Right Brain, Left Brain, AI Brain

AI’s impact on jobs and skill demand in Canada’s workforce

Vivian Li, Graham Dobbs | January 2025

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1 Executive Summary

Will AI replace workers? This question often brings a great deal of anxiety—it's too early to predict *how* Canada's workforce will be impacted by AI and to what degree. What's clear is that the use of AI in the workplace is growing. From 2021 to 2023, firm adoption in Canada has increased, from 3.7 percent to 6.8 percent,[1] particularly among some of Canada's largest firms. Policymakers, therefore, must pay significant attention to ensuring workers are equipped with the right foundational skills to ensure they are resilient in the face of technological disruption.

The most recent wave of AI technologies, a class of models called Generative Pre-trained Transformers (or GPTs), changes the discourse on AI. On November 30th, 2022, OpenAI released ChatGPT3, the first consumer-facing product that operationalized large language models (LLMs). The tool quickly garnered widespread attention, reaching 100 million users in just two months.[2] It adds the possibility of AI complementing (or assisting) a worker, rather than outright replacing a specific portion of their work.

This research focuses on this possibility. The first study of its kind in Canada, we use an **analytical framework** that allows us to categorize occupations in Canada along two measures: one that looks at the level to which occupations are **exposed** to artificial intelligence (an "exposure" measure) and another that looks at the potential for AI to **assist workers** in an occupation (a "complementarity" measure).

Approximately half of all occupations are "high-exposure", and half are low "low-exposure". Similarly, around half of all occupations are "high-complementarity", and around half are "low-complementarity".

This new analytical framework allows us to place occupations in four categories to determine how AI will impact an occupation:

- **High-Exposure, High-complementarity (HE-HC):** High exposure to AI, *and* more tasks that workers do that can be assisted by AI.

- **High-Exposure, Low-complementarity (HE-LC):** High exposure to AI, *but* more tasks that can be automated *without* human involvement.

- **Low-Exposure, High-complementarity (LE-HC):** Low exposure to AI, but more tasks that workers do that can be assisted by AI.

- **Low Exposure, Low-complementarity (LE-LC):** Low exposure to AI and high level of tasks that can be automated *without* human involvement.

We then use rich data from 13 million online job postings to analyze the labour market trends facing occupations with various levels of both exposure and complementarity.

Though occupations can move across categories as new AI technologies emerge, for policy makers, employers, and workers, the occupations that are high exposure are of the greatest interest in the near term.

High exposure, low complementarity occupations are at greatest risk of disruption with negative effects on those workers. High exposure, high complementarity occupations can be of benefit to both workers and employers.

Key findings:

1. **Across 506 occupations in the Canadian labour force of over 18 million:**[3]

- Around half of all occupations, but 56 percent of workers, have higher exposure to AI.
    - 48 percent of these workers (or 27 percent of all workers) are in occupations that have higher exposure to AI, but are also more highly complementary (HE-HC). These workers are more exposed to AI, but in jobs which have tasks that they can do with the assistance of AI. 52 percent of these workers (or 29 percent of all workers) are in occupations that have higher exposure to AI while having tasks that can be more easily automated without human involvement (HE-LC).
    - As a result, 43 per cent of workers are in occupations that have lower exposure to AI.
- Around half of all occupations, but 41 percent of workers, are currently considered as having higher complementarity to AI, in jobs which have tasks that they can do with the assistance of AI (both HC categories, HE-HC and LE-LC).

2. **The occupations in the HE-HC category possess tasks that are more likely to be assisted by AI.**

- Jobs in this category tend to be higher-paid and are more likely to require a post-secondary education. Examples of these jobs include: some engineers (e.g. civil, mechanical and chemical), certain financial and legal occupations, surgeons, and post-secondary education administrators (see Table 4).

- Skills more uniquely featured in these occupations are *cognitive and non-routine*, requiring a high degree of decision-making and greater responsibility for safety and health outcomes. Examples of these skills include planning, leadership, coaching, and critical thinking (see Table 5).

3. **Occupations in the HE-LC category have tasks that are more likely to be automated.**

- Jobs in this category are associated with more routine tasks and lower wages than HE-HC jobs. Examples include business, finance and administration roles such as administrative assistants, auditors, and accountants (see Table 6).

- The unique skills associated with these occupations tend to involve digital skills, with a higher degree of automatability, and less critical decision-making involved. Examples of these skills include accounting, data analysis, information filing and proofreading (see Table 7).

4. **Job posting data offers a timely and granular source for tracking employer demand for jobs and skills.** It is particularly helpful in assessing the changing demand for high- versus low-complementarity occupations for AI in the workplace.

   A single point-in-time snapshot of how employer hiring is informed by AI is not simple – it has recently been complicated by the COVID pandemic and ongoing labour market volatility. Continued tracking of the workforce will offer a valuable baseline over time as employers, we expect, will increasingly adopt AI technologies.

Taken together, these findings suggest:

- Generative AI could assist many different types of workers across the labour force, as it is more widely adopted. Yet AI adoption poses a risk of increasing job polarization (the erosion of middle-skill, middle-income jobs).
- AI stands to benefit the highly educated, best-compensated workers in high exposure, high complementarity (HE-HC) occupations (associated with cognitive and non-routine tasks). It increases the potential automation of tasks for workers in high exposure, low complementarity (HE-LC) occupations (jobs associated with more routine tasks with less education required and lower wages).

The job postings analysis in the report do not yet present clear evidence of AI-driven job polarization. But employment and wage trends for highly AI exposed occupations should be monitored.

The analysis in this report should be treated as *directional* rather than *predictive*, providing a framework for assessing how AI could impact jobs and skills demand across Canada's labour market.

The practical application of this analysis should help government policymakers, education and workforce development organizations, industry leaders and employers to understand how to think about, and plan for, the labour market transition that AI adoption will spur in the years ahead.

The report concludes with policy implications for Canadian workers, postsecondary programs and workforce development planning, government income support policies and programs, which includes the following:

- Supporting postsecondary access and attainment;
- Factoring in AI resilience into postsecondary program and curriculum planning;
- Informing workforce development and employment service programming with AI exposure and skills demand;
- Providing support for workers to build resilience to AI trends;
- Considering the impacts of AI-related job displacement on income support policies and programs for workers; and
- Continuing tracking and intelligence gathering about how AI is impacting workers, jobs and the labour market.

2 Introduction

Generative Pre-trained Transformers (GPTs) are a class of machine large language models trained on a large amount of human-generated text data to allow near-human-like responses to be predicted for any language query posed to them. Understanding the implications of this new generation of artificial intelligence (AI) technologies is essential for society and the economy.

Until this point, scholarship on how automation impacts work has largely focused on the fact that AI was adept at performing tasks it was explicitly designed to do. There was low risk of entire job categories being disrupted. Researchers also focused on "routine" tasks as being the most automatable, with technologies having little role influencing "non-routine" tasks.

However, one critique of this literature was its focus on the automating effect of technology without considering the role of technology in "complementing or augmenting" workers' efforts.[4] The current frontier of AI is much more well-suited to assisting workers than replacing them. This owes to two factors in particular. Firstly, these classes of AI models allow a human to modify the model's output via text prompt without understanding its technical details. Secondly, these models are statistical in nature and thus do not have systems in place to ensure that the output is accurate or factual, requiring human intervention throughout.

In this study, we build on the analytic tools of leading researchers for assessing Canadian occupational exposure to AI. We include these new classes of

GPT technologies and the complementarity of AI—or the likelihood it will augment or automate tasks—for those occupations. We then introduce a new approach to the analysis, using a large sample of Canadian online job postings to understand skills that AI could enhance or replace and how employer demand is changing for occupations on different points of the exposure and complementarity spectrum. In particular, we look at:

1. The widespread effects of occupational exposure and skill complementarity with respect to AI adoption in the Canadian workforce.

2. A framework to measure the effects of AI impact on skills requirements and hiring needs of firms in Canada.

By addressing these questions, we provide a set of early signals and indicators to guide the prioritization of skills policy and government investments in upskilling workers in Canada. We also offer insights to guide private sector investment into employee training. We hope this analysis can inform the analytical toolkits necessary for other researchers and policymakers to understand real-time dynamics of the modern economy.

3

Research Context

This study is part of a long history of researchers endeavouring to understand how technologies may impact workers in the short term. The question “is this time different?” comes up with every new technological wave. Similar to periods of technology-driven automation in the past, one potential outcome of this generation of AI adoption is increased job polarization, with the erosion of middle-skill (often referred to as routine tasks typically performed by workers who possess a high school degree, but less than a four-year post-secondary degree) and middle-income jobs.[5] [6] Job polarization from automation tends to generate economic inequalities through job displacement and wage inequality. However, few studies have examined how AI can enhance skills and tasks in the workplace, potentially reducing time, errors, and skill gaps among the broader workforce.[7] In particular, four channels were identified where AI use could translate to gains in productivity: automation (taking over tasks and/or reducing costs), task complementarity (Increasing productivity in tasks that are not fully automatable), deepening automation (increasing productivity in tasks which are already automated), and creating new tasks.[8]

Similar to periods of technology-driven automation in the past, one potential outcome of this generation of AI adoption is increased job polarization, with the erosion of middle-skill (often referred to as routine tasks typically performed by workers who possess a high school degree, but less than a four-year post-secondary degree) and middle-income jobs.

Recently, the Bank of Canada noted that while the commercialization of AI has likely been a net job creator in Canada so far, there is also a potential to cause job displacement in the future.[9] We add the caveat that with every technology advancement, the creation of new occupations, skills, and products tend to generate net positive outcomes for society, albeit with temporary job displacement during this early period. Understanding the evolution of AI skills and labour demand, in consideration of its potential for task and job replacement, is essential to ensuring adequate preparation to mitigate the impacts to workers who may face AI-related displacement.

Analysis by the Organisation for Economic Co-operation and Development (OECD) that assessed the most in-demand skills for workers exposed to AI identified management, communication, and digital skills among the top skills.[10] This includes budgeting, accounting, written communication, word processing, and spreadsheet software. In addition, social and language skills were identified as increasingly important in the past decade for occupations most likely to use AI. A recent study about digital skills demand in Canada's labour market supports the idea that most AI workers would not need specialized AI skills, and increased digitization and digital skills demand does not replace the need for soft skills.[11]

The dominant understanding of how automation technology impacts workers applies to a class of "task-based" models. This approach breaks down work into a series of distinct tasks that, when combined, create a final output (such as a good or a service). For example, a car on a manufacturing line gets each component (task) added to it, culminating in a finished automobile. A job, therefore, is a collection of these discrete tasks, and a human or machine can reasonably complete each task. Technological progress through automation in this paradigm is measured by an expansion of the set of tasks that machines can reasonably perform.[12]

A second strand of research explores the type of tasks that machines can *more easily* perform by classifying tasks into belonging to a two-by-two matrix.[13] On one axis is "manual" or "cognitive" tasks, and on another is how "routine" a task is. Routine tasks are those in which one can write down a set of rules that once followed and performed correctly, any person can achieve the same result. On the other hand, non-routine tasks are complex to articulate, may change each time the task is performed, and slight deviations or changes can result in dramatically different results.

A third strand of research *combines* these conceptual frameworks to estimate the level of exposure to automation each occupation faces, and the extent to which tasks associated with an occupation can be performed by machines. Many of these models have also been updated to reflect the current frontier of knowledge through a variety of strategies. It's important to note that while the result for many of these models produces a probability output, the interpretation of the probability varies greatly depending on the model. Some models' probability is interpreted as the likelihood that the entire occupation can be performed by automated robots[14] (e.g. a truck driver has a 40 percent chance of wholly being automated in the next 10 years). Others are interpreted as the share of tasks in an occupation that can be performed by machines (e.g. 30 percent of an economist's tasks can be performed by AI).[15] Yet others generate estimates that are interpreted as the likelihood that an occupation will be changed, or, in our study, complemented by automation technologies.[16] This third interpretation is the one that we focus on for this research.

In Canada, the most recent study that generated such exposure-complementary scores (considering recent developments in language models) was from Statistics Canada, which found that 60 percent of Canadian workers could be highly exposed to AI.[17] This finding aligns with an earlier study by the International Monetary Fund (IMF) that first introduced the AI exposure-complementarity index and applied it to the workforce across six countries, including the United States. [18]

The complementarity-adjusted AI occupational exposure index is generated across occupations to assess the degree of AI's applicability to the workplace environment (exposure), and second, the extent to which AI can complement or automate a skill or task (complementarity). In particular, Statistics Canada, applying the exposure and complementarity indices to the 2021 Canadian Census, found that Canadian workers with higher educational attainment are expected to be more likely to be highly exposed to AI. They estimate that 46 percent of those with bachelor's degrees as their highest level of education and 58 percent with a graduate degree as their highest degree of education are expected to have high potential exposure and complementarity to AI. This is compared to 13 percent of those with high school as their highest educational attainment.

4 Methodology and Data

Our analysis relies on two main methodological frameworks: **AI exposure/complementarity scores and job posting trend analysis.** This section details our approach to both and how they will work together.

AI exposure-complementarity indices

The first studies that examined the risk that specific occupations face in being impacted by automation were published almost a decade ago,[19] in the context of a rapid rise in prominence of machine learning algorithms trained on massive amounts of data. They also built on the economic literature describing how automation technologies replace human labour, emphasizing "task-based" automation, where technologies replace specific tasks instead of entire occupations.[20]

The current generation of models builds upon this transition while taking into account developments in new technologies, particularly language models. In Felten, Raj, and Seamans (2021) for example,[21] a score is constructed measuring an occupation's potential to be exposed to AI technologies (referred to as "AI Occupational Exposure" or "AIOE"), based on development scores in ten separate automating technologies with specific weightings that allow future models to be adaptable to new technological frontiers. A list of the applications that were considered to construct the scores can be found in the online Appendix A.

Our exposure score leverages this same base, using a concordance table between US occupations (based on Standard Occupational Classification, or SOC, that the original model was used on) and Canadian occupations or National Occupation Classification (NOC).[22] The online appendix provides more information on how the exposure scores are constructed using the original methodology.

However, as discussed in the introduction, just taking into account the likelihood of how an occupation is exposed to AI is not sufficient. We must augment this measure with a second dimension, the possibility with which the presence of automation technologies will likely enhance an occupation. For this, we rely on an extension of AIOE, as created by researchers at the International Monetary Fund (IMF) in the context of the International Standard of Classification of Occupations (ISCO-08).[23] [24] Following the IMF methodology, a complementarity measure is constructed based on an occupation's work context (an occupational taxonomy in the US system). Work contexts capture the physical and social factors that influence work, ranging from the physical conditions under which a worker is conducting their job, whether a worker has a high degree of responsibility for the outcome of other people, and other conditions and environments in which a job could take place. A complete list of work contexts, as well as how the complementarity scores are constructed, can be found in the online Appendix A.

Job postings

Employers generate job postings when they publicly seek to hire new employees. The posting often lists the job title, a detailed job description, required skills, knowledge, credentials, wages offered, and other occupational attributes. Job postings should always be understood as strategic documents, where employers share information to attract applicants who have a high likelihood of fitting their ideal candidate profile. As a result, job postings should not be treated as an indication of how valuable a particular skill is, or a fully reliable signal for what skills or knowledge is currently needed in the economy. However, job postings do provide valuable signals for what employers conceive as desirable skills for their specific company. In the context of understanding the potential for AI to transform the composition of skills for workers, it is essential to pinpoint skills with a higher potential to complement and/or be augmented through AI technologies. Similarly, identifying skills with a lower potential to interact with AI could signal a higher potential to transition from task completion using human labour to more efficient AI technologies.

Specifically, we use job posting data from Vicinity Jobs (vicinityjobs.net), which covers the period from January 2018 to July 2024, capturing over 13 million online job postings. It's important to note that we make no seasonal adjustments to the data (i.e. we do not control for seasonal hiring trends that affect some occupations, such as those in the tourism industry that are often represented by the annual decline in hiring during December). We also include only data where job postings which have NOC codes assigned, which would be able to be crosswalked to American SOC occupations. We focus on two primary indicators:

1. Monthly job postings count and growth (since January 2018) for each of the exposure-complementary quadrants.

2. Monthly average hourly wages offered and growth in such wage offerings (since January 2018) of job postings for each exposure-complementarity quadrant.

We also disaggregate postings associated with occupations that require a post-secondary education[25] (information we obtain from the TEER class of occupation) and the full-time versus part-time nature of these postings. The following Tables 1 and 2 provide further information about the sampling of our data.

We further analyzed job postings data from January 2023 to July 2024 to highlight prevalent skills demanded for workers in each segment of the exposure-complementarity framework. An adjusted term frequency-inverse document frequency method (TF-IDF) combines how frequently a skill appears in job postings and occupations in a quadrant, and how rare the skills are within the labour market in general, is used to determine the uniqueness of a skill. Our analysis differs from the OECD analysis of skills demand for AI workers as we account for the work context of how a skill would be used among jobs across the AI exposure spectrum. In other words, we also assess how well AI would augment and work alongside certain skills, or if it has potential to replace human labour. More information on how this analysis was constructed can be found in the online Appendix A.

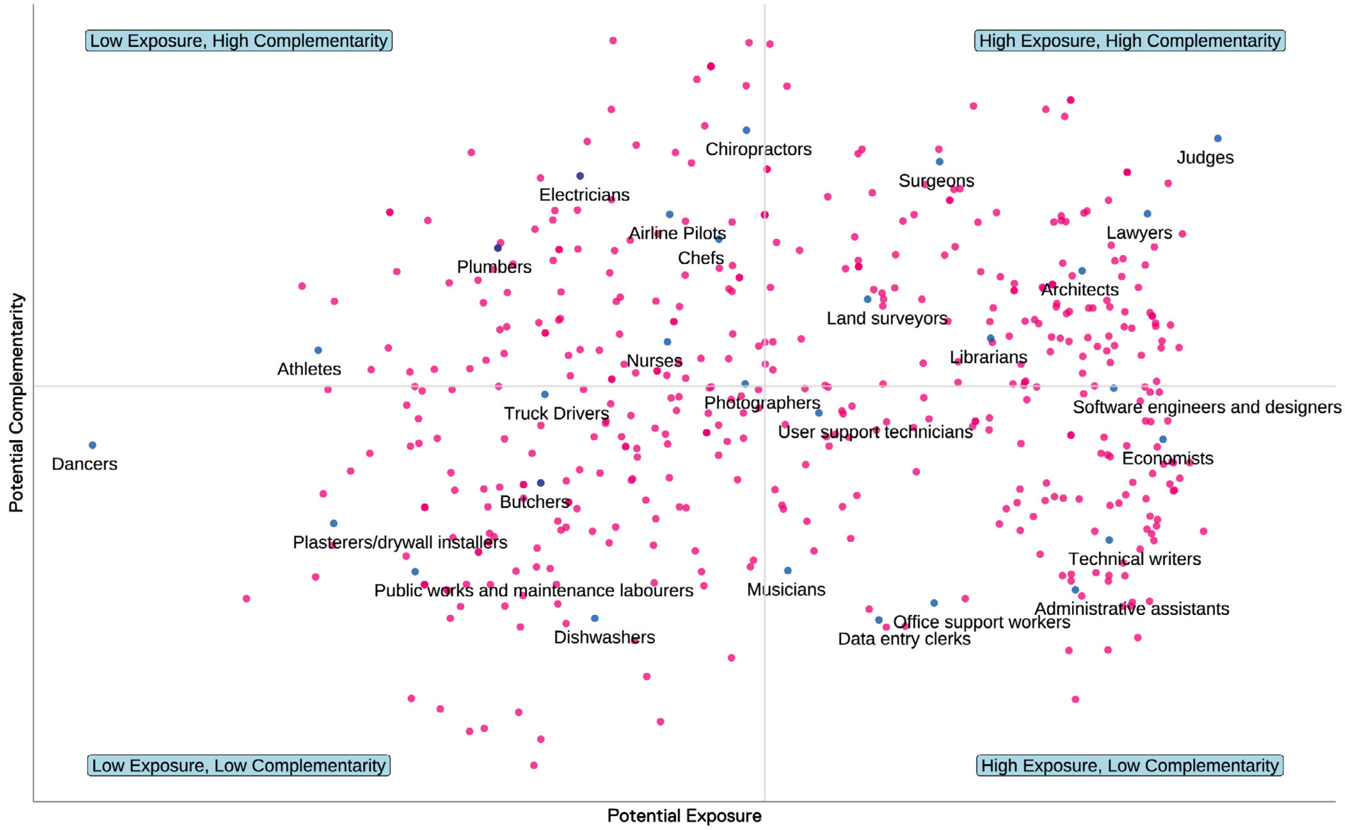
5 AI Exposure and Complementarity of Canadian Jobs

We start our analysis by examining broad occupational distribution across the exposure-complementarity axis. Figure 1 maps to occupations at the median scores of exposure and complementarity indexes, to illustrate the two-by-two matrix of AI's impact on the labour force, and identify the four main quadrants and groups of analysis. We focus primarily on the upper and bottom right portions of the matrix, identified as occupations highly exposed to AI in the workplace. The left portion of the index identifies occupations that are less likely to be impacted by AI in the workplace, which tend to be professions that require physical or manual tasks and skill sets.

The analysis and figures in this section refer to the groupings of occupations by exposure-complementarity index:

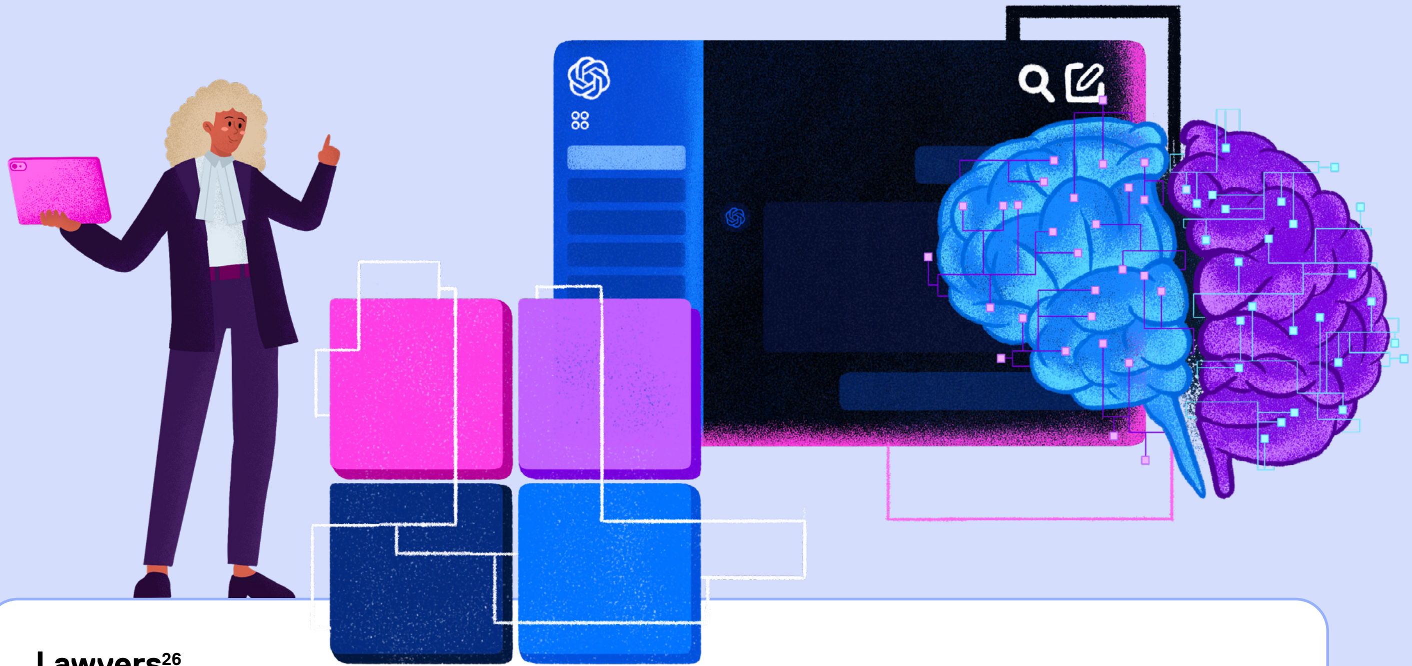
- High-Exposure, High-complementarity (HE-HC) occupations
- High-Exposure, Low-complementarity (HE-LC) occupations
- Low-Exposure, High-complementarity (LE-HC) occupations
- Low Exposure, Low-complementarity (LE-LC) occupations

Figure 1
Occupational exposure and complementarity to Artificial Intelligence technologies



What makes an occupation highly exposed/complementary to AI?

In interpreting Figure 1, it is important to focus on the broad clusters of occupations in relation to each other, rather than focusing on any specific occupations and where they are on the plane. However, we highlight two occupations here to provide an illustrative example of how our model situates occupations in the exposure-complementarity index. Note that a higher potential for AI to be resourceful in an occupational setting does not necessarily translate to the potential of adoption due to various factors (e.g. institutional or cost barriers).



Lawyers[26]

Lawyers and Quebec notaries advise clients on legal matters, represent clients before administration boards and draw up legal documents such as contracts and wills. Lawyers also plead cases, represent clients before tribunals and conduct prosecutions in courts of law. Lawyers are employed in law firms and prosecutor's offices. Quebec notaries are employed in notary offices. Both lawyers and Quebec notaries are employed by federal, provincial and municipal governments and various business establishments or they may be self-employed. Articling students are included in this unit group.

Main duties

This group performs some or all of the following duties:

- *Advise clients of their legal rights and all matters related to law*
- *Research legal precedents and gather evidence*
- *Plead clients' cases before courts of law, tribunals, and boards (lawyers only)*
- *Draw up legal documents such as real estate transactions, wills, divorces and contracts, and prepare statements of legal opinions*
- *Negotiate settlements of civil disputes (lawyers only)*
- *Perform administrative and management functions related to the practice of law*
- *May act as mediator, conciliator, or arbitrator*
- *May act as executor, trustee, or guardian in estate and family law matters*

Our model situates lawyers in the high-exposure and high-complementarity (HE-HC) quadrant. It is an occupation with high potential exposure to AI as a significant number of duties involve routine cognitive tasks (such as researching legal precedents and drawing up legal documents that are often standardized) that are particularly suited for large language models. However, as lawyers work in contexts that often involve direct responsibility for others (their clients), with significant unstructured work of a social nature (pleading clients' cases, negotiating settlements), it suggests AI could be used to assist (or complement) their work to a high degree rather than replacing (or augmenting) their tasks.

Data Entry Clerks[27]

Data entry clerks input coded, statistical, financial, and other information into computerized databases, spreadsheets, or other templates using a keyboard, mouse, or optical scanner, speech recognition software, or other data entry tools. They are employed in the private and public sectors.

Main duties

This group performs some or all of the following duties:

- *Receive and register invoices, forms, records, and other documents for data capture*
- *Input data into computerized databases, spreadsheets, or other templates using a keyboard, mouse, or optical scanner, speech recognition software or other data entry tools*
- *Import and/or export data between different kinds of software*
- *Verify accuracy and completeness of data*
- *Identify, label, and organize electronic storage media*
- *Maintain libraries of electronic storage media*

Our model situates data entry clerks in the high-exposure and low-complementarity (HE-LC) quadrant. Given the number of routine tasks (e.g. inputting data into databases and spreadsheets, importing and exporting data), AI is highly applicable through its use in image recognition to read text and perform calculations or functions. However, given that these tasks have a relatively low level of inherent risk (e.g. inputting, receiving and managing data does not have a relatively high direct impact on responsibility for the health and safety of others), and a high amount of structured work, which has a high degree of automation, it suggests that AI could be used to replace manual work in completing the tasks rather than to complement the workers in completing them.

We compared our findings with two previous studies to ensure that our analysis is consistent and captures similar dynamics. The first was the IMF study that introduced the exposure-complementarity index to analyze data from six countries using the International Standard Classification of Occupations 2008 (ISCO-08) from the International Labour Organization. Apart from a few deviations (resulting from the concordance process between the Canadian NOC with ISCO-08 and SOC), our occupational distribution in Figure 1 largely mirrors the IMF's work.[28] The second study was Statistics Canada's exposure-complementarity graph of Canadian occupations, with more information about the similarities and differences outlined in the online Appendix B.

Our analysis will proceed from this point by noting broad labour market trends we observe for each of these quadrants, before we focus on each of these quadrants and the unique skills associated with occupations in them.

Labour force distribution across AI index quadrants

We start by taking stock of the state of the labour force in the four exposure-complementarity quadrants using data from the 2021 Canadian long-form Census. That data shows that workers in Canada are roughly evenly distributed along the exposure-complementarity axis, where no single quadrant employs more than one third of the economy.

Education levels of workers across AI index quadrants

When we disaggregate workers in each of these quadrants, a clear difference by educational level emerges. The vast majority of those working in occupations with high exposure and highly complementary to AI require a post-secondary degree or diploma (over 98 percent). In comparison, two-thirds of workers in occupations highly exposed to AI with low levels of complementarity require a post-secondary degree or diploma. By contrast, the vast majority of workers working in occupations with low levels of exposure to AI do not require a post-secondary degree.[31] These trends are consistent with the idea of job polarization explored above, where lower-skilled workers face low levels of exposure to AI, while the most skilled workers are able to take advantage of new technologies, leaving the "middle skilled"[32] workers to both be highly exposed, with lower opportunity for technologies to enhance their work. While these trends are indicative of early signs of job polarization, whether these trends would continue to perpetuate or worsen depends on how complementary AI technologies will be and how they are applied.

Given these distributions, and the close relationship between credential requirements and skills trends, for simplicity of analysis, in examining broad labour market trends we combine the two low-exposure quadrants into a single "low exposure" section.

Table 1: Percentage of employment in each quadrant (2021 Canadian Census)

Quadrant	Number of workers included in quadrant[29]	Share of total labour force (2021)[30]
High Exposure-High Complementarity	4,958,770	27.0%
High Exposure-Low Complementarity	5,325,185	29.0%
Low Exposure - High Complementarity	2,580,340	14.1%
Low Exposure - Low Complementarity	5,222,830	28.5%

When we disaggregate workers in each of these quadrants, a clear difference by educational level emerges. The vast majority of those working in occupations with high exposure and highly complementary to AI require a post-secondary degree or diploma (over 98 percent).

Table 2: Percentage of employment by quadrant groups and education (2021 Canadian Census)

Exposure quadrant	Educational requirement	Share of the total labour force[33]	Share of the total labour force
High Exposure-High Complementarity (HE-HC)	Post-secondary credential	26.6%	98.4%
	No post-secondary credential	0.4%	1.6%
High Exposure-Low Complementarity (HE-LC)	Post-secondary credential	19.6%	67.4%
	No post-secondary credential	9.5%	32.6%
Low Exposure - High Complementarity (LE-HC)	Post-secondary credential	10.4%	73.9%
	No post-secondary credential	3.7%	26.1%
Low Exposure - Low Complementarity (LE-LC)	Post-secondary credential	11.6%	40.6%
	No post-secondary credential	16.9%	59.4%

Job postings analysis of workforce trends by AI index quadrant

Next, we use data from 13 million online job postings between 2018 and 2024 to assess employer demand and other characteristics of the jobs across the exposure-complementarity index we explored in Figure 1. Analyzing online job postings provides foresight into the future workforce as it reacts to the diffusion of AI technologies. It can indicate how firms are preparing for their current and future needs through the lens of the AI exposure-complementarity framework. Firms' hiring demands can also shape the future labour and income distribution.

In discussing these trends, we highlight three major dates that separate our data into four periods. The first date we selected is March 2020, or the beginning of the economic disruption brought about by the COVID-19 pandemic. The second date we note is April 2022, when every province in Canada exited the state of emergency associated with the COVID-19 pandemic. The third and final date we note is November 2023, or the public release date of ChatGPT-3, OpenAI's text-based generative AI model. We chose this particular release, as the most recent AI adoption data shows a rapid increase in AI adoption towards the end of 2023 and beginning of 2024 (where AI adoption almost doubled from four percent in 2021 to seven percent).[34] While the release of ChatGPT has not been shown directly to cause a decline in job postings, it can be argued that this technology (along with other generative AI tools) exacerbates declining trends found in HE-LC job postings.

As a result, there are four distinct periods we consider: pre-COVID-19 (that we mainly rely on as the baseline), the COVID-19 economy, post-COVID-19 emergency (but pre-generative AI), and finally post-launch of generative AI.

Firm hiring trends

Postings for HE-HC jobs have remained at similar levels since 2018, suggesting steady demand for workers in these professions, and lower turnover rates for both workers and firms. This fact is further shown by noting the lower variation job posting levels for this occupational quadrant compared to other quadrants.

Postings for HE-LC jobs (i.e. jobs with more tasks that can be *automated* by AI) had similar hiring demand as occupations less exposed to AI (LE). HE-LC job postings are also trending below their pre-COVID restriction levels, coinciding with the commercialization of large language models. The trend suggests a potential early signal indicating the impact on hiring decisions, particularly among larger firms with the highest share of HE-LC occupations, who may favour AI technologies in lieu of manual labour.

Job postings with low exposure to AI applications see the most significant seasonal demand changes, as they tend to reflect the prevalence of part-time and part-year work aligning with firms' seasonal skills demand. Interestingly, LE job postings are rising in 2024, contrary to the high-exposure group job postings.

Figure 2 shows the number of job postings in each quadrant grouping from 2018 to mid-2024. The continued decline in HE-LC postings into 2024 mirrors US job posting trends under the same exposure-complementarity framework.[35] This declining trend of job postings in 2024 for HE-LC occupations is slightly below 2018 levels. Also, note that trends in which all three quadrant groupings experience deeper troughs reflect seasonal declines in annual hiring during December.

Figure 2

Job postings for occupations by exposure-complementarity quadrant and month

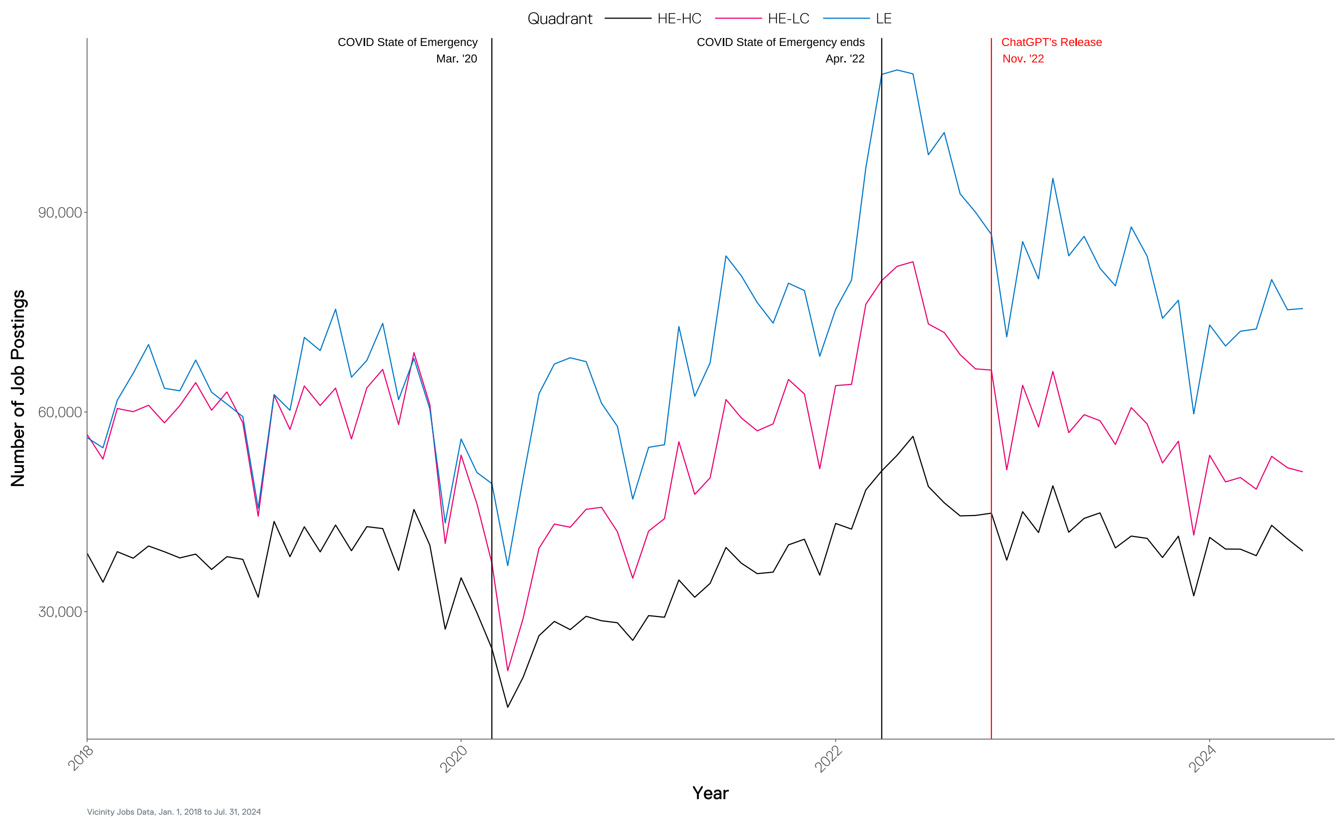
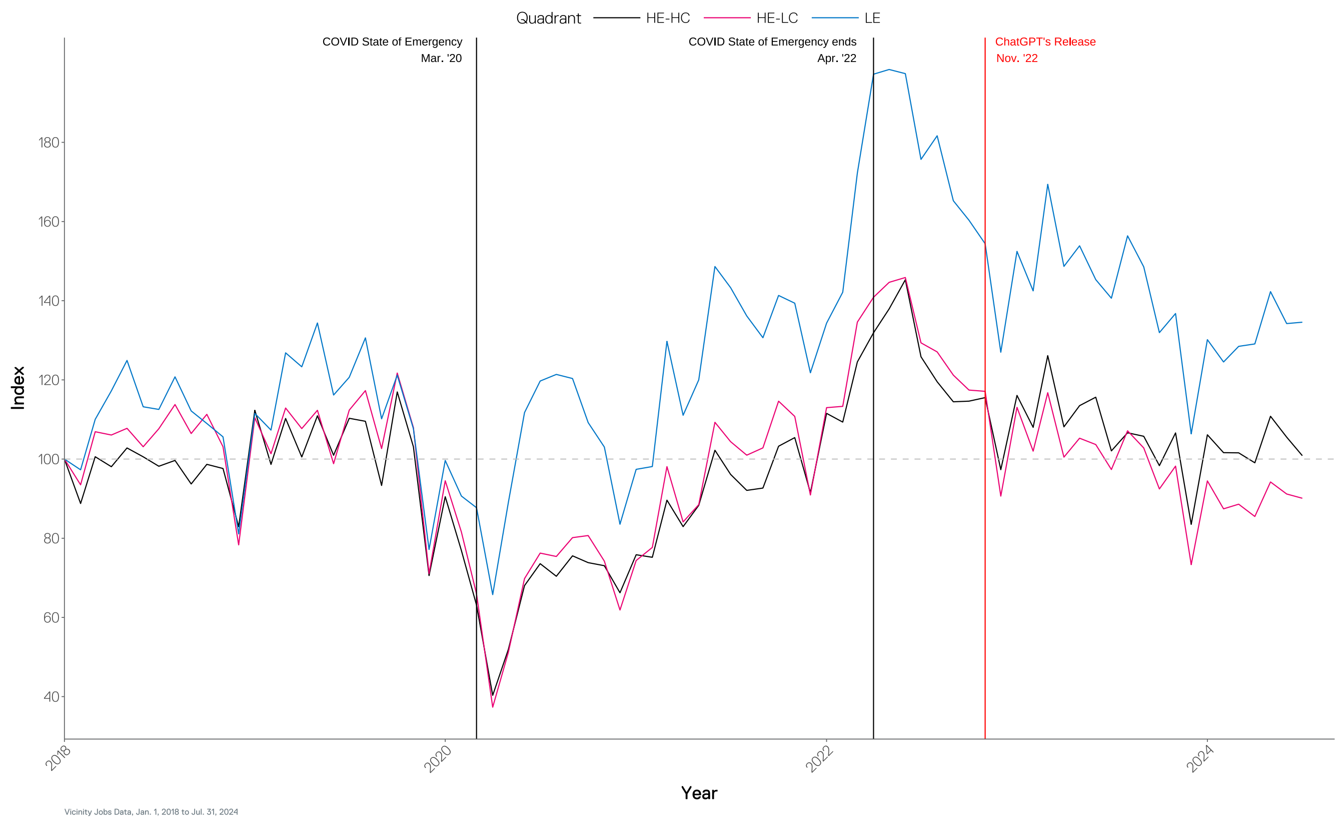


Figure 3 further looks at the differential trends exhibited by these occupational sections by indexing job postings numbers to January 2018 levels of job postings.[36] [37] Throughout the five-and-half-year period through to the end of 2022, HE-LC job postings consistently trend above HE-HC. Post-2022, HE-HC positions trend start above HE-LC relative to their January 2018 levels, with the exception of a few months. In the first half of 2024, HE-HC positions trend near their 2018 levels, while HE-LC opportunities remain consistently below their base levels. This is the first notable change in job posting trends among high-exposure groups over this time period.

Figure 3

Job postings for occupations by exposure-complementarity quadrant and month (indexed to January 2018)

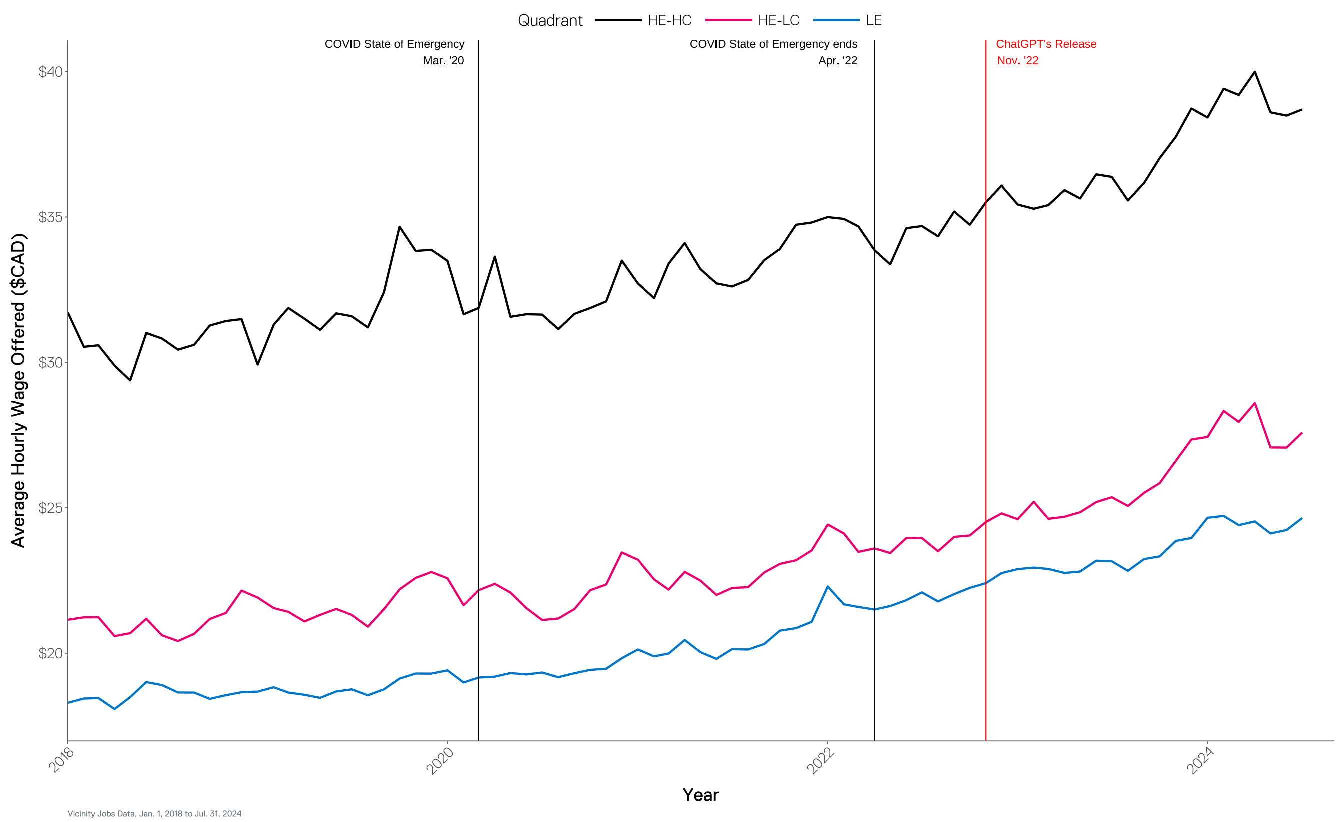


Hourly wage offering trends

Figure 4 illustrates the average wage offered among the exposure-complementarity quadrant groupings. All job postings show a relatively steady and consistent rise in hourly wage offerings over the study period. Notably, the HE-HC quadrant includes significantly higher-wage occupations, with HE-LC and LE job postings offering 60 to 70 percent of the hourly wage rate in 2024. As HE-HC workers are more likely to be assisted by AI technology, this suggests AI business adoption increases the demand for high-earning occupations.

Figure 4

Monthly average hourly wage offered in job postings for occupations by exposure-complementarity quadrant



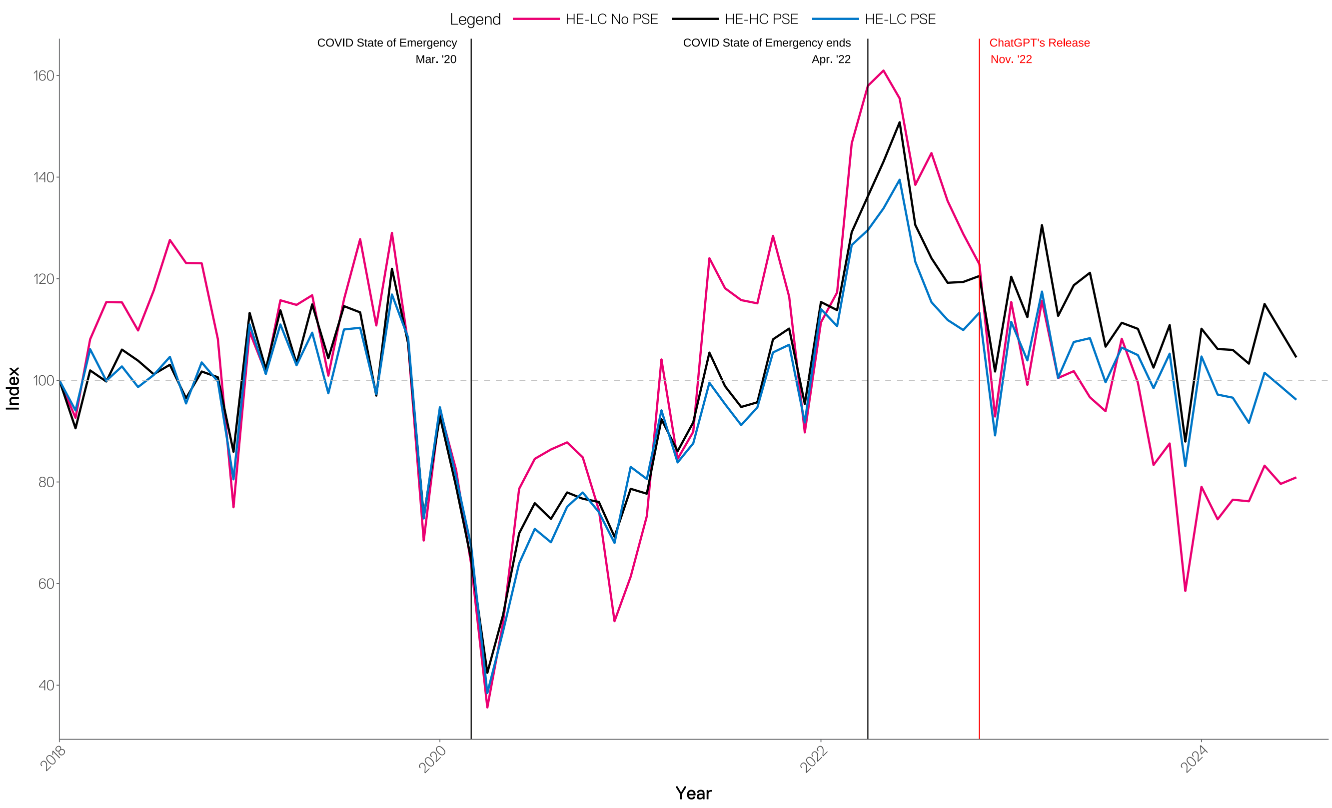
Firm hiring trends by education requirements

Figure 5 suggests the declining growth among high-exposure, low-complementarity job opportunities is driven by job postings requiring no post-secondary education, as these job postings are over 20 percent lower than their 2018 levels.

High-exposure job postings requiring post-secondary education remain steady throughout the analysis period. Since 2023, these postings have consistently grown at a higher rate than jobs with no post-secondary education (PSE) requirement. The post-2022 trends suggest that among low-complementarity jobs, those requiring PSE are more resilient to AI exposure than jobs with no PSE requirements.

Figure 5

Job postings for high-exposure occupations by complementarity, post-secondary requirement and month (indexed to January 2018)



Firm hiring trends by industry

Figure 6 examines job posting levels among service industries by exposure quadrant, which allows us to understand the concentration of AI-affected jobs by type of economic output.[38] Pre-2020, HE-LC positions were most abundant among the three groups. The beginning of 2022 shows a significant trend change for HE-LC, with more sharp declines in job postings relative to HE-LC and LE opportunities. From 2023, HE-LC hiring demand declines to levels of HE-HC, while LE job opportunities remain elevated.

Figure 6

Job postings for occupations in service industries by exposure, complementarity and month (indexed to January 2018)

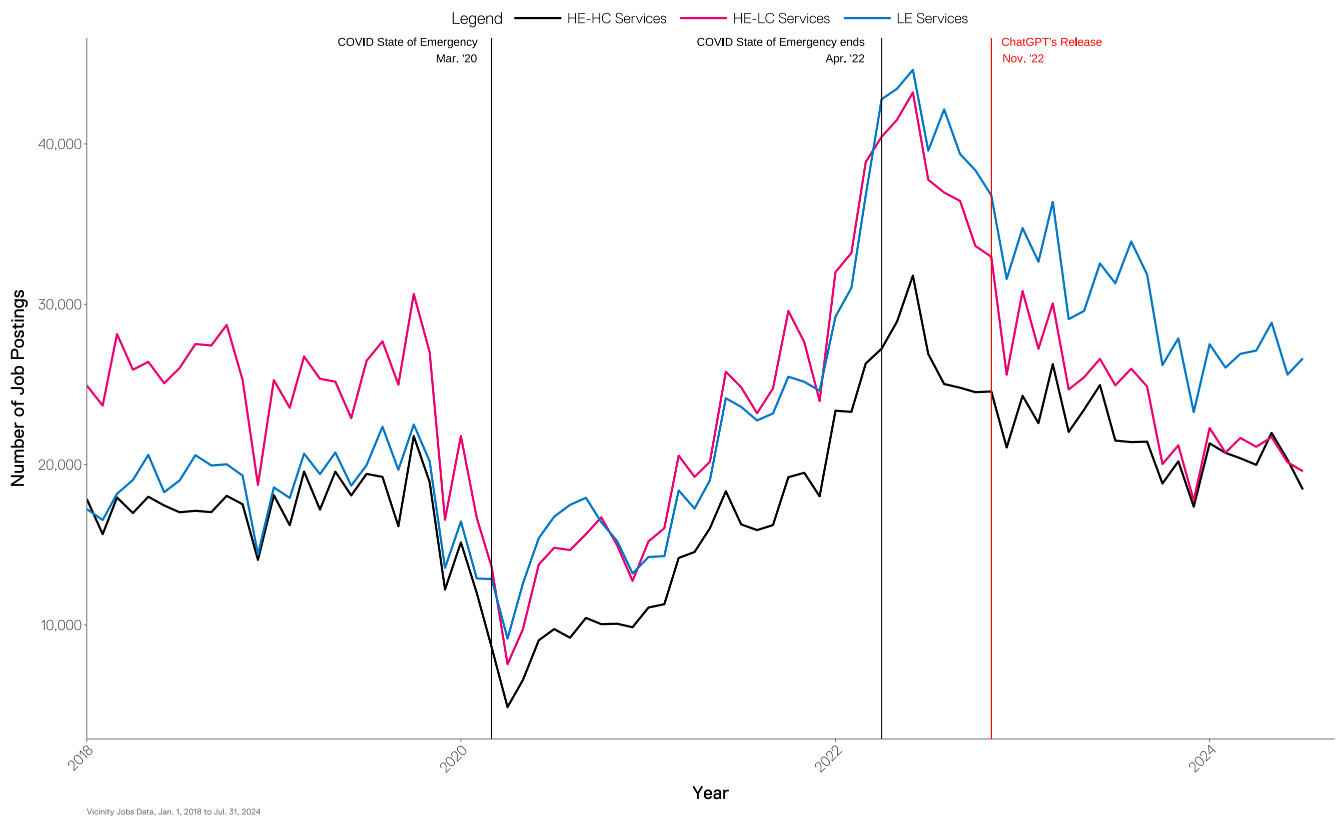
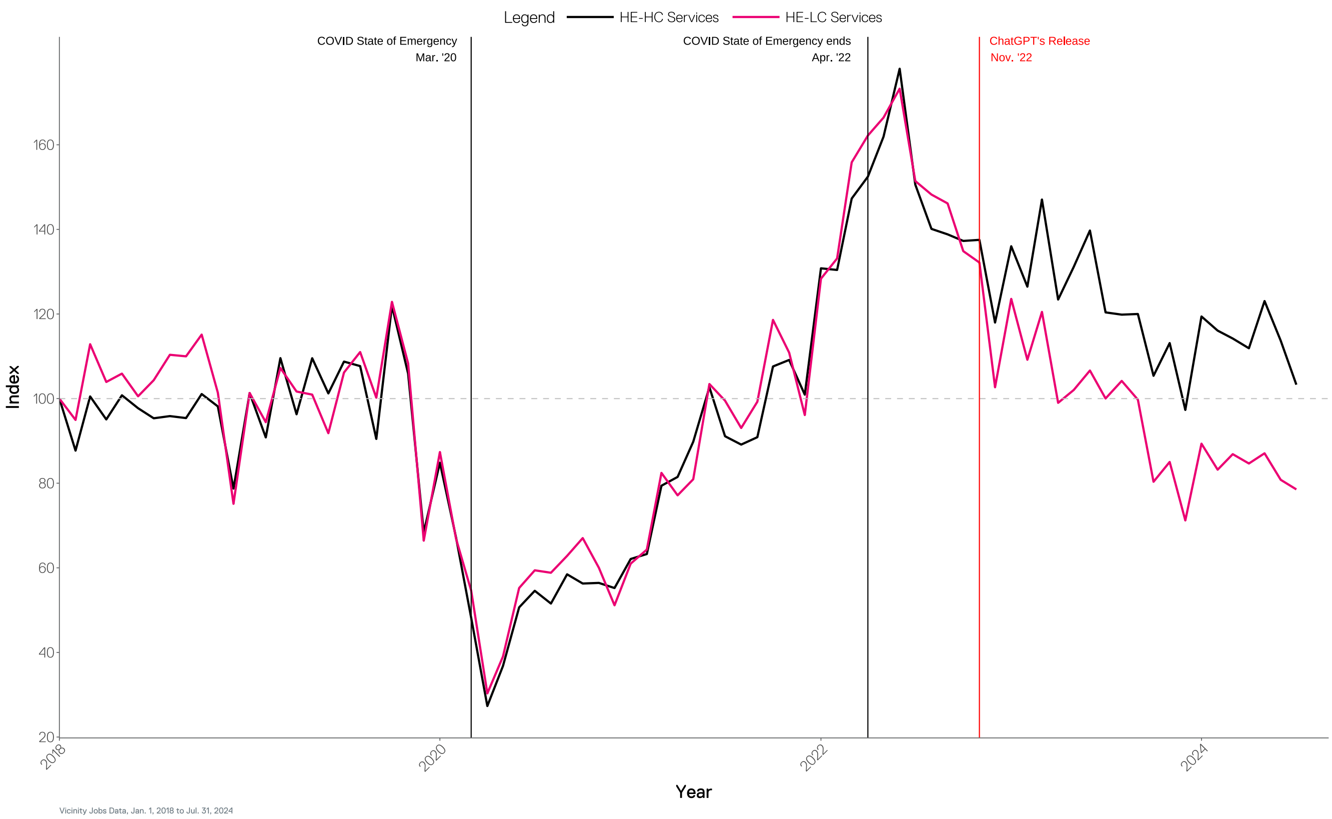


Figure 7 zooms into high-exposure job postings in the service industries, indexed to January 2018 levels. Similar to education-based hiring trends, HE-LC service industry job opportunities are over 20 percent lower than their 2018 levels, and consistently trending below HE-HC job postings since the end of 2022, relative to HE-HC hiring trends. This signifies routine and automatable work in service-sector jobs is trending downwards, with skills among jobs in these industries (e.g. retail trade, finance and insurance) having a high potential for AI replacement.

Figure 7

Job postings for high exposure occupations in service industries by complementarity level and month (indexed to January 2018)



6 The Skills Demand for Jobs Across the AI Index

The conversation around AI's impact on the labour market often concerns displacement of jobs—or, "automation." Examining AI's impact on skills offers a more nuanced way to assess the impacts of AI, as a job can be seen as a suite of tasks which respond to technological change. This allows us to analyze the context in which skills are performed, and whether those skills have the potential to be augmented or replaced by AI.

A significant body of skills literature often focuses on identifying core fundamental skills as a unit of analysis, to understand the frequency with which these fundamental skills (such as leadership and communication) show up in different occupational contexts. Such analysis then measures the different degrees to which they are exposed to automation, providing guidance to policymakers on where and how to prioritize investments in talent policies.

However, this approach misses two important facts. Firstly, the way in which these fundamental skills interact with context-specific skills means that how these fundamental skills interact with technologies are context- and occupation-specific (e.g. communication when it appears in the role of a customer service may have different technological exposure as communication when it appears in the role of a negotiator or lawyer). Secondly, focusing solely on fundamental skills means we lose the ability to identify context-specific skills that show up in areas of the labour market that may face higher levels of disruption due to exposure to AI.

Examining AI's impact on skills offers a more nuanced way to assess the impacts of AI, as a job can be seen as a suite of tasks which respond to technological change. This allows us to analyze the context in which skills are performed, and whether those skills have the potential to be augmented or replaced by AI.

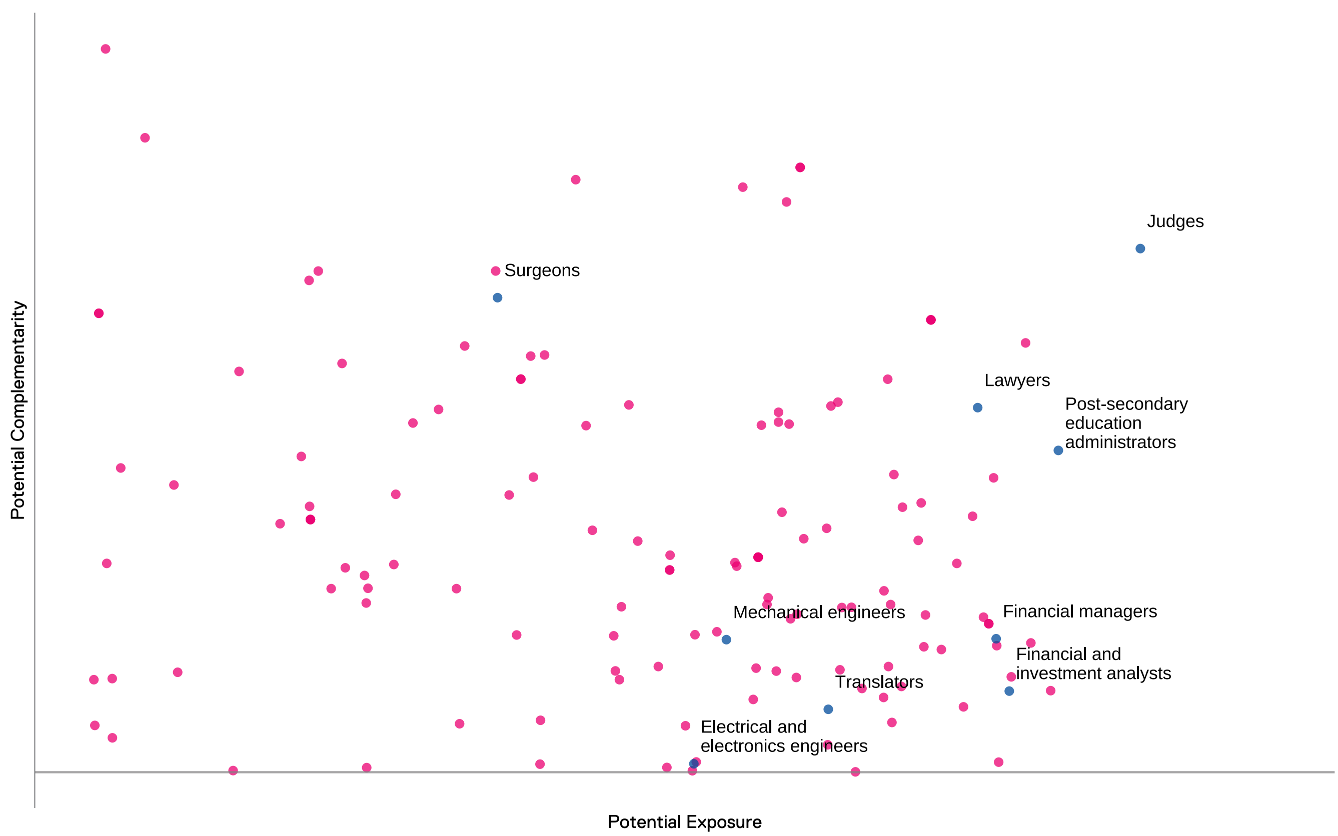
As a result, our work focuses on identifying these context-specific skills that uniquely show up in each of the four quadrants. Through this work, we allow the identification of skills that are correlated with a specific combination of exposure and complementarity with AI. Leveraging an adjusted term frequency-inverse document frequency (TF-IDF) methodology often used in text analysis, we define, for each of the four quadrants, the unique skills that are more likely to appear there (compared to other quadrants). This takes into account not only the frequency of skills appearing in a quadrant, but also how distinct a skill is throughout the labour market. More detail on how this calculation is constructed can be found in the online Appendix C.

Quadrant 1: High exposure-high complementarity occupations

Figure 8 displays a sample of occupations highly exposed to AI, with AI being highly complementary to existing work.

Figure 8

Occupations with high exposure and high complementarity to Artificial Intelligence technologies



Among these occupations are post-secondary education administrators, financial and legal occupations, surgeons, and engineers who could potentially use AI applications to help interpret, summarize, and prepare text and materials and perform calculations to support decision making. This includes the use of generative AI tools such as large language models (LLMs) and reading comprehension tools to parse through documents. For example, LLMs can be used to extract key information from financial documents, or to forecast market trends using financial data,[39] which could support firm decision making and strategy. Another example includes translators, who could interface with AI applications such as language modelling and translation to a high degree. AI has also been shown to be used by physicians to reduce administrative work and paperwork through transcription of patient interactions into notes for electronic medical records.[40] The top occupations by likelihood of exposure to AI in this quadrant are shown in Table 3.

Table 3: Top 10 occupations by potential level of AI exposure in High Exposure-High Complementarity (HE-HC) occupations

Occupation	Employment (2021 Canadian Census)	Median annual income (2021 $)[41]
Judges	3,240	$278,000
Administrators - post-secondary education and vocational training	17,785	$88,000
Purchasing managers	26,670	$93,000
Banking, credit and other investment managers	74,105	$94,000
Religious leaders	27,810	$48,800
Psychologists	18,900	$77,000
Financial and investment analysts	57,330	$79,000
Human resources professionals	94,885	$71,500
Human resources and recruitment officers	39,830	$55,200
Financial managers	74,540	$93,000

Thematically, the types of skills that are uniquely found in these occupations align with critical non-digital skills associated with higher-earning professional occupations requiring more advanced education credentials. As a key input in AI complementarity for occupations includes the gravity of decisions, it can be recognized that AI would be useful as a tool to augment decision making, but highly unlikely to replace the task of decision making itself. Other complementarity inputs such as “communication”, “responsibility for outcomes” and “responsibility for the health and safety of others”, and “consequence of error” in AI models translates to AI having a greater potential to work alongside these occupations, rather than replace their tasks with little human intervention.

Thematically, the types of skills that are uniquely found in these occupations align with critical non-digital skills associated with higher-earning professional occupations requiring more advanced education credentials. As a key input in AI complementarity for occupations includes the gravity of decisions, it can be recognized that AI would be useful as a tool to augment decision making, but highly unlikely to replace the task of decision making itself.

As seen with Table 4, skills such as leadership, planning, and coaching often align with higher-risk decisions, which ultimately cannot default to AI in order to execute decisions. As a result, senior managers, government officials, and executive decision makers would be included in this quadrant.

Similarly, medical professionals such as nurses and physicians have the capability to use machine learning-based AI tools to aid detection of patient deterioration,[42] but would ultimately still be tasked to make decisions on how to respond to and administer preventative care to patients.

Table 4: Unique skills associated with High Exposure-High Complementarity (HE-HC) occupations

Skill	Share of job postings in quadrant with this skill	Share of job postings across all quadrants with this skill
Planning	24.6%	11.6%
Coaching	6.0%	1.9%
Patient care	13.3%	6.5%
Leadership	32.4%	17.3%
Critical thinking	6.4%	2.8%
Sales	9.4%	4.9%
Problem solving	19.7%	12.3%
Budgeting	9.8%	5.6%
Advanced Cardiac Life Support (ACLS)	2.2%	0.6%
Operations management	6.1%	3.3%

Quadrant 2: High exposure-low complementarity occupations

Figure 9 presents a sample of occupations which are likely to be highly exposed to AI, but where AI tools have less potential to complement existing work. Among this group, business, finance, and administration occupations such as administrative assistants, auditors, and accountants, are likely to be using AI to a large extent, but less in contexts that would augment work tasks. The top 10 occupations by potential exposure are presented in Table 5.

Figure 9

Occupations with high exposure and low complementarity to Artificial Intelligence technologies

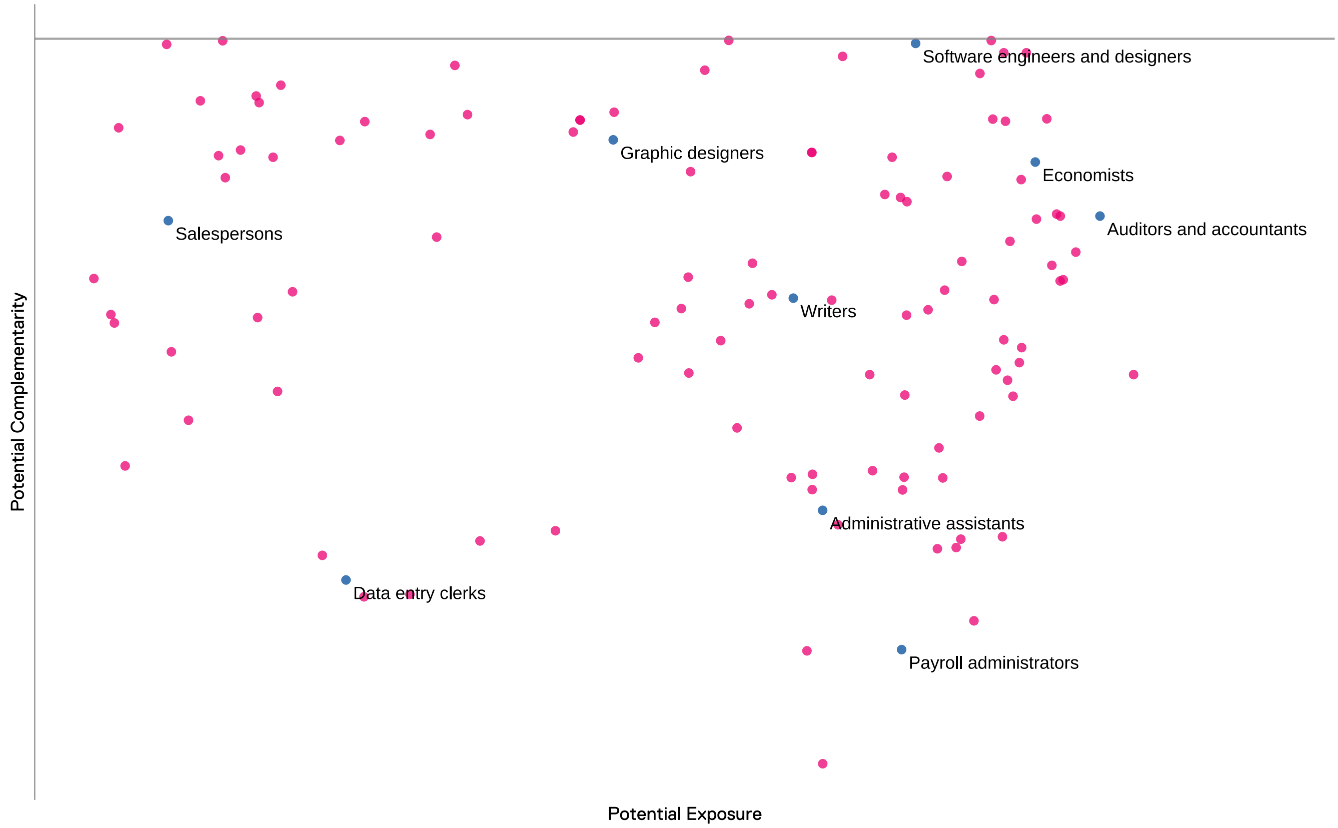


Table 5: Top 10 occupations by potential level of AI exposure in High Exposure-Low Complementarity (HE-LC) occupations

Occupation	Employment (2021 Canadian Census)	Median annual income (2021 $)[43]
Customs, ship and other brokers	4,850	$48,000
Financial auditors and accountants	197,825	$69,000
Mathematicians, statisticians and actuaries	13,205	$89,000
Financial advisors	94,315	$66,500
Production and transportation logistics coordinators	48,835	$51,600
Business development officers and market researchers and analysts	41,410	$68,000
Financial sales representatives	58,590	$53,600
Construction estimators	26,260	$65,500
Securities agents, investment dealers and brokers	12,620	$63,200
Managers in health care	37,340	$95,000

Skills associated with occupations in this quadrant tend to be digital skills with a high degree of automatability and relatively more routine than unique skills with high complementarity. These digital skills tend to be less digitally intense, require less of a technical background to use, and can be used more generally across the workforce.[44] As Table 6 shows, this includes many Microsoft Office tools such as Excel and Word. In addition to the ability to be automated, these skills tend to correlate with a relatively lower degree of risk through its responsibility for health and safety outcomes, another input in the complementarity measure. Furthermore, low complementarity is correlated with a lower degree of communication required in these tasks, which is highlighted as an area which AI could enhance in the complementarity index. As a result, AI technologies have greater potential to replace routine labour in performing these skills and tasks compared to high-complementarity skills.

AI technologies have greater potential to replace routine labour in performing these skills and tasks compared to high-complementarity skills.

Table 6: Unique skills associated with High Exposure-Low Complementarity (HE-LC) occupations

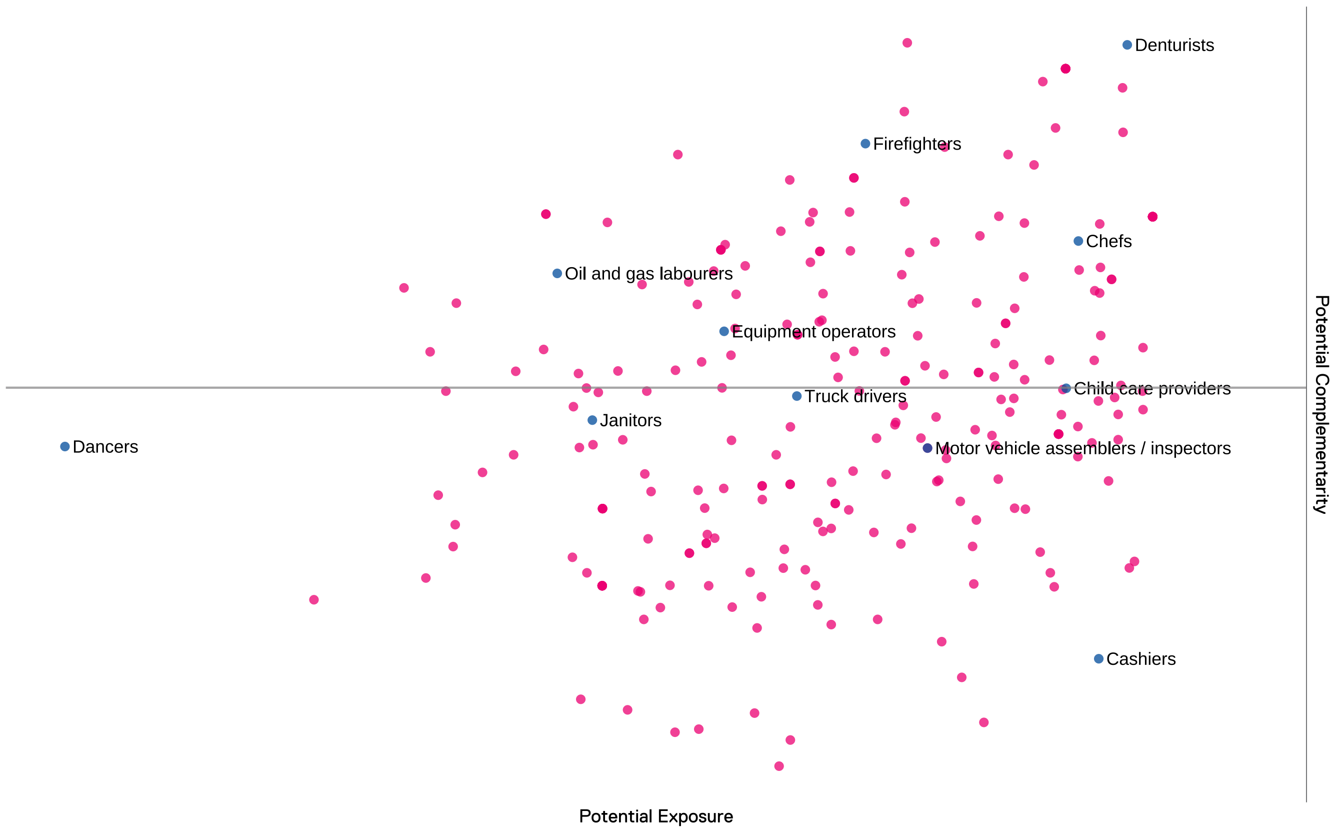
Skill	Share of job postings in quadrant with this skill	Share of job postings across all quadrants with this skill
Accounting	12.5%	5.0%
Microsoft Excel	18.6%	9.3%
Data analysis	8.2%	3.3%
Microsoft Word	15.9%	8.0%
Microsoft Office	18.5%	9.7%
Office administration	7.4%	2.9%
Information filing	5.1%	1.7%
Reports preparation	12.4%	6.5%
Filing systems	4.7%	1.6%
Proofreading	4.1%	1.4%

Quadrants 3 and 4: Low-exposure occupations

Figure 10 shows the distribution of occupations that are expected to have low exposure to AI technologies. Among those that could have low complementarity include sales and service occupations such as cashiers, cooks, food and beverage servers, and cleaners, as well as occupations in manufacturing such as labourers in food and materials processing and motor vehicle assemblers. For high-complementarity occupations, workers in the trades, transport, and equipment operation occupations such as electricians, mechanics, and telecommunications installers and repairers are prevalent, as well as health occupations such as chiropractors and physiotherapists. Supervisors in manufacturing, including those in food and beverage and materials processing, are frequently found in this quadrant.

Figure 10

Occupations with low exposure to Artificial Intelligence technologies



The top 10 occupations which are expected to have the least exposure to AI, by low- and high-complementarity quadrants, are shown in Tables 7 and 8. Given the physical and non-routine nature of the work of these occupations, there has yet to be as many AI applications that are able to sufficiently perform their tasks, as AI currently has relatively more applications among routine tasks.

Low-exposure occupations also tend to have lower education credential requirements, with almost half of workers in these occupations requiring a post-secondary education credential. Low-exposure occupations also have a higher tendency for part-year work, and low-complementarity occupations having a greater prevalence for part-time work (for full-year workers) compared to the other three quadrants.[45]

Table 7: Top 10 occupations with lowest potential level of AI exposure in Low Exposure-Low Complementarity (LE-LC) occupations

Occupation	Employment (2021 Canadian Census)	Median annual employment income (2021 $)[46]
Dancers	8,535	$7,450
Nursery and greenhouse labourers	16,345	$16,800
Landscape and horticulture technicians and specialists	23,925	$31,800
Chain saw and skidder operators	6,885	$31,400
Concrete finishers	8,785	$48,400
Harvesting labourers	12,450	$12,500
Plasterers, drywall installers and finishers and lathers	26,455	$35,200
Specialized cleaners	40,005	$21,000
Insulators	8,825	$48,400
Foundry workers	2,420	$52,000

Table 8: Top 10 occupations with lowest potential level of AI exposure in High Exposure-Low Complementarity (LE-LC) occupations

Occupation	Employment (2021 Canadian Census)	Median annual employment income (2021 $)[47]
Ironworkers	12,925	$61,200
Athletes	2,800	$17,200
Roofers and shinglers	21,680	$33,200
Bricklayers	16,300	$41,200
Longshore workers	5,710	$87,000
Underground mine service and support workers	4,195	$80,000
Mine labourers	2,765	$47,600
Oil and gas drilling, servicing and related labourers	6,830	$45,200
Other trades helpers and labourers	12,185	$28,000
Railway yard and track maintenance workers	5,665	$77,500

Among low-exposure quadrants, the top unique skills are shown in Tables 9 and 10. While occupations in both quadrants have elements of hands-on application, which AI has less ability to perform (and therefore have less exposure to the technology), AI applications that could support decision making such as image recognition and large language models could have higher applicability (and thus complementarity) for skills such as quality control, scheduling, and estimation for high-complementarity occupations. Furthermore, the presence of skills from occupations in supervisory roles in the high-complementarity quadrant reflect roles that involve judgment, decision making and responsibility for others' outcomes, which are key inputs to complementarity.

Table 9: Unique skills associated with Low Exposure-Low Complementarity (LE-LC) occupations

Skill	Share of job postings in quadrant with this skill	Share of job postings across all quadrants with this skill
Kitchen cleaning	10.6%	3.6%
Cleaning	16.4%	6.2%
Cooking / meal preparation	14.1%	5.7%
Truck driving	7.1%	2.6%
Handling heavy loads	18.2%	9.6%
Kitchen inspection	4.0%	1.3%
Kitchen management	4.6%	1.7%
Loading and unloading	6.6%	3.2%
Inspection of vehicles	3.7%	1.4%
Forklift operation	4.8%	2.1%

Table 10: Unique skills associated with Low Exposure-High Complementarity (LE-HC) occupations

Skill	Share of job postings in quadrant with this skill	Share of job postings across all quadrants with this skill
Food quality control	12.9%	1.7%
Estimating	11.3%	1.6%
Repairs / Corrective maintenance	19.9%	5.4%
Mechanical skills	9.3%	1.8%
Work scheduling	15.9%	4.1%
Machinery/equipment repair	7.9%	2.1%
Scaffolding	4.0%	0.8%
Mechanical repairs	3.1%	0.5%
Electrical repairs	3.0%	0.5%
Preventive maintenance	6.5%	2.0%

7

Summary of Findings and Policy Implications

This is the first study of its kind in Canada to apply the AI exposure-complementarity index and link it to corresponding skills demand in the economy. Given factors like the relatively recent mainstream arrival of generative AI technologies and the significant labour market volatility over the past five years through the COVID-19 pandemic, the analysis in this study should be treated with reasonable caution. With that caveat, the research and analysis in the previous sections lead us to some key findings.

- **Across the Canadian labour force of over 18 million,[48] there is significant variation in AI's impact on tasks and skills.** Twenty-seven percent of workers are in occupations that are in the high exposure-high complementarity (HE-HC) quadrant (i.e. more tasks that can be assisted by AI), 29 percent are in the high exposure-low complementarity (HE-LC) quadrant (more tasks that can be automated) and 43 percent of workers are in low-exposure occupations.

- **The high-exposure high-complementarity (HE-HC quadrant) occupations possess tasks that are more likely to be assisted by AI.** Occupations in this category tend to be higher-paid and are more likely to require a post-secondary education. This includes occupations such as post-secondary education administrators, financial and legal occupations, surgeons, and engineers. Skills that are more uniquely featured in these occupations are cognitive and non-routine and require a higher degree of decision making and greater responsibility for safety and health outcomes. Examples of these skills include planning, leadership, coaching, and critical thinking.

- **The high-exposure low-complementarity (HE-LC quadrant) occupations possess tasks that are more likely to be automated by AI.** Occupations in this category have more routine tasks, are less likely to require post-secondary education, and have lower wages compared to those more likely to be assisted by AI. These occupations include business, finance, and administration roles such as administrative assistants, auditors, and accountants. The unique skills associated with these occupations tend to be digital skills with a higher degree of automatability, and less critical decision making.

- **Job postings trends offer an up-to-date, longitudinal data source for tracking employer demand for jobs and skills over time** and, in particular, for assessing the changing demand for high- versus low-complementarity occupations. The data since 2018 is "noisy" due to the economic and labour market volatility caused by the COVID-19 pandemic, but will offer a valuable baseline over time from the public release of OpenAI's ChatGPT-3 and other LLM-based technologies in late 2022.

Taken together, these findings suggest that generative AI could assist many different types of workers across the labour force as it is more widely adopted. Yet, AI also poses a risk of increasing job polarization if it most benefits the highly educated, best-compensated workers in occupations that engage in cognitive and non-routine tasks, while increasing the potential automation of tasks for workers in occupations with less education, lower wages, and more routine work. This has significant potential implications for the future of work in Canada. While the job postings analysis in the report do not present clear evidence of AI-driven job polarization to date, employment and wage trends for highly AI-exposed occupations should be monitored.

Policy implications

The analysis in this report should be treated as *directional* rather than *predictive*, providing a framework for assessing how AI could impact jobs and skills demand across Canada's labour market. Job posting skills and trends are leading indicators of the labour market, and are subject to the adoption capacity of the Canadian workforce and market dynamics. The practical application of this analysis should help government policymakers, education, and workforce development organizations, industry leaders, and employers to understand how to think about, and plan for, the labour market transition that AI adoption will spur in the years ahead. This includes the ability to "hotspot" the types of occupations where tasks are most likely to be assisted by AI versus those most likely to be disrupted or automated, and the in-demand skills that workers will need to adapt or transition in their jobs as AI adoption progresses. Along these lines, we identify some preliminary policy implications:

- The findings broadly reinforce the **importance of post-secondary access and attainment**, for Canadian workers to develop AI-resilient skills as the technology further diffuses across the labour force. Employer demand for workers with post-secondary credentials has remained strong through the study period, and occupations requiring post-secondary education are more likely to undertake tasks that can be assisted by AI.

- **Post-secondary institutions should factor AI resilience into program and curriculum planning** for undergraduate, graduate and professional upskilling offerings. In particular, they should consider where programs and learning pathways are guiding graduates to highly AI-exposed occupations and whether the task mix is more likely to be assisted. For instance, in adapting programs for human resource management (with more *assisted* tasks) and for accounting (with more *automatable* tasks), it should also consider what AI-resilient soft skills (e.g. planning, leadership, problem solving, critical thinking) should be developed by learners, regardless of field of study and education level.

- AI exposure and skills demand trends **information should inform workforce development planning and employment service programming**. For example, AI exposure should be a consideration in regional and local employment forecasting, for industry sectors and employers seeking to prepare for tasks-based changes, and in serving employment services clients with job search services and training to ensure they reflect changing job opportunities and skills demand.

- **Workers will require support to be AI-resilient**, through awareness-building on how jobs and employer skills demands are changing, and incentives to pursue education and upskilling that is complementary to AI adoption. This could include additional government financial support for working-age Canadians to pursue post-secondary programs, continuing education and part-time training opportunities, with a focus on service industries and workers in highly AI-exposed, low-complementarity occupations that are more likely to be disrupted. It could also include incentives for employers to upskill and retrain existing staff for roles that are evolving with AI adoption, reducing their likelihood of displacing or replacing workers. Furthermore, with ongoing tracking of AI diffusion, workers can be informed about impacts of AI on jobs and tasks, complementary workforce skills, and upskilling opportunities.

- If further analysis of labour market trends indicates a structural realignment of the labour market due to AI, federal and provincial governments should **consider the impacts of AI-related job displacement and transition on income support policies and programs**. As the study finds that labour market changes will not just impact occupations and tasks, but factors like full- and part-time mix, jobs in goods or service industries, and wage- and education-related job polarization. There could be implications for personal income tax rates and targeted low-income tax credits, as well as programs such as Employment Insurance and social assistance.

- This type of **AI exposure-complementarity and skills demand analysis would be valuable on an ongoing basis**, for continued tracking and intelligence gathering about how AI adoption is impacting workers, jobs, and the labour market. A supplement to core labour market information (LMI), this analysis can provide a longitudinal resource for proactively understanding how advances in AI, and new business use cases and applications, are translating to work impacts and informing labour force preparedness.

Opportunities for further applied research

To further our understanding of the potential impacts of AI on the labour market, we also identify a few areas for further research.

1. **Mapping educational pathways to the AI exposure-complementarity index**
   A subsequent study that links the AI index analysis to the distribution of fields of study for occupations can provide insight into post-secondary education and skills development pathways for learners and workers. This analysis may provide specific recommendations as to which education programs complement AI in the workplace and a set of unique skills and abilities in high demand among these fields of study.

2. **Estimating skills needs for worker transitions from low- to high-complementarity occupations**
   Our analysis highlighted the differing sets of unique skills demand across the four-quadrant index of AI exposure-complementarity. An extension of this analysis would "pair" similar occupations to identify job transition potential from low- to high-complementary occupations. The analysis can provide actionable career transition insights for education institutions, career services, workforce development, and upskilling programs.

3. **Assessing how Generative AI adoption impacts firm hiring and skill demand**
   Our analysis found that the majority of AI exposure and complementary hiring trends began after the public release of OpenAI's ChatGPT-3 in November 2022. If generative AI has the potential for a broader range of enterprise adoption, a targeted analysis could identify more pronounced implications for Canada's workforce. A number of recent theoretical frameworks specific to generative AI are available for this exercise.

8

Conclusion

The diffusion of AI throughout the economy will likely transform how workers perform many of the *tasks* that are central to their jobs - as well as the *jobs* themselves. While previous waves of automation replaced mostly routine and non-cognitive tasks, AI has the potential to also perform cognitive and non-routine tasks with a high degree of accuracy and efficiency, leading to cost and time reductions for employers. On a macro scale, the response from employers to this transformation may lead to friction through shifting demand for workers. While there has been much excitement and hope about the potential of AI to boost workplace productivity and create efficiencies, concerns surrounding the risks of worker disruption, automation, or replacement cannot be ignored.

Ensuring that workers, employers, education and training providers, economic policymakers, and other actors are prepared for such changes, and harnessing the benefits of AI while mitigating risks, requires a deeper understanding of how adoption of this technology is influencing the labour market. In addition to identifying which occupations and segments of the workforce are most likely to be affected by AI through the lens of exposure and complementarity, using job postings data to monitor and track job and skills demand in a timely, ongoing manner informs effective planning and policy. Specifically, this can include aligning post-secondary programs and training to AI-resilient jobs and skills demand for equipping Canadians to work alongside AI; creating incentives for businesses to invest in preparing and upskilling their workers rather than replacing them; and building awareness and programming for workers to support them as part of a deliberate strategy to create AI labour force readiness and facilitate transition planning. Given the rapid development of AI applications, monitoring who will be expected to use AI and in what ways is instrumental to being proactive with regards to this new technology.

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[29] This calculation is based on a total of 18,339,455 employment income recipients in Statistics Canada's 2021 Census aged 15 and above, compared to a base of 13,589,900 employed individuals aged 18 to 64 in May 2021 presented in Statistics Canada's report.

[30] As some occupations were not mapped to an exposure score, 1.4 percent of the labour force was not captured in the quadrant analysis.

[31] We proxy for an occupation's educational requirement by looking at an occupation's training, education, or experience requirement (TEER). Specifically, any occupation that has 0, 1, 2 or 3 as the second digit in its occupational code are those that require a post-secondary education (university, college or apprenticeship program), and considered to be ones that require a post-secondary credential. For further information, see Employment and Social Development Canada, TEER category, https://noc.esdc.gc.ca/Training/TeerCategory.

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