The Conference Board of Canada

In partnership with Future Skills Centre / Centre des Compétences futures

Understanding the Influence of AI on Employment

Issue briefing | January 6, 2026

Future Skills Centre
Centre des Compétences futures

The Future Skills Centre (FSC) is a forward-thinking centre for research and collaboration dedicated to driving innovation in skills development so that everyone in Canada can be prepared for the future of work. We partner with policymakers, researchers, practitioners, employers and labour, and post-secondary institutions to solve pressing labour market challenges and ensure that everyone can benefit from relevant lifelong learning opportunities. We are founded by a consortium whose members are Toronto Metropolitan University, Blueprint, and The Conference Board of Canada, and are funded by the Government of Canada's Future Skills Program.

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Key findings

We estimate the impact of automation technologies, including AI, on labour markets using a three-phase framework:

1. exposure as the share of a job's tasks that automation technologies (e.g., AI) can perform;
2. productivity gains that would accrue to firms if the technologies were fully implemented;
3. likelihood of automation, or the probability that work is replaced by technology, given an occupation's sensitivity to job loss from technological exposure.

Additional elements can be layered into this framework, including employment dynamics. This preliminary analysis suggests the following:

- Over half of tasks performed (53 per cent) across all occupations in Canada could be performed by current artificial intelligence technologies.
- Occupations in natural and applied sciences are the most exposed to AI (82 per cent), while those in sales and people-facing services are the least exposed (37 per cent).
- The largest productivity gains are expected in sectors where many underlying occupations are highly exposed to AI, sectors such as agriculture and professional services.
- Services-based industries such as accommodation, restaurants, education, and retail are expected to gain less from AI technologies due to a higher share of tasks based on human interaction.
- Applying these estimates to a labour market scenario in our Model of Occupations, Skills, and Technology (MOST) suggests a 2 per cent increase in employment above our baseline forecast in 2045, translating to a gain of about 555,000 jobs, thanks to the long-term economic gains created by increased productivity.
- However, before the economy realizes these gains, we anticipate short-term pain as businesses reduce their workforce in favour of AI technologies. In 2030, total employment will be 535,000 jobs below our baseline forecast.

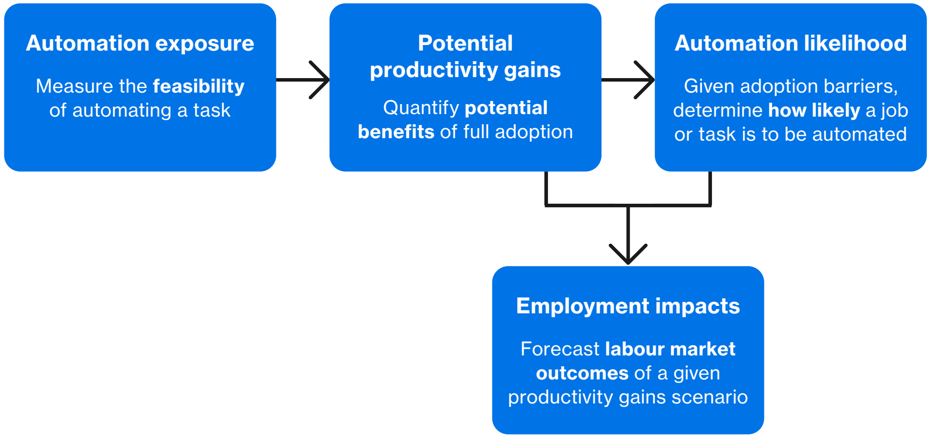
A new way to assess automation's impact on jobs

The rapid growth in awareness and adoption of generative artificial intelligence (GenAI) since the release of OpenAI's ChatGPT-3.5 in November 2022 ushered in a new wave of excitement and concern about the disruption these new tools could bring. Understanding and preparing for these impacts require knowing which tasks, jobs, and industries will be replaced or augmented by AI and other automation technologies.

To that end, we have developed a new framework to estimate the exposure of different job tasks to new technologies, the potential productivity gains of performing tasks with automation technologies, and the likely adoption rates of these technologies.

Adoption of automation is a multi-stage process. (See Exhibit 1.) First, a task, or occupation, needs to be "exposed" to a technology, meaning that some of the work can be augmented or replaced by the technology in question. Exposure, however, is no guarantee of implementation, especially in the short and medium term. Therefore, the second stage is knowing the productivity boost to be gained from the technology being fully implemented. Finally, the actual adoption of new technology will be a business and investment decision that considers costs, complementarity,[1] and other barriers that can constrain the feasibility, speed, and scale of implementation.

Exhibit 1
Analytical framework for automation technologies and labour market impacts



Source: The Conference Board of Canada.

1 On the concept of "complementarity," see Mehdi and Morissette, "Experimental Estimates of Potential Artificial Intelligence Occupational Exposure in Canada"; Pizzinelli and others, "Labor Market Exposure to AI: Cross-country Differences and Distributional Implications."

Applying this framework using Canadian task-level data

Early research on labour market disruption from technological change and automation focused on the automatability of occupations.[2] This focus on occupation-level automation doesn't account for the nature of workplace automation, which proceeds at the task level.[3] In other words, it is tasks that are replaced or augmented by technology, and the occupation—which is a collection of required tasks—may shift as a result of its underlying tasks.

It is now broadly recognized that the potential impact of automation on any given occupation depends on how well technology can replicate or enhance the experience and training of a worker, and how well it can perform or augment the tasks essential to the job.[4] Therefore, to quantify the impact of AI on employment for any given occupation, the analysis must begin with the feasibility of automating the underlying tasks.

A variety of jobs are exposed to automation

Using the descriptions of job tasks from O*NET, a U.S. source of occupational information, and the descriptions of AI task capabilities from AI patents filed with the U.S. Patent and Trademark Office (USPTO), we created an occupation-level AI exposure index for each of the 501 occupations[5] in Canada's National Occupation Classification (NOC).[6] AI exposure is determined as the average exposure to AI for each task associated with each occupation. (See Appendix A for our full methodology.)

Chart 1 shows this exposure index by occupation at the major group level (2-digit NOC). Of note, we see AI impacts on both traditionally white-collar roles, such as science-related occupations, and on blue-collar roles, such as manufacturing occupations.

White-collar roles are exposed primarily through the potential automation of their cognitive tasks, such as examining financial data or conducting a literature review. Blue-collar roles are primarily exposed through the potential automation of their key monitoring tasks using technologies such as optical sensors.

2 Frey and Osborne, "The future of employment: How susceptible are jobs to computerisation?"; Lamb, *The Talented Mr. Robot: The impact of automation on Canada's workforce.*

3 Arntz, Gregory, and Zierahn, "Revisiting the risk of automation"; Muro, Maxim, and Whiton, *Automation and Artificial Intelligence: How machines are affecting people and places.*

4 Brynjolfsson and Mitchell, "What can machine learning do? Workforce implications"; Acemoglu and Restrepo, "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment."

5 About 10 occupation titles from the NOC system were left out of this analysis as we were unable to match them with a corresponding U.S. Standard Occupational Classification (SOC) code. This does not impact the discussion or observations made in this report.

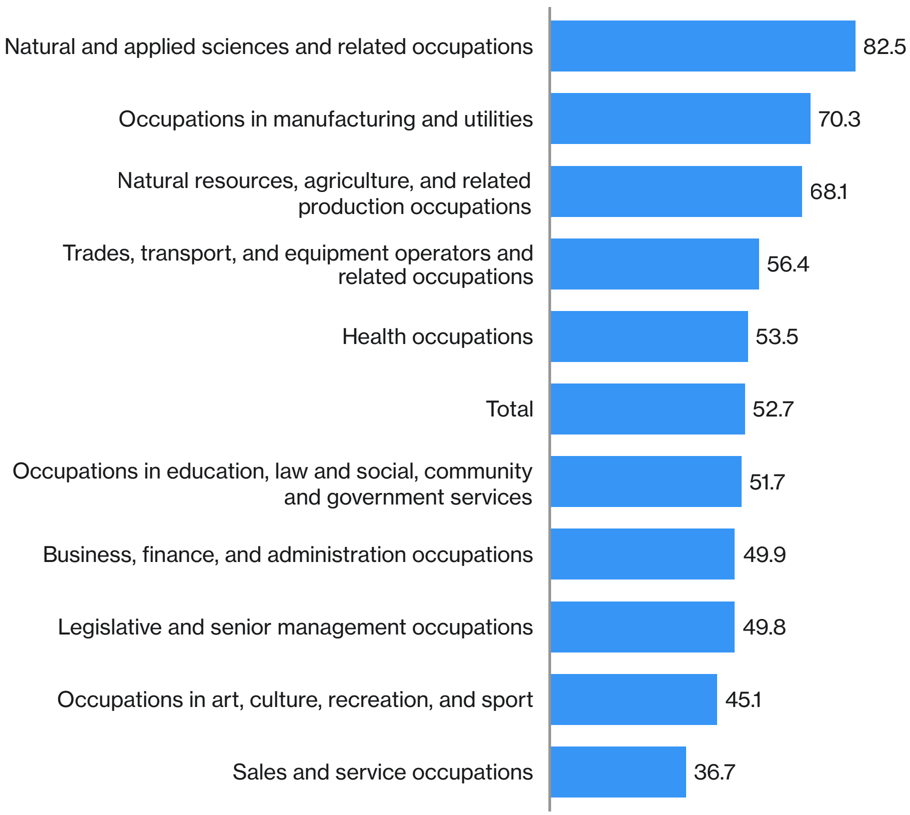
6 This approach builds on the work by Webb and by Sytsma and Sousa.

An employment-weighted average of exposure scores across all the occupations in an industry was used to construct an industry AI exposure index for each of the 304 industries in the North American Industry Classification System (NAICS).[7] (See Chart 2.)

Chart 1

Science-related occupations are most exposed to AI automation

(Canadian AI exposure index, per cent, by occupation)



Source: The Conference Board of Canada.

7 See Appendix for a detailed listing of the AI occupation and industry exposure scores.

From exposure to potential productivity impacts

To determine the potential labour productivity[8] gains from implementing AI at the industry level, we estimated the relationship between industry-level AI exposure scores and the change in real GDP between 2005 and 2020. (See Appendix A.) We then apply this relationship to our existing GDP forecasts to get the forecasted productivity gain.[9] Industries with occupations that are heavily exposed to the automation of their tasks are expected to experience the largest gains in productivity. (See Chart 3.)

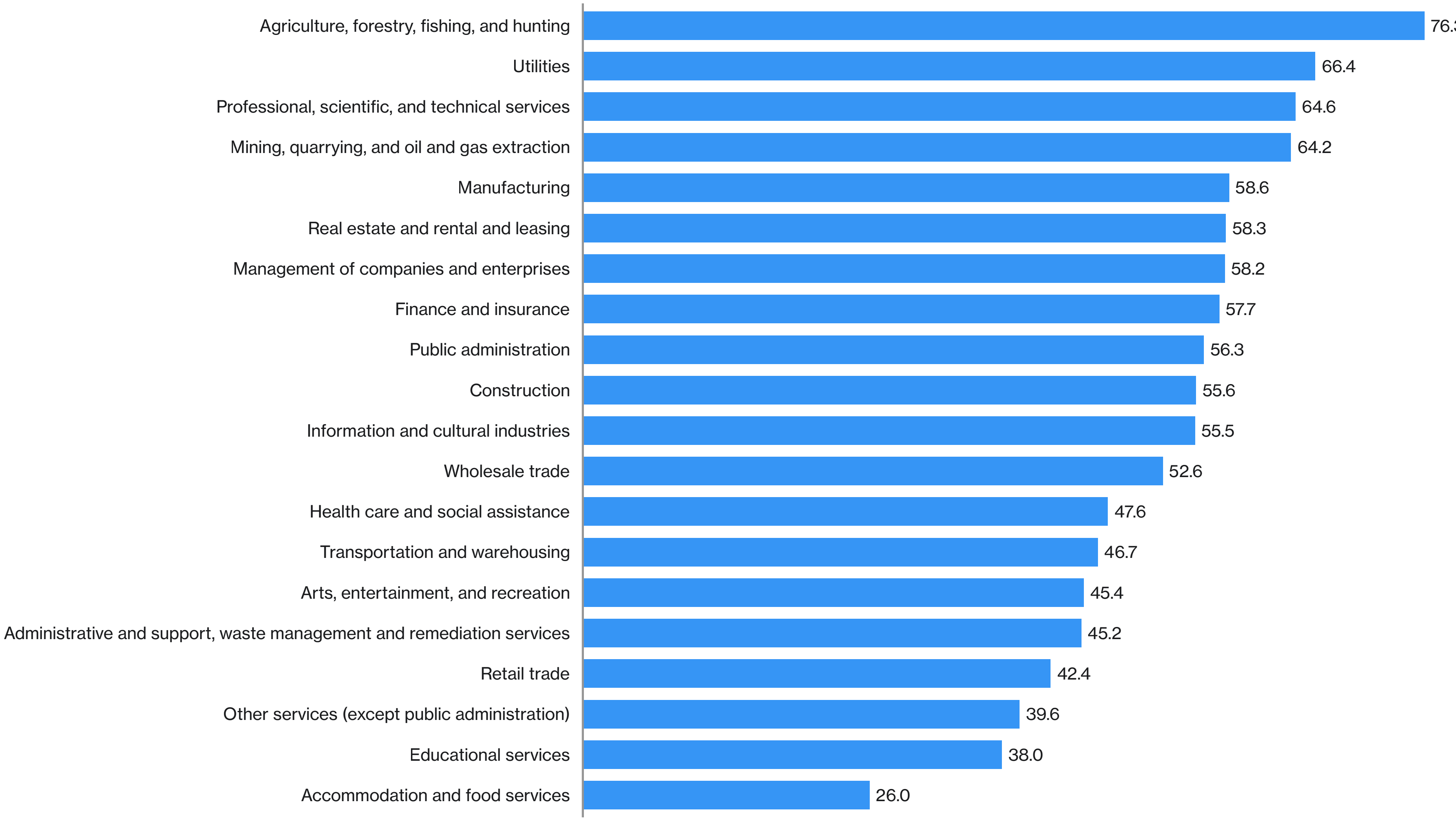
We find that the agriculture and utilities industries have the largest potential productivity gains that could be realized from AI adoption. This is partly because many manual tasks performed by labourers and technicians can be made more efficient by combining AI with other automation technologies. Similarly, professional service occupations also showed larger productivity gains. These occupations tended to feature many tasks that are heavily exposed to AI automation, including reading, writing, and analyzing data.

Conversely, industries that are more "people-facing" such as accommodation, restaurants, schools, and retail trade are less exposed to AI automation, which in turn leads to lower potential productivity gains.

8 Labour productivity measures how much output a worker can generate for a given amount of time worked.

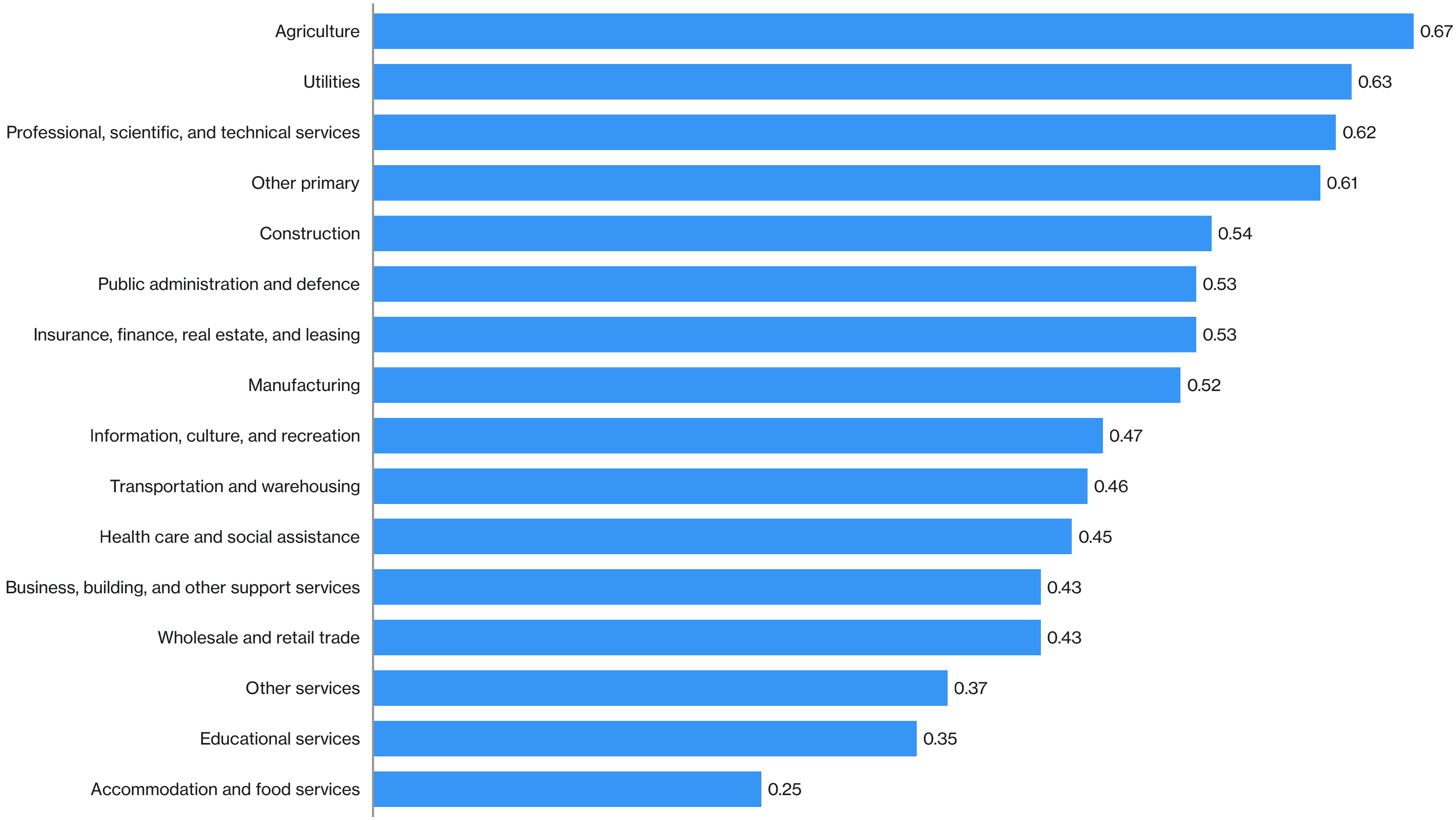
9 We assumed a "frictionless path of adoption," meaning no barriers to adopting and deploying these automation technologies over the next 20 years.

Chart 2
Primary sectors and utilities are most exposed to AI automation
(Canadian AI exposure index, per cent, by industry)



Source: The Conference Board of Canada.

Chart 3
The most exposed industries face the largest potential gains in productivity
(average annual productivity gains by industry, per cent, relative to baseline)



Source: The Conference Board of Canada.

Job transformations less likely than exposure suggests

The final component of our framework is “automation likelihood,” which captures the probability that work is automated given its exposure to AI. Automation likelihood measures the decline in employment attributable to automation over a 15-year period. However, it should not be interpreted as a measure of outright job loss. The net employment impacts of automation can be positive or negative, as the total number of tasks may increase and their mix may change as a result of automation.[10]

For example, if someone can use AI to do a task in half the amount of time, that could be interpreted as showing we only need half as many workers for that task. However, the employer could request that employees do twice as much of the task, resulting in no employment impact.[11] In essence, the amount of work is not necessarily fixed, and therefore the net employment impact would be different than what the automation likelihood might suggest on its own.

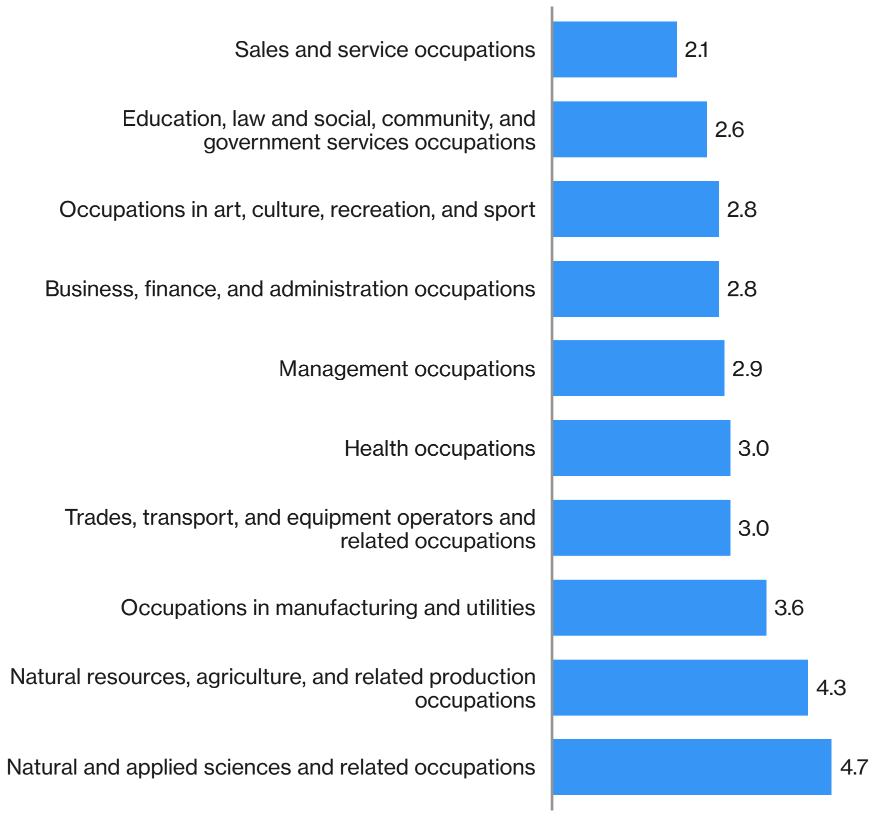
Our preliminary estimates of automation likelihood follow a similar pattern as seen for AI exposure across occupations. (See Chart 4.) We observe that a mix of white-collar and blue-collar roles are the most likely to be transformed by AI.

In this analysis, automation likelihood isolates the potential employment decline given a job’s exposure to AI. This preliminary approach indirectly accounts for the technology adoption rates observed over the past 15 years. (See Appendix A for details.) Forthcoming research will deepen this analysis to consider technology adoption rates in a more direct manner.

10 Specifically, in this preliminary analysis, we measure automation likelihood as the sensitivity of an occupation’s decline in employment to its AI exposure. See Appendix for further details.

11 As we show in the section that follows, our initial scenario indicates long-run employment gains over our baseline forecast.

Chart 4
Probability of employment declines given exposure to AI
(automation likelihood by occupation, per cent)



Source: The Conference Board of Canada.

Employment impacts of high exposure and adoption

The potential productivity gains estimated in the second step of our framework point to one of the benefits of new technologies entering the market—workers could move into new, higher-valued roles. Estimating the balance between jobs lost to technology and jobs gained because of technology requires a broad macroeconomic framework.

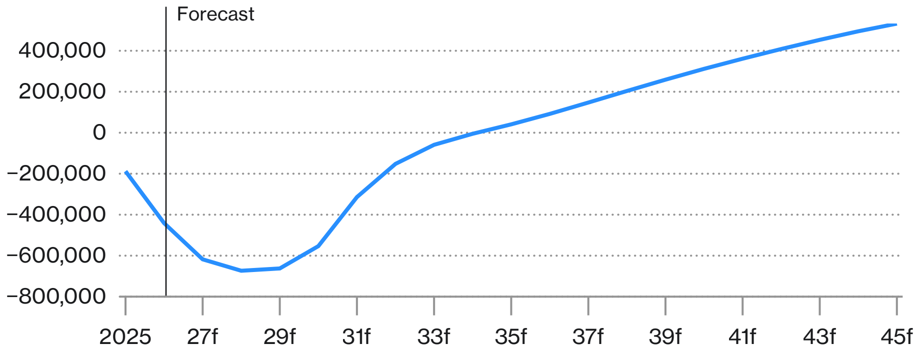
To that end, we apply the full potential productivity gains discussed above to MOST to estimate the net impact on the labour market. In other words, we assume AI is fully adopted over the coming 20 years such that the full labour productivity impacts are realized. This scenario illustrates the maximum potential magnitude of AI automation, rather than an attempt to predict the most likely path ahead for labour markets.

In total, in this full-adoption scenario, we estimate that employment increases by 2.1 per cent in 2045 (or about 535,000 additional jobs) compared with our baseline forecast.[12] This long-term growth would offset an estimated initial drop in employment of 2.6 per cent in 2030, or about 555,000 jobs. (See Chart 5.)

12 See Appendix for more details on the CBoC's Long-Term Forecasting Model.

Given that the underlying population does not change, the long-term employment gains mean that more people participate in the labour force in the long run than in our base case. This is because the productivity gains from AI adoption will lead to higher average incomes that, in turn, will pull more people into the workforce.[13]

Chart 5
In a high AI-adoption scenario, employment will sink initially before rallying due to economic growth
(change in employment, relative to baseline)



f = forecast
Source: The Conference Board of Canada.

In this full-adoption scenario, people-facing occupations such as nurses or restaurant and kitchen occupations are expected to see a large gain in jobs. This is because they benefit the most from the broader economic growth generated by technology adoption while not suffering as much from the displacement risk of automation. (See Table 1.)

Some manual occupations such as construction trades and transportation could also experience some large net gains. However, this observation is not consistent across all occupations, as employment impacts ultimately depend on available technologies, which vary across occupations.

Table 1
People-facing occupations could see the biggest gain from the boost to economic growth from AI adoption
(employment level relative to baseline, 2045)

Occupation title (5-digit NOC)	Employment impact
Food-counter attendants, kitchen helpers, and related support occupations	21,187
Retail salespersons and visual merchandisers	20,972
Transport truck drivers	15,978
Nurse aides, orderlies, and patient service associates	15,318
Construction trades helpers and labourers	9,591
Managers in agriculture	–569
Health policy researchers, consultants, and program officers	–935
Specialized livestock workers and farm machinery operators	–1,390
Real estate agents and salespersons	–1,758
Water and waste treatment plant operators	–5,708

Source: The Conference Board of Canada.

13 The additional labour demand is also accompanied by a decline in the unemployment rate in this scenario.

Research extensions

Our new three-phase framework offers a robust and flexible approach for analyzing the labour market impacts of automation technologies such as AI. Here we explore this framework and apply preliminary exposure estimates to our Model of Occupations, Skills, and Technology to get detailed occupation-level impacts. This research represents a preliminary exploration of the new methodology enabled by new big data sets and machine learning techniques.

In other published work, three important extensions were included:

1. re-estimating task-level exposures using Canada's Occupation and Skills Information System (OaSIS) rather than relying on the U.S. O*NET framework;
2. expanding the technologies examined to consider a wide array of automation technologies such as autonomous vehicles and VR/AR tools;
3. deepening the analysis of technological adoption for a more complete consideration of automation likelihood rates by occupation.

In addition, our future work will update the exposure scores to consider the most recent AI and other automation technology patents. This will enable a more up-to-date picture of how technologies interface with and reinforce the automation potential and productivity gains that could accrue if implemented.

Appendix A

Methodology

We estimate the impact of automation technologies on Canadian labour markets. The approach follows a three-phase framework:

1. calculating **exposure**, representing the share of a job's tasks that automation technologies (e.g., AI) can perform;
2. calculating **productivity gains** that would accrue for firms if the technologies were fully implemented;
3. estimating the **likelihood of automation** where work is replaced by technology, given an occupation's sensitivity to job loss from technological exposure.

Estimating Canadian exposure scores

We draw from recent research comparing the descriptions of job tasks from O*NET, a U.S. source of occupational information, and from the descriptions of AI patents from the U.S. Patent and Trademark Office (USPTO). The USPTO data contains over 8 million patents from 1900 to 2024. We extract the verb-noun combinations describing tasks (e.g., writing software code) from each patent as well as the occupation descriptions from their respective datasets and normalize them for enhanced compatibility. A high matching frequency for a given task among patents represents higher exposure. AI exposure is determined as the average exposure to AI of each task associated with each of the 964 occupations in the U.S. O*NET database.

We then mesh the descriptions of job tasks from O*NET and those in AI patents from the USPTO with occupations in Canada's National Occupation Classification (NOC) to create an occupation-level exposure index. Automation exposure is determined as the average exposure to automation of each task associated with each occupation.

Estimating the productivity impacts of automation exposure

The impacts on productivity from automation exposure were determined using the long-difference regression:

$$\Delta \log (GDP_{ij}) = \alpha + \beta^{d} \times Exposure_{ijd} + \eta_j + \gamma \log(Employment_{ij}) + \epsilon_{ij}$$

The dependent variable is the log change of GDP between 2005 and 2020 for the 4- or 3-digit NAICS industry (i), within the sector (2-digit NAICS) (j). While we optimally would prefer to observe GDP at the 4-digit NAICS level, Statistics Canada reports numbers at that resolution only for a subset of industries. In the regression, we always use the most disaggregated values available.

Independent variables

- Exposure: The employment-weighted average exposure of industry (i) in sector (j) to technology (d);
- η_j: Sector fixed effect;
- $log(Employment_{ij})$: The log of employment for industry (i) in sector (j) in 2021.

Interpretation of (βd)

The estimated coefficient on exposure represents the marginal impact of exposure on productivity. Although the dependent variable is not a direct measure of productivity, this interpretation is valid because the coefficient is conditional on both sector fixed effects and employment.

- In this specification, η_j controls for any changes in production common to all industries (i) within sector (j), including changes due to overall employment dynamics, investment, and demand.
- Controlling for the employment level in 2021 means that our change in production is conditional on employment ("keeping employment constant"), which aligns with the definition of labour productivity.

Although our analysis primarily seeks good predictive power for (βd) rather than causal identification, this specification was chosen due to the notable volatility of labour productivity. This volatility, while less problematic in classical time-series regression, can impact results in long-difference regression where the choice of years is crucial. We controlled for sector fixed effects to account for sector-specific volatility that might affect the numerator (e.g., changes in demand or world prices for agriculture). Additionally, we controlled for employment to ensure our coefficient retains its productivity interpretation but, by fixing employment to a single year, we also allow for productivity gains to be explained by changes in employment, not its level.

Preliminary estimates of automation likelihood

Using historical data on exposure and automation from the past 15 years plus a statistical approach based on long differences, we analyze the relationship between our exposure index and automation probability across occupations. The relationship of interest is the following:

$$P(Automation_{lpn}) = \alpha + \beta\ Exposure_l + Educ_l + Prov_p + Sector_n + \epsilon_l$$

where $P(Automation_l)$ is the historical probability of observing job reduction in occupation l belonging to the industry n in the province p.

It is defined as: $1 - [\min(1, Employment_l, 2020) / (Employment(l, 2005)]$, which implies the following:

- $P(Automation_{lpn}) = 0$ if employment in 2020 was equal or larger than employment in 2005.
- $1 \geq P(Automation_{lpn}) > 0$ if employment in 2020 was smaller than employment in 2005.

This probability is regressed on an occupation level by exposure to AI, a set of education controls leveraging the TEER categories of the NOC[1] nomenclature, the share that this occupation represents in each sector (two-digit NAICS), and a province-specific control allowing for different employment dynamics.

These controls take into account the fact that some industries, provinces, and/or levels of education might be both more likely to be exposed and more likely to see job contraction.

Interpretation of the results

The predicted automation likelihood is thus calculated as the following:

$(\beta\hat{}) \times Exposure_l$

This corresponds to the 15-year future marginal impact of exposure on the probability of automation, assuming trends are unchanged.

National model

Our Long-Term Forecasting Model (LTFM) was used to conduct the analysis on the Canadian employment. The LTFM is a quarterly macroeconomic model that emphasizes factors important for forecasting the long-term prospects for the economy. These factors include a detailed consideration of population and its age structure plus a disaggregated modelling of prices, employment, and investment expenditures. The government sector is also treated in detail in LTFM and reflects the most recent institutional environment. Projections of potential output allow the model to be used for long-term analysis.

There are about 1,700 variables in the model, of which 600 are behavioural equations. These variables refer to many of the variables in the National Income and Expenditure Accounts as well as related indicators for productivity, wages, prices, financial markets, international capital flows, and exchange rates. Over 900 of these variables form a single simultaneous block in the model, reflecting the interdependence of its various sectors. The most important of the 600 exogenous variables in the model are foreign economic indicators and variables relating to government expenditures and revenues and to the demographic characteristics of the population.

1 Canada, National Occupational Classification, “TEER category.”

The model is based on the neoclassical synthesis and thus possesses many of the properties associated with such models. The national model is a multi-sector model with wages and prices driven by sector-specific production functions. Investment expenditure is based on the capital stock solved as a factor in a constant elasticity of substitution (CES) production function. An effort is made to ensure that the rate of capital-labour substitution implicit in the investment equations is also reflected in the employment equations. Output is largely expenditure-determined in the model, but there are supply-side feedback through sector capacity measures that influence prices, imports, and exports, and thus, in turn, output.

Model of occupations, skills, and technology

The Model of Occupations, Skills, and Technology (MOST) was used to estimate employment impacts at a more detailed level. MOST is a tool we developed in partnership with Future Skills Centre.[2] MOST differs from traditional labour market models in its innovative approach and exceptionally detailed labour market outlook. It provides granularity by categorizing occupations into five-digit NOCs[3] and industries into four-digit NAICS,[4] while also offering insights at the provincial and territorial levels. In addition, it provides comprehensive and forward-looking analysis, with projections extending years into the future.

MOST forecasts equilibrium employment conditions and labour market frictions for each year. A key innovation in the model is the ability to estimate labour market transitions based on the degree of skill matching on both sides of the market. This simulation not only identifies labour market inefficiencies but also serves as a powerful analytical tool for policy evaluation, shedding light on unmet labour demand and supply.

Drawing on multiple regularly updated data sources, including the Census of Population, the Labour Force Survey, the Job Vacancy and Wage Survey, and our own employment and demographic projections plus high-frequency labour market data (formerly Vicinity Jobs), MOST provides a comprehensive and detailed view of the labour market.

2 The Conference Board of Canada, “The Model of Occupations, Skills and Technology (MOST).

3 The National Occupational Classification (NOC) is a system used in Canada to classify and organize occupations based on skill type and skill level.

4 NAICS stands for North American Industry Classification System that is used in Canada, the United States, and Mexico to classify businesses and industries based on similar economic activities.

Appendix B

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