in Annex E).[31]

Micro AI-using firms experience the largest revenue gains. One possible explanation is that these firms may be more nimble and hence able to implement complementary organisational changes more quickly than larger firms.

Medium AI-using firms show broad gains in not just revenue, but also total employment and profit. This could be because these firms have sufficient resources, expertise and data to make meaningful AI investments, while remaining flexible enough to integrate AI effectively.

Small AI-using firms experience increases in total employment, possibly because they are expanding their workforce in anticipation of AI-enabled output gains. However, relevant organisational changes may still need to be completed before revenue gains fully materialise.

Exhibit 7. Impact of AI use by selected firm size

Note: *** p<0.01, ** p<0.05, * p<0.1. Results that are statistically significant at the 5% level are in solid colours and labelled. Results for large firms (revenue size >$100M) not shown due to low sample size (i.e., less than 30 AI-using firms).

31 *Results for large firms (revenue size >$100M) are not shown due to low sample size (i.e., less than 30 AI-using firms).*

CONCLUSION AND POLICY IMPLICATIONS

This study develops a firm-level measure of AI use in Singapore based on data from online job postings. The measure is then linked to administrative firm-level data to enable analyses on the characteristics of AI-using firms and the impact of firms' AI use on their performance and employment to be studied.

The study's key findings are as follows. First, AI use is not a stand-alone leap for firms. Instead, it tends to build on the prior efforts of firms to adopt foundational and complementary digital technologies.

Second, firms in digital- and data-intensive sectors/clusters (i.e., information & communications, electronics, professional services and finance & insurance) are more likely to use AI. Larger firms are also more likely to use AI, even after accounting for sector and age.

Third, first-time AI use by firms is associated with firm-level increases in total employment and revenue, and these gains continue to rise as AI capabilities deepen. This could reflect the potential scale and/or innovation effects of AI (e.g., AI reducing costs and/or enables the creation of new products, thus allowing firms to expand output). At the same time, the increase in firm-level employment suggests that any worker separations that may occur at the firm are outweighed by new hiring. It may also be the case that AI tends to automate specific tasks rather than entire jobs, thus allowing workers to focus on the remaining and/or new complementary tasks.

On the other hand, firms do not see a statistically significant increase in their productivity and profit within four years of first AI adoption. This could be because the full benefits of AI may only materialise after complementary investments are made, similar to the experience of earlier transformative technologies such as the internet.

Deeper analysis on the employment effects show that they differ across worker types. Initial gains are found to be concentrated among local higher-earners and mid-career workers, as well as skilled foreign professionals. However, as firms deepen their AI capabilities, the local employment gains broaden across wage and age groups.

Fourth, heterogeneity analyses show that the impact of firms' AI use varies across sector and firm size. For example, firms in the finance & insurance, wholesale trade and information & communications sectors, as well as micro and medium firms, see larger gains in revenue on average.

These findings suggest three policy lessons to help firms and workers realise economic benefits from AI. First, it is important for firms to strengthen their foundational digital capabilities as this could aid in their AI adoption. Second, support for AI use should be differentiated by sector and firm size. This may entail identifying sector-specific AI use cases with larger returns, or the provision of support to smaller firms that may lack internal capabilities to effectively integrate AI. Third, workforce policy should focus on job transformation and worker training to help workers move toward AI-complementary tasks even as some tasks become automated.

As the study analyses firms' AI use up to 2024, the estimates should be seen as reflecting the early impact of AI diffusion, and would not capture the effects of more recent advances in AI capabilities (e.g., agentic AI) as well as broader enterprise adoption. Future studies could analyse the effects of the different AI use cases that firms are implementing using more recent data that better capture the advances in AI technology and new patterns of adoption.

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REFERENCES

Acemoglu, D. and P. Restrepo (2018). "Artificial Intelligence, Automation, and Work." NBER Working Paper No. 24196. https://doi.org/10.3386/w24196.

Acemoglu, D. and P. Restrepo (2019). "Automation and New Tasks: How Technology Displaces and Reinstates Labor." Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3.

Alderucci, D., L. Branstetter, E. Hovy, A. Runge and N. Zolas (2020). "Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata."

Autor, D. and N. Thompson (2025). "Expertise." NBER Working Paper No. 33941. https://doi.org/10.3386/w33941.
Babina, T., A. Fedyk, A. He and J. Hodson (2024). "Artificial Intelligence, Firm Growth, and Product Innovation." Journal of Financial Economics.

Bonney, K. et al. (2024). "Tracking Firm Use of AI in Real Time: A Snapshot from the Business Trends and Outlook Survey." U.S. Census Bureau CES Working Paper No. 24-16.

Brynjolfsson, E., D. Rock and C. Syverson (2021). "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies." American Economic Journal: Macroeconomics, 13(1), 333–372. https://doi.org/10.1257/mac.20180386.Calvino, F., L. Samek, M. Squicciarini and C. Morris (2022). "Identifying and Characterising AI Adopters: A Novel Approach Based on Big Data." OECD Science, Technology and Industry Working Papers No. 2022/06. Paris: OECD Publishing. https://doi.org/10.1787/154981d7-en.

Calvino, F. and L. Fontanelli (2023). "A Portrait of AI Adopters across Countries: Firm Characteristics, Assets' Complementarities, and Productivity." OECD Science, Technology and Industry Working Papers No. 2023/02. Paris: OECD Publishing. https://doi.org/10.1787/0fb79bb9-en.Calvino, F., C. Criscuolo and A. Ughi (2024), "Digital adoption during COVID-19: Cross-country evidence from microdata." OECD Science, Technology and Industry Working Papers, No. 2024/03. Paris: OECD Publishing. https://doi.org/10.1787/f63ca261-en.

Khan, S. (2024). "Impact of AI on Singapore's Labor Market." IMF Selected Issues Paper No. SIP/2024/040. Washington, D.C., International Monetary Fund.

Liu, J., and D. Webber (2026). "AI Adoption and Firms Job-Posting Behavior." FEDS Notes. Washington: Board of Governors of the Federal Reserve System, March 27, 2026, https://doi.org/10.17016/2380-7172.4026.

McElheran, K. et al. (2025). "The Rise of Industrial AI in America: Microfoundations of the Productivity J-Curve."

OECD (2025). "Identifying Emerging AI Technologies Using Patent Data: A Semi-Automated Approach." Paris: OECD Publishing. https://doi.org/10.1787/d17e9a1a-en.

ANNEX

Annex A: Characteristics of AI-using firms

Term	AI use
Manufacturing - Electronics	0.149***
Manufacturing - Chemicals	-0.028
Manufacturing - Biomedical Manufacturing	0.020
Manufacturing - Precision Engineering	-0.014
Manufacturing - Transport Engineering	-0.010
Manufacturing - General Manufacturing	-0.040
Construction	-0.052
Utilities	-0.067
Other Goods Industries	0.023
Wholesale Trade	-0.005
Retail Trade	-0.016
Transportation & Storage	-0.041
Accommodation	-0.013
Food & Beverage Services	-0.067**
Information & Communications	0.221***
Finance & Insurance	0.061*
Real Estate	-0.019
Professional Services	0.062*
Administrative & Support Services	-0.036
Other Services - Education	0.000
Other Services - Health & Social Services	-0.049
Other Services - Arts, Entertainment & Recreation	-0.040
Other Services - Others	-0.057*
Age 6-10	0.039
Age 11-20	0.030
Age >20	0.010
Employment Size 11-50	0.050***
Employment Size 51-250	0.115***
Employment Size >250	0.393***
N	19,263

Statistical significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Annex B: Extensive-margin effects of AI use

Term	log (total emp.+1)	log (local emp.+1)	log (foreign emp.+1)	log (average local wages+1)	log (revenue+1)	asinh (profit)	asinh (vapw)
year of 1st AI use	0.043**	0.027	0.056***	0.010	0.076**	0.066	-0.137
1 year after	0.066**	0.044	0.077**	0.000	0.157***	0.175	0.138
2 years after	0.034	0.014	0.074	0.001	0.133*	0.047	0.066
3 years after	-0.010	-0.017	0.000	0.007	0.088	0.087	-0.126
4 years after	-0.136	-0.154	-0.096	-0.033	0.172	0.051	0.472
lag(digital using)	0.125***	0.095***	0.115***	0.002	0.009	0.035	0.237
lag(log(cumulative grant + 1))	0.028*	0.023	0.043***	0.015**	0.055***	0.043	0.348**
N	61,533	61,533	61,533	61,533	13,646	13,646	13,646

Term	log(locals earning <$3k +1)	log(locals earning $3k-$7k +1)	log(locals earning $7k-$10k +1)	log(locals earning >$10k +1)
year of 1st AI use	0.003	0.018	0.058**	0.014
1 year after	0.029	0.023	0.085**	0.037
2 years after	0.027	-0.007	0.047	0.040
3 years after	-0.018	-0.036	0.012	0.016
4 years after	-0.119	-0.152	0.023	-0.050
lag(digital using)	0.021	0.101***	0.093***	0.047**
lag(log(cumulative grant + 1))	0.000	0.048***	0.039***	0.021
N	61,533	61,533	61,533	61,533

Term	log(local emp. aged <24 +1)	log(locals aged 25-34 + 1)	log(locals aged 35-44 + 1)	log(locals aged 45-54 + 1)	log(locals aged 55-64 + 1)	log(locals aged >65 + 1)
year of 1st AI use	0.010	0.046**	0.064***	0.016	0.002	0.010
1 year after	0.007	0.072**	0.098***	0.027	0.003	0.032
2 years after	0.068	0.024	0.099*	0.015	0.012	0.019
3 years after	-0.040	-0.051	0.064	0.025	0.018	0.002
4 years after	-0.166	-0.187	-0.008	0.001	-0.091	-0.005
lag(digital using)	0.071***	0.144***	0.078***	0.093***	0.050**	0.024
lag(log(cumulative grant + 1))	0.006	0.049***	0.042***	-0.010	0.001	0.006
N	61,533	61,533	61,533	61,533	61,533	61,533

Term	log (EP holders+1)	log (S Pass holders+1)	log (Work permit holders+1)
year of 1st AI use	0.054***	0.013	0.025*
1 year after	0.115***	0.023	0.001
2 years after	0.108**	0.002	-0.002
3 years after	0.019	-0.052	0.012
4 years after	-0.076	-0.108	0.024
lag(digital using)	0.063***	0.044**	0.052***
lag(log(cumulative grant + 1))	0.045***	0.012	0.000
N	61,533	61,533	61,533

Statistical significance level: *** p<0.01, ** p<0.05, * p<0.1.

Annex C: Intensive-margin effects of AI use

Term	log (total emp.+1)	log (local emp.+1)	log (foreign emp.+1)	log (average local wages+1)	log (revenue+1)	asinh (profit)	asinh (vapw)
lag(log(cumulative max AI job postings + 1))	0.223***	0.232***	0.178***	0.021	0.244***	-0.110	-0.289
lag(digital using)	0.197***	0.175***	0.168***	0.052**	0.130**	0.131	0.166
lag(log(cumulative grant + 1))	0.031**	0.026*	0.052***	0.019**	0.036*	0.064	0.224
N	32,173	32,173	32,173	32,173	6,837	6,837	6,837

Term	log(locals earning <$3k +1)	log(locals earning $3k-$7k +1)	log(locals earning $7k-$10k +1)	log(locals earning >$10k +1)
lag(log(cumulative max AI job postings + 1))	0.118**	0.186***	0.137**	0.208***
lag(digital using)	0.089**	0.132***	0.130***	0.118***
lag(log(cumulative grant + 1))	-0.003	0.020	0.036**	0.013
N	32,173	32,173	32,173	32,173

Term	log(local emp. aged <24 +1)	log(locals aged 25-34 + 1)	log(locals aged 35-44 + 1)	log(locals aged 45-54 + 1)	log(locals aged 55-64 + 1)	log(locals aged >65 + 1)
lag(log(cumulative max AI job postings + 1))	0.011	0.264***	0.242***	0.196***	0.049	0.034
lag(digital using)	0.065	0.206***	0.117***	0.115***	0.100***	0.027
lag(log(cumulative grant + 1))	0.016	0.039***	0.032**	-0.015	0.024	0.006
N	32,173	32,173	32,173	32,173	32,173	32,173

Term	log (EP holders+1)	log (S Pass holders+1)	log (Work permit holders+1)
lag(log(cumulative max AI job postings + 1))	0.143***	0.133***	0.092
lag(digital using)	0.117***	0.062**	0.087***
lag(log(cumulative grant + 1))	0.049***	0.019*	0.004
N	32,173	32,173	32,173

Statistical significance level: *** p<0.01, ** p<0.05, * p<0.1.

Annex D: Impact of AI use by sector

Term	log (total emp.+1)	log (local emp.+1)	log (foreign emp.+1)	log (average local wages+1)	log (revenue+1)	asinh (profit)	asinh (vapw)
Manufacturing	-0.011	0.007	-0.053	-0.010	0.060	0.099	1.355
Construction	0.197***	0.054	0.277***	-0.088***	0.012	0.130	-2.071
Wholesale Trade	0.181**	0.128	0.382***	0.040	0.243**	0.262	0.250
Information & Communications	0.186***	0.199***	0.148***	0.034	0.227***	0.161***	0.713**
Finance & Insurance	0.075	0.082	0.007	0.206**	0.261**	0.731***	1.395
Professional Services	0.099**	0.098**	0.062	0.002	0.117**	-0.125	-0.394
Administrative & Support Services	0.122	0.129	0.175	0.016	0.016	0.090	0.335
lag(digital using)	0.125***	0.095***	0.115***	0.002	0.010	0.038	0.245
lag(log(cumulative grant + 1))	0.027*	0.022	0.043***	0.015**	0.055***	0.042	0.346**

Statistical significance level: *** p<0.01, ** p<0.05, * p<0.1. Sectors with low sample size (i.e., less than 30 AI-using firms) or results that are not statistically significant are not shown.

Annex E: Impact of AI use by revenue size

Term	log (total emp.+1)	log (local emp.+1)	log (foreign emp.+1)	log (average local wages+1)	log (revenue+1)	asinh (profit)	asinh (vapw)
Micro (<$1M)	0.006	-0.017	0.159	0.007	0.179**	0.142	0.854
Small ($10M-$100M)	0.130***	0.134**	0.091*	0.003	0.135*	0.088	0.272
Medium ($10M-$100M)	0.212***	0.202***	0.191***	0.074**	0.167***	0.136	0.235
lag(digital using)	0.142***	0.112**	0.154***	0.008	0.012	0.053	0.289
lag(log(cumulative grant + 1))	-0.038	-0.050	0.030*	0.007	0.054***	0.046	0.364**

Statistical significance level: *** p<0.01, ** p<0.05, * p<0.1. Results for large firms (revenue size >$100M) not shown due to low sample size (i.e., less than 30 AI-using firms).