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Experimental Estimates of Potential Artificial Intelligence Occupational Exposure in Canada

by Tahsin Mehdi and René Morissette

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by

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Abstract

Past studies on technological change have suggested that occupations involving routine and manual tasks will face a higher risk of automation-related job transformation. However, recent advances in artificial intelligence (AI) challenge prior conclusions, as AI is increasingly able to perform non-routine and cognitive tasks. These advances have the potential to affect a broader segment of the labour force than previously thought. This study provides experimental estimates of the number and percentage of workers in Canada potentially susceptible to AI-related job transformation based on the complementarity-adjusted AI occupational exposure index of Pizzinelli et al. (2023), inspired by Felten, Raj and Seamans (2021). Results from the 2016 and 2021 censuses of population suggest that, on average, about 60% of employees in Canada could be exposed to AI-related job transformation, and about half of this group are in jobs that may be highly complementary with AI. Unlike previous waves of automation, which mainly transformed the jobs of less educated employees, AI is more likely to transform the jobs of highly educated employees. Despite facing potentially higher exposure to AI-related job transformation, highly educated employees may be in jobs that could benefit from AI technologies. Compared with employees in other industries, exposure to AI-related job transformation is higher for employees in professional, scientific and technical services; finance and insurance; information and cultural industries; educational services; and health care and social assistance. However, education and health care professionals are more likely to be in jobs that are highly complementary with AI. Employees in industries such as construction, and accommodation and food services face relatively lower exposure to AI-related job transformation. Whether occupations that may benefit from AI will experience relatively higher employment and wage growth remains to be seen, as this depends on factors such as firm productivity and the ability of workers in those occupations to leverage the potential benefits of AI.

Executive summary

Recent developments in the field of artificial intelligence (AI) have fuelled excitement, as well as concerns, regarding its implications for society and the economy. While previous waves of technological transformation raised concerns regarding the future of jobs involving routine and manual tasks, a broader segment of the labour force could be affected in an era when sophisticated large language models such as ChatGPT increasingly excel at performing non-routine and cognitive tasks typically done by highly skilled workers. AI encompasses a lot more than just natural language processing. These technologies not only have the capacity to automate routine tasks but can also augment human decision-making processes and create entirely new opportunities for innovation and efficiency. As AI continues to evolve, it has the potential to reshape industries, redefine job roles and transform the nature of work. With the transformative effects of AI already in motion, it raises renewed concerns about job transformation and the need for workforce adaptation.

This study adopts the complementarity-adjusted AI occupational exposure index of Pizzinelli et al. (2023), inspired by the original AI occupational exposure measure of Felten, Raj and Seamans (2021), and applies it to data from the 2016 and 2021 censuses of population. The experimental estimates presented in this study are largely based on the technological feasibility of automating job tasks. Employers may not immediately replace human labour with AI, even if it is technologically feasible to do so, because of financial, legal and institutional constraints. Consequently, exposure to AI does not necessarily imply a risk of job loss. At the very least, it could imply a certain degree of job transformation (Frenette and Frank, 2020). Additionally, some economists argue that the risks and benefits currently being attributed to AI may be exaggerated (Acemoglu and Johnson, 2024; McElheran et al., 2024), and productivity increases at the macroeconomic level may be modest at best (Acemoglu, 2024).

Following Pizzinelli et al. (2023), this study groups occupations into three categories based on their exposure to and complementarity with AI: (1) high exposure and low complementarity, (2) high exposure and high complementarity, and (3) low exposure. Results suggest that in May 2021, on average, around 4.2 million employees (31%) in Canada were in the first group, about 3.9 million (29%) were in the second group and about 5.4 million (40%) were in the third group. This distribution was very similar in May 2016. Unlike previous waves of automation, which mainly transformed the jobs of less educated employees performing routine and non-cognitive tasks, AI is more likely to transform the jobs of highly educated employees performing non-routine and cognitive tasks. However, highly educated employees are also more likely to hold jobs that are highly complementary with AI technologies than less educated employees. But workers will still need the skills to be able to leverage the potential benefits of AI. Compared with employees in other industries, exposure to AI-related job transformation is higher for employees in professional, scientific and technical services; finance and insurance; information and cultural industries; educational services; and health care and social assistance. However, education and health care professionals are more likely to be in jobs highly complementary with AI. Employees in industries such as construction, and accommodation and food services face relatively lower exposure to AI-related job transformation.

There is a lot of uncertainty when it comes to predicting the transformative effects of technological changes on the labour market. This study provides a static picture of AI occupational exposure based on employment compositions in May 2016 and May 2021, which were fairly similar. How workers respond and adapt to the potentially evolving labour market in the long run remains to be seen. The index used in this study is subjective and based on judgments regarding some current possibilities of AI. Consequently, the applicability of the index may decrease over time as AI capabilities grow and AI can perform an increasing number of tasks currently done by human workers. Alternative measures of AI exposure could provide further insights. Future research could also attempt to answer the question, “What happened to workers whose jobs were exposed to AI-related job transformation?”

1 Introduction

A couple of centuries ago, the Industrial Revolution and the forces of globalization coalesced to fundamentally change the global economy. These forces served as catalysts for the technological progress that has been a cornerstone of economic development. Technological advancements and innovation paved the way for machines to take over some labour-intensive tasks and allowed workers to focus on more cognitive tasks requiring creativity and critical thinking. Adoption of new technologies also led to the obsolescence of some jobs, serving as a pathway toward higher productivity. A prominent example of this is the advent of computers, which undoubtedly replaced some jobs but also created new ones in the process (see, e.g., Autor, Levy and Murnane [2003] or Graetz and Michaels [2018]). However, higher productivity may not always translate to higher wages for workers (Acemoglu and Johnson, 2024).

More generally, automation has become a defining feature of modern economies, including Canada’s. It has revolutionized various industries by streamlining processes, increasing efficiency and reducing operational costs, among other things. It has also raised concerns about the future of workers. The widely cited study by Frey and Osborne (2013), which estimated automation risks in the United States, has spurred a growing body of literature surrounding automation (see, e.g., Arntz, Gregory and Zierahn [2016]; Oschinski and Wyonch [2017]; Nedelkoska and Quintini [2018]; Frenette and Frank [2020]; and Georgieff and Milanez [2021]). Frenette and Frank (2020) estimated that approximately 1/10 of employees in Canada could be at high risk (probability of 70% or higher) of automation-related job transformation.

The prevailing thought from the automation literature is that highly educated or highly skilled individuals are less susceptible to automation-related job transformation because they are more likely to perform non-routine and cognitive tasks, which are thought to be less automatable. However, another source of disruption, which has the potential to upend prior notions, is emerging: **artificial intelligence (AI)**.[1] While AI has been around for decades (e.g., video games, image recognition), it was not until 2022 when it became mainstream and surged in popularity, partly fuelled by the release of ChatGPT by OpenAI.

The unprecedented pace of advancements in the field of AI and its increasing integration into society and the economy have led some researchers to call this a pivotal moment in history, akin to the transformative shifts brought on by the Industrial Revolution (Cazzaniga et al., 2024). ChatGPT is just one example of a large language model (LLM) that has unlocked the remarkable possibilities of AI. AI can also perform complex tasks like generating music and videos from text input (e.g., Sora by OpenAI). AI encompasses a wide range of applications, including natural language processing, machine learning, computer vision and robotics. These technologies not only have the capacity to automate routine tasks but can also augment human decision-making processes and create entirely new opportunities for innovation and efficiency. As the field of AI continues to evolve, it has the potential to reshape industries, redefine job roles and transform the nature of work. In today’s rapidly evolving technological landscape, the integration of AI into various aspects of society, from virtual assistants and recommendation algorithms to autonomous vehicles and predictive analytics, questions naturally arise regarding its impact on society and the economy. The widespread adoption of AI raises renewed concerns about job transformation, skill mismatches and the need for workforce adaptation.

1. A historical example of a high-skill occupation being transformed because of a new technology is the reduction in the number of accountants following the invention of the calculator (see, e.g., Wootton and Kemmerer [2007] and Cazzaniga et al. [2024]).

The primary objective of this study is to quantify the level of potential AI occupational exposure (AIOE) in Canada. By employing experimental methods, this study offers preliminary insights into how AI may affect the Canadian labour market and the potential risks and benefits it holds for workers.

This study adopts the **complementarity-adjusted AIOE (C-AIOE)** index proposed by Pizzinelli et al. (2023). The original AIOE index, which is often cited in the literature, was proposed by Felten, Raj and Seamans (2021) as a way of measuring how AI applications overlap with the human abilities needed to perform a given job. In light of recent advancements in LLMs, Felten, Raj and Seamans (2023) considered an alternate index that weighted language modelling more heavily and found that it was highly correlated with the original AIOE index. Recognizing that AI can complement human labour, the International Monetary Fund (IMF) study by Pizzinelli et al. (2023) proposed the C-AIOE index, which attempts to account for the potential complementarity of AI across occupations, in addition to direct exposure. These measures focus on “narrow” AI, which refers to “computer software that relies on highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future” (Broussard, 2018; Felten, Raj and Seamans, 2021). This definition encompasses generative AI (e.g., LLMs, image recognition) but does not capture exposure to “general” AI, which refers to “computer software that can think and act autonomously and is combined with automation and robot technologies” (Pizzinelli et al., 2023). International comparisons of AIOE based on the original AIOE index have been done (see, e.g., Georgieff and Hyee [2021] and OECD [2023]). An IMF study by Cazzaniga et al. (2024) compared AI exposure and potential complementarity across countries using the C-AIOE index but did not analyze Canadian data in detail. They found that around 60% of jobs in advanced economies may be highly exposed to AI-related job transformation. As will be shown, this is similar to the share estimated for Canada.

This study offers Canadian evidence on AIOE and asks the following research questions:

1. Which occupations are potentially exposed to AI-related job transformation?
2. Which occupations may benefit from AI-related job transformation?
3. How does the distribution of AIOE vary by industry, education level, employment income and other worker characteristics?

The experimental AI exposure estimates in this study are largely based on the technological feasibility of automating job tasks. Employers may not immediately replace humans with AI, even if it is technologically feasible, for several reasons (see, e.g., Bryan, Sood and Johnston [2024]), including financial, legal and institutional factors. Consequently, exposure to AI does not necessarily imply a risk of job loss. At the very least, it could imply some degree of job transformation (Frenette and Frank, 2020). AI could lead to the creation of new tasks within existing jobs or create entirely new jobs. Additionally, some economists argue that the risks and benefits of AI may be exaggerated (Acemoglu and Johnson, 2024; McElheran et al., 2024), and productivity increases at the macroeconomic level may be modest at best (Acemoglu, 2024). Evidence from the United States suggests that the adoption of AI has been more prevalent in larger firms (McElheran et al., 2024), as some employers may not yet find it economically optimal to adopt such technologies (Svanberg et al., 2024). Whether this will contribute to a productivity gap between smaller and larger firms is unclear. Predicting the effects of technological changes on the labour market is not an exact science, as some subjectivity is usually involved. For example, more than a decade after Frey and Osborne (2013), it is still difficult to precisely measure the effect of automation on labour markets, as changes are ongoing (Georgieff and Milanez, 2021). Although the diffusion of new technology can take time (Feigenbaum and Gross, 2023), measuring the impact of AI could be challenging given the rapid pace of advancements. The experimental estimates presented in this study should be interpreted with caution. Only time will tell whether predicted changes brought on by new technologies will come to fruition.

The remainder of this article is organized as follows. Section 2 briefly describes the AIOE index of Felten, Raj and Seamans (2021) and the complementarity-adjusted variant of Pizzinelli et al. (2023). Section 3 presents the results, and Section 4 provides concluding remarks and suggestions for future research.

2 Methods

The objective of this study is to estimate the extent to which occupations in Canada are potentially exposed to AI-related job transformation and the extent to which AI can potentially complement human labour in those occupations. This study uses the novel C-AIOE index of Pizzinelli et al. (2023) to achieve this objective. This measure is computed at the occupational level based on data from the Occupational Information Network (O*NET), which was created in the late 1990s by the United States Department of Labor to quantify and track the skills and abilities used across more than 1,000 different occupations (https://www.onetonline.org). Thus, the measure used in this study relies on occupational attribute data from the United States, which has a similar skill profile as Canada.

The C-AIOE index is based on the original AIOE index of Felten, Raj and Seamans (2021), which measures the relationship between 52 human abilities and 10 AI applications, weighted by the degree of complexity and importance of those skills for a given occupation i,

$$\text{AIOE}_i = \frac{\sum_{j=1}^{52} A_j L_{ji} I_{ji}}{\sum_{j=1}^{52} L_{ji} I_{ji}},$$

where j indexes 52 occupational abilities; L_{ji} is the prevalence score from O*NET and I_{ji} is the importance score from O*NET for ability j in occupation i; and $A_j = \sum_{k=1}^{10} x_{kj}$ is the exposure to AI of ability j computed as the sum of the relatedness scores, x_{kj}, of ability j with 10 AI applications.[2] This index is a relative measure of AI exposure (e.g., $AIOE_m > AIOE_n$ implies that occupation m faces greater exposure to AI-related job transformation than occupation n). See Felten, Raj and Seamans (2021) for details.

Because the AIOE index is agnostic regarding the implications of occupations being exposed to AI, Pizzinelli et al. (2023) proposed a variant of the AIOE index that accounts for the potential complementarity of AI. They make the case that certain occupations may be less conducive to the unsupervised use of AI than others. For example, judges and medical professionals are examples of occupations where job aspects such as the criticality of decisions and the gravity of the consequences of errors may require human workers to make the final decision (Cazzaniga et al., 2024). The C-AIOE of Pizzinelli et al. (2023) is computed as

$$\text{C-AIOE}_i = \text{AIOE}_i \times \left(1 - w \times \left(\theta_i - \theta_{MIN}\right)\right),$$

2. Some of the 52 occupational abilities include oral and written comprehension, memorization, originality, inductive and deductive reasoning, finger dexterity, and stamina. The 10 AI applications considered in the AIOE index are language modelling, image generation, image recognition, speech recognition, instrumental track recognition, translation, reading comprehension, visual question answering, abstract strategy games and real-time video games. The relatedness scores, *x*, are computed based on crowdsourced data from the Amazon Mechanical Turk survey, with 52 multiplied by 10 resulting in 520 scores. All the datasets and programs used by Felten, Raj and Seamans (2021) are available from https://github.com/AIOE-Data/AIOE.

where $0 \le w \le 1$ is a weight chosen by the researcher that controls the influence of the complementary parameter (θ), θ_i is the complementarity index of occupation i and θ_{MIN} is the minimum observed θ value among all occupations. A weight of $w = 0$ reverts the C-AIOE back to the original AIOE (e.g., no role for AI complementarity), while $w = 1$ allows maximum potential AI complementarity for occupation i.[3] Like the AIOE index, the complementarity index is also a relative measure, with a higher value indicating higher potential complementarity. The complementarity index for occupation i, θ_i, is computed using O*NET data on "work contexts" and "job zones" for that particular occupation. To do so, 11 work contexts (each score ranging from 0 to 100) and the job zone (ranging from 1 to 5) are combined into six components as follows:

1. Communication
    a. Face to face
    b. Public speaking

    Although AI can play a role in enhancing certain aspects of communication, the nuanced complexities of face-to-face interactions and public speaking could remain predominantly within the realm of human expertise.

2. Responsibility
    a. For outcomes
    b. For others' health

    AI has the potential to transform many sectors in the economy, including health care, where tough decisions are routinely made, and such decisions may still require human oversight and judgment.

3. Physical conditions
    a. Exposure to outdoor environments
    b. Physical proximity to others

    Jobs requiring substantial outdoor exposure and proximity to others require a certain level of adaptability and teamwork (e.g., firefighters, construction workers). Integrating AI into highly advanced machinery in diverse work environments could be costly.

4. Criticality
    a. Consequence of errors
    b. Freedom of decisions
    c. Frequency of decisions

    The importance of human oversight may become increasingly evident as AI continues to automate decision-making processes. In professions such as air traffic control or nursing, where human judgment is paramount, the combination of data analysis and instinct is essential for responding to unexpected scenarios. While AI can offer valuable data and recommendations, thereby potentially reducing human error and accelerating decision making, the indispensability of human oversight remains clear.

5. Routine
    a. Degree of automation (100 minus the O*NET score so that occupations with a low degree of automation receive higher values)

3. The aggregate C-AIOE indexes are presented in tables A.1 and A.2. However, most of this study categorizes occupations based on their exposure to AI-related job transformation and their potential complementarity with AI and presents the share of workers who fall into the different categories (Section 3).

b. Unstructured versus structured work

Occupations involving routine tasks have historically been more susceptible to technological transformation. Despite differences between AI and previous waves of automation, routine-intensive occupations remain particularly vulnerable to transformation. In contrast, less structured jobs may necessitate more advanced technologies for AI to operate autonomously.

6. Skills (job zone):

   Job zone is an indicator of the extent of preparation required for a job. This value must be rescaled to align with the five other components by multiplying it by 20, so that it ranges from 20 to 100 instead of 1 to 5. A higher value indicates more extensive preparation.

   Occupations with high educational or training requirements may be more conducive to integrating the skills complementary with AI, as providing instructions to AI and leveraging it require some level of expertise and proficiency.

A score for each of the six components is computed by averaging the work contexts within each component (e.g., the score for communication is the average of face-to-face and public speaking work contexts). For the skills component, the score is the rescaled job zone value. Then, θ is calculated as the average of the six component scores divided by 100. See Pizzinelli et al. (2023) for more details regarding the derivation of the C-AIOE index and the sensitivity analyses.

This index does have some limitations, as pointed out by Pizzinelli et al. (2023). The selection of O*NET variables that serve as inputs of the index is subjective and relies on judgment regarding the factors that matter for the interaction between AI and human workers. However, Pizzinelli et al. (2023) show that the work contexts are not all systematically related to each other and offer a multifaceted take on the potential complementarity of AI with human workers. The index considers how human abilities may overlap with 10 AI applications, but as AI capabilities improve, the likelihood of AI supplanting tasks typically performed by human workers may grow. Consequently, the applicability of the index could decrease over time.[4] Moreover, while the index captures the potential exposure of occupational abilities and tasks to AI, it does not account for advances in robotics, sensors and other technologies that could potentially integrate with AI (Felten, Raj and Seamans, 2021).

As O*NET is an American database, the occupations are coded according to the Standard Occupational Classification (SOC) system. The complementarity parameter and the AIOE index were computed based on version 28.2 of the O*NET database, which uses the 2018 SOC. The AIOE index was computed at the six-digit level, while the complementarity parameter was computed at the eight-digit level and then aggregated to the six-digit level by averaging the parameter values (e.g., the values associated with SOC codes 12-3456.01 and 12-3456.02 would be averaged to obtain the value for SOC code 12-3456). The six-digit SOC codes were then converted to the four-digit codes of version 1.3 of the Canadian National Occupational Classification (NOC) 2016 so the rich set of dimensions from the 2016 and 2021 censuses of

4. Alternative methodologies for measuring the economic effects of AI have been proposed (see, e.g., Eloundou et al. [2023], Kochhar [2023] or Webb [2020]), but they also come with caveats. See Pizzinelli et al. (2023) for a discussion on some of these alternative measures.

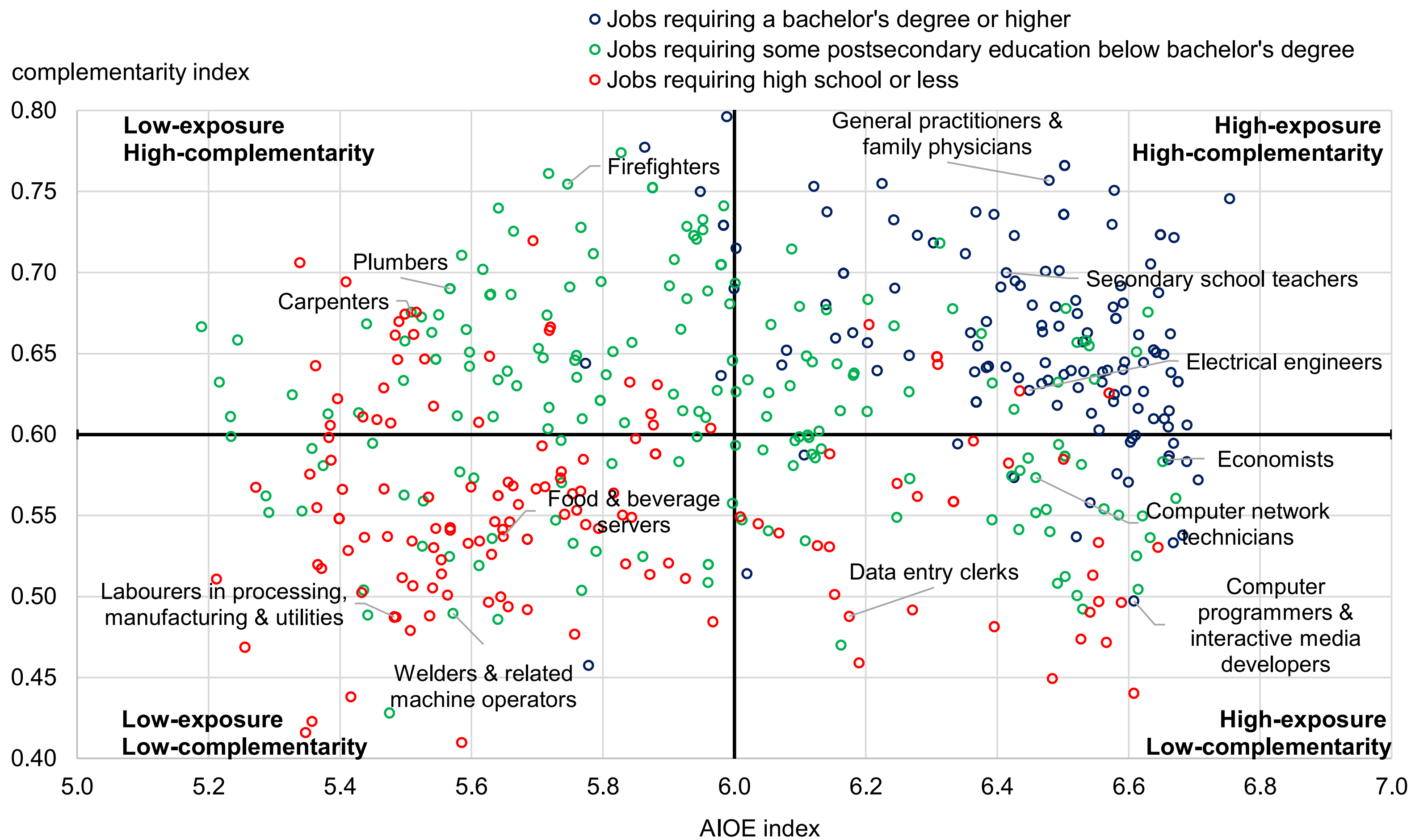
population (reference week in May) could be used to examine AIOE in Canada.[5] The sample was restricted to employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. Employment in some industries, such as accommodation and food services, decreased from May 2016 to May 2021 because of the COVID-19 pandemic, so the 2016 Census of Population was also used as a robustness check. However, results suggest that the **share** of employees exposed to AI-related job transformation changed very little in general.

3 Results

Figure 1 presents the AIOE and potential complementarity (θ) for Canadian occupations. The median AIOE was around 6.0, while the median complementarity was about 0.6. Following Pizzinelli et al. (2023), an occupation is considered “high exposure” if its AIOE exceeds the median AIOE and “low exposure” otherwise. Likewise, an occupation is considered “high complementarity” if its potential complementarity exceeds the median complementarity and “low complementarity” otherwise.[6] Based on this, occupations are grouped into four quadrants in Figure 1: high exposure and low complementarity, high exposure and high complementarity, low exposure and low complementarity, and low exposure and high complementarity. For simplicity, the latter two categories are combined into a single category, “low exposure,” in subsequent analyses. High-exposure, low-complementarity occupations are those that may be highly exposed to AI-related job transformation and whose tasks could be replaceable by AI in the future. High-exposure, high-complementarity occupations are those that may be highly exposed to AI-related job transformation but could be highly complementary with AI. However, workers will still need the necessary skills to leverage the complementary benefits of AI. Low-exposure jobs are those that may be less exposed to AI-related job transformation than others.[7]

5. All 500 NOC occupations were matched (perfectly or partially) to the SOC. If multiple SOC codes were matched to a single NOC code, then the AIOE or θ was averaged across the SOC codes and then assigned to the NOC. There were 10 occupations for which the AIOE or θ could not be computed because of a lack of O*NET data, but they accounted for less than 1% of Canadian employment (NOC code provided in parentheses): legislators (0011), financial and investment analysts (1112), health information management occupations (1252), industrial instrument technicians and mechanics (2243), employment counsellors (4156), non-commissioned ranks of the Canadian Armed Forces (4313), elementary and secondary school teacher assistants (4413), other personal service occupations (6564), taxi and limousine drivers and chauffeurs (7513), and logging and forestry labourers (8616). The concordance file for mapping NOC 2016 codes to SOC 2018 codes is available from https://www.statcan.gc.ca/en/concepts/concordances-classifications.
6. While the use of the median index to group occupational exposure may seem arbitrary, it preserves the relative exposure rankings between occupations, simplifies the analyses and offers preliminary insights into the effects of AI on labour markets.
7. Because the AIOE groups are based on indexes relative to the median, they should not be interpreted in absolute terms. For example, low-exposure occupations are not “low exposure” in the absolute sense but rather “low exposure” relative to other occupations.

Figure 1
Potential artificial intelligence occupational exposure (AIOE) and complementarity in Canada



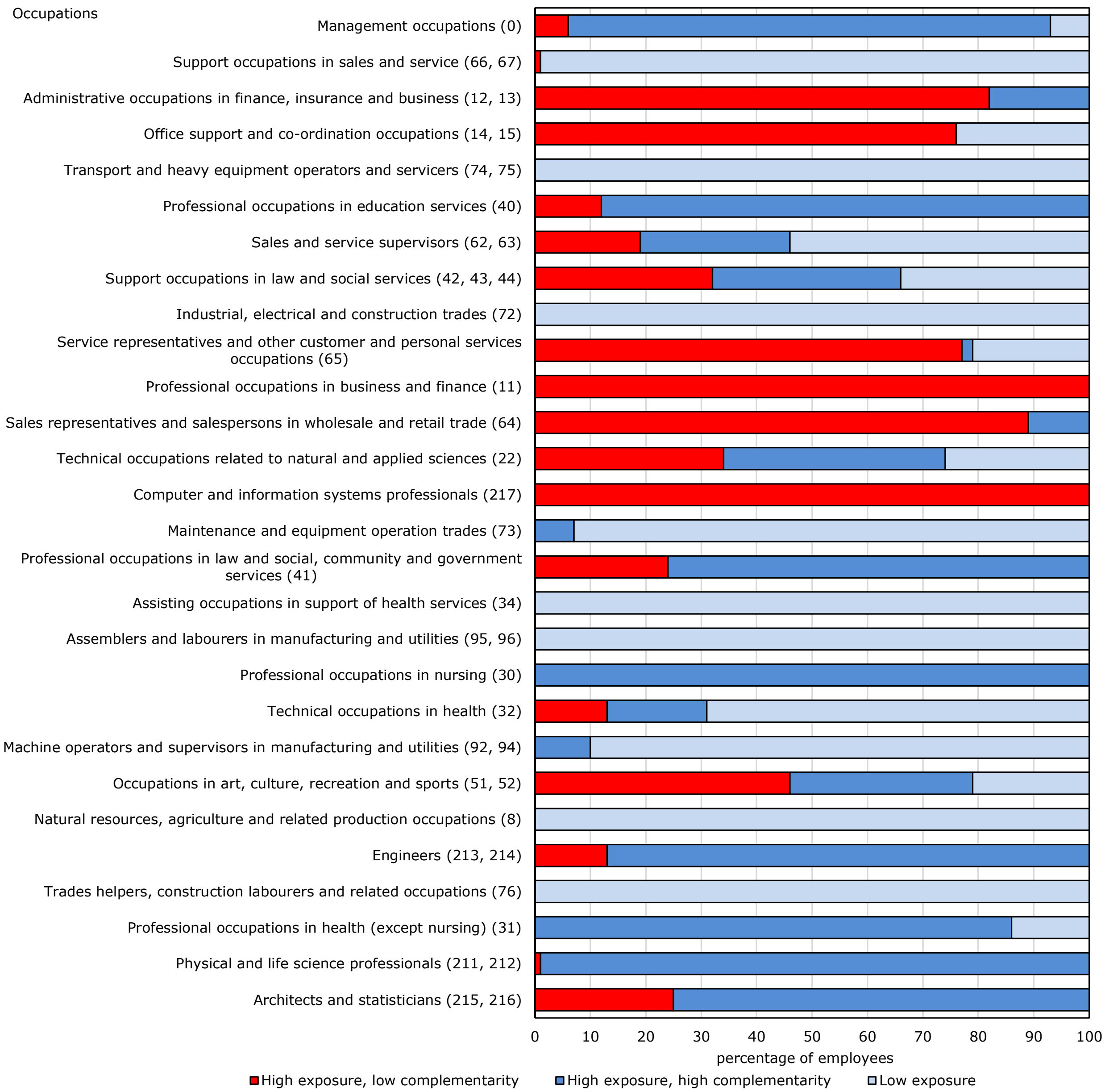
Notes: The AIOE index and potential complementarity are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). An occupation is considered high-exposure if its AIOE index exceeds the median AIOE across all occupations (6.0) and considered low-exposure otherwise. Similarly, an occupation is considered high-complementarity if its complementarity parameter exceeds the median complementarity across all occupations (0.6) and considered low-complementarity otherwise. Occupations in this chart are based on the 4-digit National Occupational Classification (NOC) 2016 version 1.3 converted from the United States Standard Occupational Classification (SOC) 2018. Of the 500 NOC occupations, 10 occupations which represented less than 1% of Canadian employment, were excluded due to a lack of Occupational Information Network (O*NET) data for computing the AIOE or complementarity parameter.
Source: Occupational Information Network (O*NET) version 28.2.

Figure 1 shows that jobs potentially highly exposed to AI-related job transformation are generally those that require higher education. Although these jobs could face relatively more exposure to AI-related transformation, occupations such as family physicians, teachers and electrical engineers may be complementary with AI technologies given their relatively high complementarity scores. In contrast, occupations such as computer programming, which may also require relatively high education, have low complementarity scores, suggesting less potential complementarity with AI. There is considerable uncertainty, however, regarding the extent to which AI can actually replace human labour.

Low-exposure occupations appear to be those that usually do not require a high level of education. Some examples of occupations facing relatively low exposure to AI-related job transformation are carpenters; welders; plumbers; food and beverage servers; labourers in processing, manufacturing and utilities; and firefighters. However, as illustrated by Figure 1, AI has the potential to transform a broad set of occupations regardless of skill level. The diffusion of AI could also have downstream general equilibrium effects. For example, although less educated employees may be in jobs potentially less exposed to AI-related job transformation, highly educated employees from high-exposure jobs could transition to low-exposure jobs, displacing less educated employees (see, e.g., Beaudry, Green and Sand [2016]).

Chart 1 aggregates the various NOC occupations into 28 distinct jobs to simplify the analysis and precisely identify the number and distribution of employees falling into the three AI exposure groups: **(1) high exposure and low complementarity**, **(2) high exposure and high complementarity**, and **(3) low exposure**. In May 2021, on average, roughly 4.2 million employees (31%) in Canada were in the first group, about 3.9 million (29%) were in the second group and about 5.4 million (40%) were in the third group.

Chart 1
Potential artificial intelligence occupational exposure and complementarity across occupations in Canada, May 2021

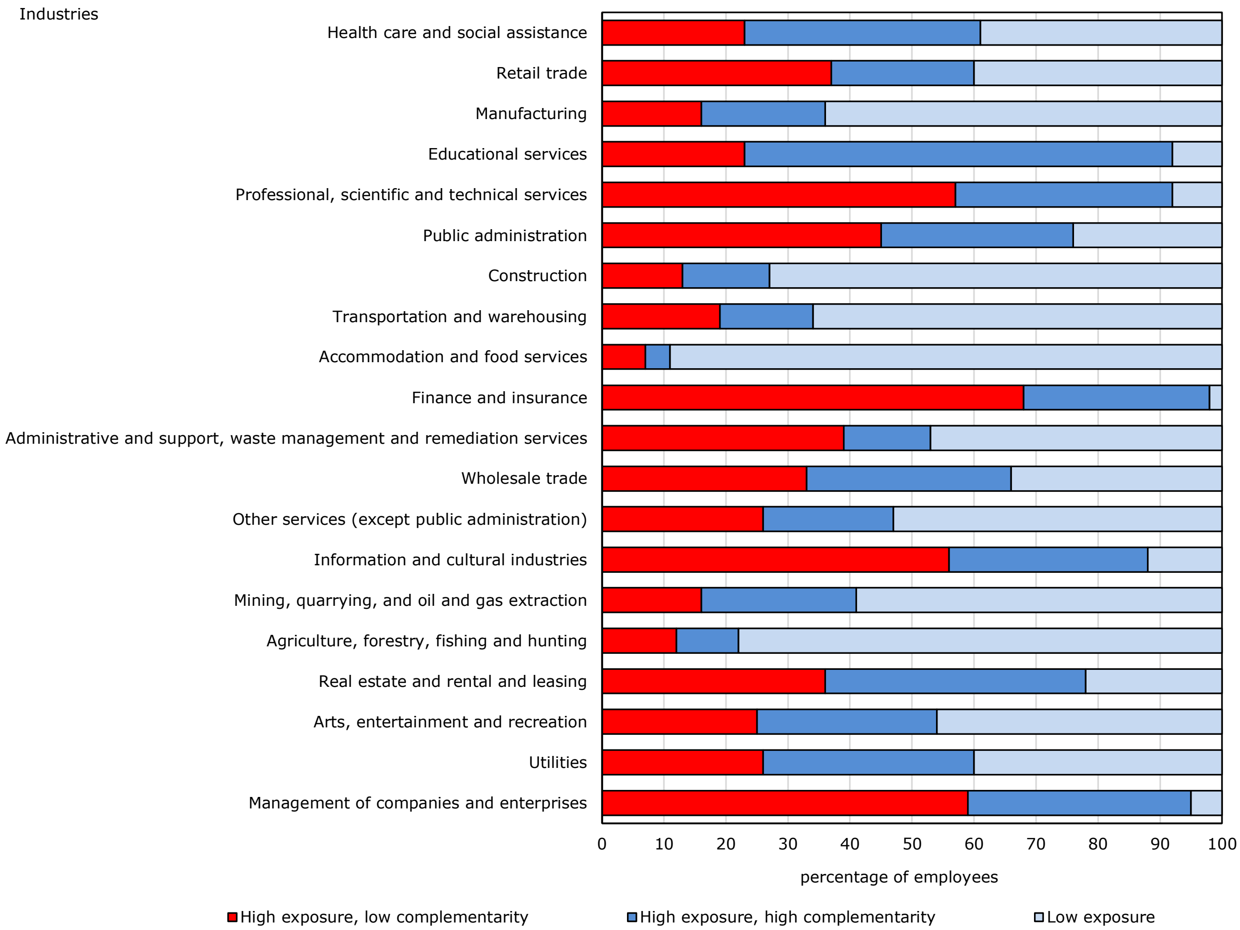


Notes: The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification 2016. The occupations are ranked according to the number of employees from most (top) to least (bottom). The artificial intelligence occupational exposure index and potential complementarity are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023).
Sources: Statistics Canada, Census of Population, 2021; and Occupational Information Network version 28.2.

At least three-quarters of employees in the following occupations were in the first group (i.e., highly exposed to AI-related job transformation and whose tasks could be replaceable with AI in the future): administrative occupations in finance, insurance and business; office support and co-ordination occupations; sales representatives and salespersons in wholesale and retail trade; service representatives and other customer and personal services occupations; professional occupations in business and finance; and computer and information systems professionals. Interestingly, among the 28 occupations, computer and information systems professionals experienced the highest growth (39%) from May 2016 to May 2021. However, this does not necessarily mean that computer and information systems professionals will be in less demand in the future because of AI. While these professionals may be in high-exposure, low-complementarity jobs, they are integral to maintaining and improving the underlying AI infrastructure, and this may lead to the creation of new tasks or jobs. Around 85% of employees or more in management occupations, professional occupations in education services and professional occupations in health (except nursing), as well as engineers, were in the second group (i.e., potentially highly exposed to AI-related job transformation, but AI can complement human labour as long as the worker possesses the necessary skills). Some occupations that could be less susceptible to AI-related job transformation (third group) were support occupations in sales and service; trades helpers, construction labourers and related occupations; assisting occupations in support of health services; and natural resources, agriculture and related production occupations.

Chart 2 shows the AI exposure distribution by industry based on the North American Industry Classification System 2017, at the two-digit level. More than half of employees in the following industries were in high-exposure, low-complementarity jobs: professional, scientific and technical services; finance and insurance; and information and cultural industries. In contrast, educational services, and health care and social assistance employed proportionately more employees who may be beneficiaries of AI. Within the health care and social assistance industry, it is mostly the professional occupations (e.g., nurses, physicians) that may be complementary with AI technologies (Figure 1). Employees in industries such as accommodation and food services, manufacturing, construction, and transportation and warehousing may face relatively lower exposure to AI-related job transformation.

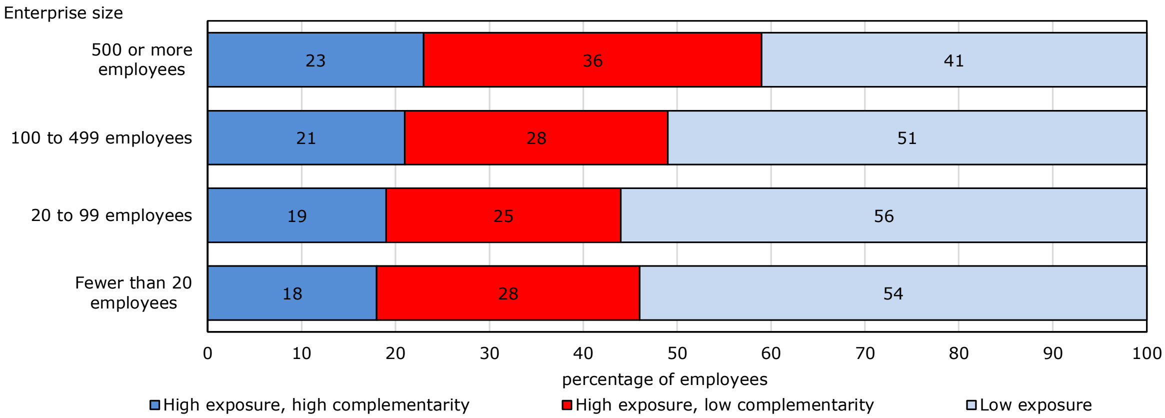
Chart 2
Potential artificial intelligence occupational exposure and complementarity across industries in Canada, May 2021



Notes: The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The industry classifications are based on the North American Industry Classification System 2017. The industries are ranked according to the number of employees from most (top) to least (bottom). The artificial intelligence occupational exposure index and potential complementarity are computed using Occupational Information Network data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023).
Sources: Statistics Canada, Census of Population, 2021; and Occupational Information Network version 28.2.

Employees in larger enterprises (in the commercial sector) may face relatively higher exposure to AI-related job transformation (Chart 3), compared with their counterparts in smaller enterprises. Roughly over one-third of workers in enterprises with 500 or more employees were in high-exposure, low-complementarity jobs in May 2016. This compares with 25% to 28% of workers in smaller enterprises. However, employees in larger enterprises were somewhat more likely to be in jobs complementary with AI than their counterparts in smaller enterprises.

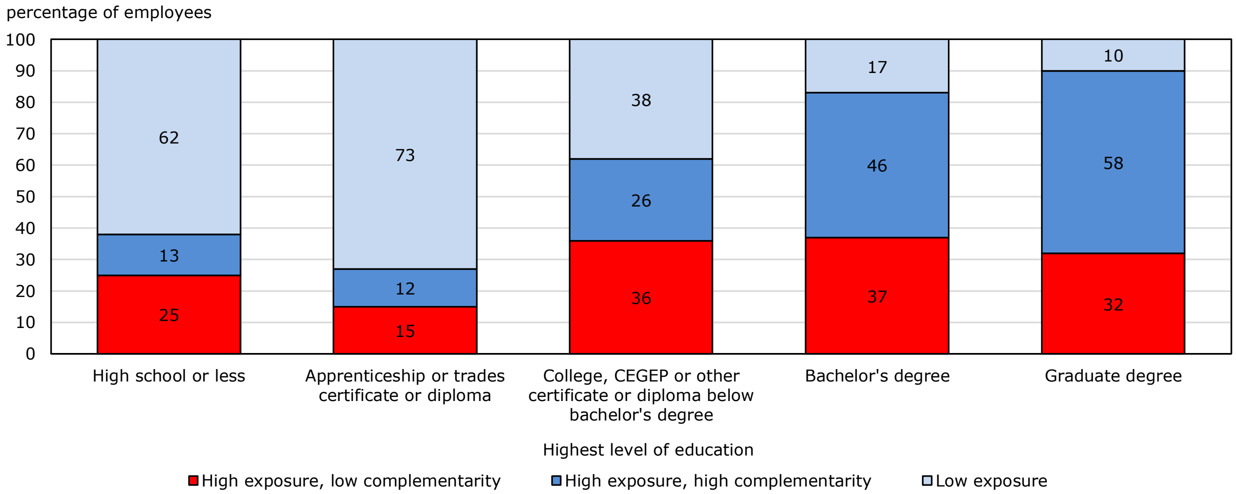
Chart 3
Potential artificial intelligence occupational exposure and complementarity in the commercial sector by enterprise size in Canada, May 2016



Notes: The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The artificial intelligence occupational exposure index and potential complementarity are computed using Occupational Information Network data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The number of employees within an enterprise was computed by integrating Census of Population data with the Longitudinal Worker File. The commercial sector excludes employees from public administration, educational services, and health care and social assistance. Other industries which were excluded: monetary authorities - central bank; religious, grant-making, civic, and professional and similar organizations; and private households.
Sources: Statistics Canada, Census of Population, 2016, and Longitudinal Worker File, 2015 and 2016; and Occupational Information Network version 28.2.

Educational attainment has historically been one of the most important indicators of whether a worker will be resilient to technological shocks. The growing consensus from the labour economics literature is that less educated workers face a higher risk of automation-related job transformation than highly educated workers because the former group is more likely to perform routine and manual tasks that are more susceptible to being automated. However, Chart 4 shows that AI could affect a broader segment of the labour force than previously thought because it has the capacity to perform non-routine and cognitive tasks. Highly educated employees may face higher exposure to AI-related job transformation, as was shown in Figure 1. The highest shares of high-exposure, low-complementarity jobs are held by employees with a bachelor’s degree (37%) or a college, CEGEP or other certificate or diploma below a bachelor’s degree (36%), followed by those with a graduate degree (32%), high school or less education (25%), and an apprenticeship or trades certificate or diploma (15%). However, employees with a bachelor’s degree or higher were more likely to hold jobs that may be highly complementary with AI than those with an education below the bachelor’s degree level, as long as the potential beneficiaries of AI possess the necessary skills. Employees with an apprenticeship or trades certificate or diploma may be less exposed to AI-related job transformation, as 73% were in low-exposure occupations. However, as previously mentioned, a more nuanced view is that while less educated workers may face potentially lower exposure to AI-related job transformation, highly educated workers from high-exposure jobs may transition to low-exposure jobs, displacing less educated workers (see, e.g., Beaudry, Green and Sand [2016]).

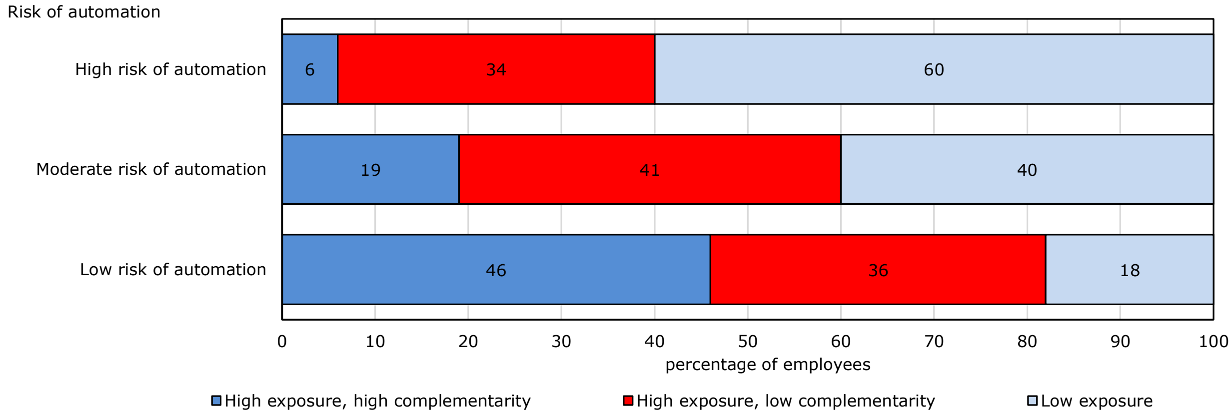
Chart 4
Potential artificial intelligence occupational exposure and complementarity across education levels in Canada, May 2021



Notes: The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The artificial intelligence occupational exposure index and potential complementarity are computed using Occupational Information Network data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023).
Sources: Statistics Canada, Census of Population, 2021; and Occupational Information Network version 28.2.

Many of the results presented so far are contrary to the findings on automation documented in the labour economics literature over the past two decades, raising concerns about the nexus of automation and AI. Frenette and Frank (2020) estimated that around 1/10 of employees in Canada were at high risk (probability of 70% or more) of automation-related job transformation in 2016. Chart 5 suggests that exposure to AI-related job transformation decreases as the risk of automation-related job transformation increases. The majority of employees (60%) in jobs at high risk of automation-related transformation were in jobs that may be least exposed to AI-related transformation (Chart 5). In contrast, 18% of employees in jobs at low risk (probability of less than 50%) of automation were in low-exposure jobs. However, although potentially highly exposed to AI-related job transformation, employees at a lower risk of automation-related job transformation hold jobs that could be highly complementary with AI. Jobs facing a moderate risk (probability of 50% to less than 70%) of automation-related transformation were most likely to be high-exposure, low-complementarity jobs. These findings are important, as they suggest that the distinction between manual and cognitive tasks and between repetitive and non-repetitive tasks used in the last two decades in labour economics to understand automation-related technological transformation may not apply to AI.

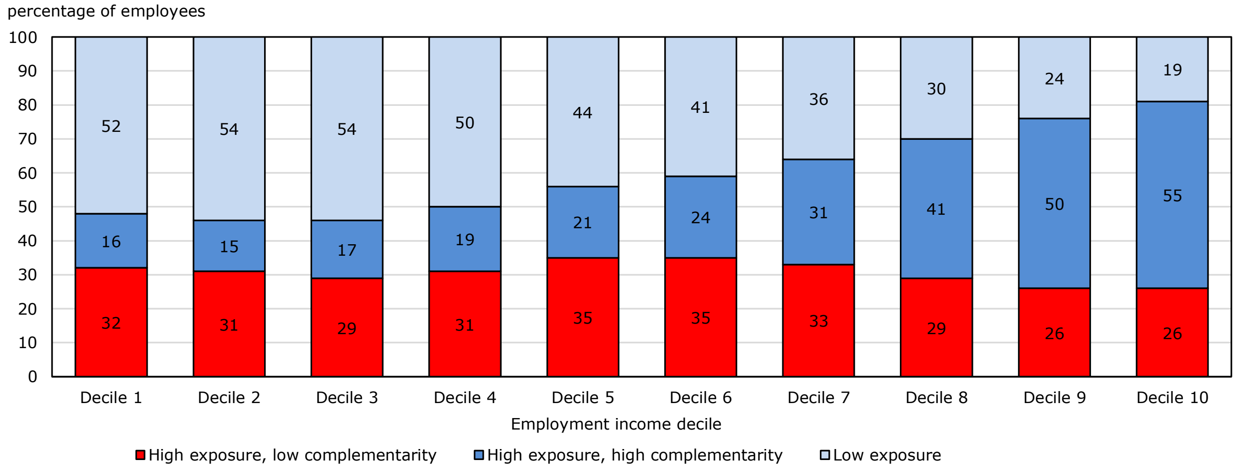
Chart 5
Potential artificial intelligence occupational exposure and complementarity by risk of automation in Canada, 2016



Notes: The sample consists of employees aged 18 to 64 from the database used by Frenette and Frank (2020). Occupations at low risk of automation are those with a probability of automation lower than 50%. Occupations with a moderate risk of automation are those with a probability of automation of 50% to less than 70%. Occupations at high risk of automation are those with a probability of automation of 70% or more. The artificial intelligence occupational exposure index and potential complementarity are computed using Occupational Information Network data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023).
Sources: Statistics Canada, Longitudinal and International Survey of Adults, 2016 (wave 3); and Occupational Information Network version 28.2.

Like previous waves of technological transformation, AI has the potential to boost productivity. But this process can also exacerbate earnings inequality. Chart 6 shows the AI exposure distribution across employment income deciles. More than half of the jobs in the bottom half of the distribution were low-exposure jobs, while around 30% were high-exposure, low-complementarity jobs. The middle of the distribution may be the most vulnerable to AI-related job transformation, with around one-third of jobs being high exposure and low complementarity. Exposure to AI-related job transformation increases with employment income, but higher earners hold jobs that may be highly complementary with AI. Although the top decile had the highest share of jobs potentially exposed to AI-related job transformation, they also had the highest share of jobs (55%) that are highly complementary with AI. If higher earners can take advantage of the complementary benefits of AI, their productivity and earnings growth may outpace those of lower earners, and this could exacerbate earnings inequality (Cazzaniga et al., 2024). However, the diffusion of AI could also potentially reduce earnings inequality if AI happens to adversely affect high-skill occupations (see, e.g., Webb [2020]).

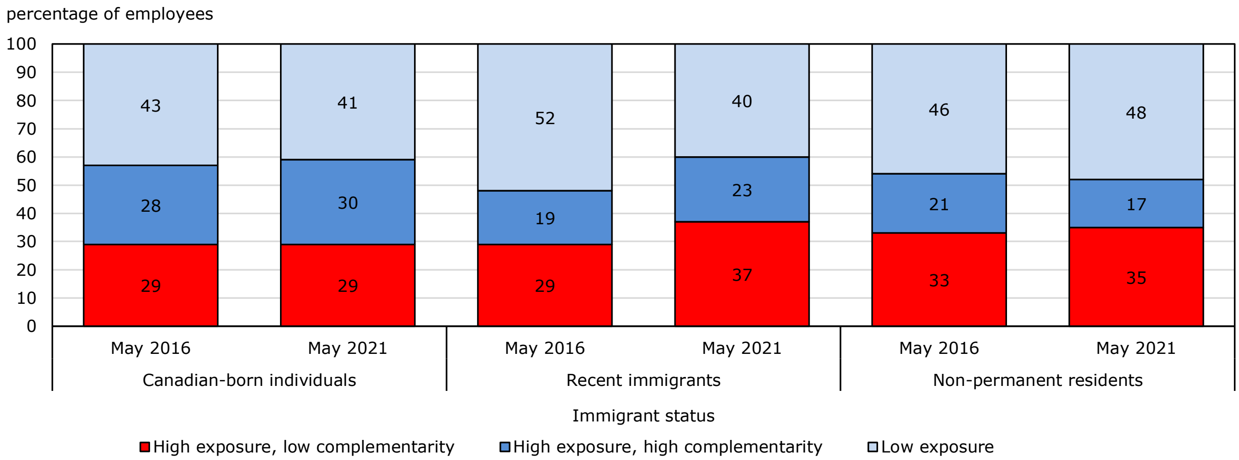
Chart 6
Potential artificial intelligence occupational exposure and complementarity across employment income deciles in Canada, May 2021



Notes: The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The artificial intelligence occupational exposure index and potential complementarity are computed using Occupational Information Network data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023).
Sources: Statistics Canada, Census of Population, 2021; and Occupational Information Network version 28.2.

Canada's record population growth, recently driven by international migration, raises questions about the future of jobs done by immigrants and non-permanent residents. In May 2016, recent immigrants (those who landed from 2011 to 2016) (29%) were just as likely as Canadian-born individuals (29%) to be in high-exposure, low-complementarity jobs (Chart 7). However, by May 2021, while the share of Canadian-born individuals in such jobs remained the same, the share of recent immigrants (those who landed from 2016 to 2021) in these jobs increased to 37%. This was partly driven by the fact that nearly 1/10 of permanent residents who landed from 2016 to 2021 were employed in computer and information systems professions in May 2021—occupations more likely to be high exposure and low complementarity. Less than 5% of permanent residents who landed from 2011 to 2016 were employed in these professions in May 2016. This increasing concentration of recent immigrants in computer and information systems professions has been documented by Picot and Mehdi (forthcoming). Another reason could be the (temporarily) falling share of employment in occupations adversely affected by the COVID-19 pandemic. Non-permanent residents were more likely to be in high-exposure, low-complementarity jobs and low-exposure jobs than Canadian-born individuals. One goal of economic immigration programs is to fill labour and skills shortages. However, perceived labour shortages may eventually incentivize some employers to adopt AI technologies, especially if such shortages are in occupations highly exposed to AI-related job transformation.

Chart 7
Potential artificial intelligence occupational exposure and complementarity among Canadian-born individuals, recent immigrants and non-permanent residents, May 2016 and May 2021



Notes: The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The artificial intelligence occupational exposure index and potential complementarity are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). Recent immigrants employed in May 2016 are permanent residents who landed in Canada from January 2011 to May 2016. Recent immigrants employed in May 2021 are permanent residents who landed in Canada from January 2016 to May 2021.
Sources: Statistics Canada, Census of Population, 2016 and 2021; and Occupational Information Network version 28.2.

Appendix Table A.1 (May 2016) and Appendix Table A.2 (May 2021) provide further results disaggregated by field of study, age group, gender, activity limitation status, selected census metropolitan area (CMA), racialized group, full-time or part-time status, union membership status, and whether the job can be done from home.

Exposure to AI-related job transformation varies substantially not only across fields of study but also on whether the employee has a bachelor's degree or higher education. For example, employees who studied engineering and engineering technology or health care at a level below a bachelor's degree were less likely to face AI-related job transformation than employees who studied the same disciplines at the bachelors' degree or higher level. However, even with increased exposure, the majority of the latter group held jobs that were highly complementary with AI. Close to 60% of employees or more who studied mathematics and computer and information sciences—regardless of where they received their postsecondary education—were in high-exposure, low-complementarity jobs. Employees who studied construction trades and mechanic and repair trades may face relatively lower exposure to AI-related job transformation.

Employees aged 18 to 24 are overrepresented in low-exposure occupations, likely because they do not yet have the necessary experience to be employed in high-skill occupations. Core working-age employees, those aged 25 to 54 years, are generally more likely to hold jobs highly exposed to AI-related job transformation than their younger and older counterparts. But core working-age employees are also more likely to hold jobs that may be highly complementary with AI.

Slightly over one-fifth of men are employed in high-exposure, low-complementarity jobs, compared with 38% of women. This is because men are more likely to be employed in the skilled trades, which may face relatively lower exposure to AI-related job transformation. However, women (33%) are more likely than men (25%) to be employed in occupations that could be highly complementary with AI.

Occupations facing AI-related job transformation are more likely to be in large population centres. The CMAs of Ottawa–Gatineau (39%) and Toronto (37%) had proportionately more high-exposure, low-complementarity employment relative to other CMAs. But urban areas also had proportionately more jobs that could be highly complementary with AI.

Chinese (45%) and South Asian (38%) employees are more likely to hold high-exposure, low-complementarity jobs than other racialized groups. This is partly driven by their relatively higher representation in computer and information systems professions, which potentially highly exposed to AI-related job transformation and whose tasks may be replaceable by AI in the future. However, as noted earlier, these occupations could be integral to maintaining and improving the underlying AI infrastructure.

Unionized employees are almost as likely as their non-unionized counterparts to be highly exposed to AI-related job transformation. However, non-unionized employees (35%) are more likely to be in high-exposure, low-complementarity jobs than unionized employees (23%). This was largely driven by a higher share of unionized employees in health care and education occupations, which are potentially highly exposed to and complementary with AI.

The COVID-19 pandemic has led to significant increases in working from home (see, e.g., Mehdi and Morissette [2021a] or Mehdi and Morissette [2021b]). These jobs are usually held by highly educated employees who may be more exposed to AI-related job transformation than their less educated counterparts. Just over half (51%) of employees with jobs that can be done from home were in high-exposure, low-complementarity occupations, compared with 14% of employees in jobs that cannot be done from home.[8] However, 47% of the former group holds jobs that could be highly complementary with AI, compared with 14% of the latter group. How the advent of AI could affect the labour market in potential future pandemics is unclear (see, e.g., Frenette and Morissette [2021]).

8. Work from home feasibility is based on the indicator developed by Dingel and Neiman (2020).

4 Conclusion

This study provides experimental estimates of the number and percentage of employees aged 18 to 64 in Canada potentially susceptible to AI-related job transformation using the C-AIOE index of Pizzinelli et al. (2023) and data from O*NET and the 2016 and 2021 censuses of population. Occupations were grouped into three distinct categories: (1) high exposure and low complementarity, (2) high exposure and high complementarity, and (3) low exposure. Being in the second group does not necessarily reduce AIOE, as workers would still need the necessary skills to be able to leverage the potential complementary benefits of AI.

On average, in May 2021, approximately 4.2 million employees (31%) in Canada were in the first group, about 3.9 million (29%) were in the second group and about 5.4 million (40%) were in the third group. This distribution was similar in May 2016. Employees in the following industries were more likely than others to be in the first group: professional, scientific and technical services; finance and insurance; and information and cultural industries. In contrast, employees in educational services, and health care and social assistance were more likely to be in the second group than other employees. Employees in industries such as accommodation and food services, manufacturing, construction, and transportation and warehousing face relatively less exposure to AI-related job transformation.

Unlike previous waves of automation, which affected routine and non-cognitive jobs, AI could affect a broader segment of the labour force than previously thought. Contrary to previous findings from the technological transformation literature, AI could transform the jobs of highly educated employees to a greater extent than those of their less educated counterparts. However, highly educated employees also hold jobs that may be highly complementary with AI. Previous labour market policy recommendations in response to the threat of automation included supporting upskilling and job transition initiatives. The findings in this article, which reflect the possible role of AI exposure and complementarity for occupations and workers in Canada, may inform future policy discussions on the topic.

The index used in this study is subjective and based on judgments regarding some current possibilities of AI. Consequently, the applicability of the index may decrease over time as AI capabilities grow and AI can perform an increasing number of tasks currently done by human workers. The index is also computed at the occupational level, implicitly assuming that tasks within a given occupation are the same across regions and worker characteristics. However, the ability to adapt and respond to changing skill demands will likely vary across worker characteristics. If tasks vary substantially across regions and worker characteristics, and if some tasks are more vulnerable to AI substitution, the index could be over- or underestimated to a certain extent. For example, computer programmers in one region who spend their work day coding may be more susceptible to AI-related job transformation if AI is proficient in writing that code. In contrast, programmers in another region who spend part of their day interacting face to face with team members may be less susceptible, assuming AI is not yet proficient in face-to-face interactions. To address this, future research could develop alternative measures of AI exposure at the worker level, similar to how Arntz, Gregory and Zierahn (2016) or Frenette and Frank (2020) estimated automation risk. Future studies could also attempt to answer the question, “What happened to workers whose jobs were exposed to AI-related job transformation?”

As AI technologies continue to evolve, they have the potential to reshape industries, redefine job roles and transform the nature of work. AI may also create new challenges and divides and push boundaries. But large-scale AI adoption may take some time, as employers may face financial, legal and institutional constraints. This study provides a static picture of AIOE based on employment compositions in Canada in May 2016 and May 2021, which were fairly similar. How AI affects productivity and how workers and firms adapt to the potentially evolving labour market in the long run remain to be seen.

Appendix

Appendix Table A.1
Potential artificial intelligence occupational exposure and complementarity in Canada across selected characteristics, employees aged 18 to 64, May 2016

	Employment	AIOE	Potential complementarity	Complementarity-adjusted AIOE	High exposure, low complementarity	High exposure, high complementarity	Low exposure
	number		average index			percent	
Total	13,943,200	6.0758	0.5953	5.3231	30	27	43
Occupation							
Management occupations (0)	1,401,800	6.4705	0.6610	5.4581	6	86	8
Support occupations in sales and service (66, 67)	1,156,000	5.5916	0.5097	5.1406	2	0	98
Administrative occupations in finance, insurance and business (12, 13)	961,000	6.4815	0.5578	5.8056	83	17	0
Office support and co-ordination occupations (14, 15)	916,800	6.2339	0.5002	5.7637	79	1	20
Sales and service supervisors (62, 63)	759,000	6.0866	0.6040	5.3035	17	30	53
Service representatives and other customer and	744,800	6.0972	0.5345	5.5326	59	3	38
Transport and heavy equipment operators and servicers (74, 75)	701,400	5.5456	0.6080	4.8267	0	0	100
Industrial, electrical and construction trades (72)	646,100	5.5706	0.6345	4.7715	0	0	100
Professional occupations in education services (40)	643,900	6.4743	0.6814	5.3975	9	91	0
Support occupations in law and social services (42, 43, 44)	624,100	6.0716	0.6286	5.2256	27	30	43
Sales representatives and salespersons in wholesale and retail trade (64)	618,600	6.0941	0.5568	5.4565	85	15	0
Technical occupations related to natural and applied sciences (22)	460,200	6.1608	0.6202	5.3268	36	37	27
Professional occupations in business and finance (11)	452,100	6.6595	0.5886	5.8600	100	0	0
Maintenance and equipment operation trades (73)	418,400	5.6468	0.6590	4.7689	0	6	94
Assemblers and labourers in manufacturing and utilities (95, 96)	371,800	5.5876	0.5226	5.0988	0	0	100
Professional occupations in law and social, community and government services (41)	364,000	6.5632	0.6446	5.5925	22	78	0
Machine operators and supervisors in manufacturing and utilities (92, 94)	334,100	5.7241	0.5783	5.0586	0	8	92
Occupations in art, culture, recreation and sports (51, 52)	311,500	6.0360	0.6035	5.2657	38	28	34
Computer and information systems professionals (217)	307,600	6.5877	0.5513	5.9195	100	0	0
Assisting occupations in support of health services (34)	294,500	5.6644	0.6101	4.9240	0	0	100
Technical occupations in health (32)	292,600	5.8853	0.6244	5.0736	14	17	69
Professional occupations in nursing (30)	289,000	6.1660	0.6995	5.0834	0	100	0
Natural resources, agriculture and related production occupations (8)	246,000	5.4174	0.5742	4.7974	0	0	100
Engineers (213, 214)	203,900	6.5441	0.6337	5.6093	13	87	0
Trades helpers, construction labourers and related occupations (76)	174,700	5.3877	0.6018	4.7027	0	0	100
Professional occupations in health (except nursing) (31)	155,100	6.3060	0.7283	5.1119	0	87	13
Physical and life science professionals (211, 212)	53,500	6.3801	0.6588	5.3913	2	98	0
Architects and statisticians (215, 216)	41,000	6.5368	0.6374	5.5940	29	71	0

.. not available for a specific reference period

… not applicable

1. Based on integrating the Census of Population data with the Longitudinal Worker File.
2. Based on the indicator of Dingel and Neiman (2020).
3. Based on the 2016 Longitudinal and International Study of Adults (wave 3) dataset used by Frenette and Frank (2020), so employment will not sum up to the total.

Notes: AIOE = artificial intelligence occupational exposure and n.i.e. = not included elsewhere. The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification (NOC) 2016. Of the 500 NOC occupations, 10 occupations, which represented less than 1% of Canadian employment, were excluded because of a lack of Occupational Information Network (O*NET) data for computing the AIOE or complementarity parameter. The AIOE index and potential complementarity are computed using O*NET data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The complementarity-adjusted AIOE is calculated using a weight of 1. An occupation is "high exposure" if its AIOE exceeds the median AIOE across all occupations (around 6.0) and "low exposure" otherwise. An occupation is "high complementarity" if its complementarity level exceeds the median complementarity level across all occupations (around 0.6) and "low complementarity" otherwise. Numbers may not sum up to the total because of rounding or non-responses.

Sources: Statistics Canada, Census of Population, 2016, Longitudinal and International Study of Adults (wave 3), 2016, and Longitudinal Worker File, 2015 and 2016; and Occupational

Appendix Table A.1
Potential artificial intelligence occupational exposure and complementarity in Canada across selected characteristics, employees aged 18 to 64, May 2016 (continued)

	Employment	AIOE	Potential complementarity	Complementarity-adjusted AIOE	High exposure, low complementarity	High exposure, high complementarity	Low exposure
	number		average index			percent	
Industry							
Health care and social assistance	1,757,800	6.0723	0.6166	5.2559	22	39	39
Retail trade	1,659,300	6.0276	0.5654	5.3706	41	22	37
Manufacturing	1,379,800	5.9026	0.5773	5.2217	16	18	66
Educational services	1,060,100	6.3636	0.6512	5.3987	22	69	9
Accommodation and food services	974,600	5.7522	0.5456	5.1790	7	3	90
Public administration	966,600	6.2384	0.6106	5.4253	43	26	31
Professional, scientific and technical services	892,700	6.4498	0.5881	5.6769	58	34	8
Construction	892,500	5.7784	0.6390	4.9378	13	14	73
Finance and insurance	672,900	6.5370	0.5806	5.7765	70	28	2
Transportation and warehousing	663,500	5.8835	0.5975	5.1514	20	15	65
Wholesale trade	557,900	6.1445	0.5926	5.3922	30	35	35
Other services (except public administration)	551,600	5.9888	0.5961	5.2458	23	18	59
Administrative and support, waste management and remediation services	549,800	5.9322	0.5568	5.3101	40	12	48
Information and cultural industries	348,000	6.2984	0.5908	5.5354	52	32	16
Arts, entertainment and recreation	238,700	5.9661	0.5830	5.2643	28	21	51
Real estate and rental and leasing	220,400	6.2789	0.6129	5.4460	31	47	22
Mining, quarrying, and oil and gas extraction	212,400	5.9766	0.6346	5.1229	18	26	56
Agriculture, forestry, fishing and hunting	196,000	5.6807	0.5810	5.0137	10	9	81
Utilities	124,500	6.1459	0.6279	5.2915	28	34	38
Management of companies and enterprises	24,200	6.4615	0.5929	5.6708	55	39	6
Highest level of education							
High school or less	4,751,200	5.8867	0.5692	5.2349	26	13	61
Apprenticeship or trades certificate or diploma	1,450,400	5.8141	0.6052	5.0680	15	12	73
College, CEGEP or other certificate or diploma below bachelor's degree	3,679,500	6.1146	0.5944	5.3629	36	26	38
Bachelor's degree	2,800,700	6.3249	0.6162	5.4764	36	47	17
Graduate degree	1,261,400	6.4227	0.6380	5.4918	29	61	10
Employment income decile							
Decile 1	1,394,320	5.9443	0.5650	5.2964	30	15	55
Decile 2	1,394,320	5.9160	0.5602	5.2867	30	13	57
Decile 3	1,394,320	5.9337	0.5679	5.2797	29	15	56
Decile 4	1,394,320	5.9766	0.5764	5.2935	30	18	52
Decile 5	1,394,320	6.0313	0.5810	5.3292	34	20	46
Decile 6	1,394,320	6.0885	0.5898	5.3543	36	23	41
Decile 7	1,394,320	6.1279	0.6028	5.3491	34	28	38
Decile 8	1,394,320	6.1767	0.6221	5.3317	29	38	33
Decile 9	1,394,320	6.2370	0.6389	5.3320	25	48	27
Decile 10	1,394,320	6.3204	0.6474	5.3769	23	54	23

.. not available for a specific reference period

… not applicable

1. Based on integrating the Census of Population data with the Longitudinal Worker File.
2. Based on the indicator of Dingel and Neiman (2020).
3. Based on the 2016 Longitudinal and International Study of Adults (wave 3) dataset used by Frenette and Frank (2020), so employment will not sum up to the total.

Notes: AIOE = artificial intelligence occupational exposure and n.i.e. = not included elsewhere. The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification (NOC) 2016. Of the 500 NOC occupations, 10 occupations, which represented less than 1% of Canadian employment, were excluded because of a lack of Occupational Information Network (O*NET) data for computing the AIOE or complementarity parameter. The AIOE index and potential complementarity are computed using O*NET data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The complementarity-adjusted AIOE is calculated using a weight of 1. An occupation is "high exposure" if its AIOE exceeds the median AIOE across all occupations (around 6.0) and "low exposure" otherwise. An occupation is "high complementarity" if its complementarity level exceeds the median complementarity level across all occupations (around 0.6) and "low complementarity" otherwise. Numbers may not sum up to the total because of rounding or non-responses.

Sources: Statistics Canada, Census of Population, 2016, Longitudinal and International Study of Adults (wave 3), 2016, and Longitudinal Worker File, 2015 and 2016; and Occupational Information Network version 28.2.

Appendix Table A.1
Potential artificial intelligence occupational exposure and complementarity in Canada across selected characteristics, employees aged 18 to 64, May 2016 (continued)

	Employment	AIOE	Potential complementarity	Complementarity-adjusted AIOE	High exposure, low complementarity	High exposure, high complementarity	Low exposure
	number		average index			percent	
Selected census metropolitan area							
Toronto	2,431,000	6.1519	0.5921	5.3990	35	29	36
Montréal	1,683,900	6.1190	0.5909	5.3740	33	29	38
Vancouver	1,029,800	6.1123	0.5946	5.3573	33	28	39
Calgary	614,000	6.1265	0.5998	5.3537	32	30	38
Ottawa–Gatineau	582,000	6.1996	0.5959	5.4301	38	32	30
Edmonton	577,900	6.0656	0.6011	5.2972	29	27	44
Québec	352,100	6.1292	0.5937	5.3749	34	29	37
Winnipeg	338,700	6.0764	0.5937	5.3285	30	27	43
Hamilton	304,700	6.0836	0.5977	5.3218	28	30	42
Kitchener–Cambridge–Waterloo	228,600	6.0757	0.5920	5.3324	30	26	44
London	198,900	6.0716	0.5944	5.3214	29	27	44
Halifax	182,300	6.1287	0.5970	5.3648	33	29	38
Other	5,419,300	…	…	…	…	…	…
Field of study based on highest level of education							
High school or less	4,751,200	5.8867	0.5692	5.2349	26	13	61
Some postsecondary below bachelor's degree	5,129,900	6.0296	0.5975	4.5294	30	22	48
Business and administration	1,075,300	6.3026	0.5687	5.6073	56	24	20
Trades (except construction trades and mechanic and repair technologies/technicians), services, natural resources and conservation	991,900	5.8747	0.5952	5.1478	19	13	68
Construction trades and mechanic and repair technologies/technicians	786,800	5.7282	0.6422	4.8855	6	12	82
Health care	784,900	5.9741	0.6062	5.2041	21	25	54
Engineering and engineering technology	407,100	6.0475	0.6157	5.2382	23	30	47
Arts and humanities	330,400	6.0925	0.5743	5.4013	41	22	37
Social and behavioural sciences	269,800	6.1189	0.5953	5.3615	30	43	27
Mathematics and computer and information sciences	216,700	6.2733	0.5750	5.5625	56	20	24
Science and science technology	109,500	6.0495	0.5926	5.3087	34	23	43
Legal professions and studies	80,300	6.3578	0.5435	5.7395	72	12	16
Education and teaching	77,200	6.1270	0.6225	5.2851	23	52	25
Bachelor's degree or higher	4,062,100	6.3552	0.6230	4.6072	34	52	14
Business and administration	797,100	6.4447	0.5981	5.6386	52	36	12
Social and behavioural sciences	619,900	6.3561	0.6069	5.5332	42	42	16
Education and teaching	474,100	6.3763	0.6719	5.3417	10	84	6
Arts and humanities	443,300	6.2917	0.6047	5.4812	39	42	19
Engineering and engineering technology	430,000	6.3772	0.6196	5.5103	29	56	15
Health care	397,200	6.1986	0.6758	5.1821	8	74	18
Science and science technology	384,900	6.2881	0.6220	5.4261	30	50	20
Mathematics and computer and information sciences	217,400	6.4472	0.5813	5.6964	66	24	10
Trades (except construction trades and mechanic and repair technologies/technicians), services, natural	211,500	6.3228	0.6330	5.4205	24	59	17
Legal professions and studies	86,700	6.4908	0.6510	5.5042	24	67	9
Construction trades and mechanic and repair technologies/technicians	0	..	..	..	..	..	..

.. not available for a specific reference period
… not applicable
1. Based on integrating the Census of Population data with the Longitudinal Worker File.
2. Based on the indicator of Dingel and Neiman (2020).
3. Based on the 2016 Longitudinal and International Study of Adults (wave 3) dataset used by Frenette and Frank (2020), so employment will not sum up to the total.

Notes: AIOE = artificial intelligence occupational exposure and n.i.e. = not included elsewhere. The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification (NOC) 2016. Of the 500 NOC occupations, 10 occupations, which represented less than 1% of Canadian employment, were excluded because of a lack of Occupational Information Network (O*NET) data for computing the AIOE or complementarity parameter. The AIOE index and potential complementarity are computed using O*NET data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The complementarity-adjusted AIOE is calculated using a weight of 1. An occupation is "high exposure" if its AIOE exceeds the median AIOE across all occupations (around 6.0) and "low exposure" otherwise. An occupation is "high complementarity" if its complementarity level exceeds the median complementarity level across all occupations (around 0.6) and "low complementarity" otherwise. Numbers may not sum up to the total because of rounding or non-responses.

Sources: Statistics Canada, Census of Population, 2016, Longitudinal and International Study of Adults (wave 3), 2016, and Longitudinal Worker File, 2015 and 2016; and Occupational Information Network version 28.2.

Appendix Table A.1

Potential artificial intelligence occupational exposure and complementarity in Canada across selected characteristics, employees aged 18 to 64, May 2016 (continued)

	Employment	AIOE	Potential complementarity	Complementarity-adjusted AIOE	High exposure, low complementarity	High exposure, high complementarity	Low exposure
	number		average index			percent	
Age							
18 to 24 years	1,818,200	5.8816	0.5621	5.2522	30	10	60
25 to 34 years	3,247,300	6.0952	0.6008	5.3245	31	28	41
35 to 44 years	3,160,700	6.1342	0.6055	5.3435	30	33	37
45 to 54 years	3,351,000	6.1096	0.6001	5.3378	29	31	40
55 to 64 years	2,366,000	6.0725	0.5927	5.3273	30	27	43
Gender							
Men	6,997,800	5.9826	0.6079	5.2034	22	24	54
Women	6,945,400	6.1697	0.5826	5.4437	38	30	32
Often or always have difficulties with daily activities							
No	12,242,500	6.0779	0.5961	5.3223	30	28	42
Yes	1,650,500	6.0655	0.5894	5.3319	31	25	44
Immigrant status							
Canadian-born individual	10,465,100	6.0753	0.5985	5.3133	29	28	43
Permanent resident (landed before 2006)	2,222,300	6.1044	0.5894	5.3653	32	27	41
Permanent resident (landed from 2006 to 2010)	513,000	6.0401	0.5819	5.3307	30	23	47
Permanent resident (landed from 2011 to 2016)	520,600	6.0023	0.5754	5.3163	29	19	52
Non-permanent resident	222,200	6.0661	0.5796	5.3600	33	21	46
Racialized group							
White	10,334,600	6.0815	0.5997	5.3149	29	29	42
South Asian	740,100	6.0995	0.5826	5.3816	35	24	41
Chinese	577,700	6.2033	0.5831	5.4717	41	27	32
Black	421,600	6.0114	0.5807	5.3101	31	21	48
Filipino	415,700	5.9028	0.5705	5.2438	23	14	63
Arab	158,400	6.1496	0.5933	5.3928	33	32	35
Latin American	213,200	5.9880	0.5763	5.3011	29	20	51
Southeast Asian	131,400	5.9479	0.5677	5.2912	25	15	60
West Asian	95,700	6.1382	0.5902	5.3922	34	29	37
Korean	64,200	6.1347	0.5896	5.3898	32	29	39
Japanese	24,700	6.1799	0.5936	5.4189	35	32	33
Racialized groups, n.i.e.	57,800	6.0614	0.5816	5.3522	33	23	44
Multiple racialized groups	247,000	6.1092	0.5863	5.3789	35	26	39
Hours worked per week							
30 or more (full-time)	11,264,800	6.1030	0.6025	5.3256	29	30	41
Less than 30, but more than 0 (part-time)	2,346,600	5.9624	0.5644	5.3149	32	17	51
Union member							
No	9,215,800	6.0886	0.5856	5.3637	34	24	42
Yes	4,727,500	6.0508	0.6141	5.2438	23	33	44
Enterprise size[1]							
Fewer than 20 employees	2,167,400	6.0170	0.5884	5.2935	29	21	50
20 to 99 employees	2,207,100	5.9952	0.5866	5.2780	25	23	52
100 to 499 employees	1,830,500	6.0315	0.5889	5.3030	28	24	48
500 or more employees	6,527,400	6.1452	0.6028	5.3612	33	32	35
Job can be done from home[2]							
No	8,171,400	5.7949	0.5927	5.0835	15	13	72
Yes	5,771,800	6.4734	0.5989	5.6622	51	47	2
Risk of automation[3]							
Low risk of automation (probability of less than 50%)	7,849,200	6.3341	0.6258	5.4453	36	46	18
Moderate risk of automation (probability of 50% to less than 70%)	4,285,800	6.0999	0.5872	5.3709	41	19	40
High risk of automation (probability of 70% or higher)	1,547,300	5.9139	0.5488	5.3215	34	6	60

.. not available for a specific reference period

… not applicable

1. Based on integrating the Census of Population data with the Longitudinal Worker File.
2. Based on the indicator of Dingel and Neiman (2020).
3. Based on the 2016 Longitudinal and International Study of Adults (wave 3) dataset used by Frenette and Frank (2020), so employment will not sum up to the total.

Notes: AIOE = artificial intelligence occupational exposure and n.i.e. = not included elsewhere. The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification (NOC) 2016. Of the 500 NOC occupations, 10 occupations, which represented less than 1% of Canadian employment, were excluded because of a lack of Occupational Information Network (O*NET) data for computing the AIOE or complementarity parameter. The AIOE index and potential complementarity are computed using O*NET data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The complementarity-adjusted AIOE is calculated using a weight of 1. An occupation is "high exposure" if its AIOE exceeds the median AIOE across all occupations (around 6.0) and "low exposure" otherwise. An occupation is "high complementarity" if its complementarity level exceeds the median complementarity level across all occupations (around 0.6) and "low complementarity" otherwise. Numbers may not sum up to the total because of rounding or non-responses.

Sources: Statistics Canada, Census of Population, 2016, Longitudinal and International Study of Adults (wave 3), 2016, and Longitudinal Worker File, 2015 and 2016; and Occupational Information Network version 28.2.

Appendix Table A.2
Potential artificial intelligence occupational exposure and complementarity in Canada across selected characteristics, employees aged 18 to 64, May 2021

	Employment	AIOE	Potential complementarity	Complementarity-adjusted AIOE	High exposure, low complementarity	High exposure, high complementarity	Low exposure
	number		average index			percent	
Total	13,589,900	6.1010	0.5989	4.5683	31	29	40
Occupation							
Management occupations (0)	1,500,200	6.4858	0.6599	4.4635	6	87	7
Support occupations in sales and service (66, 67)	1,040,700	5.5812	0.5093	4.6833	1	0	99
Administrative occupations in finance, insurance and business (12, 13)	979,700	6.4791	0.5592	5.1198	82	18	0
Office support and co-ordination occupations (14, 15)	832,500	6.2227	0.5029	5.2678	76	0	24
Sales and service supervisors (62, 63)	620,200	6.0893	0.6046	4.5206	19	27	54
Service representatives and other customer and personal services occupations (65)	516,600	6.2254	0.5300	5.1038	77	2	21
Transport and heavy equipment operators and servicers (74, 75)	702,100	5.5430	0.6095	4.0975	0	0	100
Industrial, electrical and construction trades (72)	606,000	5.5727	0.6381	3.9541	0	0	100
Professional occupations in education services (40)	675,000	6.4791	0.6780	4.3461	12	88	0
Support occupations in law and social services (42, 43, 44)	617,400	6.1154	0.6333	4.3856	32	34	34
Sales representatives and salespersons in wholesale and retail trade (64)	482,300	6.0790	0.5537	4.8267	89	11	0
Technical occupations related to natural and applied sciences (22)	477,100	6.1674	0.6195	4.5010	34	40	26
Professional occupations in business and finance (11)	491,600	6.6558	0.5901	5.0478	100	0	0
Maintenance and equipment operation trades (73)	408,500	5.6534	0.6609	3.8844	0	7	93
Assemblers and labourers in manufacturing and utilities (95, 96)	343,400	5.5736	0.5196	4.6156	0	0	100
Professional occupations in law and social, community and government services (41)	406,600	6.5639	0.6414	4.6434	24	76	0
Machine operators and supervisors in manufacturing and utilities (92, 94)	302,400	5.7288	0.5829	4.3706	0	10	90
Occupations in art, culture, recreation and sports (51, 52)	277,500	6.1135	0.6011	4.5674	46	33	21
Computer and information systems professionals (217)	426,900	6.5851	0.5516	5.2472	100	0	0
Assisting occupations in support of health services (34)	374,000	5.6574	0.6095	4.1815	0	0	100
Technical occupations in health (32)	309,200	5.8897	0.6250	4.2623	13	18	69
Professional occupations in nursing (30)	317,500	6.1660	0.6995	4.0007	0	100	0
Natural resources, agriculture and related production occupations (8)	221,300	5.4180	0.5746	4.1757	0	0	100
Engineers (213, 214)	210,800	6.5463	0.6340	4.6747	13	87	0
Trades helpers, construction labourers and related occupations (76)	186,800	5.3881	0.6021	4.0165	0	0	100
Professional occupations in health (except nursing) (31)	153,500	6.2932	0.7266	3.9209	0	86	14
Physical and life science professionals (211, 212)	59,900	6.3805	0.6591	4.4004	1	99	0
Architects and statisticians (215, 216)	50,200	6.5470	0.6391	4.6462	25	75	0

.. not available for a specific reference period

… not applicable

1. Starting in 2021, the category “Men+” includes men (and boys), as well as some non-binary people, and the category “Women+” includes women (and girls), as well as some non-binary people.

2. Based on the indicator of Dingel and Neiman (2020).

Notes: AIOE = artificial intelligence occupational exposure and n.i.e. = not included elsewhere. The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification (NOC) 2016. Of the 500 NOC occupations, 10 occupations, which represented less than 1% of Canadian employment, were excluded because of a lack of Occupational Information Network (O*NET) data for computing the AIOE or complementarity parameter. The AIOE index and potential complementarity are computed using O*NET data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The complementarity-adjusted AIOE is calculated using a weight of 1. An occupation is "high exposure" if its AIOE exceeds the median AIOE across all occupations (around 6.0) and "low exposure" otherwise. An occupation is "high complementarity" if its complementarity level exceeds the median complementarity level across all occupations (around 0.6) and "low complementarity" otherwise. Numbers may not sum up to the total because of rounding or non-responses.

Sources: Statistics Canada, Census of Population, 2021; and Occupational Information Network version 28.2.

Appendix Table A.2
Potential artificial intelligence occupational exposure and complementarity in Canada across selected characteristics, employees aged 18 to 64, May 2021 (continued)

	Employment	AIOE	Potential complementarity	Complementarity-adjusted AIOE	High exposure, low complementarity	High exposure, high complementarity	Low exposure
	number		average index			percent	
Industry							
Health care and social assistance	1,955,500	6.0762	0.6154	4.4512	23	38	39
Retail trade	1,549,400	6.0176	0.5659	4.7014	37	23	40
Manufacturing	1,295,400	5.9164	0.5795	4.5381	16	20	64
Educational services	1,091,300	6.3759	0.6516	4.4403	23	69	8
Accommodation and food services	663,800	5.7734	0.5548	4.5682	7	4	89
Public administration	1,025,900	6.2976	0.6099	4.6612	45	31	24
Professional, scientific and technical services	1,045,200	6.4585	0.5912	4.8910	57	35	8
Construction	958,000	5.7966	0.6388	4.1124	13	14	73
Finance and insurance	661,500	6.5431	0.5824	5.0093	68	30	2
Transportation and warehousing	671,700	5.8772	0.5969	4.4172	19	15	66
Wholesale trade	498,000	6.1463	0.5921	4.6445	33	33	34
Other services (except public administration)	468,000	6.0246	0.6002	4.5052	26	21	53
Administrative and support, waste management and remediation services	499,400	5.9396	0.5639	4.6524	39	14	47
Information and cultural industries	318,100	6.3207	0.5909	4.7896	56	32	12
Arts, entertainment and recreation	157,000	6.0105	0.5981	4.5039	25	29	46
Real estate and rental and leasing	169,800	6.2870	0.6070	4.6585	36	42	22
Mining, quarrying, and oil and gas extraction	194,600	5.9483	0.6345	4.2483	16	25	59
Agriculture, forestry, fishing and hunting	192,300	5.7126	0.5830	4.3605	12	10	78
Utilities	136,800	6.1356	0.6309	4.4107	26	34	40
Management of companies and enterprises	38,300	6.5039	0.5938	4.9061	59	36	5
Highest level of education							
High school or less	4,155,800	5.8823	0.5719	4.5637	25	13	62
Apprenticeship or trades certificate or diploma	1,280,100	5.8122	0.6100	4.2933	15	12	73
College, CEGEP or other certificate or diploma below bachelor's degree	3,437,800	6.1139	0.5965	4.5994	36	26	38
Bachelor's degree	3,148,400	6.3328	0.6157	4.6383	37	46	17
Graduate degree	1,567,800	6.4232	0.6327	4.5959	32	58	10
Employment income decile							
Decile 1	1,358,990	5.9766	0.5684	4.6553	32	16	52
Decile 2	1,358,990	5.9462	0.5651	4.6525	31	15	54
Decile 3	1,358,990	5.9558	0.5745	4.6049	29	17	54
Decile 4	1,358,990	5.9874	0.5802	4.5973	31	19	50
Decile 5	1,358,990	6.0515	0.5857	4.6158	35	21	44
Decile 6	1,358,990	6.1037	0.5948	4.6010	35	24	41
Decile 7	1,358,990	6.1473	0.6088	4.5477	33	31	36
Decile 8	1,358,990	6.2050	0.6259	4.4846	29	41	30
Decile 9	1,358,990	6.2724	0.6398	4.4473	26	50	24
Decile 10	1,358,990	6.3596	0.6447	4.4786	26	55	19

.. not available for a specific reference period

… not applicable

1. Starting in 2021, the category “Men+” includes men (and boys), as well as some non-binary people, and the category “Women+” includes women (and girls), as well as some non-binary people.

2. Based on the indicator of Dingel and Neiman (2020).

Notes: AIOE = artificial intelligence occupational exposure and n.i.e. = not included elsewhere. The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification (NOC) 2016. Of the 500 NOC occupations, 10 occupations, which represented less than 1% of Canadian employment, were excluded because of a lack of Occupational Information Network (O*NET) data for computing the AIOE or complementarity parameter. The AIOE index and potential complementarity are computed using O*NET data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The complementarity-adjusted AIOE is calculated using a weight of 1. An occupation is “high exposure” if its AIOE exceeds the median AIOE across all occupations (around 6.0) and “low exposure” otherwise. An occupation is “high complementarity” if its complementarity level exceeds the median complementarity level across all occupations (around 0.6) and “low complementarity” otherwise. Numbers may not sum up to the total because of rounding or non-responses.

Sources: Statistics Canada, Census of Population, 2021; and Occupational Information Network version 28.2.

Appendix Table A.2
Potential artificial intelligence occupational exposure and complementarity in Canada across selected characteristics, employees aged 18 to 64, May 2021 (continued)

	Employment	AIOE	Potential complementarity	Complementarity-adjusted AIOE	High exposure, low complementarity	High exposure, high complementarity	Low exposure
	number		average index			percent	
Selected census metropolitan area							
Toronto	2,267,500	6.1981	0.5960	4.6586	37	31	32
Montréal	1,725,500	6.1426	0.5960	4.6171	34	31	35
Vancouver	1,033,200	6.1407	0.5975	4.6068	34	30	36
Calgary	576,500	6.1420	0.6011	4.5856	32	31	37
Ottawa–Gatineau	591,300	6.2361	0.6005	4.6613	39	34	27
Edmonton	549,000	6.0803	0.6023	4.5328	29	29	42
Québec	350,800	6.1568	0.6000	4.6043	34	31	35
Winnipeg	338,900	6.0912	0.5939	4.5909	32	27	41
Hamilton	286,900	6.1237	0.6022	4.5635	29	33	38
Kitchener–Cambridge–Waterloo	229,900	6.1113	0.5953	4.5971	31	28	41
London	195,800	6.0900	0.5980	4.5639	30	29	41
Halifax	184,700	6.1574	0.6023	4.5911	33	32	35
Other	5,259,900	…	…	…	…	…	…
Field of study based on highest level of education							
High school or less	4,155,800	5.8823	0.5719	4.5637	25	13	62
Some postsecondary below bachelor's degree	4,717,900	6.0321	0.6002	4.5164	30	22	48
Business and administration	961,300	6.2916	0.5703	4.8946	55	23	22
Trades (except construction trades and mechanic and repair technologies/technicians), services, natural resources and conservation	872,500	5.8886	0.5985	4.4130	21	14	65
Construction trades and mechanic and repair technologies/technicians	734,100	5.7238	0.6458	4.0197	6	12	82
Health care	736,600	5.9753	0.6078	4.4265	22	24	54
Engineering and engineering technology	371,800	6.0478	0.6157	4.4294	23	30	47
Arts and humanities	299,600	6.1089	0.5786	4.6975	42	23	35
Social and behavioural sciences	256,600	6.1349	0.5981	4.6009	31	44	25
Mathematics and computer and information sciences	227,600	6.2656	0.5762	4.8378	56	21	23
Science and science technology	107,000	6.0589	0.5927	4.5756	34	23	43
Legal professions and studies	74,600	6.3818	0.5443	5.1366	73	12	15
Education and teaching	75,900	6.1162	0.6356	4.3581	21	58	21
Bachelor's degree or higher	4,716,200	6.3628	0.6213	4.6242	36	50	14
Business and administration	993,900	6.4376	0.5977	4.8297	52	36	12
Social and behavioural sciences	679,800	6.3792	0.6085	4.7188	43	43	14
Education and teaching	475,600	6.3819	0.6733	4.3027	9	85	6
Arts and humanities	455,600	6.3101	0.6068	4.6728	40	43	17
Engineering and engineering technology	545,300	6.3778	0.6170	4.6615	32	52	16
Health care	484,100	6.1900	0.6708	4.1924	10	72	18
Science and science technology	443,900	6.3077	0.6209	4.5867	32	50	18
Mathematics and computer and information sciences	299,400	6.4409	0.5792	4.9545	67	23	10
Trades (except construction trades and mechanic and repair technologies/technicians), services, natural resources and conservation	234,900	6.3347	0.6339	4.5215	23	61	16
Legal professions and studies	103,500	6.4863	0.6449	4.5546	27	63	10
Construction trades and mechanic and repair technologies/technicians	0	..	..	..	..	..	..

.. not available for a specific reference period
… not applicable
1. Starting in 2021, the category "Men+" includes men (and boys), as well as some non-binary people, and the category "Women+" includes women (and girls), as well as some non-binary people.
2. Based on the indicator of Dingel and Neiman (2020).
Notes: AIOE = artificial intelligence occupational exposure and n.i.e. = not included elsewhere. The sample consists of employees aged 18 to 64 living off reserve in private dwellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification (NOC) 2016. Of the 500 NOC occupations, 10 occupations, which represented less than 1% of Canadian employment, were excluded because of a lack of Occupational Information Network (O*NET) data for computing the AIOE or complementarity parameter. The AIOE index and potential complementarity are computed using O*NET data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The complementarity-adjusted AIOE is calculated using a weight of 1. An occupation is "high exposure" if its AIOE exceeds the median AIOE across all occupations (around 6.0) and "low exposure" otherwise. An occupation is "high complementarity" if its complementarity level exceeds the median complementarity level across all occupations (around 0.6) and "low complementarity" otherwise. Numbers may not sum up to the total because of rounding or non-responses.
Sources: Statistics Canada, Census of Population, 2021; and Occupational Information Network version 28.2.

Appendix Table A.2
Potential artificial intelligence occupational exposure and complementarity in Canada across selected characteristics, employees aged 18 to 64, May 2021 (continued)

	Employment	AIOE	Potential complementarity	Complementarity-adjusted AIOE	High exposure, low complementarity	High exposure, high complementarity	Low exposure
	number		average index			percent	
Age							
18 to 24 years	1,628,200	5.9022	0.5644	4.6251	31	11	58
25 to 34 years	3,318,100	6.1252	0.6036	4.5607	33	29	38
35 to 44 years	3,246,800	6.1555	0.6091	4.5480	30	34	36
45 to 54 years	2,978,500	6.1408	0.6054	4.5578	29	34	37
55 to 64 years	2,418,300	6.0797	0.5940	4.5806	29	28	43
Gender[1]							
Men+	6,870,600	6.0050	0.6088	4.4363	23	25	52
Women+	6,719,300	6.1993	0.5888	4.7032	38	33	29
Often or always have difficulties with daily activities							
No	11,564,000	6.1006	0.5998	4.5625	30	29	41
Yes	1,991,100	6.1056	0.5938	4.6025	33	28	39
Immigrant status							
Canadian-born individual	9,686,900	6.0977	0.6033	4.5397	29	30	41
Permanent resident (landed before 2011)	2,249,600	6.1366	0.5930	4.6298	33	29	38
Permanent resident (landed from 2011 to 2015)	533,500	6.0598	0.5868	4.6083	30	24	46
Permanent resident (landed from 2016 to 2021)	606,900	6.1120	0.5818	4.6786	37	23	40
Non-permanent resident	513,000	6.0388	0.5746	4.6668	35	17	48
Racialized group							
White	9,227,700	6.1029	0.6045	4.5360	29	31	40
South Asian	1,025,500	6.1364	0.5848	4.6801	38	24	38
Chinese	560,000	6.2699	0.5880	4.7628	45	30	25
Black	542,600	6.0402	0.5857	4.6016	32	23	45
Filipino	482,100	5.9042	0.5753	4.5577	22	16	62
Arab	203,800	6.1793	0.5950	4.6499	35	33	32
Latin American	264,500	6.0398	0.5820	4.6210	32	23	45
Southeast Asian	145,400	6.0104	0.5745	4.6429	28	19	53
West Asian	121,100	6.1892	0.5938	4.6638	36	32	32
Korean	75,800	6.1699	0.5941	4.6460	33	31	36
Japanese	23,200	6.1845	0.5908	4.6787	36	31	33
Racialized groups, n.i.e.	95,400	6.1198	0.5921	4.6231	33	29	38
Multiple racialized groups	343,000	6.1698	0.5937	4.6509	36	30	34
Hours worked per week							
30 or more (full-time)	11,088,000	6.1293	0.6056	4.5500	30	32	38
Less than 30, but more than 0 (part-time)	1,854,000	5.9815	0.5664	4.6709	33	17	50
Union member							
No	8,815,300	6.1187	0.5893	4.6404	35	26	39
Yes	4,774,600	6.0685	0.6166	4.4352	23	35	42
Job can be done from home[2]							
No	7,610,100	5.7993	0.5978	4.3454	14	14	72
Yes	5,979,800	6.4850	0.6003	4.8518	51	47	2
Usually worked from home							
No	10,535,000	5.9985	0.5987	4.4910	24	26	50
Yes	3,054,900	6.4548	0.5994	4.8347	53	40	7

.. not available for a specific reference period

… not applicable

1. Starting in 2021, the category “Men+” includes men (and boys), as w ell as some non-binary people, and the category “Women+” includes w omen (and girls), as w ell as some non-binary people.

2. Based on the indicator of Dingel and Neiman (2020).

Notes: AIOE = artificial intelligence occupational exposure and n.i.e. = not included elsew here. The sample consists of employees aged 18 to 64 living off reserve in private dw ellings, excluding full-time members of the Canadian Armed Forces. The numbers in parentheses indicate the codes from version 1.3 of the National Occupational Classification (NOC) 2016. Of the 500 NOC occupations, 10 occupations, w hich represented less than 1% of Canadian employment, w ere excluded because of a lack of Occupational Information Netw ork (O*NET) data for computing the AIOE or complementarity parameter. The AIOE index and potential complementarity are computed using O*NET data and are based on Felten, Raj and Seamans (2021) and Pizzinelli et al. (2023). The complementarity-adjusted AIOE is calculated using a w eight of 1. An occupation is “high exposure” if its AIOE exceeds the median AIOE across all occupations (around 6.0) and “low exposure” otherw ise. An occupation is “high complementarity” if its complementarity level exceeds the median complementarity level across all occupations (around 0.6) and “low complementarity” otherw ise. Numbers may not sum up to the total because of rounding or non-responses.

Sources: Statistics Canada, Census of Population, 2021; and Occupational Information Netw ork version 28.2.

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