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Machine learning and the labour market

A portrait of occupational and worker inequities in Canada

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Executive summary

Machine learning, an artificial intelligence subfield, is increasingly being used by Canadian firms to drive innovation and raise productivity. The capacity for machine learning to learn, adapt, and generate outputs with increasing independence means that the technology could be used to partially or fully perform job tasks that are physical or cognitive in nature, across a broad range of industries and occupations.

Concerningly, the potential negative and positive impacts of machine learning may be distributed inequitably across occupations and worker groups. Workers who are better positioned in the labour market may be more likely to capitalize on positive economic advantage stemming from machine learning when compared to those from socially and economically disadvantaged groups. Those in socially or economically disadvantaged positions in the labour market may be negatively affected by machine learning.

In this report, we utilized a novel analytical approach to examine the extent to which different Canadian occupations may be exposed to machine learning. This means that they consist of job tasks that are suitable to being completed by the technology. Through this approach, we estimated different occupational and worker characteristics that related to high or low occupational machine learning exposure.

Three main objectives were addressed by our research

- Estimated the number of workers in occupations characterized by job tasks with high or low suitability to be performed by machine learning in Canada.
- Examined how potential for machine learning exposure differs according to workers' socio-demographic (e.g., educational attainment, gender) and occupational characteristics (e.g., hourly wages, job skills, training and experience requirements).
- Determined whether the association between educational attainment, job skills, training and experience requirements, hourly wages, and potential machine learning exposure is the same or different for men and women.

Summary of methodological approach

We pooled data from eight years of Statistics Canada's Labour Force Survey (LFS) questionnaires. The suitability for machine learning (SML) measure was used to examine occupational exposure to machine learning. Developed using the United States (US) O*NET database, the SML estimates the extent to which actions and outputs for a specific job task can be learned by a machine. SML scores based on O*NET codes were mapped to Canadian National Occupational Classification codes according to their matching attributes. Through this approach we categorized occupations with high machine learning exposure (top 10 percentile of SML scores) and low machine learning exposure (bottom 10 percentile of SML scores). We produced weighted estimates of the number of workers in Canada in occupations with high machine learning exposure or low machine learning exposure. Gender-stratified models were developed to estimate the relationship between educational attainment, hourly wages and occupational job skill, training and experience requirements, and likelihood of employment in high or low machine learning exposure occupations for men and women.

Key findings

Overall, 1,902,050 Canadian workers were employed in occupations characterized by high machine learning exposure. That is, they had the greatest proportion of job tasks are suitable for machine learning. Women were more likely to be employed in occupations with high machine learning exposure than men.

744,250 workers were employed in occupations characterized by low machine learning exposure. That is, there was a smaller proportion of job tasks are suitable for machine learning. Men were more likely to be employed in occupations with low machine learning exposure than women.

Workers with greater educational attainment and in occupations with higher wages and greater job skills, training and experience requirements were less likely to be exposed to machine learning.

Women workers with greater educational attainment and in occupations with high job skill, training, and experience requirements, were disproportionately more likely to be employed in occupations characterized by low machine learning exposure when compared to women with lower levels of education or in occupations with low job skill, training, and experience requirements.

Conclusion

Our research provides a snapshot of occupational machine learning exposure in Canada's labour market and the extent to which high and low occupational machine learning exposure may be associated with worker sociodemographic and occupational characteristics. Result should not be interpreted as the amount of actual machine learning utilization that will take place within these occupations, and we are unable to speculate on the specific impacts machine learning will have on workers and job performance. Additionally, our chosen measure may not encompass all AI forms and work automation, such as those driven by the latest advances in generative AI.

Despite these limitations, our study offers essential evidence to focus efforts and initiatives on occupations and worker segments most directly affected by machine learning. Like other technological transformations that have shaped Canada's labour market, vulnerable segments of the workforce may be most likely to have their occupations affected by machine learning. We also show that machine learning may have a gendered effect and disproportionately impact women when compared to men. Results offer a critical evidence base to direct policy and programmatic attention to workers and occupations most impacted by growing AI adoption and be used to promote sustainable and equitable employment in the future of work.

Introduction

Many experts agree that the Canadian job market is in the midst of an artificial intelligence (AI) revolution that is growing in speed and scope.[1] This revolution has been driven by the rapid progress of machine learning, a subset of AI, and its increasing use across various Canadian industries.[1-5] Firms adopt machine learning technologies in part to drive innovation and raise productivity.

It is important to highlight that the adoption of the technology may have both positive and negative impacts on tasks that workers perform and on working conditions more broadly. Much focus has been on the consequences of machine learning adoption, in particular understanding negative labour market outcomes and the polarization of the labour market.[6] However, the adoption of machine learning in workplaces may also be associated with opportunities for Canadian workers including the use of the technology to perform job tasks with greater precision and speed or the application of machine learning to automate strenuous job tasks.[1,7]

While existing studies focus on overall labour market trends, there's a lack of detailed research on how machine learning may replace the job tasks that different workers perform. Such research is crucial for identifying potentially vulnerable worker groups and designing targeted policies and support programs. Our study uses a novel analytical approach and national labour force data to estimate the number of Canadian workers in occupations with high or low machine learning exposure. We then look closely at the characteristics of these jobs and the workers in them to understand why some jobs have more machine learning exposure and others have less.

Machine learning and the automation of work

Machine learning involves using statistical algorithms on large amounts of data to find patterns in structured or unstructured data and make predictions. Workplaces across all industries are using machine learning as a tool to help make decisions or improve processes.[5,8] Examples of the use of machine learning exist in health-care settings (e.g., to detect disease in medical imaging[9]), financial services (e.g., as fraud detection tools[10]) and the transportation sector (e.g., for real-time hazard identification in automated vehicles[11]). Deep learning, a subset of machine learning that uses neural networks (i.e., algorithms with structures inspired by human brain function), has driven recent advancement in machine learning. At the time of this article, innovations in deep learning have been at the forefront of machines being able to match or surpass humans in performing certain types of tasks, including some involving image and speech recognition.

Growing affordability, improved computational power, and the increased availability of big data have meant that machine learning is more accessible and has widespread applicability across Canada's labour market.[1,12] However, our current understanding of how much machine learning is used by Canadian firms is unclear and can change depending on how people measure the adoption of machine learning. For example, a global survey of business leaders found that about 34 per cent of companies use machine learning, while 42 per cent are considering using AI.[13] This survey also noted that machine learning adoption rates can differ significantly between regions; for instance, 58 per cent of Chinese companies use AI compared to 29 per cent of Canadian companies.[13] Recent studies in Canada, using national surveys that track how firms adopt technology, found that less than four per cent have actually utilized AI to perform at least some job tasks.[14] In the survey, it was found that the adoption of AI is most common among larger Canadian companies (with over 100 employees) and in certain industries like utilities (17 per cent), finance and insurance (13 per cent), and information and culture (13 per cent).[14]

Past research on the automation of work

Throughout history, technological transformations in the economy, such as the use of personal computers, the development of mobile devices, and the automation of work processes, have led to improvements in how much work can be done. Technological transformations have also increased the likelihood of labour substitution, contributing to partial or full job displacement for workers in certain occupations and potentially eroding working conditions for those who remain employed (e.g., growth in precarious working conditions for workers employed in the digital platform economy).[15-17] However, there's a mix of opinions in the research about how much certain jobs are affected by new digital technologies, like machine learning, and how they contribute to automating work, mainly because there isn't a standard way to measure this yet.

To inform our research on the impact of machine learning on the labour market, we look at research from the late 2010s that explored how automation affects different jobs and workers. At first, experts thought that automation could replace entire jobs, affecting many workers. For example, early estimates in the United States suggested that almost half of all jobs could be fully automated by computers.[18] Similarly, studies in Canada estimated that anywhere from 11 to 42 per cent of jobs could be significantly impacted by automation.[19,20] These findings raised concerns among workers and policy-makers about the potential for job losses due to new technology.

Contemporary research on the automation of work has examined the extent to which occupations are exposed to different technologies. Studies of automation exposure begin by breaking down occupations into individual job tasks, each of which could either be done by people or by machines.[21] Estimating occupational automation exposure, researchers estimated that around five per cent of jobs were made up entirely of tasks that could be fully automated, and 60 per cent of jobs had at least one-third of tasks that could be automated.[22] Job tasks most likely to be automated were those that were routine, structured, or repetitive; they are often found in administrative or service-based jobs (e.g., data entry clerks).[16,17,19]

Previous studies on the automation of work provide insights into how technology can change and redistribute job tasks between humans and machines. Some technologies can handle repetitive, unsafe, or boring tasks, allowing people more time for creative, social, or cognitive tasks.[22,23]

Automation has not only increased the need for roles related to developing, maintaining, or deploying new technologies but has also led to the creation of entirely new occupations.[22,24] Additionally, past research on work automation highlights the importance of job training programs to protect workers from being replaced entirely by automation.

Automation through machine learning adoption

Machine learning could impact the job market in ways distinct from previous automation waves.[16] Machine learning's ability to learn, adapt, and work independently means it can handle tasks, whether physical or mental, across a broader range of occupations.[5]

Studies in the US and Canada examining the extent to which job tasks that make up different occupations are suitable to being performed by machine learning - from this point forward referred to as occupational machine learning exposure - suggest that nearly all jobs have some tasks that can be performed by the technology.[25] Some research even suggests that about 19 per cent of US jobs could be highly affected by machine learning.[26] However, like past automation trends, no single job can be fully taken over by machine learning.[16] As a result, machine learning is unlikely to be used by workplaces to fully substitute human workers for machines. Instead, machine learning may increase the risk of job displacement due to workforce reduction or alternatively be used to enhance the productivity of certain groups of workers.[16,27] This emphasizes the need to understand how many Canadian workers are in jobs with the potential for high exposure to machine learning as they could be more directly impacted by this technology.

It's crucial to note that machine learning technology is rapidly advancing, with its processing power doubling every four to nine months.[16] This means that machine learning's learning abilities are constantly evolving, leading to changing impacts on both workers and workplaces. Additionally, improvements in deep learning are expected to boost machine learning's performance and its ability to automate a wider range of tasks, including tasks like image and speech recognition and predictive analytics. These advancements could have significant effects on the workforce.[28] For instance, a recent study focused on the labour market effects of large language models (LLMs), which are deep learning models pre-trained using extensive datasets. This study estimated that approximately 80 per cent of US workers could have at least ten per cent of their job tasks affected by LLMs, and 19 per cent of workers could have at least 50 per cent of their job tasks influenced by LLMs.[28]

AI and labour market segmentation

Our study is based on labour market segmentation models, which help us understand how working conditions, job opportunities, and job security can vary across different occupations and groups of workers.[29] In Canada, as in many other industrialized economies, technological changes have not only brought significant economic shifts but have also created both advantages and challenges for workers. Workers in more favorable positions in the labour market, such as those with higher education levels and in well-paying and higher skilled jobs, have generally been able to benefit more from past technological changes; they have seen wages increase at a faster rate and greater access to better-quality jobs. On the other hand, workers from disadvantaged backgrounds or in precarious working situations, such as low-wage or unstable jobs, have often faced negative impacts from technological changes; they have experienced job losses and declines in job quality and security.[17,30] While machine learning might affect jobs differently than past technological shifts, there's a possibility that vulnerable groups in the job market could still face challenges. Understanding how machine learning exposure varies across different jobs and worker groups is crucial for identifying and addressing emerging inequalities in the job market.

> **"Machine learning is unlikely to be used by workplaces to fully substitute human workers for machines. Instead, machine learning may increase the risk of job displacement due to workforce reduction or alternatively be used to enhance the productivity of certain groups of workers.**

Workers' sociodemographic (e.g., educational attainment and gender) and occupational characteristics (e.g., job skills, training and experience requirements, hourly wages) can be associated with the automation of work. Workers with higher levels of educational attainment might find themselves in jobs that offer more protection during periods of technological disruption.[19,20,22,31] As an example, data from past automation waves suggest that highly educated workers tend to be in jobs with varying and complex tasks, which are less likely to be automated by software or robots.[31-33] Relatedly, the job skill, training and experience requirements of an occupation provide a picture of the complexity of responsibilities involved in work and may be a marker for automation susceptibility.[32] Past data have shown that general-skilled occupations with the least amount of job skills, training and experience requirements are more likely to consist of routine job tasks that are susceptible to automation, when compared to managerial or professional occupations with greater job skills, training and experience requirements. An example in the legal sector highlights the differential impact of automation on occupations according to worker educational attainment and job skills, training and experience requirements. Legal assistant jobs, which require college training and have more clerical responsibilities (e.g., data entry and transcription, filing documents) are more susceptible to being performed by technology than lawyers, which require post-graduate education and multiple years of training, and consist of cognitively demanding tasks like managing legal proceedings or communicating with courts.

Unlike past automation trends, however, machine learning doesn't just target simple, repetitive tasks; it can also automate tasks involving planning, learning, problem-solving, and prediction. These tasks are often found in jobs that require higher skills, training, and education levels, affecting workers in different ways.[5] As a result, the impact of machine learning on the job market is expected to be significant and distinct for workers and different occupations.

Wages are another aspect of jobs that could be related to how likely a worker might be affected by automation. US data published in 2021 found about 50 to 70 per cent of change in the wage structure between 1980 to 2016 could be attributed to the wage declines among worker groups who specialized in routine tasks and were in industries that underwent rapid automation.[17,34] US data also suggests that higher-paid workers tend to have lower exposure to machine learning.[3] Similarly, a study using Canadian census data from 2019 investigated how machine learning exposure relates to median hourly wages across different occupations. In this study, the authors found no direct correlation between the median hourly wages of an occupation and machine learning exposure.[25] It's worth noting, however, that this study did not collect individual worker earnings data.

Differences between men's and women's job types and the working conditions they encounter may play a role in how much they are exposed to occupational machine learning. Previous studies on automation have shown mixed results regarding its impact on men and women.[35] Some research suggests that industries where men are commonly employed (e.g., repair, construction, and transportation) often involve repetitive and physical job tasks that are suitable for automation by robots or machines.[36] On the other hand, jobs held mostly by women (e.g., education, health care, and administration) often require social and emotional skills that are currently less likely to be automated.[37] Women might also be under-represented in managerial or professional roles and in science, technology, engineering, and mathematics (STEM) jobs, which could benefit most from increased productivity due to new digital technologies.[35,38,39]

US data suggest that men and women with higher education levels are less likely to work in jobs at risk of automation and may see wage increases.[34] Whether occupational machine learning exposure differs based on gender in the Canadian workforce remains uncertain.

Machine learning exposure and the job skills ecosystem in Canada

The rapid speed and potentially large-scale impact of AI adoption on Canadian workplaces poses a distinct challenge for skills and workforce development systems in Canada, systems which are less agile. While it may be tempting to hope that AI as a technological innovation might, if anything, alleviate already critical and widespread skills shortages in the Canadian economy, the reality will of course be more nuanced with different occupational groups experiencing benefits and drawings. The necessary policy and program innovation tools used to mitigate the negative impacts of AI and to maximize its benefits will be similarly nuanced. Volatile and unpredictable change may put pressure on different ecosystem actors--employers and unions, provincial and governments, post-secondary education institutions, employment service delivery organizations and community agencies acting on behalf of different and often disadvantaged populations—to coordinate action and collaborate in ways that have not always been characteristic of the Canadian skills ecosystem.

Developing an evidence-based understanding of the problem and monitoring its evolution through labour market data, is a critical first step to identify groups of workers who may benefit most from policy and programmatic attention.

Objectives

Our study examined the extent to which occupations and workers may be exposed to machine learning. Building on a body of research on past periods of automation, we described the potential of machine learning across Canadian occupations and if these effects differ for groups of workers.

Our research:

1. Estimated the number of workers in occupations characterized by high or low machine learning exposure in Canada where the greatest and lowest proportion of job tasks are suitable for machine learning, respectively.
2. Examined how potential machine learning exposure differs according to workers' sociodemographic (e.g., educational attainment, gender) and other occupational (e.g., job skill level requirements, hourly wages) characteristics.
3. Determined whether the association between educational attainment, job skill requirements, hourly wages, and potential machine learning exposure is the same or different for men and women.

Insights from our research can enable a better understanding of divisions in Canada's labour market related to the ongoing adoption of machine learning; that, in turn, can help identify groups of workers who could be most affected by the technology. Findings can also inform targeted policies and programs that optimize the benefits of machine learning and address the potential adverse effects of the technology on workers, especially amongst groups with the highest occupational exposure.

Data and approach

Canada's Labour Force Survey

We conducted a pooled cross-sectional analysis of eight years of Statistics Canada's Labour Force Survey (LFS; 2013-2019, 2022). The Labour Force Survey is a nationally representative monthly cross-sectional survey of the household population (15 years of age or older); its sample of approximately 100,000 Canadians is built using probability sampling procedures.[41] Excluded from the survey's coverage are Canadians who are not currently employed, self-employed, living on reserves and other Indigenous settlements, full-time members of the Canadian Armed Forces, living in institutions or households in extremely remote areas with very low population density. Statically weighted monthly cycles were combined to produce nationally representative annual estimates. Labour Force Surveys between January 2020 and December 2021 were excluded from the analysis due to the considerable economic impact of the COVID-19 pandemic. Given the unequal impacts of COVID-19 on labour market participation across industries and labour force subgroups, the inclusion of these waves may not be representative of usual labour market participation patterns in general, and across labour market groups of interest.[42]

Suitability for Machine Learning measure to estimate occupational machine learning exposure

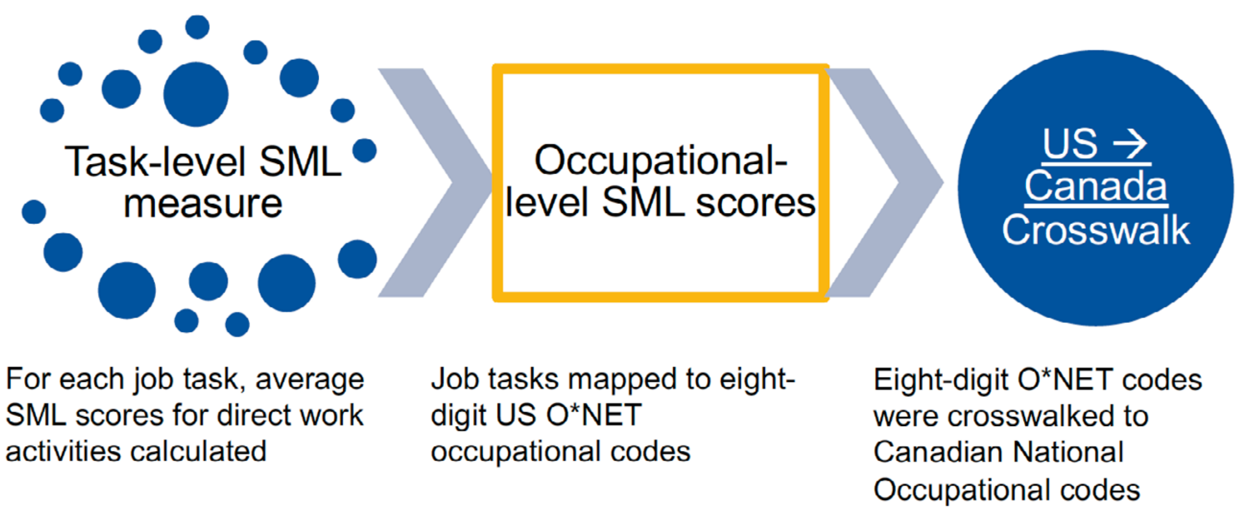
To measure occupational exposure to machine learning, we used the suitability for machine learning (SML) measure developed by Brynjolfsson and colleagues in the US. The SML estimates the extent to which actions and outputs for a specific job task are suitable to being performed by a machine. The SML measure offers detailed information about task-level exposure to machine learning that can be aggregated to study the impact of machine learning on the economy.[15]

SML scoring was developed using the US O*NET database, which is an American occupational information database describing nearly 1,000 occupations and occupation-specific information. Using standardized job-oriented descriptors and worker-oriented descriptors,[25] O*NET describes 2,069 direct work activities and 18,156 job tasks categorized across 873 standardized occupations.[43,44]

A 21-question SML rubric was established to evaluate the criteria required for a machine to substitute a job task. The rubric consisted of 23 statements that were evaluated on a five-point scale (5 = strongly agree; 1=strongly disagree), which were used to score each direct work activity by multiple raters. Average SML scores of direct work activities associated with each job task were calculated to generate a task-level SML measure. Occupation-level SML scores were then produced by taking the weighted average, by importance, of the tasks mapped to eight-digit O*NET codes and could range from 1 to 5.[15,16] Occupations with a high SML value represent those where machine learning has the greatest potential to transform a job.

To estimate SML values among Canadian occupations, we cross-walked or matched O*NET codes to 5-digit Canadian National Occupation Classification codes.[45] which were recently updated in 2021 (NOC 2021). Ultimately, 873 eight digits O*NET codes were mapped to 512 NOC codes with matching attributes[45] (Figure 1).

FIGURE 1.
Process of applying the Suitability for Machine Learning (SML) measure to Canadian Data.



Out of 512 occupations for which we can assign a SML value, all Canadian occupations had at least some exposure to machine learning; no occupation was estimated to be completely exposed to machine learning (SML score = 5). Based on the SML values, we categorized occupations as high machine learning exposure (top 10 percentile of SML scores, SML score 3.60) and low machine learning exposure (bottom 10 percentile of SML scores, SML score 3.35).

Outcome variables*

SML scores were used to create two binary outcome variables. The first outcome variable was high occupational machine learning exposure, where occupations have an SML score in the top ten percentile. The second outcome was low occupational machine learning exposure where occupations have an SML score in the bottom ten percentile. Both outcomes were compared to the reference group of all other Canadian occupations.

Independent variables

Gender: For this analysis, a gender variable was created based on participant reports; workers identifying as men or women were included in the analytical sample.

Educational attainment: The level of educational attainment of workers was measured using the Labour Force Survey question, "What is the highest certificate, diploma or degree you have obtained?" Based on responses, a four-level categorical variable was created (some post-secondary or less, trades certification or diploma, college or bachelor's degree, university degree above a bachelor's degree).

Hourly wages: Hourly wages were measured using the Labour Force Survey question, "What is your hourly rate of pay?" Based on the participant responses, a four-level categorical variable was created. Data was divided into one of four groups. Quartile 1 (Q1) represents earners in the lowest 25th percentile; quartile 2 (Q2) represents earners in the 26th to 50th percentile; quartile 3 (Q3) are earners in the 51st to 75th percentile (Q2); and quartile 4 (Q4) represents those who earned more than the 75th percentile.

Job skill, training and experience requirements: TEER (Training, Education, Experience, and Responsibilities) categorizations were assigned to each Canadian occupation by Employment and Social Development Canada's Career Handbook, reflecting the nature of jobs skills, training and experience requirements to enter an occupation and the complexity of its responsibilities.[45] TEER categories included: management occupations (TEER 0), professional occupations requiring a university degree (TEER 1), skilled, technical, or supervisory occupations requiring a college diploma, apprenticeship training or have supervisory roles (TEER 2), semi-skilled occupations requiring a college diploma, apprenticeship training or more than six months of on-the-job training (TEER 3) and general skilled occupations requiring a high school diploma or several weeks of on-the-job training or need short-term work demonstration and no formal education (TEER 4/5).

* In research, an outcome variable is the focus of the study and is examined based on whether it differs across levels of the independent variable. In this study, the outcome variable is high or low exposure to machine learning. The independent variables are worker sociodemographic characteristics (such as gender and educational attainment) or occupational characteristics (such as hourly wages and job skill, training and experience requirements).

Study covariates

Based on information collected in the Labour Force Survey, several covariates were collected in each survey year. These included: sociodemographic characteristics (age [years], recent immigration status [less than 10 years: yes/no] and province of residence) and work context variables (work hours [hours worked/week], industry [goods producing industries or service producing industries], job permanency [e.g., permanently employed, or non-permanently employed] and unionization [yes/no]).

Analytical approach

We used sample weights so that estimates were representative of the Canadian population. Descriptive statistics (weighted counts [n] and percentages [%]) were utilized to describe worker and workplace characteristics according to high or low machine learning exposure groups. Multivariable logistic[†] regressions models were fitted to estimate odds of employment in high or low machine learning exposure occupations within 95% confidence intervals.[‡] Each set of multivariable models were run using one of three independent variables (educational attainment [model 1], hourly wage [model 2], job skills, training and experience requirements [model 3]). Models adjusted for sociodemographic and work context covariates. Also, for each of these models, findings were examined separately for men and women to examine potential gender differences.

† Logistic regression is a statistical modeling method. It estimates the probability of an event or outcome occurring (e.g., high or low occupational machine learning exposure) across levels of an independent variable. Usually, the level of the independent variable thought to be at the highest or lowest risk is set as a reference group, and the probability of the outcome from other groups are compared to the probability of the outcome within this reference group. Multivariable logistic regression accounts for one or more independent variables while accounting for study covariates.

‡ Confidence intervals are a range of values, above and below a finding, in which the actual value is likely to fall. The confidence interval represents the accuracy or precision of an estimate.

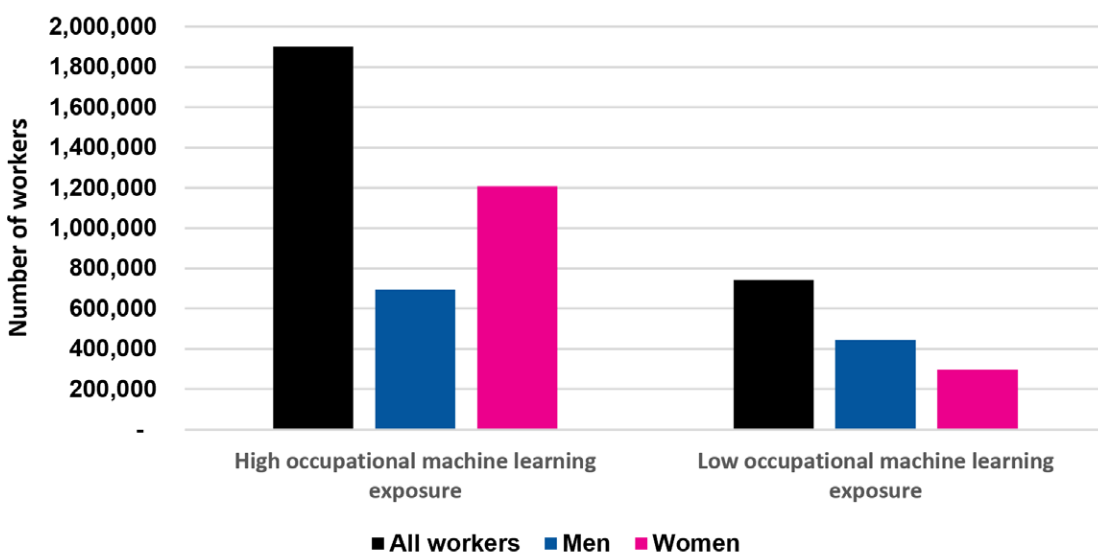
Results

Overall, 1,902,050 Canadian workers were employed in occupations categorized as having high machine learning exposure where the greatest proportion of job tasks were suitable for machine learning. This figure represents 12 per cent of the Canadian workforce.

In comparison, about 744,250 workers were employed in occupations categorized as having low machine learning exposure where a smaller proportion of job tasks were suitable for machine learning. This represents 4.7 per cent of the Canadian workforce. A full list of occupations categorized as high or low machine learning exposure is presented in Appendix 1.

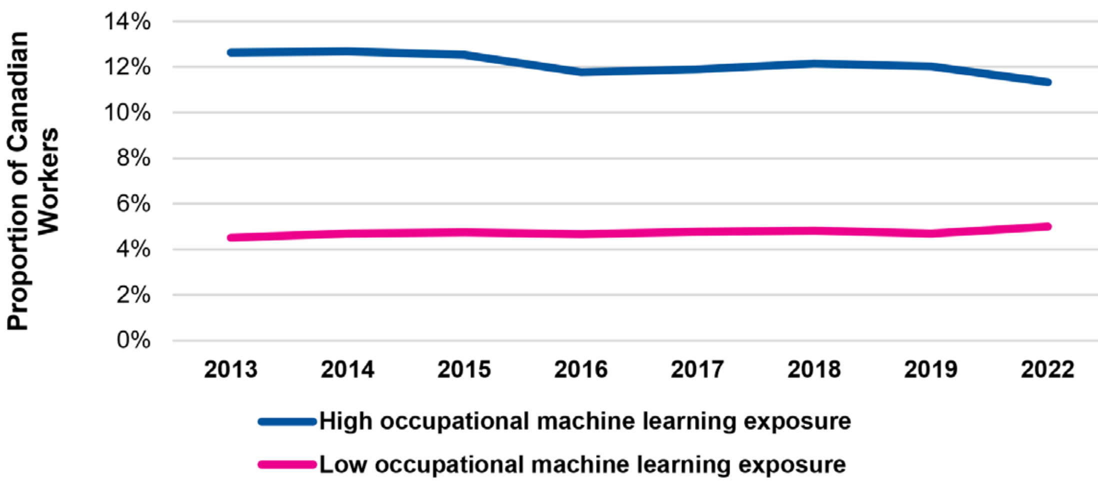
In occupations characterized by high machine learning exposure, women made up a larger proportion than men (63.4 per cent vs. 36.6 per cent). In contrast, in occupations characterized by low machine learning exposure, men outnumbered women (59.9 per cent vs. 40.1 per cent). (Figure 2).

FIGURE 2.
Number of Canadian workers with high and low occupational exposure to machine learning.



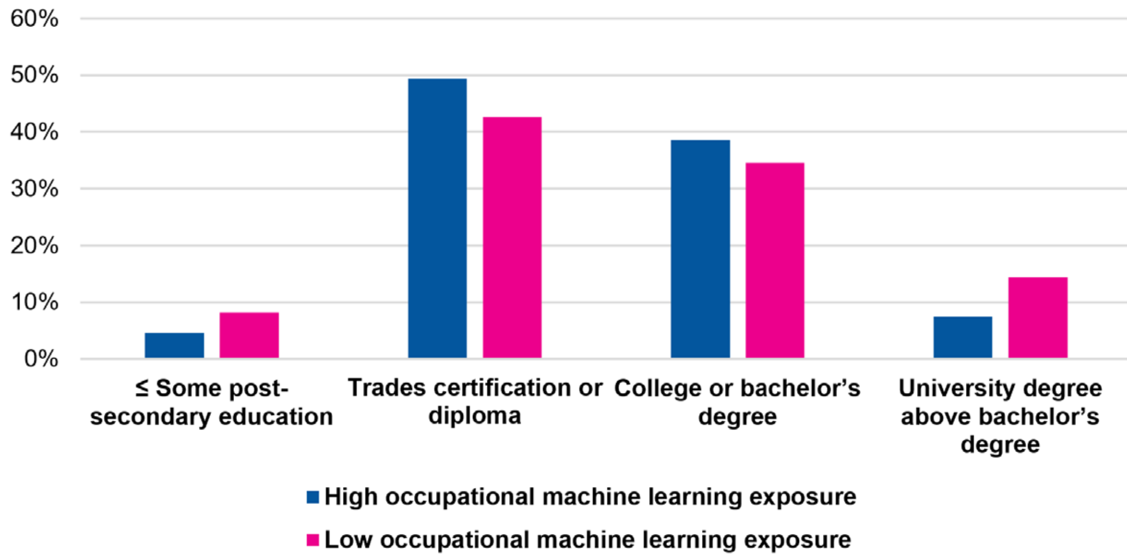
The proportion of Canadian workers in occupations characterized by high or low exposure to machine learning remained relatively unchanged over each wave of the survey (Figure 3). Data from each survey wave were combined for the remaining portions of the analysis presented in the next sections.

FIGURE 3.
Proportion of Canadian workers in occupations with high and low exposure to machine learning over the eight waves of the Labour Force Survey.



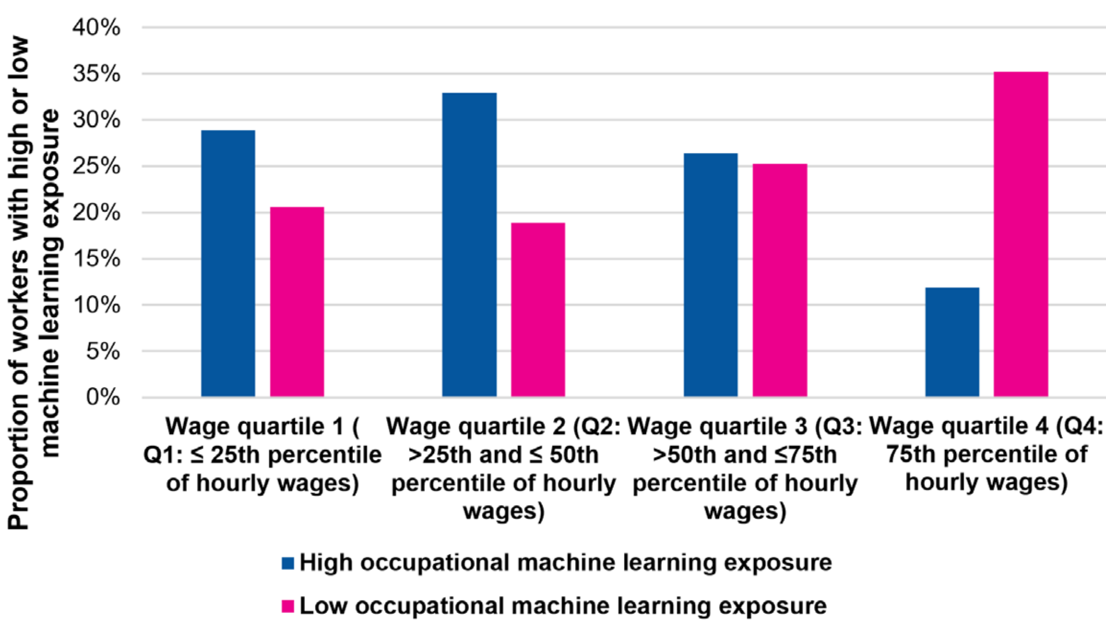
Next, using descriptive statistics, we illustrate how machine learning exposure differs according to educational attainment, hourly wages and job skills, training and experience requirements. Findings showed that the proportion of workers in high and low exposure to machine learning also differed according to educational attainment. When compared to occupations with low exposure, occupations characterized by high exposure to machine learning had a larger share of workers with a trades certification or diploma (49.4 per cent vs. 42.7 per cent vs.) and college or bachelor's degree (38.6 per cent vs. 34.6 per cent). When compared to occupations with low machine learning exposure, occupations characterized by high exposure to machine learning had a smaller proportion of workers with some post-secondary education or less (4.6 per cent vs. 8.2 per cent) or a university degree above a bachelor's degree (7.4 per cent versus 14.4 per cent) (Figure 4).

FIGURE 4.
Distribution of educational attainment across occupations with high and low exposure to machine learning. Canadian labour force 2012-2019, 2022.



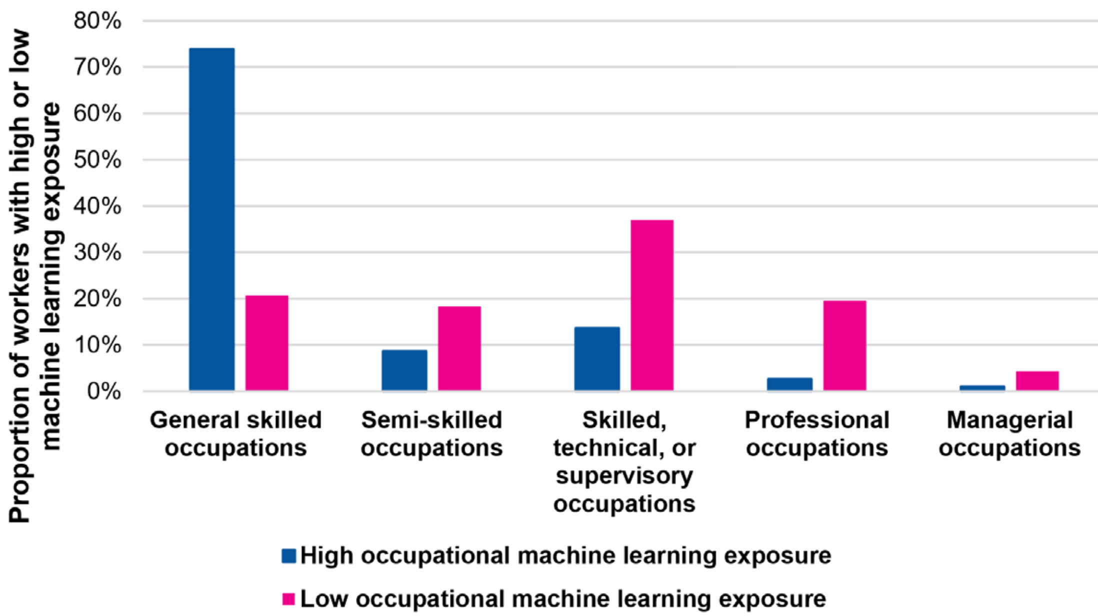
When compared to occupations with low exposure to machine learning, occupations with high exposure to machine learning were composed of a greater proportion of workers in the two lower-earning quartiles (21 per cent vs. 29 per cent of the lowest earning quartile; 19 per cent vs. 33 percent of earners in the second-lowest earning quartile). Occupations with low exposure to machine learning had larger shares of the top earners compared to occupations with high machine learning exposure (35 per cent vs. 12 per cent of workers in the top earning quartile) (Figure 5).

FIGURE 5.
Proportion of Canadian workers in occupations with high and low exposure according to hourly wages.



In comparison to occupations characterized by low machine learning exposure, a greater proportion of high machine learning exposure occupations were composed of workers in general skilled occupations with the lowest amount of job skills, training and experience requirements (73.9 per cent vs. 20.7 per cent). Occupations characterized by low machine learning exposure had more workers in jobs with greater job skills, training and experience requirements than those with high occupational machine learning exposure (Figure 6).

FIGURE 6.
Distribution of job skills, training and experience requirements across occupations with high and low exposure to machine learning. Canadian labour force 2012-2019, 2022.



Odds rations from logistic regression models for the probability of high and low potential exposure to machine learning across levels of educational attainment, hourly wages and job skills, training and experience requirements are presented in Figures 7-12. A full summary of the models including odds ratios and confidence intervals are available in Appendix 2. Models 1 look at educational attainment (Figures 7 and 8), models 2 look at hourly wages (Figures 9 and 10), and models 3 look at job skills, training, and experience requirements (Figures 11 and 12). Each of the models separates out findings for men and women. Also, each model examines two outcomes: (a) the odds of high occupational machine learning exposure when compared to all other Canadian workers and (b) the odds of low occupational machine learning exposure when compared to all other Canadian workers. Results controlled for study covariates including age, recent immigration status, province of residence, work hours, industry, job permanency and unionization.

Results indicated that having a university degree above a bachelor's degree (highest educational attainment category) was associated with a lower odds of high occupational machine learning exposure for both men (55% lower odds) and women (62% lower odds) when compared to the Canadian working population (Figure 7). Differences between men and women emerged when examining odds of low occupational machine learning exposure (Figure 8). When compared to women with some post-secondary education or less (the lowest educational attainment category), women with a university degree above a bachelor's degree (64% greater odds), college or bachelor's degree (27% greater odds) or trades certification or diploma (172% greater odds) had a greater likelihood of low occupational machine learning exposure. When compared to men with lowest educational attainment, men with a university degree above a bachelor's degree (20% lower odds) or a college or bachelor's degree (8% lower odds) had a lower likelihood of low machine learning occupational exposure (Figure 8). Unlike for women, greater levels of education in men did not raise their likelihood of being in jobs with low machine learning exposure. In particular, men with a university degree above a bachelor's degree had 20% lower odds of low occupational machine learning exposure.

FIGURE 7.
Summary of multivariable logistic regression model examining the association between educational attainment and high occupational machine learning exposure.

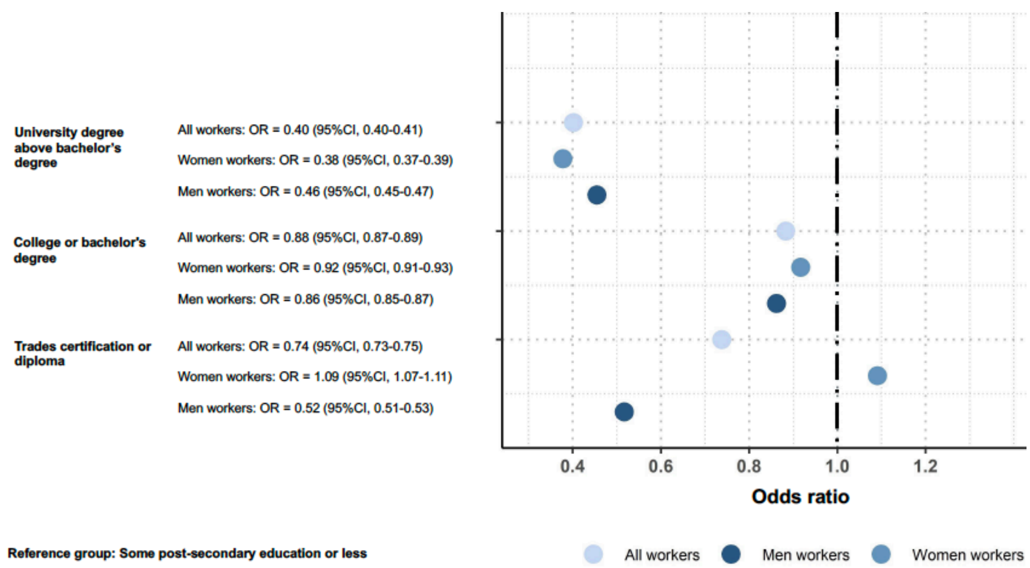
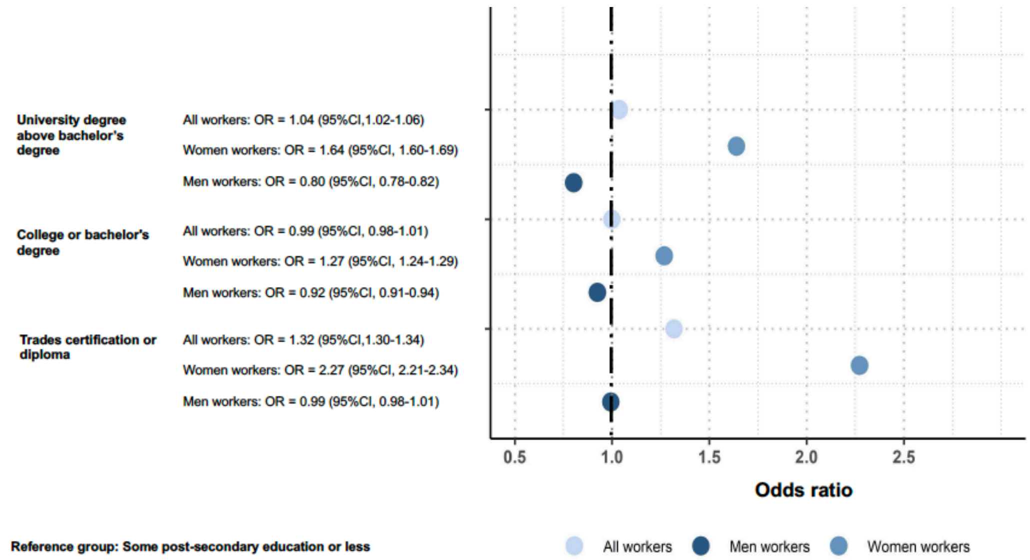


FIGURE 8.
Summary of multivariable logistic regression model examining the association between educational attainment and low occupational machine learning exposure.



Earners in the highest wage quartile were less likely to make up the workers with high occupational machine learning exposure for both men (59% lower odds) and women (50% lower odds) (Figure 9). Women with hourly wages in second quartile (85% greater odds) and third quartile groups (56% greater odds) had a greater likelihood of high occupational exposure to machine learning when compared to lowest wage women earners in quartile one (Figure 9). In contrast, men (103% greater odds) and women (98% greater odds) in the highest wage quartile were more likely to make up the workers in low machine learning exposure occupations (Figure 10).

FIGURE 9.
Summary of multivariable logistic regression model examining the relationship between hourly wages and high occupational machine learning exposure.

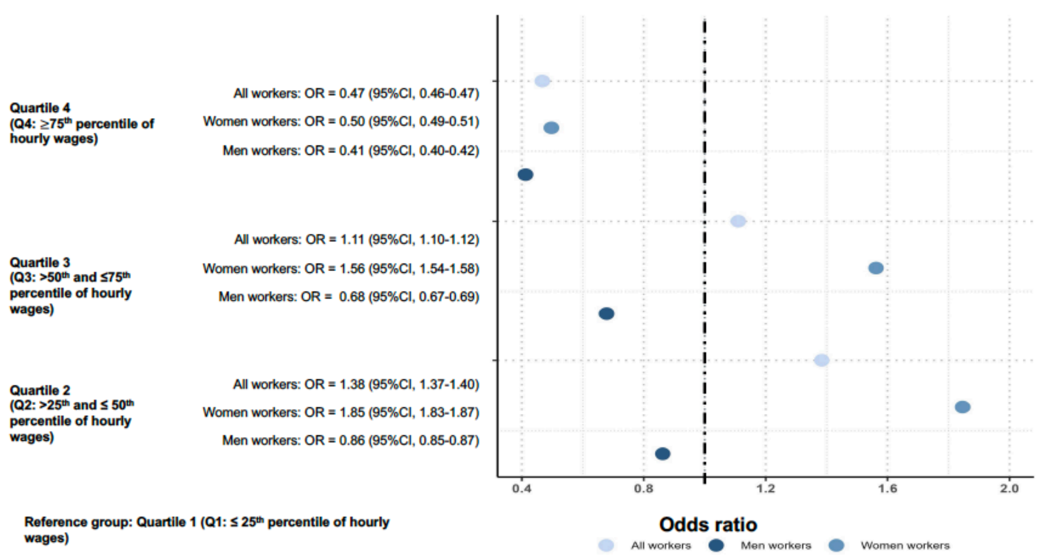
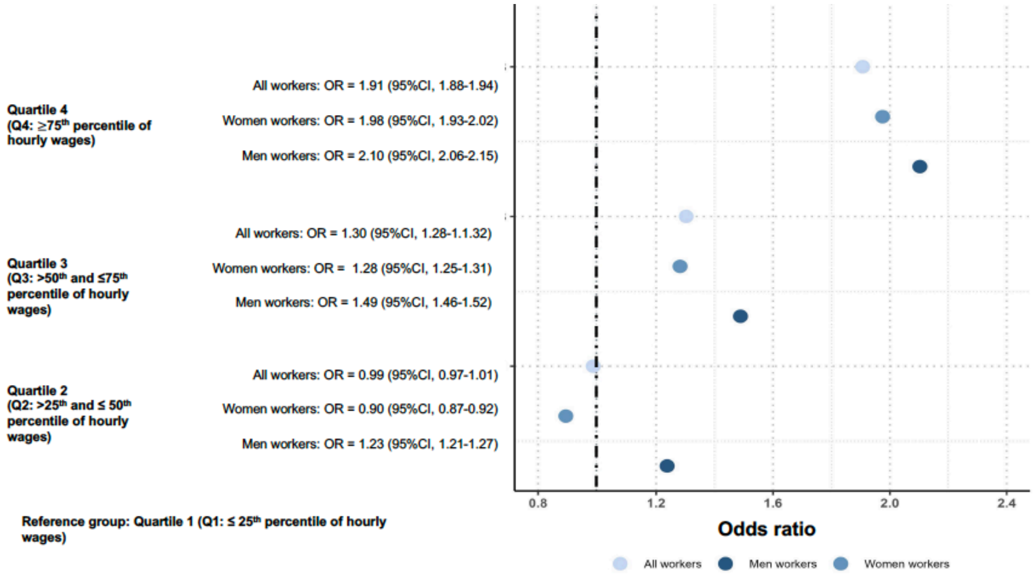


FIGURE 10.
Summary of multivariable logistic regression model examining the relationship between hourly wages and low occupational machine learning exposure.



Finally, greater job skills, training and experience requirements were associated lower occupational exposure to machine learning. Men (94% lower odds) and women (97% lower odds) in managerial occupations were less likely to be employed in jobs with high machine learning (Figure 11).

For the most part men and women workers in jobs with greater skills, training and experience requirements were related to a higher likelihood of reporting low occupational exposure to machine learning (Figure 12). Interestingly, men workers in managerial occupations (with the highest job skills, training, and experience requirements) had a 14% lower likelihood of low occupational machine learning exposure when compared to those in general skilled occupations. Women in managerial positions, on the other hand, had a 77% greater odds of low machine learning exposure when compared to women in general skilled occupations (Figure 12).

FIGURE 11.
Summary of multivariable logistic regression model examining the relationship between occupational job skills, training and experience requirements and high occupational machine learning exposure.

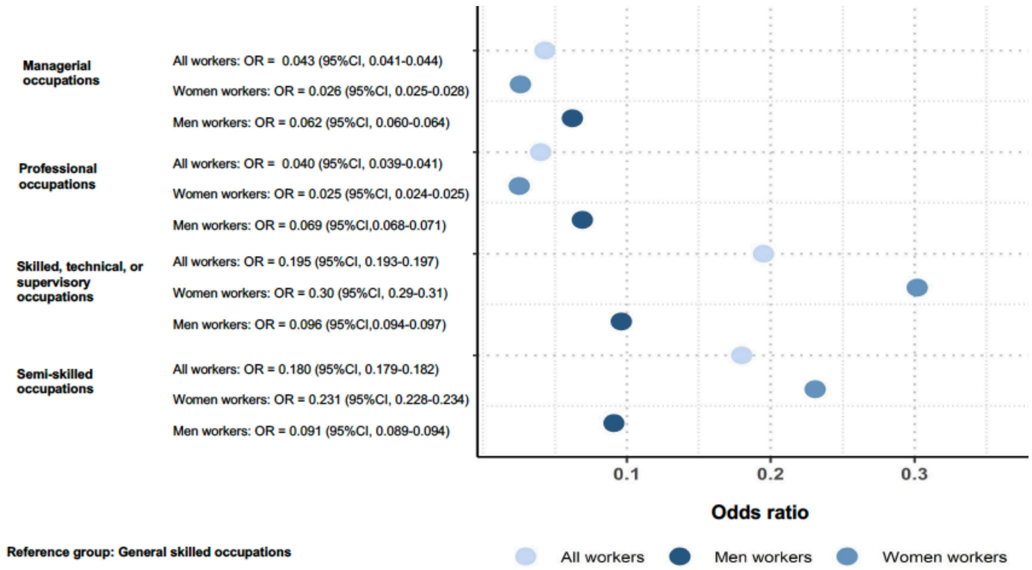
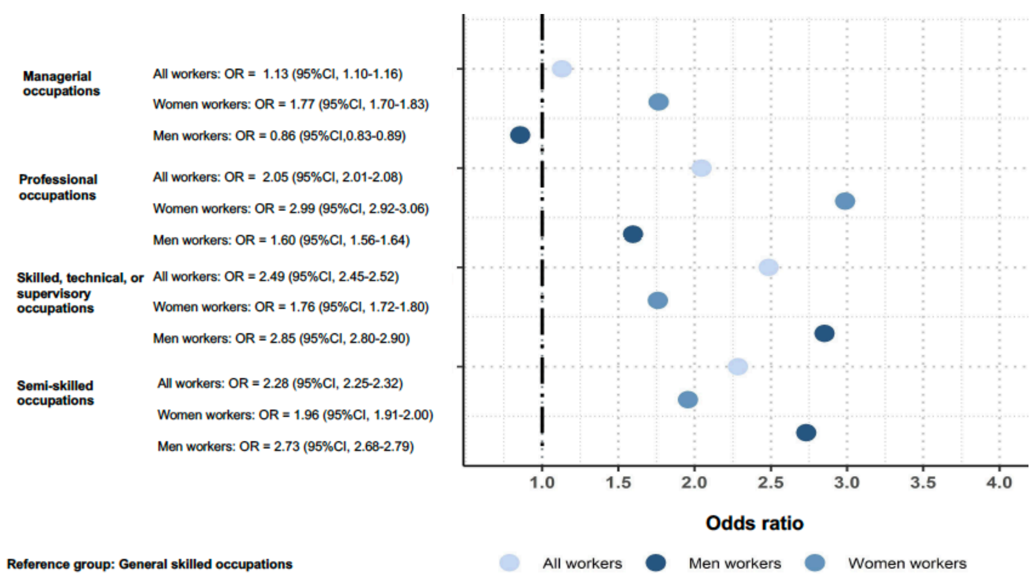


FIGURE 12.
Summary of multivariable logistic regression model examining the relationship between occupational job skills, training and experience requirements and low occupational machine learning exposure.



Implications for policy and practice

The integration of machine learning within Canadian workplaces has the potential to bring about significant changes to the nature and availability of jobs, and potentially worsening existing workforce disparities.

To our knowledge, our study stands out as one of the few attempts to provide an overview of potential machine learning exposure in different occupations across Canada's labour market and how this exposure varies according to worker sociodemographic and occupational characteristics.

Like other technological transformations that have shaped Canada's labour market, we showed that vulnerable segments of the workforce may be most likely to have their occupations affected by machine learning. We also showed that machine learning may have a gendered effect and disproportionately shape the working experiences of women when compared to men. These results serve as a crucial foundation for guiding policy and programmatic efforts toward supporting workers and occupations that are most affected by the increasing adoption of AI. They can help promote sustainable and fair employment practices as we navigate the evolving landscape of work.

We employed an innovative analytical method to categorize Canadian occupations based on their suitability for machine learning tasks. This allowed us to estimate the number of workers in occupations with high likelihood of machine learning exposure (i.e., those most suitable for machine learning tasks) and low likelihood of machine learning exposure (i.e., those least suitable for machine learning tasks). Based on our categorization of high and low machine learning exposure, we showed that nearly two million Canadian workers are in occupations with a high propensity for machine learning, accounting for about 12 per cent of the total workforce. Conversely, fewer workers, approximately 744,250 individuals representing 4.5 per cent of the workforce, were in low machine learning exposure occupations.

It is not clear based on our analytical approach whether workers in jobs with high exposure to machine learning will experience advantage or disadvantage stemming from the technology and findings should be interpreted by considering this complexity. First, workers in occupations with high exposure to machine learning could be at risk of partial or full job displacement. Second, the use of machine learning may complement the work performed by workers in high exposure jobs and free up time for high value activities and productivity gains.[3,15,46] While those with low occupational machine learning exposure are more likely to work in a job where they face less of a risk of being displaced by AI, they may be less likely to leverage benefits associated with machine learning to the performance of their job tasks. Further research is necessary to build on our findings and explore how machine learning impacts employment and working conditions for various worker groups, both positively and negatively.

Our research revealed that every Canadian occupation includes at least some job tasks that could be executed by machine learning. These results are consistent with earlier studies conducted in both Canada and the US, indicating machine learning's broad economic impact.[15,25] At the same time, no single occupation could be completely suitable to being performed by machine learning and the ability for machines to match humans in all job tasks remains limited.[16] These findings reinforce the ongoing view that machine learning will bring about changes in Canadian workplaces and the roles of workers. It also highlights the necessity of preparing all workers for the increasing adoption of machine learning and other AI technologies to enable them to collaborate effectively with these technologies. As machine learning continues to advance, gaining more autonomy and potentially surpassing human capabilities in learning and reasoning, the significance of studying its impact on work dynamics will only grow.[1,2,47]

Researchers have previously suggested that the integration of machine learning into the workforce will affect workers in higher-skilled and better-paying jobs more significantly, particularly those involving prediction tasks.[5,32,34] However, our findings paint a different picture and are in line with previous automation trends. We show that workers with lower educational levels, those in lower-paying jobs, and occupations with minimal job skills, training and experience requirements are more likely to have high exposure to machine learning tasks. This raises concerns about potential inequities reinforced or widened by machine learning adoption in the labour market.

One major concern is the potential for machine learning to contribute to wage disparities between workers with differing machine learning exposure levels. The shift of tasks from humans to machines is expected to reduce labour costs, leading to downward pressure on wages that could disadvantage vulnerable worker groups.[15,34] Further research is necessary to delve into our findings and gain a deeper understanding of how machine learning can affect wages among different worker groups, both positively and negatively. This understanding will be crucial for developing targeted policy interventions and support measures that address income inequality.

Exposure to machine learning within Canadian occupations may exhibit gender-related patterns. Men and women often cluster in distinct job sectors, influencing their work experiences and exposure to various technologies.[36,48] Our research contributes to understanding gender segregation in the job market concerning technological advancements. We show that Canadian women may be employed in occupations where their tasks are most suitable to machine learning and may be more likely to experience high exposure to machine learning.[49] Our findings may suggest that men may be shielded from potential job disruption related to machine learning. Men may also be more likely to be excluded from the economic opportunities that can emerge because of machine learning adoption. Results from our study highlight the importance of future research to unpack how machine learning adoption may impact men and women differently and the potential need for gender-sensitive policy and programmatic approaches to address the challenges and opportunities of machine learning for Canadian workers.

To delve further into gender differences, our study investigated whether the link between educational level, hourly wages, job skills, training, experience requirements, and exposure to machine learning varied between women and men. Our results showed that women with higher educational attainment and occupying managerial roles tended to have lower exposure to machine learning in their occupations when compared to those with less educational attainment and those in jobs with fewer job skills, training and experience requirements. Previous research has suggested that educational attainment is especially crucial for women, shielding them from economic risks like those brought on by the automation of work.[32,50] Highly educated women and those in managerial positions may also miss out on machine learning-related economic prospects, potentially exacerbating gender disparities in the long-term. Further research is essential to deepen our understanding of how machine learning affects the work experiences of men and women in the job market, considering differences in worker and job characteristics.

Implications for the job skills ecosystem in Canada

Our research has significant implications for policy-makers and workforce development actors. We found that nearly all Canadian occupations encompass bundles of tasks suitable and unsuitable for machine learning and could impact the ways in which workers work alongside intelligent machines. Some economists propose potential benefits from firms segregating and reorganizing tasks based on their machine learning suitability 16. Firms could optimize machine learning by using the technology to perform job tasks that have a high suitability for machine learning and reallocating human labour towards specializing in job tasks which have a low suitability for machine learning. The result of redistributing job tasks between humans and machine learning is that job skills profiles for different occupations may substantially change.

Our study's evidence can inform the design of job skills development programs in light of the AI revolution that are undertaken within workplace, community and educational settings. There may be a necessity to target upskilling and reskilling efforts towards workers highly exposed to machine learning, helping them gain a competitive edge, collaborate effectively with machine learning, and maximize human-only skills where machine learning has limited applicability (e.g., communication, socioemotional and interpersonal skills) 51. The importance of skill development may be especially pertinent for women in roles with heightened machine learning exposure 48. Implementing public policies that drive employer investment in upskilling and reskilling of workers has the potential to enable companies to develop the workforce talent they require to optimize the use of machine learning and other forms of AI.

Study strengths and limitations

Our study had several strengths and limitations. We employed an innovative analytical method to gauge the proportion of various Canadian occupations comprising tasks suitable for machine learning. Utilizing eight cycles of Canada's Labour Force Survey, we generated population-based estimates of machine learning exposure. Furthermore, we characterized occupations with high and low machine learning exposure based on occupational and worker attributes. These findings offer a crucial depiction of how machine learning might transform Canada's labour market and contribute to labour market segmentation. However, there are notable limitations. Our measurement focused solely on the technical feasibility of machine learning and its task suitability and should not be interpreted as the amount of machine learning uptake that will take place within these occupations, as this will be influenced by the practical feasibility and application of machine learning across industries and workplaces.[15,25] As such, we could accurately speculate on the specific impacts machine learning will have on workers and job performance. Our findings also did not delve into the economic, organizational, legal, cultural, and societal factors influencing machine learning adoption in the labour market and its effects on occupations and workers. While we employed a standardized measure of occupational machine learning exposure, alternative measures exist, including those capturing AI exposure at industry or geographic levels,[52] and those examining how AI complements or substitutes workers.[46] Moreover, our chosen measure did not encompass all AI forms and work automation, such as those driven by the latest advances in generative AI.[28] Therefore, ongoing research is necessary to assess how emerging AI forms will impact workers and workplaces.

Conclusion

Machine learning, an AI subfield, holds the potential to significantly change Canada's labour market. Our analysis of labour force data paints a crucial picture of the occupations that are most potentially influenced by machine learning, showing that a sizeable number of Canadians work in roles likely exposed to machine learning.

Workers in occupations with heightened machine learning exposure may encounter both challenges and opportunities stemming from both the potential and actual application of this technology. We highlight how machine learning exposure in occupations could contribute to labour market inequalities based on factors like educational attainment, wages, and job-specific skills and training requirements. Notably, the impact of machine learning on work experiences across education, income and skill level may vary based on gender. Further investigation is needed to fully examine how machine learning will actually impact working conditions across different worker groups. Our study offers essential evidence to focus efforts and initiatives on occupations and worker segments most directly affected by machine learning. This strategic approach will ensure inclusivity in an evolving labour market landscape shaped by machine learning and other AI advancements.

References

1. Agrawal A, Gans J, Goldfarb A. *Prediction machines: the simple economics of artificial intelligence.* Harvard Way, BA: Harvard Business Press; 2018.
2. Goldman Sachs. Generative AI could raise global GDP by 7%. Goldman Sachs. https://www.goldmansachs.com/intelligence/pages/generative-ai-could-raise-global-gdp-by-7-percent.html. Published 2023. Accessed June 6, 2023.
3. Brynjolfsson E, Rock D, Tambe P. How Will Machine Learning Transform the Labor Market? *Governance in an Emerging New World.* 2019;619.
4. Autor D, Mindell D, Reynolds E. *The work of the future: building better jobs in an age of intelligent machines.* Cambridge, Massachusetts: MIT Work of the Future;2020.
5. Webb M. The impact of artificial intelligence on the labor market. *SSRN.* 2019:61.
6. Green DA, Sand BM. Has the Canadian labour market polarized? *Canadian Journal of Economics/Revue canadienne d'économique.* 2015;48(2):612-646.
7. Jetha A, Bakhtari H, Rosella LC, et al. Artificial intelligence and the work–health interface: A research agenda for a technologically transforming world of work. *Am J Ind Med.* 2023;66(10):815-830.
8. Brown S. Machine learning, explained. https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained. Published 2021. Accessed November 1, 2023.
9. Li W, Jia F, Hu Q. Automatic segmentation of liver tumor in CT images with deep convolutional neural networks. *Journal of Computer and Communications.* 2015;3(11):146-151.
10. Yee OS, Sagadevan S, Malim NHAH. Credit card fraud detection using machine learning as data mining technique. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC).* 2018;10(1-4):23-27.
11. Navarro PJ, Fernandez C, Borraz R, Alonso D. A machine learning approach to pedestrian detection for autonomous vehicles using high-definition 3D range data. *Sensors.* 2016;17(1):18.
12. Manyika J, Chui M, Miremadi M, et al. *A future that works: automation, employment, and productivity.* Toronto (ON): McKinsey Global Institute;2017.
13. IBM Inc. IBM Global AI Adoption Index 2022. https://www.ibm.com/watson/resources/ai-adoption. Published 2022. Accessed Febuary 1, 2024.
14. Lockhart A. Automation Nation? AI Adoption in Canadian Businesses. Toronto, ON: The Dais;2023.
15. Brynjolfsson E, Mitchell T. What can machine learning do? Workforce implications. *Science.* 2017;358(6370):1530-1534.

16. Brynjolfsson E, Mitchell T, Rock D. What can machines learn, and what does it mean for occupations and the economy? *AEA Papers and Proceedings.* 2018;108:43-47.

17. Autor D, Dorn D. The growth of low-skill service jobs and the polarization of the US labor market. *Am Econ Rev.* 2013;103(5):1553-1597.

18. Frey CB, Osborne MA. The future of employment: how susceptible are jobs to computerisation? *Technol Forecast Soc Change.* 2017;114:254-280.

19. Lamb C. The talented Mr. Robot: the impact of automation on Canada's workforce. Brookfield Institute for Innovation+ Entrepreneurship. https://brookfieldinstitute.ca/the-talented-mr-robot/. Published 2016. Accessed January 22, 2023.

20. Frenette M, Frank K. *Automation and job transformation in Canada: who's at risk?* Ottawa, ON: Statistics Canada. 29 June 2020 2020.

21. Autor D, Levy F, Murnane R. The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics.* 2003;118(4):1279-1333.

22. Manyika J, Lund S, Chui M, et al. Jobs lost, jobs gained: workforce transitions in a time of automation. 2017.

23. Acemoglu D, Restrepo P. Artificial intelligence, automation and work (NBER working paper series no. 24196). *National Bureau of Economic Research.* 2018.

24. Autor D, Chin C, Salomons A, Seegmiller B. *New Frontiers: The Origins and Content of New Work, 1940–2018.* National Bureau of Economic Research;2022.

25. Amarasinghe U, Han F, Oschinski M, Rowe A, Madhusoodhanan R, Deery S. *Automation affecting Canadians: Understanding the impact of machine learning on the Canadian labour force.* Toronto, ON: MaRS Discovery District;2020.

26. Kochhar R. Which US Workers Are More Exposed to AI on Their Jobs? 2023.

27. Di Battista A, Grayling S, Hasselaar E, et al. Future of jobs report 2023. Paper presented at: World Economic Forum, Geneva, Switzerland. https://www.weforum.org/reports/the-future-of-jobs-report-20232023.

28. Eloundou T, Manning S, Mishkin P, Rock D. Gpts are gpts: An early look at the labor market impact potential of large language models. *arXiv preprint arXiv:230310130.* 2023.

29. Reich M, Gordon DM, Edwards RC. A theory of labor market segmentation. *The American Economic Review.* 1973:359-365.

30. Jetha A, Shamaee A, Bonaccio S, et al. Fragmentation in the future of work: a horizon scan examining the impact of the changing nature of work on workers experiencing vulnerability. *Am J Ind Med.* 2021;64(8):649-666.

31. OECD. Education at a glance 2022: OECD indicators. OECD Paris; 2022.

32. Acemoglu D, Restrepo P. Low-skill and high-skill automation. *J Hum Cap.* 2018;12(2):204-232.

33. Frey CB, Osborne M. The future of employment. 2013.

34. Acemoglu D, Restrepo P. Tasks, automation, and the rise in us wage inequality. *Econometrica.* 2022;90(5):1973-2016.

35. Devillard S, Bonin G, Madgavkar A, et al. *The present and future of women at work in Canada.* McKinsey;2019.
36. Madgavkar A, Manyika J, Krishnan M, et al. *The future of women at work: Transitions in the age of automation* McKinsey Global Institute;2019.
37. Baboolall D, Pinder D, Stewart III S. How automation could affect employment for women in the United Kingdom and minorities in the United States. *The McKinsey Quarterly.* 2019.
38. Cortes GM, Jaimovich N, Siu HE. *The" end of men" and rise of women in the high-skilled labor market.* National Bureau of Economic Research;2018.
39. Dabla-Norris E, Kochhar K. Women, technology, and the future of work. https://www.imf.org/en/Blogs/Articles/2018/11/16/blog-Women-Technology-the-Future-of-Work#:~:text=Digitalization%2C%20artificial%20intelligence%2C%20and%20machine,to%20break%20the%20glass%20ceiling. Published 2018. Accessed.
40. Casey M, Nzau S. The differing impact of automation on men and women's work. 2019.
41. Statistics Canada. Labour Force Survey (LFS). https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=3701. Published 2024. Accessed March 1, 2024.
42. Statistics Canada. COVID-19 in Canada: A one-year update on social and economic impacts. 11 March 2021.
43. U.S. Department of Labor. O*NET. https://www.dol.gov/agencies/eta/onet. Published 2021. Accessed November 1, 2023.
44. U.S. Bureau of Labor Statistics. Standard Occupational Classification. https://www.bls.gov/soc/2018/home.htm. Published 2018. Accessed November 1, 2023.
45. Statistics Canada. National Occupational Classification (NOC) 2021 Version 1.0. https://www23.statcan.gc.ca/imdb/p3VD.pl?Function=getVD&TVD=1322554&adm=0&dis=0. Published 2021. Accessed Novmber 1, 2023.
46. Pizzinelli C, Panton AJ, Tavares MMM, Cazzaniga M, Li L. *Labor market exposure to AI: Cross-country differences and distributional implications.* International Monetary Fund; 2023.
47. Russell S. Human-Compatible Artificial Intelligence. 2022.
48. Collett C, Gomes LG, Neff G. *The effects of AI on the working lives of women.* UNESCO Publishing; 2022.
49. Quinn EK, Harper A, Rydz E, Smith PM, Koehoorn MW, Peters CE. Men and women at work in Canada, 1991–2016. *Labour & Industry: a journal of the social and economic relations of work.* 2020;30(4):401-412.
50. Moyser M. *Women and Paid Work.* Ottawa, ON: Statistics Canada;2017.
51. World Economic Forum. Reskilling revolution: preparing 1 billion people for tomorrow's economy. World Economic Forum. https://www.weforum.org/impact/reskilling-revolution/. Published 2023. Accessed April 4, 2023.
52. Felten E, Raj M, Seamans R. Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal.* 2021;42(12):2195-2217.

Appendix

Appendix 1. Canadian occupations with high (a) and low (b) machine learning exposure according to National Occupational Classifications (NOC)

APPENDIX 1A.
Canadian occupations with high machine learning exposure

NOC	Occupational title	Suitability for machine learning score
11103	Securities agents, investment dealers and brokers	3.610908742
12100	Executive assistants	3.667400778
12101	Human resources and recruitment officers	3.684424177
12110	Court reporters, medical transcriptionists and related occupations	3.589442916
12112	Records management technicians	3.73140233
12200	Accounting technicians and bookkeepers	3.621127474
12202	Insurance underwriters	3.595530158
13111	Legal administrative assistants	3.648844173
13112	Medical administrative assistants	3.618173473
14100	General office support workers	3.611310696
14101	Receptionists	3.612529205
14111	Data entry clerks	3.649970475
14112	Desktop publishing operators and related occupations	3.629745056
14200	Accounting and related clerks	3.680055921
14201	Banking, insurance and other financial clerks	3.610483393
14400	Shippers and receivers	3.679297628
14401	Storekeepers and parts persons	3.618311702
14403	Purchasing and inventory control workers	3.594498716
14404	Dispatchers	3.620302654
14405	Transportation route and crew schedulers	3.679408127
21223	Database analysts and data administrators	3.634366963
22212	Drafting technologists and technicians	3.63404329
22222	Information systems testing technicians	3.615949979
53110	Photographers	3.59268563
53125	Patternmakers - textile, leather and fur products	3.68646023

NOC	Occupational title	Suitability for machine learning score
60010	Corporate sales managers	3.592096816
63100	Insurance agents and brokers	3.591783811
64101	Sales and account representatives - wholesale trade (non-technical)	3.594378603
64310	Travel counsellors	3.712819507
64312	Airline ticket and service agents	3.602959836
64313	Ground and water transport ticket agents, cargo service representatives and related clerks	3.605719206
64320	Tour and travel guides	3.608783599
64321	Casino workers	3.614833185
64322	Outdoor sport and recreational guides	3.608783599
64400	Customer services representatives - financial institutions	3.683425824
65102	Store shelf stockers, clerks and order fillers	3.597132392
65109	Other sales related occupations	3.647746736
65210	Support occupations in accommodation, travel and facilities set-up services	3.58609209
72604	Railway traffic controllers and marine traffic regulators	3.679408127
74101	Letter carriers	3.614497191
94150	Plateless printing equipment operators	3.597617501
94151	Camera, platemaking and other prepress occupations	3.598799354

APPENDIX 1B.
Canadian occupations with low machine learning exposure

NOC	Occupational title	Suitability for machine learning score
10022	Advertising, marketing and public relations managers	3.045158082
11202	Professional occupations in advertising, marketing and public relations	3.315162387
21201	Landscape architects	3.350203955
21320	Chemical engineers	3.301206574
31102	General practitioners and family physicians	3.337137368
32111	Dental hygienists and dental therapists	3.317867647
32200	Traditional Chinese medicine practitioners and acupuncturists	3.110136586
32201	Massage therapists	2.853439264
32209	Other practitioners of natural healing	3.110136586
41409	Other professional occupations in social science	3.336057787
42100	Police officers (except commissioned)	1.715057266
42101	Firefighters	3.309474347
51122	Musicians and singers	3.320337127
52114	Announcers and other broadcasters	3.255573427
53120	Dancers	3.199743809
53200	Athletes	3.212524023
53201	Coaches	3.274160768
53202	Sports officials and referees	3.333100583
63210	Hairstylists and barbers	3.34474068
64300	Maîtres d'hôtel and hosts/hostesses	3.337287857
65220	Pet groomers and animal care workers	3.349168362
65229	Other support occupations in personal services	2.853439264
65320	Dry cleaning, laundry and related occupations	3.323146247
72012	Contractors and supervisors, pipefitting trades	3.338367016
72013	Contractors and supervisors, carpentry trades	3.328013012
72014	Contractors and supervisors, other construction trades, installers, repairers and servicers	3.341689813
72302	Gas fitters	3.342984582
72421	Appliance servicers and repairers	3.309223288
72422	Electrical mechanics	3.338315998
72423	Motorcycle, all-terrain vehicle and other related mechanics	3.350846193
72500	Crane operators	3.349581182
72999	Other technical trades and related occupations	3.331525918
73100	Concrete finishers	3.278164765
73102	Plasterers, drywall installers and finishers and lathers	3.181052524

NOC	Occupational title	Suitability for machine learning score
73112	Painters and decorators (except interior decorators)	3.306261863
74200	Railway yard and track maintenance workers	3.244955113
74203	Automotive and heavy truck and equipment parts installers and servicers	3.308451739
82020	Supervisors, mining and quarrying	3.328013012
82021	Contractors and supervisors, oil and gas drilling and services	3.328013012
83101	Oil and gas well drillers, servicers, testers and related workers	3.346337392
84100	Underground mine service and support workers	3.29009901
84101	Oil and gas well drilling and related workers and services operators	3.336190804
94142	Fish and seafood plant workers	3.339859109
94210	Furniture and fixture assemblers, finishers, refinishers and inspectors	3.320629515

APPENDIX 2.
Multivariable logistic regressions models to estimate the likelihood of employment in high machine learning exposure occupations and likelihood of employment in low machine learning exposure occupation when compared to all other Canadian workers.

	Outcome a: High occupational ML exposure[a]						Outcome b. Low Occupational ML exposure[b]					
Models	Women workers			Men workers			Women workers			Men workers		
	OR	Low CI	High CI	OR	Low CI	High CI	OR	Low CI	High CI	OR	Low CI	High CI
Models 1: Educational attainment‡												
<Some post-secondary education	ref			ref			ref			ref		
Trades certification or diploma	1.091	1.074	1.110	0.517	0.507	0.527	2.272	2.208	2.338	0.993	0.975	1.010
College or bachelor's degree	0.917	0.909	0.925	0.862	0.853	0.871	1.268	1.244	1.291	0.924	0.911	0.937
University degree above bachelor's degree	0.378	0.370	0.385	0.455	0.445	0.465	1.640	1.595	1.687	0.803	0.782	0.824
Models 2. Hourly wages (interquartile categories) ‡												
≤ 25th percentile of hourly wages (Quartile 1)	ref			ref			ref			ref		
>25th and ≤ 50th percentile of hourly wages (Quartile 2)	1.846	1.827	1.866	0.862	0.85	0.874	0.895	0.874	0.916	1.238	1.21	1.268
>50th and ≤75th percentile of hourly wages (Quartile 3)	1.562	1.544	1.581	0.678	0.668	0.688	1.282	1.252	1.313	1.489	1.455	1.523
>75th percentile of hourly wages (Quartile 4)	0.497	0.489	0.505	0.412	0.405	0.418	1.975	1.928	2.024	2.103	2.056	2.152
Model 3. Job skill, experience and training requirements‡												
General skilled occupation	ref			ref			ref			ref		
Semi-skilled occupations	0.231	0.228	0.234	0.091	0.089	0.094	1.956	1.908	2.004	2.732	2.675	2.791
Skilled, technical, or supervisory occupations	0.302	0.299	0.306	0.096	0.094	0.097	1.759	1.717	1.802	2.851	2.799	2.902
Professional occupations	0.025	0.024	0.025	0.069	0.068	0.071	2.986	2.919	3.055	1.597	1.560	1.636
Managerial occupations	0.026	0.025	0.028	0.062	0.060	0.064	1.765	1.700	1.832	0.856	0.825	0.889

Notes: a = SML score in the top ten percentile compared to the reference group of occupational SML scores outside of the top ten percentile; b = occupations with an SML score in the bottom ten percentile were compared to the reference group of occupational SML scores outside of the bottom ten percentile; OR = odds ratios; CI = confidence interval; Each model adjusted for sociodemographic and work context covariates; ‡ = indicates significant difference between men and women at p <.001.

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