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Harnessing Generative AI: Navigating the Transformative Impact on Canada's Labour Market

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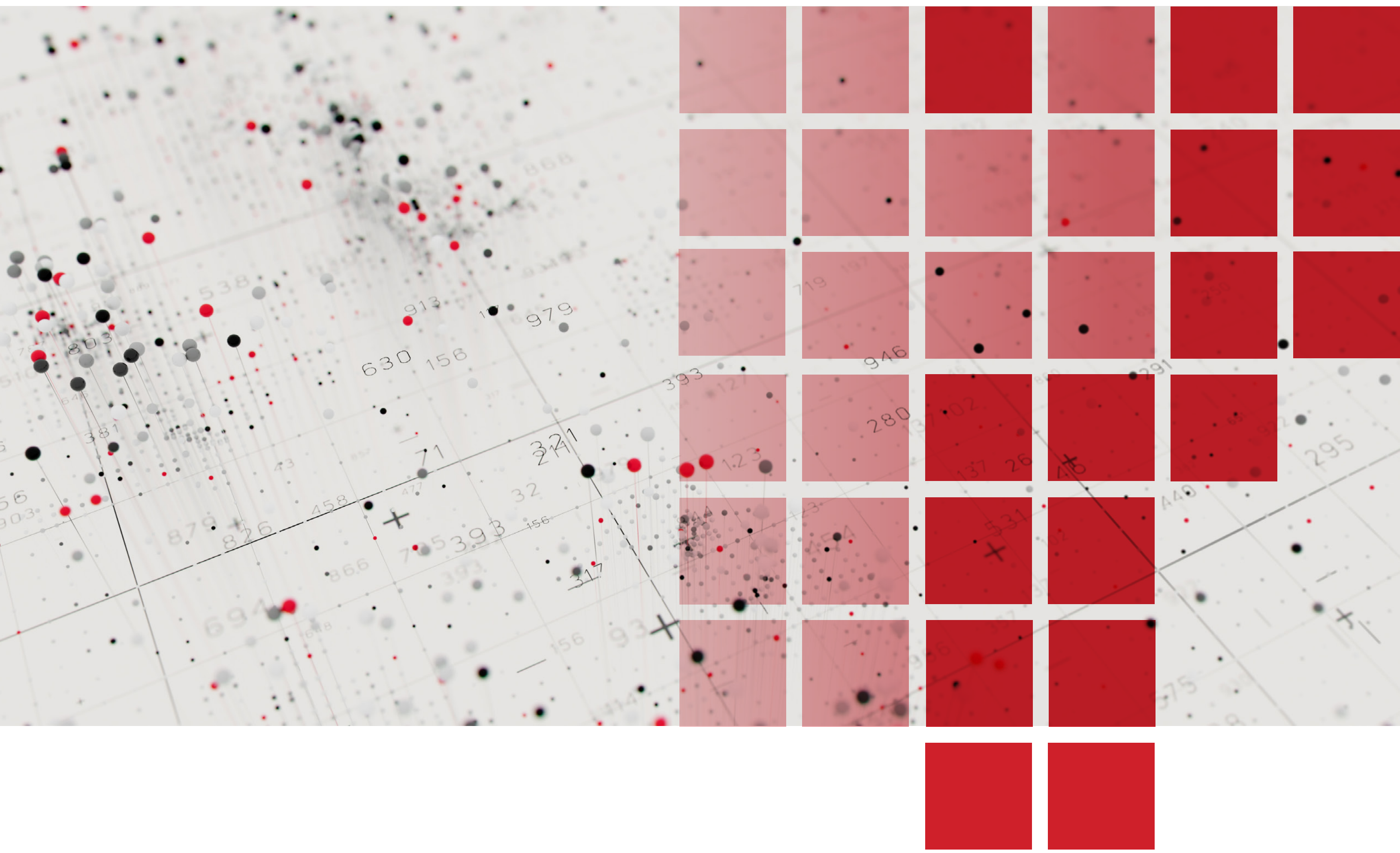

EMPOWERING CANADA'S WORKFORCE

ABOUT THIS STUDY

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KEY FINDINGS

This study explores the potential impact of generative AI on the Canadian workforce over the next five years. Through two novel approaches — using ChatGPT to evaluate the generative AI automation risk of occupations and employing the recently established Occupational and Skills Information System (OaSIS) database — we analyze how generative AI might transform work activities and skill requirements across different sectors and regions of the Canadian economy.

We do this by evaluating the estimated technical ability of generative AI to handle the various skills and work activities associated with all occupations in Canada. Importantly, this does not account for the full set of considerations that might go into a firm's decision to automate a particular job. Automation of some occupations might, for example, be constrained by the need for large capital investments, new technologies, or changes to laws and regulations. However, by focusing only on the technical feasibility of generative AI, our estimates can be used to anticipate a wider spectrum of risks and opportunities.

Our analysis reveals three significant patterns that have important implications for productivity enhancement and workforce development. First, the impact of AI varies substantially across different types of skills and work activities, with clerical and data-processing tasks showing the highest automation risk due to generative AI. Skills involving human interaction, social perception, and instruction demonstrate markedly lower vulnerability.

Second, rather than eliminating entire occupations, generative AI is more likely to transform the composition of work activities within jobs. This is indicated by our results which show that occupations representing 50 per cent of total Canadian employment exhibit a moderate automation risk from generative AI, suggesting partial rather than complete automation.

Third, significant variations exist across industries and regions, based on the type and number of occupations present. Sectors like transportation and warehousing show the highest share of at-risk occupations (56.4 per cent), while others like educational services demonstrate greater resilience (3.1 per cent). These differences are more pronounced in certain regions, like Nunavut and the Northwest Territories, where manufacturing, mining, and transportation exhibit higher shares of high-risk employment than in the rest of the country.

Automation risk also varies by region when looking at the kinds of occupations that are currently in high demand. In Ontario and Manitoba, for example, in-demand occupations have a higher average automation risk from generative AI when compared to those in Prince Edward Island and Newfoundland & Labrador.

These findings have important implications for policymakers and business leaders seeking to leverage generative AI for productivity growth. Geographic and industry variation suggests the need for targeted approaches to workforce development and AI adoption. Additionally, realizing productivity benefits from generative AI will require addressing significant implementation challenges, particularly in developing the necessary workforce skills.

While generative AI could help address Canada's productivity challenges, capturing these gains requires a coordinated approach to infrastructure development and workforce preparation. Our results suggest that upskilling and retraining initiatives should prioritize developing complementary skills — those skills that show low automation risk but high value in an AI-augmented workplace. This includes social, managerial, and leadership skills that our analysis shows are least at risk from automation due to generative AI. The study thus contributes to an understanding of how generative AI can be deployed to boost Canadian productivity while supporting broader workforce adaptation.

FAITS SAILLANTS

Cette étude explore l'impact potentiel de l'intelligence artificielle (IA) générative sur la main-d'œuvre canadienne au cours des cinq prochaines années. Grâce à deux approches novatrices — l'utilisation de ChatGPT pour évaluer le risque d'automatisation de l'IA générative dans les professions et l'utilisation de la base de données du Système d'information sur les professions et les compétences (SIPeC) récemment créée — nous analysons comment l'IA générative pourrait transformer les activités professionnelles et les exigences en matière de compétences dans différents secteurs et régions de l'économie canadienne.

Pour ce faire, nous évaluons la capacité technique estimée de l'IA générative à composer avec les diverses compétences et activités professionnelles associées à toutes les professions au Canada. Il est important de noter que cela ne tient pas compte de l'ensemble des considérations qui peuvent entrer en ligne de compte dans la décision d'une entreprise d'automatiser un emploi particulier. L'automatisation de certaines professions peut, par exemple, être limitée par la nécessité d'investissements importants, de nouvelles technologies ou de modifications des lois et réglementations. Toutefois, en se concentrant uniquement sur la faisabilité technique en lien avec l'IA générative, nos estimations peuvent être utilisées pour anticiper un spectre plus large de risques et d'opportunités.

Notre analyse révèle trois tendances significatives qui ont des implications importantes pour l'amélioration de la productivité et le développement de la main-d'œuvre. D'abord, l'impact de l'IA varie considérablement selon les différents types de compétences et d'activités professionnelles, les tâches de bureau et de traitement des données présentant le risque d'automatisation le plus élevé. Les compétences impliquant les interactions interpersonnelles et sociales et l'enseignement sont nettement moins vulnérables.

Ensuite, plutôt que d'éliminer des professions entières, l'IA générative est plus susceptible de transformer la nature des tâches au sein d'une activité professionnelle donnée. C'est ce qu'indiquent nos résultats, qui montrent qu'une liste de professions représentant 50 % de l'emploi total au Canada présente un risque d'automatisation modéré du fait de l'IA générative, ce qui laisse supposer une automatisation partielle plutôt que complète.

Enfin, il existe d'importantes variations entre les industries et les régions, en fonction du type et du nombre de professions présentes. Des secteurs comme le transport et l'entreposage affichent la plus forte proportion de professions à risque (56,4 %), tandis que d'autres, comme les services éducatifs, font preuve d'une plus grande résilience (3,1 %). Ces différences sont plus prononcées dans certaines régions, comme le Nunavut et les Territoires du Nord-Ouest, où les secteurs de la fabrication, de l'exploitation minière et des transports affichent des parts plus élevées d'emplois à risque que dans le reste du pays.

Le risque d'automatisation varie également d'une région à l'autre lorsqu'on examine les types de professions qui sont actuellement en forte demande. En Ontario et au Manitoba, par exemple, les professions en demande présentent un risque moyen d'automatisation lié à l'IA générative plus élevé qu'à l'Île-du-Prince-Édouard et à Terre-Neuve-et-Labrador.

Ces résultats ont d'importantes implications pour les décideurs politiques et les chefs d'entreprise qui cherchent à tirer parti de l'IA générative pour accroître la productivité. Principalement, les variations géographiques et sectorielles suggèrent la nécessité d'approches ciblées pour le développement de la main-d'œuvre et l'adoption de l'IA, et la réalisation des avantages de l'IA générative en termes de productivité nécessitera de relever d'importants défis de mise en œuvre, en particulier pour développer les compétences nécessaires de la main-d'œuvre.

L'IA générative pourrait contribuer à relever les défis du Canada en matière de productivité, mais la capture de ces gains nécessite une approche coordonnée du développement de l'infrastructure et de la préparation de la main-d'œuvre. Nos résultats suggèrent que les initiatives d'amélioration des compétences et de formation devraient donner la priorité au développement de compétences complémentaires — les compétences qui présentent un faible risque d'automatisation mais une valeur élevée dans un milieu de travail qui fait usage de l'IA. Il s'agit notamment des compétences sociales, managériales et de leadership qui, selon notre analyse, sont les moins menacées par l'automatisation due à l'IA générative. Cette étude contribue donc à la compréhension de la manière dont l'IA générative peut être déployée pour stimuler la productivité canadienne tout en soutenant une adaptation plus large de la main-d'œuvre.

INTRODUCTION

In the rapidly evolving landscape of technological innovation, artificial intelligence (AI) has emerged as a potential solution to Canada's persistent productivity challenge (Billy-Ochieng' et al., 2024). With productivity growth stagnating at just 0.2 per cent annually over the past decade (Caranci & Marple, 2024), and mounting economic pressures from potential trade disruptions, the need to enhance productivity has become increasingly urgent. Generative AI — artificial intelligence systems capable of creating new content, such as text, images, music or code — offers particularly promising opportunities for productivity gains, while simultaneously raising important questions about workforce adaptation.

AI is an umbrella term, used to describe a set of technologies able to perform tasks commonly associated with natural intelligence, such as identifying objects from visual data (vision) or processing natural language (speech) (Oxford University Press, 2023). Approaches vary across technologies, but a common throughline between them is that, generally, AI algorithms are built to be able to modify and refine the way that they work based on exposure to large amounts of data.

Its potential to boost productivity through task automation, process optimization and augmentation of human capabilities has led economists to recognize it as a general, purpose technology with significant economic, social and policy implications (Acemoglu, 2024a; Agrawal et al., 2019; Bick et al., 2024; Council of Economic Advisers, 2024). Due to AI's expected impact on society, it has been described as a "Gutenberg moment," likening its influence to that of the printing press (Nuño, 2023).

However, realizing these productivity gains requires significant implementation challenges to be addressed. Canada currently lags behind other G7 countries in AI adoption, with only 3.1 per cent of companies having adopted AI technologies by 2022, due in large part to infrastructure limitations and skills gaps (Pamma, 2024). This underscores the importance of understanding how generative AI might reshape labour market demands and identifying the skills needed to effectively harness these technologies.

CONTEXT AND APPROACH

The potential impact of digital technologies on work started to receive significant attention in 2013 with a study by Frey and Osborne that found that 47 per cent of all occupations were at high risk of being replaced by computerization. The authors reasoned that, in essence, computerization is a form of automation. The process of automation, in turn, tends to replace lower-skilled occupations and augment higher-skilled occupations, raising concerns about increased unemployment and rising income inequality. Unlike past technological shifts that primarily affected manual labour, computerization threatens roles previously deemed difficult to automate, including routine-based service occupations in sectors like logistics, office support and certain service roles.

Later studies on the effects of computerization and machine learning — the study of an algorithm's ability to improve performance on a given task without specific instructions — on work demonstrated that the impacts are more nuanced. A common practice in this approach is to view individual occupations as collections of tasks and assess which tasks could be transformed by technology (Acemoglu & Restrepo, 2022; Brynjolfsson et al., 2018; Moll et al., 2022). Studying the impact of machine learning (ML) on occupations, Brynjolfsson et al. (2018) utilize a task-based approach to analyze how technology can alter job functions within occupations. They used a crowdsourcing platform to obtain ratings for a series of job tasks within U.S. occupations, with regard to their suitability for machine learning on a given scale. Using these ratings, the authors then calculated a "suitability for machine learning" score for each task. This approach allows for a better understanding of how technology can reshape job responsibilities rather than merely replacing entire occupations. Applying it to the Canadian labour market, Frank and Frenette (2021) find that new technologies have shifted the nature of work toward more non-routine tasks between 2011 and 2018. Yet they also note that these changes were rather modest in scale.

Accelerated development and adoption of machine learning technologies have led to an increased focus on AI as a so-called general-purpose technology. This term is often used for innovations that have widespread applications across various occupations and industries.

Felten et al. (2021) applied the task-based approach to explore specifically how AI technologies might affect occupations in the United States. The increased focus on AI is tied to its role as a general-purpose technology (Acemoglu, 2024; Agrawal et al., 2019; Bick et al., 2024, Council of Economic Advisers, 2024). Examples of general-purpose technologies include the steam engine, electricity and microchips. Due to their applicability across the economy, general purpose technologies commonly cause significant economic disruption, thereby creating winners and losers (Trajtenberg, 2018). Using a crowdsourced survey, Felten et al. linked common AI applications, such as image recognition and language processing, to workplace abilities. They then used occupational data to determine the level of occupational exposure to AI technologies. This exposure measure is agnostic with regard to AI's ultimate impact on a specific occupation. In some cases, high exposure can lead to automation; in other cases, an AI technology can complement a human worker.

More recently, the rise in popularity and availability of AI tools capable of generating content like text, audio or visuals — popularly referred to as "generative AI" — has led to renewed interest in the impact of technology on labour and skills. This is especially the case since generative AI's capability to create new content allows it to take on a host of cognitive and creative tasks previously perceived as the prerogative of humans. As a consequence, occupations formerly thought of as immune from computerization may now also be experiencing some transformation (Gmyrek et al., 2023).

Focusing primarily on generative AI, Eloundou et al. (2023) measured occupational exposure to large language models (LLMs) — a type of machine learning model that is trained on large amounts of language data (see box 1). In particular, they assessed the potential time savings that generative AI tools could provide for various tasks and work activities within a given occupation. They found that approximately 19 per cent of the U.S.

workforce might face significant disruption to their roles. Notably, the authors pointed out that, while generative AI can enhance productivity by streamlining tasks, it may also require workers to adopt new skills to remain relevant in a rapidly evolving job market.

Pizzinelli et al. (2023) determined both the level of exposure and complementarity of U.S. occupations to generative AI. Similar to Felten et al. (2021), the study applied an AI exposure index to assess the level of automation risk of different jobs due to generative AI based on task composition and automation potential. In addition, it determined complementarity — whether AI could enhance productivity in specific jobs — or substitution — where AI might displace jobs. One of the main findings is that higher-skilled occupations might experience more complementarity with generative AI, while lower-skilled jobs could face higher displacement risks.

From a policy standpoint, understanding how generative AI will change the demand for skills is particularly important for guiding people about to enter the labour market. Individuals currently in school or university need insight into which skills will gain or lose importance, so as to make informed career choices. In addition, assessing the impact of generative AI on occupations is crucial for policy interventions aimed at the current workforce, enabling support through retraining and upskilling.

Two recent studies analyze the potential impact of generative AI on Canada's labour market. Using a combination of qualitative analysis, expert insights and case studies, Burt (2023) analyzed the effects of generative AI on routine and cognitive tasks. It found that the most significant occupational impact from the deployment of such tools appears to be on writing and programming skills. Their results show that the top 10 occupations where these skills predominate are either associated with STEM occupations, such as computer network technicians, software engineers and designers; or with cognitive occupations, such as journalists.

More recently, Mehdi and Morissette (2024) assessed the potential impact of AI on Canadian workers. Applying the methodology developed by Pizzinelli et al. (2023) to Canadian occupations, the study categorized workers into three groups based on their exposure to AI: those whose jobs may benefit from AI due to high complementarity, those at risk of having their tasks replaced by AI, and those less affected. The authors determined that around 31 per cent of Canadian employees, equivalent to 4.2 million workers, are in occupations that could be negatively impacted by AI.

Our study takes a novel approach to understanding generative AI's potential impact on the Canadian workforce. We first analyze the automation risk of generative AI across skills and work activities, then examine the likely effect on Canadian occupations and industries. To do this, we introduce two methodological innovations.

First, we leverage the capabilities of one of the largest and most popular all-purpose generative AI tools (ChatGPT — an LLM-based chatbot by company OpenAI) to assess the automation risk of generative AI across different skills and work activities. Trained on vast amounts of data encompassing diverse fields, including labour market trends and technological advancements, tools like ChatGPT can synthesize and analyze information to provide a comprehensive assessment of generative AI's capabilities. Specifically, recent research has demonstrated that LLMs can effectively analyze structured data formats when provided with appropriate frameworks (Jiang et al., 2023). We define "automation risk" as the technical feasibility of a generative AI system replacing or significantly transforming a specific occupational skill or work activity. Importantly, our analysis focuses solely on technical capabilities, without considering potential implementation barriers such as organizational, regulatory or financial constraints.

Second, our methodology draws on the Occupational and Skills Information System (OaSIS), a comprehensive database developed by Employment and Social Development Canada that provides detailed information on skills, abilities and competencies across nearly 900 Canadian occupations. The systematic, structured nature of OaSIS makes it particularly well-suited for AI-driven analysis, as it allows us to distill occupations into their major elements, which can then be individually evaluated by an AI chatbot.

LLMs offer distinct advantages in this assessment. They can systematically process standardized task descriptions and skill requirements, maintaining analytical consistency across multiple occupational categories. This approach allows us to identify which tasks involve routine, rule-based actions that align with current AI capabilities, and which require complex human skills that remain difficult to automate.

The reliability of this approach is supported by emerging research showing LLM assessments to be in line with traditional expert evaluations. Eloundou et al. (2023) compared occupation ratings of automation risk done by humans familiar with LLMs to responses from ChatGPT (GPT 4) and found strong correlations between the two. While AI ratings were lower on average, responses from both sources have a very similar trend.

To our knowledge, this is the first study of its kind using OaSIS to examine the impact of generative AI on Canada's labour market.

METHODOLOGY

We assess the impact of generative AI on Canada's workforce by analyzing how it affects skills and work activities. In doing so, we determine the risk of automation for each skill and work activity related to Canadian occupations.

As noted earlier, there are two important caveats with our approach. First, the risk of automation from generative AI focuses solely on technical feasibility, consistent with other literature on the topic (Acemoglu & Restrepo, 2019; Eloundou et al., 2023; Frey & Osborne, 2017). As such, it does not take into account regulatory frameworks, cultural acceptance, and other factors that would influence the adoption of generative AI. For instance, while self-driving transport trucks may be technically feasible, public skepticism and regulatory hurdles could significantly delay or limit their deployment, reducing the actual impact on employment in that sector.

Secondly, we focus on changes over the next five years, as predictions beyond this time horizon likely have a higher degree of uncertainty given the rapid technological developments in this space. Throughout our analysis, it is important to keep in mind that adoption barriers may result in slower, more uneven implementation of generative AI across different sectors and regions.

We note also that the inclusion of both skills and work activities in our analysis is deliberate. The way in which OaSIS defines skills and work activities does not allow for a clear delineation between what might be an innate human ability (skill), and an action that might be more highly correlated with a job description (work activity). For example, Quality Control Testing is listed as a skill in OaSIS but could quite as easily be explained as a work activity. As such, any separation in analysis between work activities and skills would not yield a clearer or comparable analysis due to the ambiguity and fluidity of the way the items are defined. Furthermore, OaSIS organizes its descriptions into eight categories, five of which pertain to individual traits and requirements and three to the work environment. "Skills" is included from the individual characteristics and requirements category while "work activities" comes from the work environment; as such, including both in the analysis enables a more comprehensive analysis.

As it is our goal to determine the impact of generative AI on Canada's workforce, we apply occupational information from the newly established OaSIS. Developed by Employment and Social Development Canada (ESDC) with support from Statistics Canada and the Labour Market Information Council (LMIC) in 2021-22, OaSIS is Canada's database on occupations and associated competencies. The database was constructed using best practices from international examples such as the Occupational Information Network (O*NET) in the United States, and the European Skills, Competencies, Qualifications and Occupations (ESCO).[1]

OaSIS links the existing Skills and Competencies Taxonomy to Canada's National Occupational System (NOC). It provides detailed information on the skills, abilities, personal attributes, knowledge and interests needed for over 900 occupations in Canada. For our analysis, we extract data on the 34 unique skills and 41 unique work activities across all occupations.

For each work activity and skill, OaSIS provides a score, on a scale from 0 to 5, measuring the proficiency required for competency in a given occupation. The ratings are conducted by trained HR analysts. On this scale, 0 means that the competency does not apply to the occupation and 5 means that it is essential. We consider only those competencies most relevant for a given vocation. For this reason, we include only the subset of skills and work activities with a proficiency weight of 3 and higher for each occupation.[2]

[1] These databases can be accessed using the following links: OaSIS: https://noc.esdc.gc.ca/Oasis/Oasis Welcome; O*NET: https://www.onetcenter.org/database.html; ISCO: https://data.europa.eu/data/datasets/european-skills-competences-qualifications-and-occupations?locale=en.

[2] Note: Excluding weights from 0 to 2 does not impact our final results.

Box 1. Background on LLMs

A large language model (LLM) is a type of AI algorithm that is trained on large amounts of text data to perform natural language processing tasks, or the ability to process data resembling human speech. These models form the basis of most AI chatbots, like ChatGPT or Microsoft's Copilot, which allow users to interact with the tool in a way that resembles a conversation. Through a cloud-based Application Programming Interface (API) (e.g., the ChatGPT API used in this study), users are able to access these powerful models to integrate AI capabilities into research, products, or applications.

LLMs use machine learning techniques in order to identify patterns in text data. Trained on unprecedentedly large amounts of data, these models are able to output responses based on the estimated probability of a given response being "correct" or "appropriate," based on learned patterns throughout the training process. This means that, when a chatbot is given a prompt, the model relies on these observed patterns from its training data to parse the request and consequently produce a response. Importantly, output that is provided is not necessarily "new," as the term "generative" might imply.

These models are stochastic, which means that they are capable of generating different responses to the same prompt due to random elements involved in their processing. The level of randomness can be altered, depending on the model being used, using different inputs to parameters that govern consistency in output (appendix B).

LLMs are useful because they are able to generate human-like text responses. In the case of research, using a model trained on a big portion of all web-published data can mean approximating responses that one would receive through a survey. However, the accuracy, reliability and biases of responses, are greatly influenced by the training data and process.

Applying the information on skills and work activities for each Canadian occupation provided by OaSIS allows us to determine automation risk scores in the following way.

We asked ChatGPT to rate how easy or difficult it would be for a specific skill and work activity to be performed by generative AI. When using a chatbot, results can differ based on three components. First, the output generated by a chatbot can depend on how a specific question is phrased. Second, results may depend on which particular model of chatbot is used. Finally, each model allows the user to specify certain parameters that influence the response, such as the level of randomness and the length of the generated output. To account for this, we use two different models of ChatGPT, vary the way we phrase our question by using different prompt structures, and modify specific parameters. Box 2 describes this approach in more detail, and further details on the prompt structure are provided in appendices B, C and D. Ultimately, we leverage these components to generate an average score of the risk of automation to provide a more comprehensive and robust estimate than if we were to simply report the output from one version of the question phrasing, one model or one set of inputs to the model parameters.

In total, we obtained 12 responses for the 34 unique skills and 41 unique work activities associated with all recorded occupations (listed in appendix E). This mimics the approach taken by Brynjolfsson et al. (2018) who surveyed 7 human experts across each of O*NET tasks. Next, we calculate the average automation risk scores for each work activity and skill which provides us with the potential automation risk from generative AI by skill and work activity for the over 900 occupations contained in the OaSIS.

Box 2. Obtaining responses from ChatGPT

Our aim is to obtain a score for the automation risk of skills and work activities to generative AI within the next 5 years. To achieve this, we ask the chatbot to provide us with a rating between 1 and 5 for each skill and work activity from OaSIS. On this scale, 1 equals a low likelihood and 5 a high likelihood of automation.

Responses from chatbots can differ by the way the question, or prompt, is phrased. Moreover, results may differ based on the model used and on how certain parameters in each model are specified.

For our purposes, we use two different models of ChatGPT: GPT-4-0613 and Instruct-GPT. The purpose of using two different models instead of just one is to account for some degree of training variability in the models and aggregate to a more consistent result. Further details on the differences between the two models we used can be found in appendix A.

In addition, we set specific parameters for the models so as to limit creativity in the answers (i.e., how diverse or conservative outputs are in the vocabulary used). This ensures that responses are more consistent, and ratings are always closest to what ChatGPT would report as the most likely rating, based on the question and the information it has access to. Further details on what these parameters are and how they work can be found in appendix B.

Having chosen the two models and parameter settings, we vary our question, or prompt. We do this as answers can differ based on how a question is phrased. An example of one prompt is the following: "Please rate the automatability of {the skill} in the context of generative AI development over the medium term (next 5 years) on a scale of 1 to 5." In addition, we tell the chatbot the definition of the scale by specifying "Where, 1 = Not automatable, 2 = Slightly automatable, 3 = Moderately automatable, 4 = Highly automatable, and 5 = Fully automatable. Please provide a single numerical rating based on this scale."

In total, we use 12 different prompts, thus obtaining 12 responses for each skill and work activity. We find that running the same prompt on the same model when asked several times yields the same results, due to the parameter specifications used to improve consistency. A comprehensive list of all 12 prompts we used can be found in appendix C. A prompt structure highlighting the placement and variation of specific nouns and verbs can be found in appendix D.

THE IMPACT OF GENERATIVE AI ON OCCUPATIONS, SKILLS AND WORK ACTIVITIES

Applying our methodology provides us with an average risk of automation score for each unique skill and work activity. As described, this score is averaged over 12 different prompts fed into the API, which varied in certain parameter values and vocabulary used, and across two different models of ChatGPT. This allows us to determine the likelihood of the risk of automation for each of the 900 occupations contained in OaSIS.

Our comprehensive analysis of generative AI's automation risk for the Canadian workforce reveals three significant patterns in the data. First, clerical and data-processing skills and work activities demonstrate the highest automation risk from generative AI, with activities like entering and storing information scoring above 4 out of 5 on our risk scale. These are followed closely by activities involving operation monitoring, data analysis and scheduling, which all score above 3.5. Writing skills and activities also emerge as having a high risk of automation, aligning with recent empirical studies on generative AI's capabilities in content creation and documentation (Burt, 2023).

Second, skills and work activities involving human interaction, social perception and instruction show markedly lower automation risk from generative AI. This pattern indicates that social, managerial and leadership skills will remain predominantly human domains in the near term, with generative AI having limited capability to automate these inherently interpersonal activities.

Third, our findings suggest that generative AI is more likely to transform the composition of skills and work activities within occupations rather than completely automate entire occupations. This is evidenced by our analysis of occupations representing 50 per cent of total Canadian employment in 2021, which show moderate automation risk scores between 2.77 and 3.3. For instance, retail salespersons demonstrate lower automation risk scores, particularly in activities requiring negotiation and persuasion, suggesting their roles will evolve to emphasize these human-centric skills while potentially seeing automation of more routine activities.

Overall, our analysis reveals distinct patterns of automation risk that vary significantly across skills, work activities and occupations. At the skill and work activity level, we find a clear divide between highly automatable activities such as data processing and monitoring, and more resilient human-centred skills such as instruction and social perception. At the occupational level, these risks manifest in three distinct patterns. Occupations requiring high levels of social interaction or manual skill show the lowest automation risk, suggesting that there will be minimal changes to their skill requirements and work activities. A second group of occupations shows high automation potential for certain activities but maintains important human-centred skill requirements, indicating likely shifts in work composition rather than a complete transformation. Finally, occupations centred primarily on routine information processing and monitoring activities show the highest automation risk, suggesting a more substantial transformation of their required skills and work activities.

Level of generative AI automation risk by skills and work activities

Table 1 shows the results for the skills and work activities with the highest risk of automation scores.[3] In short, amid the skills and work activities listed in table 1, clerical activities — which include entering, transcribing or storing information — carry the highest automation risk from generative AI, with an average score of 4.29 out of 5. Skills and work activities related to monitoring, scheduling and data analysis also rate relatively high. Moreover, and in line with recent empirical studies, writing is among the top 5 skills/work activities with the highest automation risk.

Table 2 shows our results for the skills and work activities with the lowest automation risk scores. Instructing, meaning the capability to teach others knowledge, has the lowest overall risk score at 2.04, followed by social perceptiveness and assisting and caring for others. These results demonstrate that social, managerial and leadership skills are among those with the least risk of automation by generative AI.

[3] For the complete list of skills and work activities with their associated level of automation risk, see appendix E.

Table 1. Clerical activities appear to have the highest automation risk from generative AI
Top 10 highest levels of generative AI automation risk

Skills/Work activities	Automation risk score
Clerical Activities	4.29
Operation Monitoring of Machinery and Equipment	3.96
Analyzing Data or Information	3.92
Monitoring	3.88
Writing	3.71
Interacting with Computers	3.67
Getting Information	3.62
Oral Communication: Oral Expression	3.62
Scheduling Work and Activities	3.62
Identifying Objects, Actions and Events	3.58
Numeracy	3.58
Decision Making	3.5

Table 2. Instructing appears to be the skill with the lowest risk of automation from generative AI
10 lowest levels of generative AI automation risk

Skills/Work activities	Automation risk score
Oral Communication: Active Listening	2.42
Repairing	2.38
Persuading	2.33
Management of Personnel Resources	2.25
Supervising Subordinates	2.25
Coordinating the Work and Activities of Others	2.21
Coaching and Developing Others	2.17
Assisting and Caring for Others	2.08
Social Perceptiveness	2.08
Instructing	2.04

Generative AI automation risk by occupation

Table 3 lists the top 10 occupations with the highest average automation risk from generative AI. According to our results, data entry clerks, general office support workers, and shippers and receivers exhibit the highest automation risk. This aligns with our previous findings, as these occupations comprise a relatively large share of clerical skills and information-processing work activities.

As described, the score for each occupation is obtained by averaging only the subset of skills and work activities that are the most relevant to it (i.e., with a proficiency weight of 3 and higher). So, the fact that "Data entry clerks" exhibit a high automation risk score in table 3 means that all of the skills and work activities most necessary for that occupation exhibit, on average, a high risk of automation.

A closer examination of these high-risk occupations reveals how generative AI might transform their skills and work activities. For instance, health information management occupations (automation risk score: 3.41) combine both highly automatable skills and work activities, like data processing and documentation, with skills and work activities requiring human judgment and interpersonal capabilities. While generative AI shows high potential for automating their information-processing and record-keeping activities, others, such as co-ordinating with health care providers and ensuring compliance with regulations, may exhibit lower automation risk. Similarly, for general office support workers (automation risk score: 3.67), while routine documentation and data entry work activities show high automation potential, their skills in facilitating workplace communication and providing personalized administrative support are likely to remain important human-centred components of the occupation.

In general, it is important to note that automation risk scores reflect the technical feasibility of generative AI replacing or transforming tasks within occupations. However, real-world adoption also depends on economic factors, business incentives and investment costs. With regard to bakers, for example, while large-scale commercial baking operations may find automation cost-effective for streamlining production (e.g., to monitor ingredient usage or predict demand fluctuations), small bakeries may lack the financial incentive to invest in AI-driven systems.

A similar dynamic applies to other occupations with a high average risk score. While generative AI has the potential to automate or assist with cognitive-heavy tasks, full automation would likely require additional advancements in robotics and physical automation. For example, shippers and receivers, who are responsible for processing shipments, tracking inventory and moving materials, may see AI assist with logistics optimization and automated record-keeping. However, the physical aspects of loading, unloading and transporting goods would require robotics rather than generative AI alone. Similarly, while general office support workers could see many of their administrative duties — such as document generation and email drafting — automated by AI, tasks that

Table 3. Data entry clerks, general office support workers, and shippers and receivers are likely to be the most impacted by generative AI

Top 10 highest average levels of generative AI automation risk

NOC	Occupation	Automation risk score
14111	Data entry clerks	3.81
14100	General office support workers	3.67
14400	Shippers and receivers	3.47
63202	Bakers	3.42
12111	Health information management occupations	3.41
94212	Plastic products assemblers and finishers	3.41
74205	Public works maintenance equipment operators and related workers	3.4
94213	Industrial painters and coaters	3.4
94104	Inspectors and testers, mineral and metal processing	3.39
93101	Central control and process operators, petroleum, gas and chemical processing	3.38

Table 4. Occupations requiring social skills and manual work activities are less likely to be impacted by generative AI

10 lowest average levels of generative AI automation risk

NOC	Occupation	Automation risk score
64300	Maîtres d'hôtel and hosts/hostesses	2.75
64201	Image, social and other personal consultants	2.73
44100	Home child care providers	2.7
63210	Hairstylists and barbers	2.67
63211	Estheticians, electrologists and related occupations	2.62
65109	Other sales related occupations	2.62
64401	Postal services representatives	2.61
43100	Elementary and secondary school teacher assistants	2.56
64100	Retail salespersons and visual merchandisers	2.54
65229	Other support occupations in personal services	2.5

require co-ordination across multiple departments or handling sensitive information may still require human oversight. These limitations highlight the fact that, while generative AI can transform certain work activities and affect skills demand, full automation often depends on additional investments in complementary technologies.

Table 4 shows the occupations with the lowest average automation risk from generative AI. In line with our previous results, occupations requiring intensive use of social skills and manual work activities show lower automation risk. The relatively low automation risk for retail salespersons, for example, is because skills and work activities such as "negotiating", "selling or influencing others," and "persuading" are among their most essential requirements. This finding is consistent with the existing literature on automation, which shows that non-routine manual and interpersonal communication activities have lower automation risk (Lesonsky, 2023). This pattern is particularly evident in occupations requiring direct interpersonal interaction, such as hairstylists and barbers, home child care providers, and personal service workers.

Generative AI automation risk and employment shares

The implication that, over the medium term, generative AI is more likely to change the composition of work activities and skills *within* occupations rather than rendering entire occupations obsolete, is illustrated by figure 1. It plots the level of automation risk for occupations with the highest employment share. Importantly, the automation risk scores included here are based on skills and work activities essential to the occupation.

Combined, the occupations included in figure 1 accounted for approximately 50 per cent of total employment in Canada in 2021. Overall, automation risk scores among these occupations range in ranking from 2.77, for cashiers and other sales support occupations, to 3.3 for longshore workers and material handlers. As such, taking an average risk score of 3 to indicate moderate automatability, we note that the roles in which employment is most concentrated face a moderate level of automation risk.

Many occupations involve a mix of tasks, some of which have a higher risk of automation than others. For example, we have already seen that skills and work activities related to monitoring tend to have higher automation risk. This means that the moderate automatability (i.e., 2.77-3.3) observed in occupations employing the largest share of workers points to a partial rather than total impact. These roles consist of enough low-risk work activities and skills to maintain an overall automation risk that is moderate rather than high. In other words, the most common jobs are not highly automatable as a whole because they involve both high- and low-risk work activities and tasks.

That said, some occupations within this group may appear more or less automatable depending on the lens through which automation risk is assessed. For example, while our findings suggest that cashiers have a moderate generative AI automation risk score (2.77), other research (e.g., Oschinski & Nguyen, 2022) has classified cashiers as highly automatable. This difference reflects the distinction between generative AI automation and broader automation trends. While self-checkout kiosks and cashier-less stores may reduce the need for traditional cashier roles, our analysis focuses specifically on how generative AI, rather than retail automation in general, impacts the skills and tasks within occupations. In this sense, cashiers remain a role where AI can assist with certain cognitive tasks (e.g., handling customer inquiries via AI chatbots or generating reports), but physical transaction processing and customer interaction remain largely human-driven.

More broadly, this pattern is consistent across many high-employment occupations. Rather than fully replacing jobs, generative AI is likely to automate specific work activities, shifting skill requirements, while leaving others unchanged. Since the occupations in

Figure 1. Occupations with the highest employment shares will be moderately impacted by generative AI over the medium term

Occupations with the most employees and their automation risk scores

Source: Author calculations and Statistics Canada (table 98-10-0594-01).

figure 1 account for half of total employment, moderate automation scores imply a shift in skill demand rather than the complete automation of occupations. In other words, generative AI is more likely to transform certain tasks while leaving others to humans, making the complete elimination of high-employment roles unlikely.

In summary, advances in generative AI are more likely to alter the composition of skills and work activities for most workers than render occupations obsolete. While nearly all occupations listed in figure 1 are likely to be impacted by generative AI, the impact will primarily involve a shift in tasks performed by humans.

Industry risk of automation

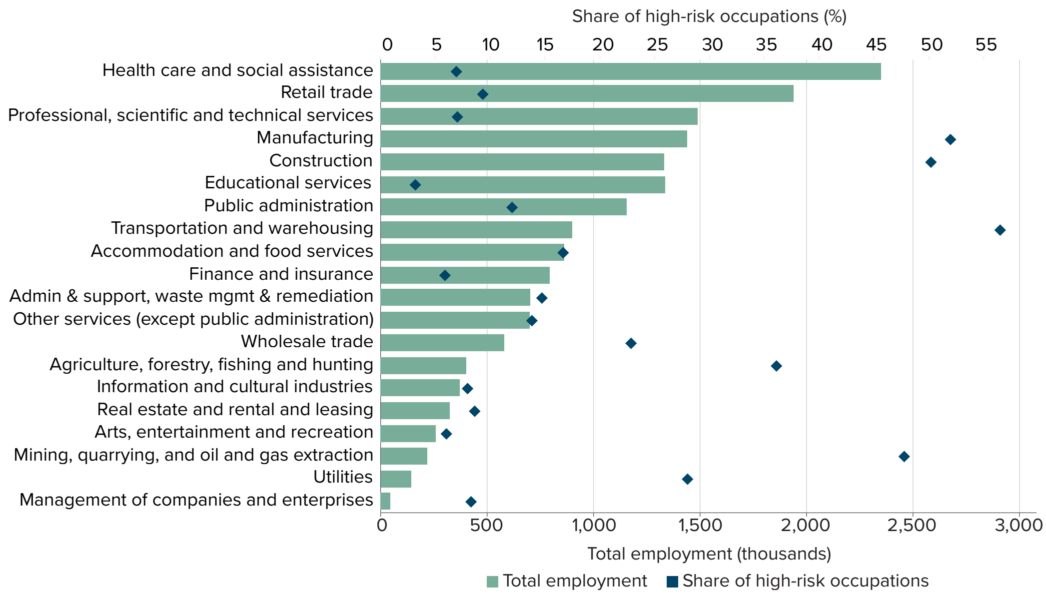
Having calculated the risk of automation for the skills and work activities related to certain occupations, we may now analyze the risk at industry level in Canada. To do this, we use detailed employment data by industry from Statistics Canada and calculate the share of high-risk occupations by industry.[4] High-risk occupations here are defined as the top 25 per cent of occupations with the highest risk ratings.

Figure 2 shows industries by total level of employment and each industry's share of high-risk occupations. The top 5 industries with the highest share of at-risk occupations include transportation and warehousing (56.4 per cent); manufacturing (51.9 per cent); construction (50 per cent); mining, quarrying, and oil and gas extraction (47.7 per cent); and agriculture, forestry, fishing and hunting (36 per cent). Our data suggest that occupations involving routine, standardized tasks such as data entry, basic customer inquiries and administrative work are at the highest risk of automation from generative AI technologies across these industries. In general, these roles involve a high degree of repetitive, predictable tasks. In fields like transportation, warehousing, manufacturing and construction, generative AI can optimize workflows, analyze data, generate schedules and support customer service. In agriculture, generative AI can further take over work activities involving crop and livestock monitoring, supply chain management and market analysis (Rane et al., 2024). In mining, key applications of generative AI include enhancing prospecting and deposit analysis, optimizing mining methods, improving worker safety and environmental monitoring, and increasing operational efficiency throughout the supply chain (Corrigan & Ikonnikova, 2024).

The industries with the lowest shares of high-risk occupations include educational services (3.1 per cent), finance and insurance (5.8 per cent), arts, entertainment and recreation (5.9 per cent), health care and social assistance (6.9 per cent), and professional, scientific and technical services (7 per cent). Industries with a low share of high-risk occupations typically involve roles that emphasize human-centric skills, complex decision-making and adaptability in unstructured environments — qualities that are less easily replaced by automation. While generative AI might assist in those occupations, it cannot easily replace nuanced communication, empathy, human judgment or ethical decision-making. Furthermore, creative and unstructured work, common in arts and entertainment, resists automation because it hinges on individual creativity, which AI struggles to codify. Finally, roles requiring high expertise, such as university researchers, demand years of specialized

[4] Note: We use occupation by industry data at the 4-digit NOC level (Statistics Canada, table 98-10-0594-01). This requires us to aggregate our occupational risk scores from the 5-digit NOC level to the 4-digit NOC level.

Figure 2. High-risk employment shares vary across industries
Total employment and share of occupations at high risk of automation from generative AI, by industry



Source: Author calculations and Statistics Canada (table 98-10-0594-01).

training and ongoing education to evaluate complex information, making them less vulnerable to AI-driven substitution and more likely to see AI as a complementary tool.

Our assessment indicates that industries vary considerably with regard to their share of at-risk occupations. It should be noted here, however, that the actual impact of generative AI on specific industries depends on both the speed and the nature of technology adoption.

Existing research suggests the pace of AI adoption may differ across regions and industries based on factors like firm size, R&D investment, available talent and quality of the IT infrastructure (Ali et al., 2024). Larger firms and tech-intensive industries may be able to integrate AI solutions quicker than smaller firms, or those in more traditional sectors (Bonney et al., 2024).

Additionally, the types of generative AI technologies implemented can significantly influence their workforce impacts. Firms have a choice in how they deploy these tools — whether to primarily automate and replace human labour, or to augment and enhance worker capabilities (Acemoglu & Johnson, 2023). Industries that strategically leverage AI to complement their human workforce may be able to mitigate job displacement risks.

Further, although some of Canada's largest employers, such as health care and social assistance, and professional, scientific, and technical services, have relatively low shares of occupations at high risk from automation by generative AI, the total number of employees affected could still be considerable. Due to the large workforce in these sectors, more than 10,000 workers in each are vulnerable to potential job transformation from AI-driven automation.

Finally, the potential risk of automation from generative AI at the industry level will likely vary across regions. This is because different regions have distinct industry patterns, with some areas displaying a larger concentration of sectors with higher shares of at-risk occupations. As such, regions with a greater concentration of industries like manufacturing, transportation and warehousing could face more significant workforce disruptions, while those with a higher share of lower-risk sectors, such as health care and education, may experience less immediate impacts. We discuss regional labour market vulnerabilities in more detail next.

ASSESSING REGIONAL LABOUR MARKET VULNERABILITIES — AUTOMATION RISK SCORES AND ONLINE JOB POSTING DATA

The impact of generative AI on the labour market may differ within Canada according to differences in economic structure, workforce composition and industry presence. For policymakers, it is important to know which regions could be most adversely affected in order to react with appropriate policy interventions. Consequently, this section considers the impact of generative AI on the regional demand for occupational labour in Canada. To accomplish this, we leverage data from online job postings as a measure of demand. As such, combining our measure of automation risk with the online job posting data allows us to discern differences in demand for occupations that are the most and least vulnerable to advances in generative AI by geographical location. By investigating this relationship, we aim to determine regional labour market trends in the context of technological change, and assess any patterns that may arise.

To achieve this, we introduce data into our analysis from the Labour Market Information Council (LMIC). Updated weekly, the LMIC's Canadian Job Trends Dashboard includes labour market information based on online job posting trends across Canada. The dashboard tracks movements in employers' demand for work skills, knowledge requirements and occupational vacancies. Although many employers actively recruit online, it is important to note that job posting is not an all-encompassing metric for all job vacancies. In particular, research suggests that online job postings might oversample high-skilled occupations (Carnevale et al., 2014).

To determine labour market trends, it is important that we first define a method of establishing what high demand looks like for an occupation versus low demand. In other words, we assess the relative demand for an occupation in a province compared to its demand at the national level. To do this, we use a normalized score.

Normalization adjusts variables to a standard scale, allowing for fair regional comparison. An example of this is the use of per capita values to better compare data across areas with varying population levels. In our context, we calculate the relative proportion of postings for a specific occupation in a province, compared to the national level, to assess proportionate demand.

Specifically, we use the measure of the location quotient (LQ), following Alabdulkareem et al. (2018). We generate the LQ by province to indicate whether a province has a relatively higher or lower demand for a particular occupation. The score can be interpreted as follows:[5]

1. LQ > 1: the province has a higher share of job postings for a particular occupation than the national average
2. LQ = 1: the province's share of job postings for the occupation is in line with the national average
3. LQ < 1: the province has a lower share of job postings for a particular occupation than the national average

These values simply allow us to determine some relative method of explaining which occupations have a higher or lower demand. To reiterate, this is important because we are interested in identifying which in-demand occupations exhibit a high automation risk. It assists in informing policy about which occupations are primed for job-training investment, namely those exhibiting relatively higher demand but low levels of automation risk, and where they are in demand. For example, if the occupation "Electrician" is in high demand in Alberta and has a low level of automation risk, this would indicate there is a growing need for electricians in Alberta with a low likelihood of this demand declining due to technological change in the near future.

However, generative AI's impact on an occupation is not solely determined by the share of tasks the tool can handle, but also by the types of tasks, their importance, and the context in which they are required. In contrast to automation risk, this concept – referred to as complementarity – is meant to capture the degree to which generative AI can enhance or supplement human tasks rather than entirely replace and automate them. Pizzinelli et al. (2023) built an index of AI complementarity at the occupation level, based on data on occupations and their work context (conditions, characteristics and relationships) from O*NET. We incorporate this dataset into our analysis, which was generously provided by the authors, by adapting it to align with the OaSIS framework.

Combining automation risk scores with complementarity scores allows us to determine which occupations are likely to experience the most fundamental disruption from generative AI. In other words, considering occupations that are in high demand, but that face high automation risk and low complementarity, is one way to identify those that may be positioned to face significant job losses. This subgroup of occupations is particularly vulnerable because these roles currently require filling (i.e., they are in high demand) but firms can choose between investing in modernization or human labour (i.e., due to high automation risk). This means that it may be more beneficial for a firm to invest in modernization than in human labour (i.e., due to low complementarity), leading to high displacement. Displacement does, however, depend on sector-based incentives. For example, it may be more difficult for a smaller firm to adopt automation due to financial

[5] To calculate this normalized score, the total number of postings for an occupation in a province was divided by the total number of provincial postings. This result was then divided by the result of the total number of postings for an occupation in Canada, divided by the total number of national postings.

or resource constraints, despite the automation risk. Conversely, larger firms with more capital may find it easier to invest in technology, resulting in greater displacement of workers in these high-risk, low-complementarity roles.

A Brookings Institution report by Kinder et al. (2024) draws attention to a significant shift in how generative AI impacts the labour market. Unlike previous waves of automation, which predominantly affected manual, routine tasks, generative AI is poised to disrupt routine cognitive tasks in office-oriented and information-based roles. In contrast, occupations that were once most vulnerable to automation — typically lower-skilled, routine manual jobs — are likely to be more insulated from displacement in this context. This is due to the slower adoption of advanced AI technologies in these industries, which often lack the resources or need for such investments. Conversely, sectors that rely on routine cognitive tasks, such as administrative work or customer service, may see greater disruption, but workers in these roles are also more likely to benefit from AI-driven productivity enhancements. The extent of job displacement will depend on factors such as firm size and sector characteristics. Larger firms and industries with more cognitive, routine tasks are better positioned to adopt generative AI, while smaller firms in sectors that rely on manual or complex tasks may face slower adoption. Thus, the impact of generative AI on job displacement will vary across industries and will be influenced by each sector's capacity to invest in new technologies. As a result, the impact of generative AI on job displacement will not be uniform across industries and will be shaped by each sector's unique needs and resources.

For occupations currently in high demand but with a high level of automation risk and low complementarity with generative AI, a sound course of action will be (with the caveats mentioned previously) to adopt automation in the field and manage transitions for workers expecting to be displaced in preparation for a different or altered line of work. Following Bender and Li (2002), who define additional intervals of a mathematically similar measure, we define the following categories of relative demand for more detailed insights:

Category 1: LQ > 2: very high overrepresentation
Category 2: 2 > LQ > 1: high overrepresentation
Category 3: LQ = 1: average representation
Category 4: 1 > LQ > 0.5: low representation
Category 5: If 0.5 > LQ > 0: very low representation

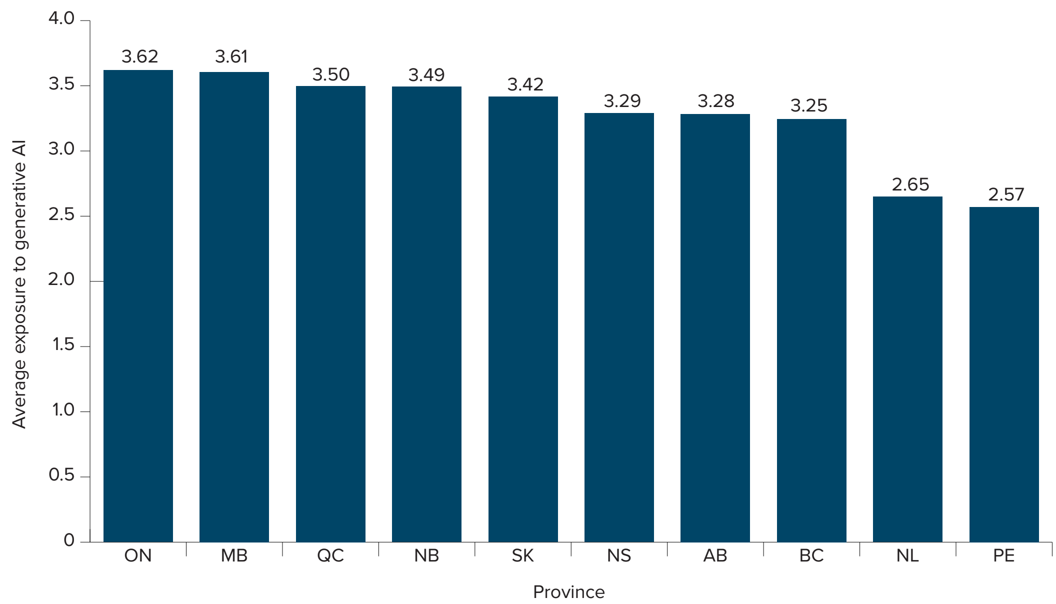
From a policy perspective, we are most interested in those occupations that are significantly overrepresented and, more specifically, highly represented in each province and with respect to their automation risk and complementarity scores (Categories 1 and 2).

It is also interesting to consider to what extent the location quotient is a reflection of regional economic specialization. For example, our data find that British Columbia has a very high over-representation for "Contractors and supervisors, carpentry trades" and Nova Scotia in "Conservation and fishery officers."

To determine a macro-level understanding of regional differences in labour market automation risk, we aggregate the Category 1 data detailed above. That is, we generate

Figure 3. Occupations with very high labour demand in Ontario and Manitoba have, on average, higher automation risk from generative AI than those in P.E.I. and Newfoundland and Labrador

Average level of automation risk for Category 1 occupations by province



Source: Author calculations and the LMIC'S Canadian Job Trends Dashboard.
Notes: Category 1 occupations are those that are significantly over-represented in the province, compared to the national average.

the average level of generative AI automation risk for the highest in-demand occupations (those with an LQ greater than 2) in each province.

Using just Category 1 data allows us to gain further detail on specialization. Recall that, if the LQ is greater than 2, it demonstrates a significantly higher concentration of job postings for a specific occupation in a province than the national average.

Comparing the expected level of susceptibility to generative AI for those occupations most in demand in each province is a useful policy tool, as it may indicate priorities for strategic workforce planning from a macro perspective, serving as a high-level indicator. Figure 3 shows the average level of generative AI automation risk for the most in-demand occupations by province.

We note that focusing on in-demand occupations does not account for automation risk in occupations where firms may already be choosing between investing in modernization or closing. Then, for the most in-demand occupations, we see that Ontario exhibits the highest average level of generative AI automation risk at 3.62, followed by Manitoba. In contrast, Prince Edward Island and Newfoundland and Labrador have the lowest average levels. Thus, occupations with the highest labour demand in Ontario and Manitoba have, on average, higher automation risk due to advances in generative AI compared to those in Prince Edward Island and Newfoundland and Labrador.

The implications of this insight are manifold. For example, workers in Ontario and Manitoba may face higher risks of job displacement, which could lead to increased unemployment or exacerbate economic inequality if workers struggle to transition to new roles or technology. On the other hand, Prince Edward Island and Newfoundland and Labrador may experience higher resiliency in their most specialized fields, indicating a lesser level of urgency in terms of upskilling or retraining policy efforts.

As noted above, the ultimate impact of generative AI on a specific occupation is going to depend on the level of automation risk as well as its level of complementarity with this technology. Automation risk refers to the likelihood that the activities required by an occupation can be reasonably performed by generative AI tools. Complementarity refers to the tasks within an occupation that can be augmented or enhanced by AI, rather than fully automated. This is determined by factors such as whether the tasks require human communication, complex decision-making, physical presence, or other uniquely human capabilities. For example, workers in occupations with high automation risk and high complementarity, like lawyers, are less likely to be at risk of displacement and more likely to see productivity gains — since generative AI is expected to be able to augment or enhance rather than replace their tasks.

As such, we compare the most in-demand occupations by province in terms of their complementarity and automation risk. Figures 4 and 5 plot regional comparisons of the distribution of the most in-demand occupations with high automation risk and high complementarity vs. low complementarity.

We define relatively high automation risk as those occupations with an automation risk score greater than or equal to 3.02. We follow Pizzinelli et al. (2023) and define relatively high complementarity as being greater than 0.58.

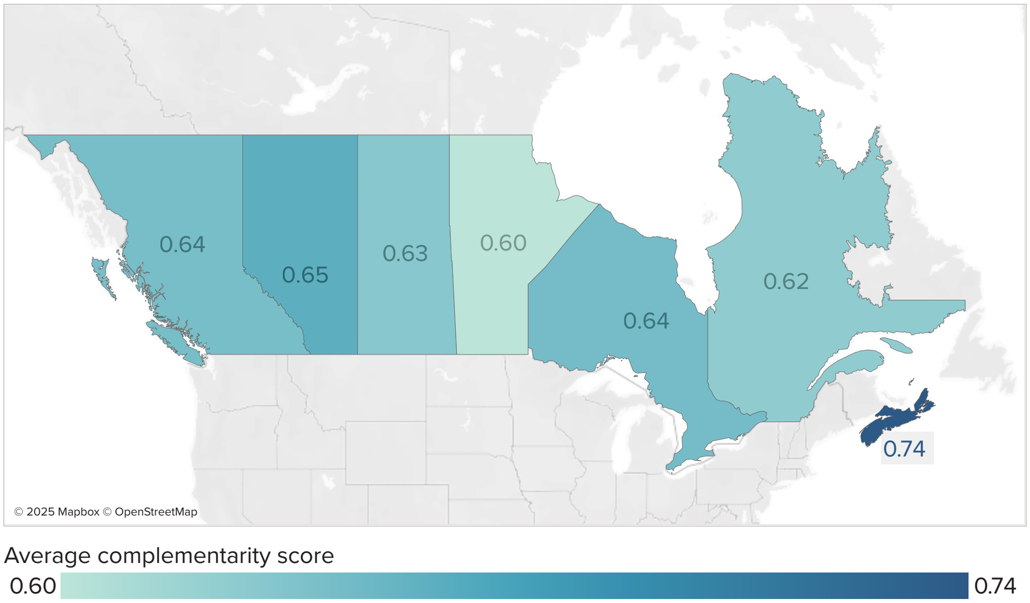
As mentioned previously, occupations exhibiting high automation risk alongside high complementarity indicate a likelihood of benefiting positively from advances in generative AI since there exists a high degree to which generative AI may enhance or supplement, rather than replace, tasks. Similarly, occupations with high automation risk and low complementarity are more likely to face negative repercussions, such as job replacement.

Given this, we can identify regions that are best positioned to benefit from advances in generative AI. These are areas with in-demand occupations that have both high automation risk and high complementarity. Occupations meeting these criteria have a higher potential for augmentation and benefit from generative AI; therefore, the imminent changes caused by advancements in generative AI are more likely to be positive for these regions.

Figure 4 highlights how well positioned each province is to benefit from generative AI in its most in-demand and at-risk roles. We focus on occupations that are both highly exposed to AI-driven automation and likely to benefit from it — those with a high automation risk and high complementarity score. These occupations are matched with a dataset of the most in-demand occupations by province. We then calculate the average complementarity score for each province. The resulting map shows where AI is more likely to enhance rather than replace in-demand jobs, offering key insights for workforce planning and investment in skills development.

Figure 4. In places like Nova Scotia, Alberta, British Columbia and Ontario, in-demand occupations at high risk of generative AI automation with high complementarity are, on average, better positioned to benefit from advances in the technology

Map showing the average complementarity scores of in-demand occupations with high automation risk and high complementarity by province.



Source: Author calculations and the Labour Market Information Council's Canadian Job Trends Dashboard

Figure 5 is similarly constructed but instead focuses on occupations highly exposed to AI-driven automation and unlikely to benefit from it — those with a high automation risk and low complementarity score.

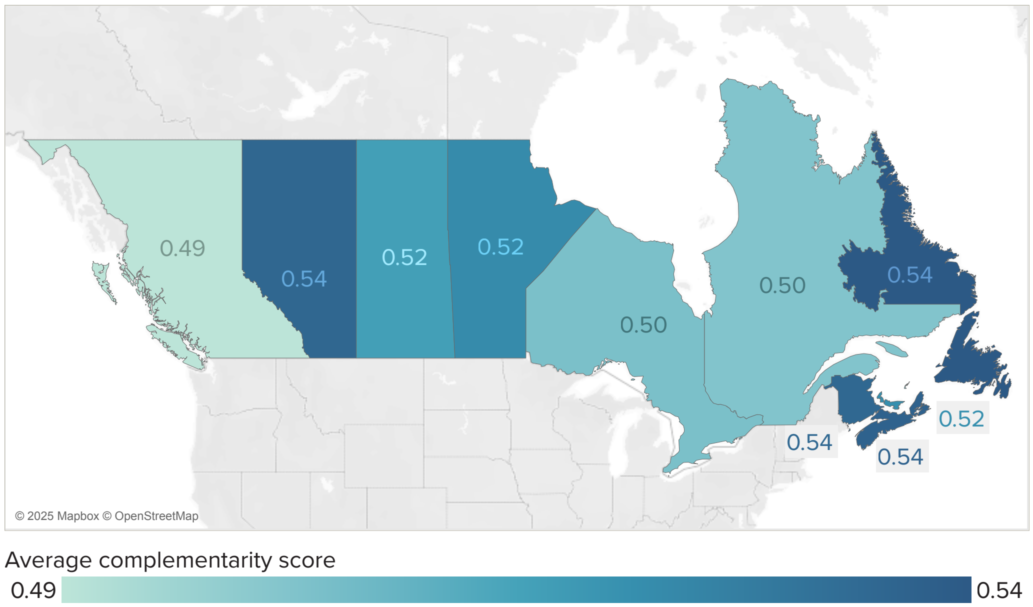
Figure 4 shows that Nova Scotia, Alberta, British Columbia, and Ontario's in-demand occupations with high automation risk show relatively higher complementarity scores. In contrast, some provinces, such as New Brunswick, are not represented on the map, as they do not have occupations that are in high demand and that exhibit high automation risk with a high level of complementarity.

This highlights a critical key takeaway: not all provinces are poised to benefit equally from advances in generative AI. For policymakers, understanding which provinces are less likely to benefit — such as Newfoundland and Labrador or Manitoba — can inform targeted regional interventions to improve labour market robustness.

Moreover, our data reveal clear regional differences in terms of vulnerability. A region is considered vulnerable if it has more in-demand occupations with high generative AI automation risk and low complementarity. Occupations meeting these criteria, as shown in figure 5, are more likely to be negatively impacted by advances in generative AI, as the technology is less likely to complement the required skills and work activities.

Figure 5. In British Columbia, Quebec and Ontario in-demand occupations at high risk of generative AI automation with low complementarity are, on average, more vulenrable to displacement

Map showing the average complementarity scores of in-demand occupations with high automation risk and low complementarity by province.



Source: Author calculations and the Labour Market Information Council's Canadian Job Trends Dashboard.

We observe that more populous provinces like Ontario and Quebec have lower average complementarity across in-demand, high-automation risk, lowcomplementarity occupations than provinces like Newfoundland and Labrador, Nova Scotia, or Alberta. Economic specializations may play a role in these findings; these provinces often employ trades requiring skills and work activities in natural resource sectors, such as fishing, oil, or mining, where certain skills might offer slightly greater complementarity with technology despite high automation risk.

In contrast to figure 4, all provinces are represented in figure 5. This indicates another key takeaway: all Canadian provinces have occupations that are in high demand and likely to see a negative impact from advancements in generative AI. This is significant from a policy perspective, as having high-demand occupations across all provinces vulnerable to generative AI advancements could pose widespread challenges.

If widely held jobs are vulnerable to AI, a significant portion of the workforce could face displacement or the need for rapid reskilling. This could lead to economic instability, including higher unemployment rates and income inequality, which are traditionally addressed through government policy and programs.

At the same time, effective reskilling programs and workforce transitions are not just about mitigating risks — they are also key to ensuring that workers and businesses fully capture the productivity gains made possible by generative AI, in particular for occupations that have high automation risk and high complementarity. By equipping workers with the skills needed for AI-augmented roles, governments and employers can help unlock higher efficiency, innovation, and economic growth.

Governments have a critical role in funding and designing reskilling programs to help workers transition to new roles or adapt their skills to AI-augmented tasks. Without intervention, the workforce might not be able to meet the demands of the evolving labour market.

Overall, these maps highlight a critical asymmetry in the geography of generative AI disruption and opportunity. While workers in some provinces are better positioned (high risk, high complementarity) to benefit in advances in generative AI through the augmentation of existing roles, others face a disproportionate risk of replacement (high risk, low complementarity).[6] The absence of proactive intervention may deepen existing regional inequalities. With regionally tailored support, generative AI can be harnessed to promote inclusive transformation across regions.

REGIONAL EMPLOYMENT VULNERABILITY BY INDUSTRY

While the preceding analysis focused on in-demand occupations and their automation risk, policymakers must also consider the general distribution of high-risk employment across industries and regions. Understanding these patterns is critical for designing effective workforce transition policies, particularly in sectors with a high share of vulnerable jobs. As noted earlier, industries such as transportation, manufacturing, construction, mining and agriculture face a high share of at-risk occupations due to generative AI, particularly those involving routine, standardized tasks. These roles are most vulnerable to automation, as generative AI can optimize workflows, support customer service, and handle tasks like data entry, scheduling and monitoring, leading to efficiency gains across these sectors.

Given regional variations in the types of occupations within industries, the distribution of high-risk employment is likely to differ across regions as well. Accordingly, figure 6 presents the percentage of employment within each industry and province/territory that is categorized as high-risk due to generative AI. As mentioned throughout the report, "automation risk" refers purely to the technical feasibility of a generative AI system replacing or significantly transforming a specific occupational skill or work activity. As such, it does not account for regulatory barriers or the fact that the implementation of AI systems in some cases might require substantial investments and thus take some time to materialize.

As shown in figure 6, the share of high-risk employment varies considerably both by industry and by region. Across the country, industries are made up of slightly different mixes of occupations, reflecting firm-specific differences such as production methods, size, and the availability of labour and resources. We find that some regions have a larger share of people employed in occupations more likely to be impacted by generative AI, even within the same industries.

[6] In some regions, like Ontario and British Columbia, there's a significant presence of in-demand at-risk occupations with both high and low complementarity scores relative to other provinces.

Figure 6. Manufacturing and mining face the highest automation risk in several provinces and territories

Heatmap showing the share of employment at high risk of automation across industries and provinces/ territories in Canada. Manufacturing, mining and transportation sectors exhibit particularly high vulnerability, with notable regional variation.

	Newfoundland and Labrador	Prince Edward Island	Nova Scotia	New Brunswick	Quebec	Ontario	Manitoba	Saskatchewan	Alberta	British Columbia	Nunavut	Northwest Territories	Yukon
Accommodation and food services	16%	16%	17%	16%	23%	14%	16%	17%	15%	15%	14%	20%	11%
Admin & support, waste mgmt & remediation	15%	11%	14%	14%	15%	14%	13%	16%	16%	14%	23%	19%	19%
Agriculture, forestry, fishing and hunting	46%	48%	46%	48%	39%	35%	33%	27%	30%	42%	57%	55%	41%
Arts, entertainment and recreation	6%	7%	4%	7%	6%	6%	7%	6%	6%	6%	0%	13%	2%
Construction	57%	62%	55%	57%	52%	48%	54%	55%	48%	50%	67%	57%	58%
Educational services	4%	5%	3%	4%	3%	2%	5%	5%	4%	4%	7%	4%	4%
Finance and insurance	5%	9%	5%	7%	6%	6%	8%	8%	5%	6%	12%	13%	0%
Health care and social assistance	7%	6%	7%	7%	5%	7%	8%	8%	8%	8%	13%	7%	9%
Information and cultural industries	7%	6%	12%	11%	7%	8%	10%	12%	11%	7%	7%	6%	13%
Management of companies and enterprises	8%	23%	19%	16%	11%	6%	8%	14%	10%	10%	33%	0%	
Manufacturing	64%	58%	57%	58%	50%	52%	59%	55%	52%	51%	67%	68%	67%
Mining, quarrying, and oil and gas extraction	49%	64%	54%	59%	55%	52%	59%	56%	41%	53%	67%	62%	63%
Other services (except public administration)	15%	17%	13%	13%	14%	13%	13%	15%	18%	12%	19%	20%	14%
Professional, scientific and technical services	9%	7%	7%	7%	6%	7%	9%	9%	9%	7%	22%	12%	10%
Public administration	19%	16%	12%	12%	12%	10%	17%	15%	14%	13%	20%	13%	15%
Real estate and rental and leasing	15%	9%	10%	14%	9%	7%	12%	11%	12%	8%	38%	23%	23%
Retail trade	8%	8%	9%	9%	10%	9%	9%	10%	9%	9%	13%	10%	9%
Transportation and warehousing	53%	64%	58%	60%	58%	55%	58%	66%	57%	56%	45%	39%	48%
Utilities	27%	43%	34%	32%	18%	32%	29%	35%	29%	28%	64%	48%	56%
Wholesale trade	28%	32%	23%	23%	24%	21%	26%	29%	24%	23%	24%	23%	14%

High risk share (%)
0% – 68%

Source: Author calculations and the LMIC's Canadian Job Trends Dashboard.

In construction, between 47 per cent and 67 per cent of occupations across all provinces and territories exhibit high risk, with the highest vulnerability in Prince Edward Island (62 per cent) and Nunavut (67 per cent). Similarly, manufacturing shows high vulnerability with 50-67 per cent of occupations at high risk across regions, peaking at 67 per cent in the Northwest Territories and Yukon. This could leave them more susceptible to larger vocational displacement, though it will depend on the technological, financial and social feasibility of automating certain tasks.

Resource-based industries also demonstrate substantial vulnerability. In mining, quarrying, and oil and gas extraction, the share of high-risk employment ranges from 41 per cent in Alberta to almost 67 per cent in Nunavut. While generative AI can optimize certain tasks within these sectors, the manual aspects — such as equipment operation and fieldwork — will likely require significant investments in specialized equipment and technology. These investments may only be feasible where considerable capital has already been committed.

Transportation and warehousing also shows high risk shares, while agriculture, forestry, fishing and hunting exhibits notable variations, from 27 per cent in Saskatchewan to 56 per cent in Nunavut.

In contrast, certain industries show consistently lower shares of high-risk employment. Educational services demonstrate the lowest vulnerability across all provinces, followed by arts, entertainment and recreation, and finance and insurance. Health care and social assistance also shows relatively low risk shares.

These findings complement our earlier analysis of in-demand occupations in important ways. While Ontario exhibits high average automation risk from generative AI for its most in-demand occupations, we also see that several industries in Ontario have moderate shares of high-risk employment compared to other provinces. For example, Ontario's construction industry shows a 48 per cent high-risk share, which is lower than most other provinces. Conversely, while our LQ analysis indicated lower average risk in Prince Edward Island's most in-demand occupations, the province shows elevated high-risk shares in several key industries, including construction and transportation.

Regional patterns also emerge that may require policy attention. Nunavut consistently shows very high shares of high-risk employment across multiple industries. The Northwest Territories similarly shows elevated vulnerability across several sectors. Further studies are needed to understand the economic factors behind these differences in the occupational structures of industries across regions.

These patterns suggest that certain regions may face more widespread workforce disruption from generative AI than others, across both current and indemand employment.

From a policy perspective, regions with high shares of high-risk occupations across multiple industries may need more comprehensive transition strategies, even in cases where the most in-demand occupations in these regions show lower average risk. This dual perspective — considering both occupational demand patterns and the current distribution of high-risk employment — provides a more complete foundation for targeted policy intervention.

WHAT DOES THE EVIDENCE REVEAL SO FAR?

Concern about artificial intelligence's impact on work has intensified with the emergence of generative AI — systems capable of creating content across text, code and other media. While previous waves of automation primarily affected routine manual and cognitive tasks, generative AI's ability to perform complex cognitive and creative tasks has raised new questions about its implications for Canada's workforce. This study provides empirical evidence of how generative AI could affect Canadian workers over the next five years, examining its impact across skills, work activities, occupations, industries and regions.

Our analysis of generative AI's automation potential reveals three significant patterns in the Canadian labour market. First, the impact varies substantially across different types of skills and work activities. Clerical activities show the highest automation risk (4.29 out of 5), followed by operation monitoring (3.96) and data analysis (3.92). In contrast, skills involving human interaction and judgment — such as instructing (2.04), social perceptiveness (2.08) and coaching (2.17) — demonstrate markedly lower automation risk. This pattern suggests that, while generative AI may significantly transform information processing and monitoring tasks, it is less likely to replace activities requiring interpersonal skills and judgment-based functions.

Second, the evidence indicates that generative AI is more likely to transform the composition of work within occupations rather than eliminate entire job categories. Among occupations representing about 50 per cent of total Canadian employment, automation risk scores fall within a moderate range (2.77-3.3), suggesting partial rather than complete automation. In other words, most occupations will evolve rather than disappear, with workers needing to adapt to changing task compositions. However, the extent of this transformation will depend on factors beyond technical feasibility, including employer adoption strategies, worker reskilling efforts, and policy interventions. Governments will play a critical role in supporting workforce transitions through education and training investments, while businesses will need to implement AI in ways that enhance, rather than replace, human work.

Third, our analysis reveals significant regional and industry variations in automation risk. Transportation and warehousing (56.4 per cent), manufacturing (51.9 per cent), and construction (50 per cent) show the highest shares of high-risk occupations, while educational services (3.1 per cent) and finance and insurance (5.8 per cent) demonstrate lower vulnerability. Regional analysis indicates that Ontario and Manitoba have higher concentrations of at-risk occupations in their most in-demand jobs, while Prince Edward Island and Newfoundland and Labrador show greater resilience. These patterns suggest that the impact of generative AI will not be uniform across Canada's economy, necessitating targeted policy responses.

The evidence also highlights important implementation challenges that will influence the pace and impact of generative AI adoption. Canada currently lags other G7 countries in AI adoption, with only 3.1 per cent of companies having implemented AI technologies by 2022. Two critical barriers emerge from the data: insufficient AI-enabling infrastructure and a shortage of AI-ready talent. Canada's recent drop to 23rd place globally in AI infrastructure underscores these challenges. This suggests that, while generative AI offers significant potential for workplace transformation, actual changes may occur more gradually than technical feasibility alone would indicate.

Looking ahead, our analysis indicates that the ultimate impact of generative AI on Canada's workforce will depend on several interrelated factors. While traditional AI adoption is constrained by infrastructure limitations, generative AI presents a unique dynamic. Unlike traditional AI systems that require significant organizational investment, generative AI tools are increasingly accessible to individual workers through consumer-facing applications. However, this accessibility creates both opportunities and risks. Without proper AI literacy and digital skills, workers may use these tools ineffectively or inappropriately, potentially reducing rather than enhancing productivity. This is echoed in a recent study by the Conference Board of Canada on the use of generative AI. According to the authors, generative AI has the potential to provide a significant boost to Canada's economy — adding around 2 per cent to GDP — if deployed correctly (The Conference Board of Canada, 2024). Crucially, the report notes that AI talent and an AI-ready workforce are key factors in this process. Yet, a lack of an AI-ready workforce appears to be one of the biggest bottlenecks (Pamma, 2024).

The key challenge for policymakers and business leaders will therefore be the following:

1. **Accelerate AI Infrastructure Investment**
   The federal government should continue investing in AI infrastructure, including AI compute capacity, data centres and broadband access as part of the AI Compute Access Fund and the Canadian AI Sovereign Compute Strategy (ISED, 2025a, 2025b). This will enable AI researchers, startups and businesses to have the necessary resources to innovate and scale AI solutions, ensuring equitable access across all regions.

   Canada has made strides with the $2 billion AI investment in Budget 2024 but significant gaps remain in AI infrastructure (Finance Canada, 2024) These investments should be scaled to ensure equitable access for small businesses and underrepresented regions, supporting the overall AI ecosystem. High-performance computing is critical to ensuring that AI innovation is both scalable and sustainable. However, without widespread broadband access, regions with limited internet connectivity may be left behind in the AI revolution, as access to AI tools and cloud-based computing requires reliable, high-speed internet.

2. **Foster a National AI Literacy Initiative**
   The federal government should work with the provinces and territories to implement a comprehensive AI literacy program across secondary, post-secondary and adult learning levels. This program should focus on digital literacy and complementary skills — such as critical thinking, problem-solving and leadership skills — that are vital in an AI-augmented workforce and exhibit low automation risk. Importantly, AI literacy should also emphasize human oversight and ethical engagement with AI tools.

   Digital and AI literacy are crucial to preparing workers across all sectors for AI integration (Oschinski et al., 2024). Recent Canadian government AI consultations highlight the skills gap in AI knowledge and the lack of readiness among workers to engage with AI tools effectively (Government of Canada, 2024).

3. **Strengthen Public-Private Partnerships for Workforce Reskilling**
   The government should facilitate work-based learning programs that provide hands-on experience in AI. These programs should be collaborative in nature, with input from businesses, industry associations and educational institutions to create industry-relevant AI curricula. Apprenticeships and internships have proven to be effective at connecting education to real-world industry needs, particularly in AI fields. Moreover, they are effective pathways for underrepresented groups to gain access to emerging jobs (Koslosky & Feldgoise, 2025). By providing workers with both technical skills and practical experience, Canada can enhance the talent pipe-

line and ensure workers are ready to step into AI roles directly. This approach also empowers workers to anticipate how generative AI is reshaping their industries and to proactively identify opportunities where their skills can be applied. In this context, expanding the programs like the National Research Council's AI Assist Program, ISED's AI Compute Access Fund and the Regional Artificial Intelligence Initiative (ISED 2024 and 2025c), could help small and medium-sized businesses to adopt AI tools while simultaneously upskilling their workforce in AI technologies.

4. **Support Region-Specific Workforce Development Strategies**
   To address the regional disparities in AI adoption, the government should implement regional workforce strategies tailored to the specific economic contexts of each province/territory. These strategies should focus on reskilling workers in high-risk sectors and regions with high concentrations of vulnerable occupations.

   As our analysis has shown, the impact of AI will not be uniform across Canada. Different regions have varying levels of AI infrastructure access and exposure to automation risks. Developing region-specific programs is key to ensuring equitable workforce development. In this context, expanding the Sectoral Workforce Solutions Program (ESDC, 2022) funding to target specific regions with higher automation risks could be part of a broader regional development strategy.

5. **Strengthen AI Talent Development and Retention**
   Canada should invest in AI talent development through research grants, AI-related apprenticeships, and collaborations with businesses. This includes attracting and retaining AI researchers and practitioners, especially in emerging fields of AI application, by offering competitive incentives and training programs.

   To strengthen its position in AI, Canada must expand its AI talent pipeline and ensure that research institutes and startups can attract and retain skilled professionals. AI-related apprenticeships, industry collaborations and effective workforce training programs can contribute to building a sustainable talent pool, ensuring that Canada can compete effectively on the global AI stage (Koslosky and Feldgoise, 2025; Oschinski et al., 2024).

While this study provides an important baseline assessment of generative AI's potential impact, further research is needed to fully understand how automation risk translates into real-world workforce shifts. Future studies could examine employer adoption strategies, firm-level AI investment trends, and the effectiveness of reskilling programs in preparing workers for AI-augmented roles. Additionally, longitudinal research tracking workforce adaptation over time will be crucial for evaluating how generative AI reshapes employment patterns in practice.

Monitoring these changes will be crucial as generative AI continues to evolve. Ongoing assessment of how Canadian jobs actually transform as this technology is deployed will be essential for informing policy responses and workforce development strategies.

APPENDICES

APPENDIX A

As OpenAI develops its models, it retires older versions. At the time of analysis, GPT-4 was running on version GPT-4-0613, the model used in this research. A comparison between each of the model versions used in this paper is shown in table A1. This bolsters the thoroughness of the methodology described in the paper, as it takes into account another source of variation in GPT's ability to provide consistent automation risk scores.

Table A1. Comparison of GPT models used

GPT-4-0613	Instruct-GPT
Version from GPT-4 model series	Name of model series
Training data up to September 2021	Trained with human feedback
Released June 13, 2023	Used as the default language model in the API
Improves upon GPT-3.5	Better at following English instructions
Can understand and generate natural language or code	Makes up facts less often; significantly preferred on prompts submitted to the InstructGPT and GPT-3 models on the API

Source: OpenAI (n.d.-a., n.d.-b.).

APPENDIX B

Below is a list of prompt parameters and hyperparameters. In writing a script to use the GPT API, there are certain technical specifications that users may input to alter the consistency, length or any of the other response traits that arise. The hyperparameters most relevant to our study — and which were used in some of our prompts — are listed below to provide a complete view of the thoroughness of our approach.

- Temperature: Controls the randomness of the output. Setting this close to 1.0 may introduce some randomness; a value closer to 0 will produce deterministic rankings.
- Top_P: 0.1: How many options GPT considers before choosing the next word in its response. If set to 0.1, the model only looks at words that make up the top 10 per cent of the most likely options. If set closer to 0, the choices will be narrower. Only used in prompts that use post-processing explanations.
- Batch Size: Number of data points used in each iteration during training (impacts model convergence).
- Template-Based Prompt: Suggested method of creating prompt structures (as seen in appendix C) to improve consistency in outputs.
- Frequency Penalty: Used to penalize the frequency of words in the model's output. Only used in prompts that use post-processing explanations.
- Presence Penalty: Discourages the use of words from the input prompt in the response. Can create more/less diverse ranking. Only used in prompts that use post-processing explanations.
- Prompt Ranking Criteria: Use of defined ranking criteria (e.g., 1 = some explanations, 5 = some explanation) to improve consistency in outputs.

APPENDIX C

Below are the different prompts that were fed to the ChatGPT Application Programming Interface (API) in order to retrieve automation risk scores for skills and work activities. The purpose of using different prompt variations in this process was to be able to average out automation risk scores and ensure consistency in the API outputs.

Version 1

Please rate the automatability of the skill in the context of generative AI development over the medium term (next 5 years) on a scale of 1 to 5, where:

1 = Not automatable
2 = Slightly automatable
3 = Moderately automatable
4 = Highly automatable
5 = Fully automatable

Please provide a single numerical rating based on this scale!

Version 2

As an AI expert how would you rate the automatability of the following skill over the medium term (next 5 years). Please provide a short explanation and rate automatability on a scale of 1 (=not automatable) to 5 (=fully automatable).

Version 3

Same prompt as version 2. In this version, skills and work activities include descriptions from OaSIS.

Version 4

Assume you are an expert in generative AI: As such rate how the following skill can be automated by generative AI. Please use a scale from 1 to 5 whereby 1 = 'not automatable' and 5 = 'fully automatable'. As an answer, please just give 1 single number!

Version 5

Assume you are an expert in generative AI: As such rate how the following skill can be automated by generative AI. Please use a scale from 1 to 5 whereby 1 = 'not automatable' and 5 = 'fully automatable'. As an answer, please give 1 single number and a short explanation for your rating!

Version 6

Please rate the following occupational skill for its susceptibility to advances in generative AI over the next 5 years on a scale of 1 to 5, where:

1 = Not automatable: This skill is unlikely to be automated by generative AI in the next 5 years.
2 = Slightly automatable: This skill may see limited automation by generative AI in the next 5 years.

3 = Moderately automatable: This skill has a moderate chance of being automated by generative AI in the next 5 years.
4 = Highly automatable: This skill is likely to be automated by generative AI to a significant extent in the next 5 years.
5 = Fully automatable: This skill is highly likely to be completely automated by generative AI in the next 5 years.

Please provide a single numerical rating for each skill based on this scale. Also include a brief and concise explanation for the rating.

Version 7

Same prompt as version 6. In this version, the frequency penalty is set to 0.2 and presence penalty is set to 0.5. In version 6, both penalty values were set to 0.

Version 8

Please assess the following occupational skill for its susceptibility to automation due to developments in generative AI over the next 5 years on a scale of 1 to 5, where:

1 = Not automatable: This skill is unlikely to be automated by generative AI in the next 5 years.
2 = Slightly automatable: This skill may see limited automation by generative AI in the next 5 years.
3 = Moderately automatable: This skill has a moderate chance of being automated by generative AI in the next 5 years.
4 = Highly automatable: This skill is likely to be automated by generative AI to a significant extent in the next 5 years.
5 = Fully automatable: This skill is highly likely to be completely automated by generative AI in the next 5 years.

Please provide a single numerical rating for each skill based on this scale. Also include a brief and concise explanation for the rating.

Version 9

Same prompt as version 8. In this version, the frequency penalty is set to 0.2 and presence penalty is set to 0.5. In version 8, both penalty values were set to 0.

Version 10

Please rate the following skill for its susceptibility to advances in generative AI over the medium term (next 5 years) on a scale of 1 to 5, where:

1 = Not automatable: This skill is unlikely to be automated by generative AI in the next 5 years.
2 = Slightly automatable: This skill may see limited automation by generative AI in the next 5 years.
3 = Moderately automatable: This skill has a moderate chance of being automated by generative AI in the next 5 years.

4 = Highly automatable: This skill is likely to be automated by generative AI to a significant extent in the next 5 years.
5 = Fully automatable: This skill is highly likely to be completely automated by generative AI in the next 5 years.

Please provide a single numerical rating for each skill based on this scale.

Version 11

As an expert in labour and technology how would you rate the automatability of the following skill over the medium term (= the next 5 years). Please rate the automatability on a scale of 1 (=not automatable) to 5 (=fully automatable).

Version 12

As an expert on skills and emerging technologies how would you rate the automatability of the following skill over the medium term (= the next 3-5 years). Please rate the automatability on a scale of 1 (=not automatable) to 5 (=fully automatable).

APPENDIX D

To ensure consistency across prompts and the scores generated by GPT, a prompt structure was used as a tool to generate the prompt variations seen in appendix C. This structure is a loose outline and was modified slightly across prompts that asked for explanations or for the API to assume the role of an expert.

- Verb 1: rate, assess
- Noun 1: skill, work activity, occupational skill
- Verb 2: automatability, susceptibility to, automation
- Noun 2: in the context of, advances in, due to developments in
- Period: over the medium term (next 5 years), over the next 5 years, over the medium term (the next 3-5 years)
- Verb 3: return, give
- Return: single number, single numerical rating

Each bolded area below indicates where one of the above variables would be inserted:

Please [**Verb 1**] the following [**Noun 1**] for its [**Verb 2**] [**Noun 2**] generative AI [**Period**], where:

1 = ...
2 = ...
3 = ...
4 = ...
5 = ...

Please [**Verb 3**] a [**Return**] based on the defined scale.

APPENDIX E

Table A2. OaSIS skills and work activities with associated automation risk scores

Skill/Work activity	Descriptor	Automation risk score
Clerical Activities	Entering, transcribing, recording, storing, or maintaining all types of information in written or electronic form.	4.29
Operation Monitoring of Machinery and Equipment	The capability to watch gauges, dials, digital displays or other indicators to ensure a machine or piece of equipment is working according to specifications.	3.96
Analyzing Data or Information	Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.	3.92
Monitoring	The capability to monitor and assess the performance of yourself, other individuals or the organization, to make improvements or take corrective action.	3.88
Writing	The capability to communicate in text by using written words, sentences, paragraphs, symbols, and images, adapted for the needs of the audience.	3.71
Interacting with Computers	Using computers, computer systems (including hardware and software), and equipment with digital interface to program, write software, set up functions, enter data, process information, or control machines.	3.67
Getting Information	Observing, receiving, or obtaining information from all relevant sources.	3.62
Oral Communication: Oral Expression	The capability to talk to others and convey information effectively.	3.62
Scheduling Work and Activities	Scheduling events, programs, and activities, as well as the work of others.	3.62
Identifying Objects, Actions, and Events	Identifying information by categorizing, recognizing differences or similarities, measuring, investigating, and detecting changes in circumstances or events.	3.58
Numeracy	The capability to understand, use and report numbers and other mathematical information presented through words, numbers, symbols, and graphics.	3.58
Decision Making	The capability to analyze information among a set of alternatives, to evaluate potential outcome and choose the most appropriate solutions to achieve a predetermined objective.	3.5
Estimating the Quantifiable Characteristics of Products, Events, or Information	Estimating cost, resources or materials needed to perform a work activity.	3.5
Monitoring Processes, Materials, or Surroundings	Tracking and reviewing information from materials, events, or the environment to detect or assess problems and progress.	3.5
Preventative Maintenance	The capability to perform maintenance on equipment, devices, buildings or machinery, to keep them functional and to prevent damage or failures.	3.5
Mechanical Maintenance	Servicing, repairing, adjusting, or testing machines, devices, moving parts, and equipment that operate on mechanical principles.	3.46

Table A2. OaSIS skills and work activities with associated automation risk scores (cont.)

Skill/Work activity	Descriptor	Automation risk score
Operation and Control	The capability to maneuver and control operations of equipment, machines, vehicles or systems.	3.46
Processing Information	Compiling, categorizing, tabulating, auditing, or verifying information or data.	3.46
Reading Comprehension	The capability to understand written information presented through words, sentences, paragraphs, symbols, and images in work-related documents.	3.46
Using New Relevant Knowledge	Keep up-to-date on relevant theorical and technical knowledge and apply them at work.	3.46
Controlling Machines and Processes	Using mechanisms or physical activity to control the operation of machines or processes (excluding computers or vehicles).	3.42
Performing General Physical Activities	Performing physical activities that require use of your arms and legs, and moving your whole body, such as climbing, lifting, balancing, walking, stooping, and handling materials.	3.42
Judging Quality	Assessing the value, importance or quality of materials, products, services or people.	3.29
Management of Material Resources	The capability to plan and manage the purchase, inventory, warehousing, transportation, or distribution of products or materials and their use.	3.25
Planning and Organizing	Developing specific goals and plans to prioritize and organize tasks to get work done.	3.21
Making Decisions	Choosing the best solution based on analysis of information and the evaluation of potential results.	3.17
Operating Vehicles, Mechanized Devices, or Equipment	Manoeuvring, navigating, or driving vehicles or mechanized equipment, such as forklifts, passenger vehicles, aircraft, or watercraft.	3.17
Interpreting the Meaning of Information for Others	Translating or explaining what information means and how it can be used.	3.12
Quality Control Testing	The capability to conduct tests or inspections of prototypes, products, services, or processes to ensure their quality.	3.12
Digital Production	The capacity to design, develop, adapt, or integrate hardware, software applications, electronic devices or digital technologies while adhering to cybersecurity standards.	3.08
Inspecting Equipment, Structures, or Material	Inspecting equipment, structures, or material to identify the cause of errors, problems or defects.	3.08
Thinking Creatively	Generating innovative or creative ideas to develop or design new applications, products, including artistic contributions.	3.08
Time Management	The capability to manage one's own time and the time of others.	3.08
Setting Up	The capability to set up, adjust, install and assemble equipment, machines, parts, or to prepare them for their functioning and use.	3.04
Critical Thinking	The capability to use logic and reasoning to question, discern, interpret and analyze various types of information to form an evidence-based conclusion or judgment.	3

Table A2. OaSIS skills and work activities with associated automation risk scores (cont.)

Skill/Work activity	Descriptor	Automation risk score
Systems Analysis	The capability to determine how a system should work and how changes in conditions, operations, and the environment will affect outcomes.	3
Digital Literacy	The capability to understand and use digital devices and tools to obtain, exchange, create or process digital information in a secure manner.	2.96
Handling and Moving Objects	Using hands and arms to install, fabricate and repair objects; or to move or manipulate objects and materials (excluding construction occupations).	2.96
Coordinating	The capability to organize people or groups by adjusting activities in relation to others' activities, so that they work effectively as a whole.	2.92
Managing Resources	Determining, acquiring, monitoring and controlling any kind of resources and overseeing the spending of money.	2.92
Evaluating Information to Determine Compliance with Standards	Using relevant information and individual judgment to determine whether events or processes comply with laws, regulations or standards.	2.88
Product Design	The capacity to design and develop layouts for the construction of objects, equipment, machinery, structures, or engineering systems (excluding software and hardware).	2.88
Troubleshooting	The capability to determine causes of operating errors in equipment, machinery, or technological systems, and decide how to resolve the issues.	2.88
Electronic Maintenance	Servicing, repairing, calibrating, regulating, fine-tuning, or testing machines, devices, and equipment that operate on electrical or electronic principles.	2.83
Negotiating	The capability to participate in, or facilitate, communication between parties, in order to resolve differences, and reach a mutually acceptable or viable agreement.	2.83
Performing for, or Working Directly with, the Public	Working or interacting directly with the public, or performing for public audiences.	2.83
Communicating with Persons Outside Organization	Sharing or exchanging information with people outside the organization, representing the organization to customers, the public, government or other external sources.	2.79
Developing Technical Instructions	Providing documentation, detailed instructions, drawings, or specifications to tell others about how devices, parts, equipment, or structures are to be fabricated, constructed, assembled, modified, maintained, or used.	2.79
Evaluation	The capability to systematically assess products, services or processes using measurable indicators, with the goal of ensuring or improving performance.	2.79
Management of Financial Resources	The capability to plan, organize, direct, control or monitor financial resources and activities and account for the use of these resources to ensure their utilization conforms to the objectives and purposes.	2.79
Developing Objectives and Strategies	Define and establish medium to long-term objectives, and determine strategies and actions to achieve them.	2.75

Table A2. OaSIS skills and work activities with associated automation risk scores (cont.)

Skill/Work activity	Descriptor	Automation risk score
Staffing	Recruiting, interviewing, selecting, hiring, and promoting employees in an organization (excluding non-recruitment interviews).	2.75
Oral Communication: Oral Comprehension	The capability to listen to and understand information and ideas presented through spoken words and sentences.	2.71
Providing Consultation and Advice	Providing guidance and expert advice to management or other groups on technical, systems, or process related topics.	2.71
Resolving Conflicts and Negotiating with Others	Handling complaints, settling disputes, and resolving grievances and conflicts, or otherwise negotiating with others.	2.71
Equipment and Tool Selection	The capability to choose between two or more types of tools, equipment or machinery to perform a job.	2.67
Problem Solving	The capability to identify problems and review related information to develop solutions or feasible options to achieve the desired end state.	2.67
Training and Teaching	Identifying the educational needs of others, developing formal educational, training programs or classes, and teaching or instructing others.	2.67
Team Building	Encouraging and building mutual trust, respect, and cooperation among team members.	2.62
Selling or Influencing Others	Convincing others to buy goods or services, or to change their minds or actions.	2.58
Learning and Teaching Strategies	The capability to select and use training/instructional methods and procedures appropriate for the situation when learning or teaching new things.	2.54
Communicating with Co-workers	Sharing or providing information or advice to management, supervisors, co-workers and subordinates on work related topics.	2.5
Establishing and Maintaining Interpersonal Relationships	Developing respectful, constructive, and cooperative working relationships with others, and maintaining them over time.	2.42
Oral Communication: Active Listening	The capability to give full attention to what other people are saying, take time to understand the points being made, ask questions as appropriate, and not interrupt at inappropriate times.	2.42
Repairing	The capability to replace, restore or adjust defective or deficient components in equipment, machines, and technical systems and test for function, appearance, operation and safety.	2.38
Persuading	The capability to convince others to change their minds, beliefs, intentions or behaviours.	2.33
Management of Personnel Resources	The capability to recruit, train, motivate, develop and direct employees, identify the best person for the tasks to be performed, and establish their work objectives in relation to the objectives of the organization.	2.25
Supervising Subordinates	Provide guidance and direction to subordinates, including the establishment of work outcomes for performance monitoring.	2.25
Coordinating the Work and Activities of Others	Getting members of a group to work together to accomplish tasks.	2.21

Table A2. OaSIS skills and work activities with associated automation risk scores (cont.)

Skill/Work activity	Descriptor	Automation risk score
Coaching and Developing Others	Identifying the developmental needs of others and coaching, mentoring, or otherwise helping others to improve their knowledge or skills.	2.17
Assisting and Caring for Others	Providing personal assistance, medical attention, emotional support, or other care to customers, clients, or patients.	2.08
Social Perceptiveness	The capability to be aware of others' reactions, unspoken communication, body language cues and feelings and discern the reasons behind their behaviours.	2.08
Instructing	The capability to impart knowledge on others, or how to do something.	2.04

REFERENCES

Acemoglu, D. (2024a, May 21). Don't believe the AI hype. *Project Syndicate*.

Acemoglu, D., & Johnson, S. (2023). *Power and progress*. PublicAffairs.

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labour. *Journal of Economic Perspectives*, *33*(2), 3-30.

Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in U.S. wage inequality. *Econometrica*, *90*(5), 1973-2016.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial intelligence: The ambiguous labor market impact of automating prediction. *Journal of Economic Perspectives*, *33*(2), 31-50.

Alabdulkareem, A., Frank, M. R., Sun, L., AlShebli, B., Hidalgo, C., & Rahwan, I. (2018). Unpacking the polarization of workplace skills. Science Advances, 4(7), https://doi.org/10.1126/sciadv.aao6030

Ali, H., ul Mustafa, A., & Aysan, A. F. (2024). Global adoption of generative AI: What matters most? *Journal of Economy and Technology.*

Bender, S., & Li, K.-W. (2002). *The changing trade and revealed comparative advantages of Asian and Latin American manufacture exports*. http://www.econ.yale.edu/~egcenter/http://papers.ssrn.com/abstract=303259.

Bick, A., Blandin, A., & Deming, D. J. (2024). *The rapid adoption of generative AI.* Working Paper 32966. National Bureau of Economic Research.

Billy-Ochieng', R., Anusha, A., & Garcia, D. (2024, May 28). *Artificial intelligence technologies can help address Canada's productivity slump.* TD Economics.

Bonney, K., Breaux, C., Buffington, C., Dinlersoz, E., Foster, L. S., Goldschlag, N., Haltiwanger, J. C., Kroff, Z., & Savage, K. (2024). *Tracking firm use of AI in real time: A snapshot from the Business Trends and Outlook Survey.* Working Paper 32319. National Bureau of Economic Research.

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can machines learn and what does it mean for occupations and the economy? *AEA Papers and Proceedings*, *108*, 43-47. https://doi.org/10.1257/pandp.20181019.

Burt, M. (2023). *ChatGPT: Organizational and Labour Implications. (2023, November 16).* The Conference Board of Canada. https://www.conferenceboard.ca/product/chatgpt_november2023/

Caranci, B., & Marple, J. (2024, September 12). *From bad to worse: Canada's productivity slowdown is everyone's problem.* TD Economics.

Carnevale, A. P., Jayasundera, T., & Repnikov, D. (2014). *Understanding online job ads data*. https://cew.georgetown.edu/wp-content/uploads/2014/11/OCLM.Tech_.Web_.pdf.

Conference Board of Canada. (2024). *Real talk: How generative AI could close Canada's productivity gap and reshape the workplace — Lessons from the innovation economy*. Conference Board of Canada.

Corrigan, C. C., & Ikonnikova, S. A. (2024). A review of the use of AI in the mining industry: Insights and ethical considerations for multi-objective optimization. *The Extractive Industries and Society, 17,* Article 101440.

Council of Economic Advisers. (2024, July 10). *Potential labor market impacts of artificial intelligence: An empirical analysis.* The White House.

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). *GPTs are GPTs: An early look at the labour market impact potential of large language models*. http://arxiv.org/abs/2303.10130.

Employment and Social Development Canada (ESDC). (2022). About the Sectoral Workforce Solutions Program. Government of Canada. https://www.canada.ca/en/employment-social-development/programs/sectoral-workforce-solutions-program.html.

Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal, 42*(12), 2195-2217.

Finance Canada. (2024). *Budget 2024: Fairness for every generation.* Government of Canada. https://budget.canada.ca/2024/home-accueil-en.html.

Frank, K., & Frenette, M. (2021). *Are new technologies changing the nature of work? The evidence so far.* IRPP Study 81. Institute for Research on Public Policy.

Frey, C. B., & Osborne, M. (2013). *The future of employment*. Oxford Martin School Working Paper.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019.

Gmyrek, P., Berg, J., & Bescond, D. (2023). *Generative AI and jobs: A global analysis of potential effects on job quantity and quality*. ILO Working Paper 96. International Labour Organization. https://www.ilo.org/wcmsp5/groups/public/---dgreports/---inst/documents/publication/wcms_890761.pdf.

Government of Canada. (2024, November 22). *What we heard report: Consultations on AI Compute*. https://ised-isde.canada.ca/site/ised/en/what-we-heard-report-consultations-ai-compute.

Innovation, Science and Economic Development Canada (ISED). (2024, October 22). *Federal government launches programs to help small and medium-sized enterprises adopt and adapt artificial intelligence solutions* [News release]. Government of Canada. https://www.canada.ca/en/innovation-science-economic-development/news/2024/10/federal-government-launches-programs-to-help-small-and-medium-sized-enterprises-adopt-and-adapt-artificial-intelligence-solutions.html.

Innovation, Science and Economic Development Canada (ISED). (2025a). *AI Compute Access Fund.* Government of Canada. https://ised-isde.canada.ca/site/ised/en/canadian-sovereign-ai-compute-strategy/ai-compute-access-fund.

Innovation, Science and Economic Development Canada (ISED). (2025b). *Canadian Sovereign AI Compute Strategy.* Government of Canada. https://ised-isde.canada.ca/site/ised/en/canadian-sovereign-ai-compute-strategy.

Jiang, J., Zhou, K., Dong, Z., Ye, K., Zhao, W. X., & Wen, J. R. (2023). StructGPT: A general framework for large language model to reason over structured data. arXiv preprint. arXiv:2305.09645.

Kinder, M., Muro, M., Liu, S., & de Souza Briggs, X. (2024, October 10). *Generative AI, the American worker, and the future of work*. Brookings. https://www.brookings.edu/articles/generative-ai-the-american-worker-and-the-future-of-work/.

Koslosky, L., & Feldgoise, J. (2025). *The state of AI-related apprenticeships.* CSET Data Brief, February 2025. https://cset.georgetown.edu/publication/the-state-of-ai-related-apprenticeships/.

Lesonsky, R. (2023, April 17). The future of retail: What the stats say about retailers in 2023. *Forbes Newsletter*.

Mehdi, T., & Morissette, R. (2024, September 3). *Experimental estimates of potential artificial intelligence occupational exposure in Canada.* Statistics Canada.

Moll, B., Rachel, L., & Restrepo, P. (2022). Uneven growth: Automation's impact on income and wealth inequality. *Econometrica*, *90*(6), 2645-2683. https://doi.org/10.3982/ecta19417.

Nuño, B. S. A. (2023, June 8). *The Gutenberg Moment in AI and it's shadow, the end of digital presumption of veracity.* Blog post. https://world.hey.com/brunosan/the-gutenberg-moment-in-ai-and-it-s-shadow-the-end-of-digital-presumption-of-veracity-02893edd.

OpenAI. (n.d.-a). *OpenAI platform documentation*. https://platform.openai.com/docs/models/.

OpenAI. (n.d.-b). *OpenAI research: Aligning language models to follow instructions.* https://openai.com/research/instruction-following.

Oschinski, M., Crawford, A., & Wu, M. (2024). *AI and the future of workforce training.* CSET Issue Brief, December 2024. https://cset.georgetown.edu/publication/ai-and-the-future-of-workforce-training/

Oschinski, M., and Nguyen, T. (2022). *Finding the Right Job: A Skills-Based Approach to Career Planning*. IRPP Study 86. Montreal: Institute for Research on Public Policy. DOI: https://doi.org/10.26070/5paz-x420

Oxford University Press. (2023). Artificial intelligence. In *Oxford English Dictionary.*

Pamma, A. (2024, January 23). AI adoption in Canada rising, but upskilling remains top barrier: IBM. *IT World Canada*. https://www.itworldcanada.com/article/ai-adoption-in-canada-rising-but-upskilling-remains-top-barrier-ibm/556849.

Pizzinelli, C., Panton, A. J., Tavares, M. M. M., Cazzaniga, M., & Li, L. (2023). *Labor market exposure to AI: Cross-country differences and distributional implications*. International Monetary Fund.

Rane, J., Kaya, O., Mallick, S. K., & Rane, N. L. (2024). Smart farming using artificial intelligence, machine learning, deep learning, and ChatGPT: Applications, opportunities, challenges, and future directions. In J. Rane, O. Kaya, S. K. Mallick, & N. L. Rane (Eds.), *Generative artificial intelligence in agriculture, education, and business* (pp. 218-272). DeepScience.

Trajtenberg, M. (2018). *AI as the next GPT: A political-economy perspective*. Working Paper No. 24245. National Bureau of Economic Research.

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