

The Right AI Tool for the Job

The Productivity Potential of AI Applications in Canada

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Key findings

- Artificial intelligence (AI) exposure measures the extent to which AI capabilities can perform the abilities required in a worker's job. Exposure increases through three main channels: the adoption of AI applications, advances in AI capabilities that enable more work tasks to be performed, and the integration of AI into existing tools and technologies.
- Industries in which workers historically have higher exposure to AI show faster labour productivity growth than industries with lower exposure. When organizations match specific AI applications to these tasks, they unlock higher potential productivity gains. As a baseline estimate, economy-wide labour productivity grows annually by 2.32 percentage points when work is increasingly exposed to AI.
- We examined the productivity effects of AI across four levels: 1) individual AI applications, 2) broader AI system categories, 3) industry-level AI exposure, and 4) industry-application pairings that match specific AI tools to sector needs. At the AI application level, real-time strategy AI applications, like agentic tools, are associated with the highest productivity gains of all tools, followed by visual question answering and image-recognition AI tools.
- At the AI system level, reasoning systems are associated with the highest potential productivity gains. Computer vision systems follow closely, while large language systems generate more modest gains. These results highlight the higher productivity potential of decision-focused and visual-processing AI systems.
- At the industry level, industries with higher potential productivity growth concentrate in service industries, with retail trade, educational services, professional services, and healthcare seeing the highest productivity growth.
- At the industry-application level, the highest productivity gains emerge when organizations match specific AI applications to industry needs. Retail trade and educational services see the highest gains across all industry-application combinations.

AI exposure and productivity in Canada

Artificial intelligence (AI) is expected to revolutionize work and drive productivity gains not seen in years.¹ But these gains aren't yet showing up in jobs or productivity data.² Not all industries and workers will benefit equally from AI adoption due to differences in task compositions.³

To assess the potential impact of AI, this analysis links AI application exposure to industry-level productivity outcomes. Our measure of AI exposure builds on the artificial intelligence exposure index developed by Felten and others and extends prior work on AI exposure estimates in Canada and automation-driven productivity forecasting⁴ by assessing industry- and application-specific productivity potential. We address the following research questions:⁵

- Which AI applications and systems are associated with the highest productivity gains?
- Which Canadian industries are associated with the highest labour productivity gains from AI exposure?
- Which industry–application pairings are associated with the highest productivity gains?

We applied an occupation-based AI exposure framework to answer these questions.⁶ While exposure is not a direct measure of adoption, it's a proxy for AI's capacity to perform tasks, which we also expect to increase over time. Our analysis provides predictive identification of productivity rather than a causal assessment of AI-driven productivity growth. This approach treats AI as a set of distinct applications, not a single technology. It examines where specific AI applications deliver the greatest value. The framework links individual AI applications or systems (combinations of related tools) to the abilities required to perform tasks in occupations.⁷ This approach allows us to assess how productivity gains from different AI applications vary across industries. (See Exhibit 1.) By examining AI-task alignment across multiple levels of analysis, the framework shows that productivity gains are not driven by AI exposure alone. Rather, the highest gains occur when specific AI capabilities are matched to the tasks and workflows where they are most effective.

¹ Loertscher, *Economic Impact of Going All In*; and Li and Liu, "Role of Complementary Capabilities."

² Filippucci and others, "Miracle or Myth?"; and Filippucci and others, "Macroeconomic Productivity Gains."

³ Signal49 Research, *The Productivity Potential*; and Mehdi and Morissette, *Experimental Estimates*.

⁴ Felten and others, "Occupational, Industry, and Geographic Exposure"; and Mehdi and Morissette, *Experimental Estimates*.

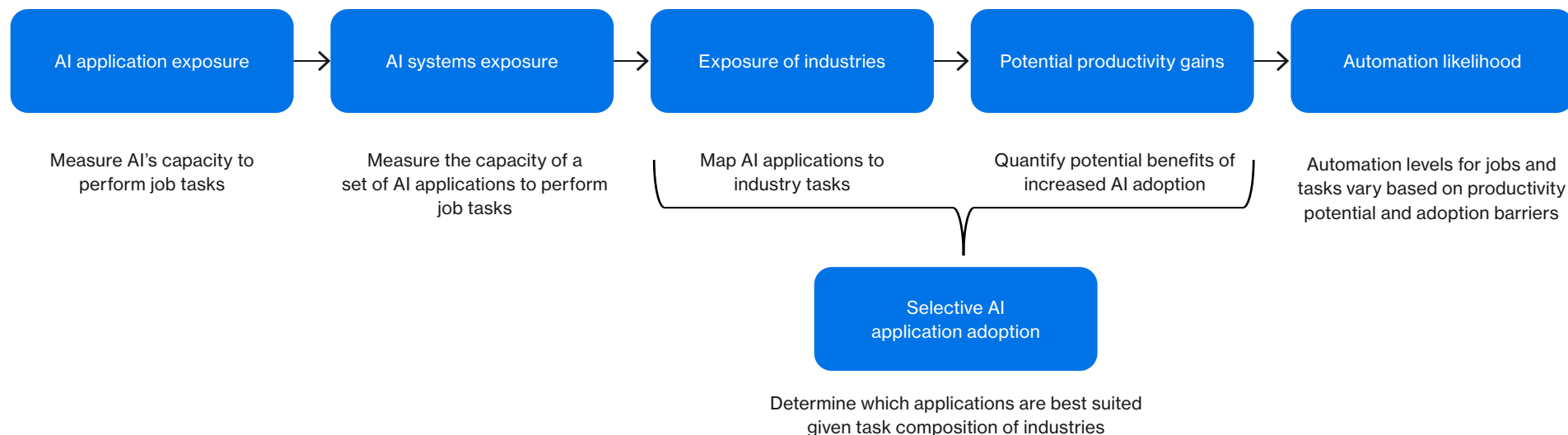
⁵ In the regression model we built to answer these questions, the estimated coefficient on exposure represents the marginal effect of AI exposure increasing by 10 per cent on labour productivity.

⁶ Felten and others, "Occupational, Industry, and Geographic Exposure."

⁷ The framework we use to examine the impact of AI is based on previous work that classifies 10 distinct AI applications and their capacity to perform 52 worker abilities from the O*NET labour classification system.

Exhibit 1

Framework for estimating AI-driven automation exposure and potential productivity gain



Note: Adoption—not exposure alone—is the critical step in translating AI capabilities into productivity gains. In this sense, our approach of increase in AI exposure should be regarded as scenario testing for estimating potential productivity effects, not a direct assessment of AI adoption.

Source: Signal49 Research.

Throughout this briefing, estimated coefficients are interpreted as the change in labour productivity associated with a 10 per cent increase in AI exposure. The analysis measures AI productivity potential rather than realized effects by aligning specific AI capabilities with industries that have historically achieved higher productivity growth. We use historical data from 2001 to 2024, accounting for economic output and industry workforce compositions.

This baseline allows us to estimate how AI exposure could influence productivity using existing industry patterns. We find that targeted deployment at the industry level yields greater productivity potential through higher levels of worker ability (or job task) exposure to AI. Further details on the modelling methodology are provided in the text boxes below and in Appendix A.

This briefing contributes to a broader project, Main Street AI, that helps small and medium-sized enterprises (SMEs) and SME-serving organizations move from general interest in AI to practical adoption guidance. SMEs drive a major share of Canada's economy and jobs,⁸ but many of these businesses are not clear on the benefits, technical requirements, and workforce impacts that come with AI use. These challenges make evidence-based guidance essential.

Businesses need to understand where AI delivers value, which applications fit their work, and how adoption affects existing roles and responsibilities. This briefing addresses those gaps by identifying which applications offer the highest productivity potential based on job tasks and industry patterns. It provides the foundation for the next phases of the project, which translate these findings into a needs-based assessment of AI use cases and implementation pathways.



Building on previous Signal49 research

Similar to one of our previous studies,⁹ we estimate the relationship between exposure measures and real value-added growth across Canadian industries from 2001 to 2024. This approach allows us to identify where AI exposure aligns with potential productivity gain and which applications provide the highest potential industry-level productivity growth. This analysis assumes industry-wide exposure will increase over time, which we represent as a 10 per cent increase in AI exposure as our baseline estimate.

While our prior research used a similar potential productivity model related to industry-level automation exposure, this study uses a different exposure framework constructed at the individual AI application level. Future research could integrate these approaches to provide a more comprehensive assessment of the productivity effects of automation and AI.

⁸ As of December 2023, 99.7 per cent of Canadian businesses were SMEs (with one to 499 employees). SMEs accounted for 53.8 per cent of total employment in Canada in 2023, employing nearly 9.5 million Canadians. See Innovation, Science and Economic Development Canada, *Key Small Business Statistics 2024*.

⁹ Signal49 Research, *The Productivity Potential*; Signal49 Research, *Understanding the Influence of AI on Employment*; and Loertscher, *Economic Impact of Going All In*.



AI industry exposure

Exposure measures the capacity of AI to perform worker abilities. Workers experience greater exposure to AI applications in the economy through three main channels:

- increasing adoption of AI applications¹⁰
- expanded AI capabilities to perform work tasks¹¹
- integration of AI into existing tools and technologies

While newer frameworks focus on generative AI, they often take a narrower view of AI capabilities. As discussed in Appendix A, this analysis uses a worker-ability-to-AI-application lens to increase granularity and position generative tools alongside classical classification and prediction models.

Categorizing AI tools and technologies

Industries benefit from AI in different ways based on the tasks their workers perform. In finance and insurance, workers rely on reading, drafting, and data analysis, which creates higher exposure to language modelling and reading-comprehension applications. In mining, workers focus on operating equipment and inspecting outputs, which align with real-time strategy and image-recognition applications. While both industries can adopt a range of AI tools, productivity growth potential improves when applications match the underlying job task composition. This approach captures these differences and models productivity estimates accordingly.

¹⁰ Do and others, *Analysis on Artificial Intelligence Use*.

¹¹ METR, "Measuring AI Ability."

Ten AI applications and three systems

We identify 10 distinct types of AI applications (see “AI application definitions”) and group them into three systems based on their capacity to process language, images, and complex tasks¹²:

- **reasoning systems:** real-time strategy and abstract strategy applications
 - example: agentic platforms such as Claude Code or OpenAI Codex
- **computer vision:** visual question answering, image generation, and image-recognition applications
 - example: computer vision platforms such as Roboflow
- **large language systems:** reading comprehension, instrumental track recognition, speech recognition, language modelling, and translation applications
 - example: large language model (LLM) platforms such as Microsoft Copilot

AI application definitions

The following AI applications were identified and related exposure measure was constructed in 2021,¹³ before the onset and commercial availability of LLMs such as ChatGPT and Copilot. Therefore, they potentially represent a more conservative estimate of LLM exposure and productivity growth.

Abstract strategy: The ability to reason, plan, and make decisions in structured environments that require evaluating alternatives and anticipating future outcomes. While this capability is often measured using abstract strategy games such as chess, it’s also relevant to business tasks involving planning, resource allocation, and strategic decision-making.

Real-time strategy: The ability to make decisions, plan actions, allocate resources, and adapt to changing conditions in real time. This capability is commonly evaluated using real-time strategy game environments of increasing complexity.

Image recognition: The determination of what objects are present in a still image.

Visual question answering: The recognition of events, relationships, and context from a still image.

Image generation: The creation of complex images.

Reading comprehension: The ability to answer simple reasoning questions based on an understanding of text.

Language modelling: The ability to model, predict, or mimic human language.

Translation: The translation of words or text from one language into another.

Speech recognition: The recognition of spoken language into text.

Instrumental track recognition: The recognition of instrumental musical tracks.

We structure the analysis across four layers: a) 10 types of AI applications, b) three system-level groupings, c) an industry-level exposure score, and d) industry–application pairings that match specific AI tools to sector needs.

¹² Electronic Frontier Foundation, *Measuring the Progress of AI Research*.

¹³ Felten and others, “Occupational, Industry, and Geographic Exposure.”

From AI exposure to potential productivity gain

Productivity gains emerge when AI tools align closely with operational and cognitive workflows. The results suggest that broad-based AI enablement strategies deliver relatively fewer benefits than application-specific approaches. This finding highlights the importance of understanding which AI applications, systems, and contexts are associated with the greatest productivity gains. The following sections outline which applications, systems, and industries show the greatest productivity potential as AI exposure increases in the Canadian economy.

Real-time strategy tools generate the highest potential productivity gains

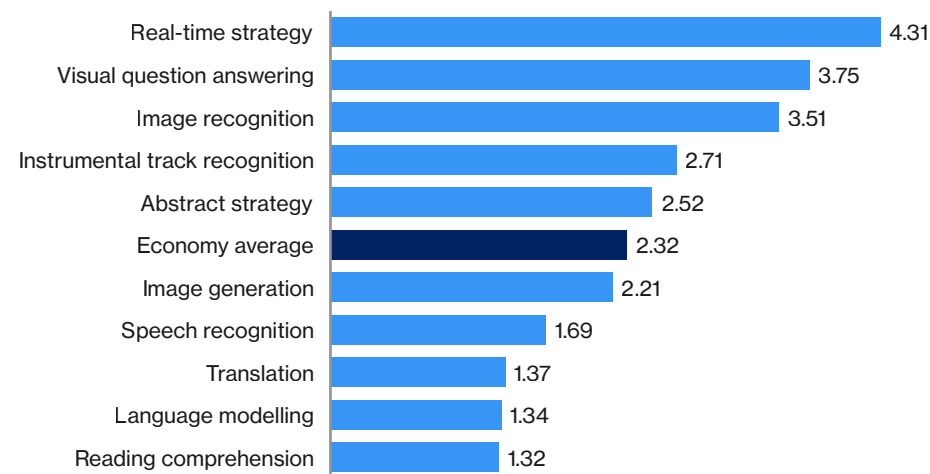
The results show clear differences in productivity potential across AI application types. (See Chart 1.) Real-time strategy applications are associated with the highest estimated productivity gain, with a growth of 4.31 percentage points per year, followed by visual question answering (3.75) and image recognition (3.51). These three application categories are the only ones that exceed three percentage points, and all perform well above the economy-wide average of 2.32 percentage points.

The pattern suggests that applications designed for real-time decision-making and visual-information processing are associated with higher productivity gains than other AI application types. Instrumental track recognition (2.71) and abstract strategy (2.52) also exceed the average, reinforcing the value of task-specific analytical and decision-support capabilities.

Chart 1

Visual processing and real-time strategy applications lead potential productivity gains

(annualized labour productivity growth in percentage points associated with a 10 per cent increase in AI exposure)



Note: Estimates are statistically significant at the 5 per cent level ($p < 0.05$). See Appendix A and B for more details.

Source: Signal49 Research.

By contrast, language-based applications tend to be associated with lower productivity gains. Speech recognition (1.69) and image generation (2.21) are below the average, while reading comprehension (1.32), language modelling (1.34), and translation (1.37) rank at the bottom of the distribution. Overall, the results suggest that AI applications aligned with specific operational tasks tend to generate higher productivity gains than more general-purpose information-processing applications.¹⁴

Overall, while the estimated productivity gains are modest in absolute terms, the highest-performing applications generate productivity gains well above the economy-wide average, suggesting that targeted AI deployment offers greater potential benefits than general AI exposure alone.

Reasoning and computer vision systems provide large productivity potential

At the systems level, grouping AI applications by functional capability helps reveal broader patterns in productivity growth that may not be apparent when examining individual applications alone. Industries with higher exposure to reasoning systems grew by 3.33 percentage points per year, and those more exposed to computer vision systems grew by 3.27 percentage points, both above the economy-wide average. (See Chart 2.)

The results suggest that AI systems designed for decision-making and visual processing are associated with higher productivity gains than language-based systems. While individual applications vary in performance, the pattern remains consistent when they're grouped into broader AI system categories. By contrast, industries more exposed to large language systems—which include several widely used language-based applications—grew by a more modest 1.55 percentage points.

Taken together, these findings suggest that the productivity benefits of AI are not evenly distributed across AI systems. Reasoning and computer vision systems are associated with higher productivity gains, while language-focused systems are associated with lower gains relative to the economy-wide average.

Chart 2

Reasoning systems lead to highest productivity gains
(annualized labour productivity growth in percentage points associated with a 10 per cent increase in AI exposure)



Note: Estimates are statistically significant at the 5 per cent level ($p < 0.05$). See Appendix A and B for more details.

Source: Signal49 Research.

¹⁴ LLMs became widely deployable at the end of 2022, and this estimate should be considered as a conservative estimate and not a forecast of future generative AI returns.

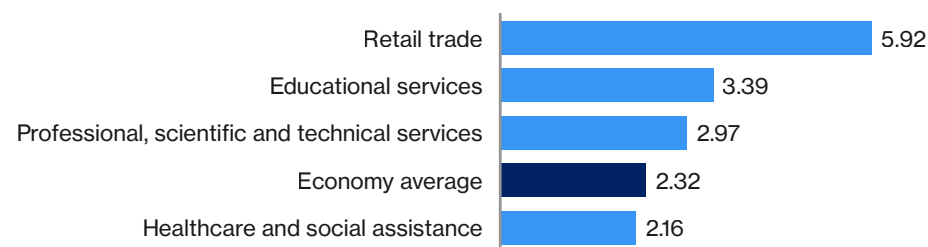
AI benefits are concentrated in a small number of service industries

Productivity gains associated with AI exposure are concentrated in a few service industries. (See Chart 3.) Retail trade (5.92 percentage points per year) and educational services (3.39) are associated with the highest productivity gains, followed by professional, scientific, and technical services (2.97) and healthcare and social assistance (2.16). These industries share a common reliance on information processing, decision-making, and customer-facing tasks.¹⁵

Chart 3

AI productivity gains concentrate in a few service sectors

(annualized labour productivity growth in percentage points associated with a 10 per cent increase in AI exposure)



Note: All industry estimates shown are statistically significant at the 5 per cent level ($p < 0.05$).

See Appendix A and B for more details.

Source: Signal49 Research.

The results suggest that industries benefit most when AI capabilities align closely with their underlying task requirements.¹⁶ AI exposure alone does not guarantee higher productivity gains; productivity outcomes depend on how effectively AI capabilities can be applied to the tasks performed within each industry.¹⁷

Targeted AI deployment has the greatest potential gains

To identify which industries could benefit from specific AI applications, we examined all combinations of industries and 10 applications (135 pairs). The top industry–application pairings highlight the scale of productivity growth when AI applications pair with specific industries. The top pairings with highest potential productivity gain are concentrated in retail trade and educational services. Retail trade shows the highest potential annual gains when paired with real-time strategy (8.17 percentage points), image recognition (7.43), and visual question answering (7.42).¹⁸ (See Table 1.) Educational services follow, with real-time strategy (7.69) and image recognition (7.45). Real-time strategy application in the retail industry supports decision-making in time-sensitive operations related to inventory management, supply-chain coordination, product allocation, and pricing.

¹⁵ Signal49 Research, *Canada's Workforce in Transition*.

¹⁶ The remaining industries show effects that are not statistically distinguishable from the economy-wide pattern: agriculture, forestry, fishing and hunting; mining, quarrying, oil and gas; utilities; manufacturing; wholesale trade; transportation and warehousing; information and cultural industries; real estate, rental, and leasing; other services; public administration; finance and insurance; administrative and support services; accommodation and food services; and arts, entertainment and recreation.

¹⁷ High costs to adopt, capital and machinery integrations, and lower applicability of AI to industry use drive the lower potential value for some industries. While AI may have shorter-term potential for service industries, other automation technologies like robotics can improve the long-term value of AI adoption, especially in goods-producing industries. See Signal49 Research, *The Productivity Potential*.

¹⁸ The retail trade estimate should be interpreted cautiously because it rests on three sub-industries and is sensitive to changes in these sub-industries.

These large estimates should be interpreted as indicators of where AI capabilities align most closely with industry tasks rather than as expected annual productivity gains from AI implementation. The estimates are based on the historical relationship between AI exposure and productivity growth and assume that organizations can effectively deploy AI in relevant tasks. In practice, realized gains will depend on factors such as adoption rates, organizational changes, workforce capabilities, and the extent to which AI applications are integrated into existing workflows.

Overall, the findings suggest that the greatest productivity potential comes not simply from increasing AI exposure but from matching specific AI applications to the tasks and operational requirements of an industry.

Table 1

Industry-specific AI pairings provide highest potential benefits for labour productivity
(annualized labour productivity growth in percentage points associated with a 10 per cent increase in AI exposure)

AI application/industry	Retail trade	Educational services	Professional, scientific and technical services
Real-time strategy	8.17	7.69	0.00
Image recognition	7.43	7.45	0.00
Visual question answering	7.42	5.34	0.00
Abstract strategy	6.39	4.31	0.00
Instrumental track recognition	6.14	4.74	3.66
Image generation	6.11	5.50	0.00
Speech recognition	5.16	2.52	2.31
Translation	4.77	2.06	1.91
Language modelling	4.60	2.06	1.85
Reading comprehension	4.59	2.10	0.00

Note: Estimates are statistically significant at the 5 per cent level ($p < 0.05$). See Appendix A and B for more details.
Source: Signal49 Research.

AI specificity matters for adoption success

AI is not a uniform productivity tool. It operates as a targeted technology that delivers results when specific applications align closely with industry task compositions. As a result, adoption—not exposure alone—is the critical step in translating AI capabilities into productivity gains. For businesses, successful adoption means embedding AI into core workflows and decision-making processes rather than layering it onto existing tasks as a general-purpose tool.

At the economy level, increased AI exposure delivers modest productivity gains of 2.32 percentage points per year. However, larger gains emerge when organizations adopt AI applications that are well matched to the tasks they perform. Businesses that integrate reasoning and computer vision systems into closely aligned workflows achieve productivity growth between 2 and 6 percentage points. At the highest level of application–task alignment, top industry–application pairings generate gains between 5 and 8 percentage points.

These findings suggest that productivity growth depends neither on the availability of AI technologies nor on broad-based adoption alone. Rather, it depends on the successful adoption of the right AI applications in the right operational contexts. Organizations that intentionally and selectively align AI deployment with their task requirements are best positioned to realize meaningful productivity gains and unlock the full value of AI investment.



Appendix A

Methodology

AI exposure framework

Our study's AI exposure measure is built on the artificial intelligence exposure index of Felten and others,¹ the same index that Statistics Canada applies in its assessment of the Canadian labour market.² We adapt this framework to the Canadian economy to measure the productivity potential of AI. The approach follows a two-phase framework:

1. Calculating AI exposure at the industry level, representing the share of worker abilities that AI can perform.
2. Estimating productivity gains that would be associated with increased use of these AI applications at the industry level.

Estimating exposure scores

Exposure scores are a composite index of 10 AI application subindices defined by the Electronic Frontier Foundation, which collects and maintains statistics on the progress of AI across applications. Felten and co-authors first measure how closely each of the 52 human abilities catalogued in the O*NET database relates to each of 10 distinct AI applications, drawing on crowd-sourced relatedness scores across all 520 ability-by-application pairings. An occupation's AI exposure is the sum of its relatedness across the 10 applications, weighted by the prevalence and importance of each ability to that occupation. An industry's exposure is the employment-weighted average of the occupational scores within that industry.

We retain both the composite score and its 10 application-specific components so that exposure can be traced to the AI applications driving it. These 10 subindices are the central focus of our analysis: they provide a granular measure of AI industry exposure (AIIE) for estimating potential labour productivity growth. More recent frameworks have provided a narrower focus on generative AI capabilities. Alternative AI exposure frameworks link occupational abilities to patent text, expert forecasts, usage data, and AI benchmarks.³ Recent studies show that the approach of Felten and colleagues remains consistent with these newer measures.⁴

Methods and data

Construction of the AIIE

To estimate the average AI exposure of an industry, we assigned each occupation 10 application scores reflecting how well each AI application performs the abilities that job requires. We weighted these scores by 2021 Census employment shares within each province at the four-digit North American Industry Classification System (NAICS) level, then aggregated them to the two-digit NAICS level to produce the AIIE.⁵ We also grouped the application-level scores into three AI systems:

- **reasoning systems:** real-time strategy and abstract strategy applications
- **computer vision:** visual question answering, image-generation, and image-recognition applications
- **large language systems:** reading comprehension, instrumental track recognition, speech recognition, language modelling, and translation applications

We link these exposure scores to historical industry data at the most granular level available, allowing us to estimate potential productivity growth across Canadian industries and AI application types.

Data sources and estimation sample

Our estimation sample is a panel of provinces by the most detailed available industry, observed annually from 2001 to 2024, with real value added, hours worked, and employment counts. We restrict the panel to industries with non-zero AIIE scores. The 2001–24 window is set by the overlap between the Statistics Canada series and the occupational composition used to build the AIIE from the 2021 Census. We merge the data sources by Canadian industry and occupation classification codes:

- Occupational composition data comes from Statistics Canada's 2021 Census of Population (catalogue no. 98-500-X), five-digit National Occupational Classification (NOC) employment counts crossed with four-digit NAICS and province. The 2021 Census provides the occupational composition used to map AI's applications to industry exposure.

1 Felten and others, "Occupational, Industry, and Geographic Exposure."

2 Mehdi and Morissette, *Experimental Estimates*.

3 Handa and others, "Which Economic Tasks Are Performed With AI?"; Eloundou and others, "GPTs Are GPTs"; and Gulati, "Benchmarking the Future of Work."

4 See Filippucci and others, "Macroeconomic Productivity Gains," 32, Figure A.1.

5 Felten and others, "Occupational, Industry, and Geographic Exposure."

- Ten AI applications and their application-by-ability scores are from Felten and others.⁶ The adaptation and alignment of these scores to Canadian NOC-based occupational ability profiles is based on Mehdi and Morissette.⁷
- Real value added, hours and employment data come from Statistics Canada Table 36-10-0480-01⁸ by the most granular industry and geographic level by measure (real value added, hours worked, and employment). Real value added is in chained 2017 dollars.

The final sample covers two-digit NAICS industries crossed with the 10 provinces, excluding construction (NAICS 23), management of companies and enterprises (NAICS 55), and owner-occupied dwellings (NAICS 53) because of low sample counts. All retained cells have non-zero economic indicators over 2001 to 2024.

Estimation

We compute cumulative real value-added growth as the log-difference between 2001 and 2024 ($\text{Change(RVA)} = \log(\text{RVA}_{2024}) - \log(\text{RVA}_{2001})$). We compute cumulative hours worked and employment the same way. We drop cells with missing values in any covariate or outcome.

We then estimate the relationship between exposure and productivity using a weighted least squares (WLS) long-difference regression:

$$\Delta \log(\text{RVA})_k = \beta \cdot \text{exposure}_k + \gamma \cdot \Delta \log(\text{hours})_k + \delta_p + \alpha_i + \varepsilon_k$$

The dependent variable is the cumulative log-change in real value added over the 24-year window. The independent variables are:

- exposure_k : the AI exposure of panel cell k (a province by the most granular NAICS level)
- $\Delta \log(\text{hours})_k$: the cumulative log-change in hours worked
- δ_p : province fixed effects (p denoting the province)
- α_i : two-digit NAICS fixed effects (i denoting the parent industry)

We repeat the regression separately for each exposure measure: the AII in aggregate, each of the three AI systems (reasoning systems, computer vision, and LLMs), and each of the 10 individual applications.

Charts 1 through 4 in this briefing re-estimate the regression with exposure in logarithmic form. The resulting coefficients express the annualized percentage point change in labour productivity growth associated with a 10 per cent increase in exposure sustained over the 24-year window.

Interpretation of β

The estimated coefficient on exposure represents the marginal effect of AI exposure increasing by 10 per cent on labour productivity. Although the dependent variable is not a direct measure of labour productivity, this interpretation is valid because the coefficient is conditional on regional and/or sectoral differences as well as employment and changes in working hours.

- The province fixed effects (δ_p) absorb region-specific shocks common to all industries in a province, such as differences in demand, prices, or policy, while the two-digit NAICS fixed effects (α_i) absorb shocks within the broader industry group, such as sector-wide changes in global prices or demand.
- Controlling for the cumulative log-change in hours worked isolates the change in real value added attributable to labour input, so what remains is output growth per unit of labour, consistent with the definition of labour productivity. Additionally, each industry is weighted by its 2024 employment as a share of the national employment base, meaning our change in productivity is conditional on employment changes.

AI adoption has already tripled from 6.1 in 2024 to 19.2 per cent since 2024.⁹ We expect this trend will continue and that exposure will increase over time as AI tools become more effective at completing tasks¹⁰ and as AI is integrated into existing tools and technologies, such as Microsoft Office and Google Workspace.

⁶ Felten and others.

⁷ Mehdi and Morissette, *Experimental Estimates*.

⁸ Statistics Canada, Table 36-10-0480-01.

⁹ Do and others, *Analysis on Artificial Intelligence Use*.

¹⁰ METR, "Measuring AI Ability."

Appendix B

Detailed results tables

Headline estimates and significance levels for 10 AI applications

Table 1
Productivity gains vary by AI application
(annualized percentage-point change in productivity growth per +10 per cent increase in AI exposure)

AI application	pp/yr per +10% exposure
Real-time strategy	4.31
Visual question answering	3.75
Image recognition	3.51
Instrumental track recognition	2.71
Abstract strategy	2.52
AI industry exposure	2.32
Image generation	2.21
Speech recognition	1.69
Translation	1.37
Language modelling	1.34
Reading comprehension	1.32

Note: All estimates are statistically significant at the 5 per cent level ($p < 0.05$).
Source: Signal49 Research.

Headline estimates and significance levels for AIIE and the three aggregate AI systems

Table 2
Reasoning systems show the highest productivity gains
(annualized percentage-point change in productivity growth per +10 per cent increase in AI exposure)

AI system	pp/yr per +10% exposure
Reasoning systems	3.33
Computer vision	3.27
AI industry exposure	2.32
Large language systems	1.55

Note: All estimates are statistically significant at the 5 per cent level ($p < 0.05$).
Source: Signal49 Research.

Industry-specific productivity estimates and significance levels

Table 3

Four out of 18 industries show statistically significant productivity gain from AI exposure
(annualized percentage-point change in productivity growth per +10 per cent increase in AI exposure)

NAICS code	Industry	pp/yr per +10% exposure	Significance
11	Agriculture, forestry, fishing and hunting	1.23	—
21	Mining, quarrying, oil and gas	−6.19	—
22	Utilities	1.61	—
31-33	Manufacturing	0.2	—
41	Wholesale trade	1.63	—
44-45	Retail trade	5.92	*
48-49	Transportation and warehousing	−1.99	—
51	Information and cultural industries	7.4	—
52	Finance and insurance	n/a	—
53	Real estate and rental and leasing	−0.5	—
54	Professional, scientific and technical services	2.97	*
56	Administrative and support services	n/a	—
61	Educational services	3.39	*
62	Healthcare and social assistance	2.16	*
71	Arts, entertainment and recreation	n/a	—
72	Accommodation and food services	n/a	—
81	Other services	0.06	—
91	Public administration	−0.52	—

Notes: The estimate for retail trade (44-45) rests on only three sub-industry components and is sensitive to their inclusion; in our sensitivity analysis, dropping a single sub-industry can remove its statistical significance. All estimates with asterisks are statistically significant at the 5 per cent level ($p < 0.05$). Cells with “—” indicate that the estimated relationship between AI exposure and productivity is not statistically significant at conventional levels ($p < 0.05$).

Source: Signal49 Research.

Industry–AI application pairings

Table 4

Industry level labour-productivity growth depends on the application of the right AI tool

(annualized percentage-point change in productivity growth per +10% increase in AI exposure)

NAICs Code	Industry	Application	pp/yr per +10% exposure
44-45	Retail trade	Real-time strategy	8.17
61	Educational services	Real-time strategy	7.69
61	Educational services	Image recognition	7.45
44-45	Retail trade	Image recognition	7.43
44-45	Retail trade	Visual question answering	7.42
44-45	Retail trade	Abstract strategy	6.39
44-45	Retail trade	Instrumental track recognition	6.14
44-45	Retail trade	Image generation	6.11
61	Educational services	Image generation	5.5
61	Educational services	Visual question answering	5.34
44-45	Retail trade	Speech recognition	5.16
44-45	Retail trade	Translation	4.77
61	Educational services	Instrumental track recognition	4.74
44-45	Retail trade	Language modeling	4.6
44-45	Retail trade	Reading comprehension	4.59
61	Educational services	Abstract strategy	4.31
54	Professional, scientific and technical services	Instrumental track recognition	3.66
61	Educational services	Speech recognition	2.52
54	Professional, scientific and technical services	Speech recognition	2.31
61	Educational services	Reading comprehension	2.1
61	Educational services	Language modeling	2.06
61	Educational services	Translation	2.06
54	Professional, scientific and technical services	Translation	1.91
54	Professional, scientific and technical services	Language modeling	1.85

Significance: All estimates are statistically significant at the 5% level ($p < .05$).

Note: This table displays the industry–application pairings that remain statistically significant after applying the Benjamini-Hochberg false-discovery-rate correction to the 135 pairings evaluated.

Source: Signal49 Research.

Appendix C

Bibliography

Do, Vicky, Shivani Sood, and Chris Johnston. *Analysis on Artificial Intelligence Use by Businesses in Canada, Second Quarter of 2026*. Ottawa: Statistics Canada, June 11, 2026. <https://www150.statcan.gc.ca/n1/pub/11-621-m/11-621-m2026010-eng.htm>.

Electronic Frontier Foundation. *Measuring the Progress of AI Research*. Electronic Frontier Foundation, 2017. <https://www.eff.org/files/ai-progress-metrics.html>.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock. "GPTs Are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models." arXiv, March 17, 2023. <https://arxiv.org/abs/2303.10130v5>.

Felten, Edward, Manav Raj, and Robert Seamans. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42, no. 12 (2021): 2195–2217. <https://doi.org/10.1002/smj.3286>.

Filippucci, Francesco, Peter Gal, Katharina Laengle, and Matthias Schief. "Macroeconomic Productivity Gains From Artificial Intelligence in G7 Economies." *OECD Artificial Intelligence Papers*, no. 41. Paris: OECD Publishing, June 30, 2025. <https://doi.org/10.1787/a5319ab5-en>.

Filippucci, Francesco, Peter Gal, and Matthias Schief. "Miracle or Myth? Assessing the Macroeconomic Productivity Gains From Artificial Intelligence." *OECD Artificial Intelligence Papers*, no. 29. Paris: OECD Publishing, November 22, 2024. <https://doi.org/10.1787/b524a072-en>.

Gulati, Kris. "Benchmarking the Future of Work: Mapping AI Progress to Occupational Tasks." SSRN Scholarly Paper no. 5452354. Social Science Research Network, September 6, 2025. <https://doi.org/10.2139/ssrn.5452354>.

Handa, Kunal, Alex Tamkin, Miles McCain, Saffron Huang, Esin Durmus, Sarah Heck, Jared Mueller, and others. "Which Economic Tasks Are Performed With AI? Evidence From Millions of Claude Conversations." arXiv, February 11, 2025. <https://doi.org/10.48550/arXiv.2503.04761>.

Innovation, Science and Economic Development Canada. *Key Small Business Statistics 2024*. Ottawa: Government of Canada, 2025. <https://ised-isde.canada.ca/site/sme-research-statistics/en/key-small-business-statistics/key-small-business-statistics-2024>.

Li, Jiang, and Huju Liu. "Role of Complementary Capabilities in Artificial Intelligence Adoption and Productivity: Firm-Level Evidence From Canada." *Canadian Public Policy* 52, no. S1 (2026): 36–57. <https://doi.org/10.3138/cpp.2025-065>.

Loertscher, Oliver. *Economic Impact of Going All In on Automation*. Ottawa: Signal49 Research, 2026. https://www.signal49.ca/product/economic-impact-of-going-all-in-on-automation_jun2026/.

Mehdi, Tahsin, and René Morissette. *Experimental Estimates of Potential Artificial Intelligence Occupational Exposure in Canada*. Ottawa: Statistics Canada, September 3, 2024. <https://www150.statcan.gc.ca/n1/pub/11f0019m/11f0019m2024005-eng.htm>.

METR. "Measuring AI Ability to Complete Long Software Tasks." METR, March 19, 2025. <https://metr.org/blog/2025-03-19-measuring-ai-ability-to-complete-long-tasks/>.

Pizzinelli, Carlo, Augustus J. Pantan, Marina Mendes Tavares, Mauro Cazzaniga, and Longji Li. "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications." *IMF Working Papers* 2023, no. 216 (2023): 1–55. <https://doi.org/10.5089/9798400254802.001.A001>.

Signal49 Research (formerly operating as The Conference Board of Canada). *Canada's Workforce in Transition: How AI Is Shaping the Future of Work*. Ottawa: Signal49 Research, 2025. https://www.signal49.ca/product/how-ai-is-shaping-the-future-of-work_sept2025/.

—. *The Productivity Potential of Automation Technologies*. Ottawa: Signal49 Research, 2025. https://www.signal49.ca/product/automation-technologies-productivity-potential_sept2025/.

—. *Understanding the Influence of AI on Employment*. Ottawa: Signal49 Research, 2026. https://www.signal49.ca/product/understanding-the-influence-of-ai-on-employment_jan2026/.

Statistics Canada. "Census of Population." Ottawa: Statistics Canada, 2021. <https://www12.statcan.gc.ca/census-recensement/2021/>.

Statistics Canada. Table 36-10-0480-01. "Labour Productivity and Related Measures by Business Sector Industry and by Non-commercial Activity Consistent With the Industry Accounts, Inactive." Statistics Canada, May 20, 2025. <https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3610048001>.

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Accessibility Officer, Signal49 Research

Tel.: 613-526-3280 or 1-866-711-2262 | Email: accessibility@signal49.ca

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