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Machine learning and the labour market: A portrait of occupational and worker inequities in Canada

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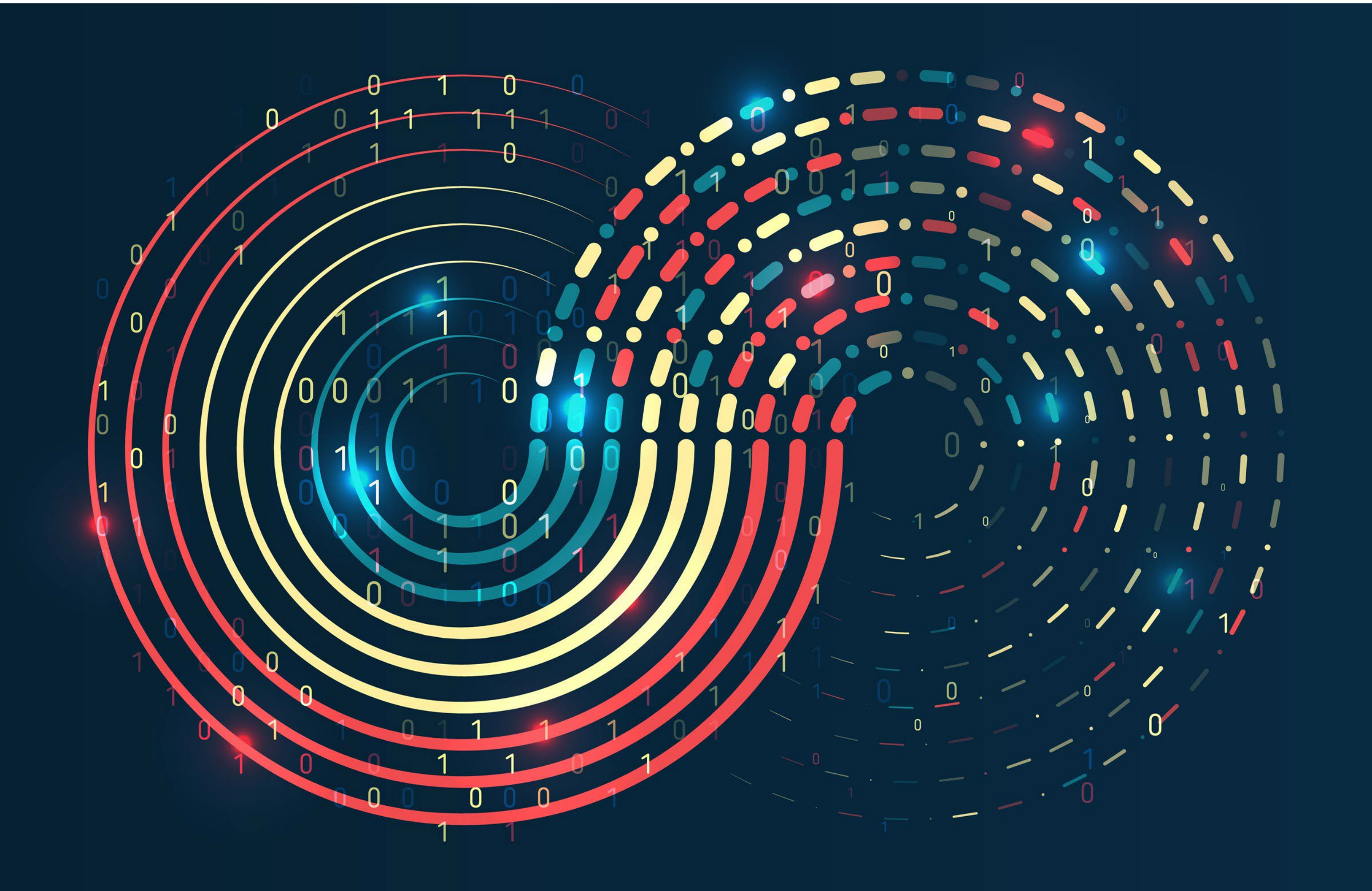

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Machine learning and the labour market: A portrait of occupational and worker inequities in Canada

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Ethics approval was not required for this secondary analysis of data.

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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 can 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 impact of machine learning may be inequitable; working conditions and employment opportunities emerging from machine learning adoption within the workplace may vary across occupations and worker groups. Workers better positioned in the labour market may be more likely to capitalize on economic advantage stemming from machine learning when compared to those from socially and economically disadvantaged groups. In this report, we utilize a novel analytical approach to examine the extent to which different Canadian occupations may be exposed to machine learning, meaning that they consist of job tasks that can be potentially completed by the technology. Through this approach, we can estimate different occupational and worker characteristics that relate to high or low occupational machine learning exposure.

Our research addressed three main objectives, which include:

1. Estimating the number of workers in occupations characterized by high or low machine learning exposure in Canada.
2. Examining how machine learning exposure differs according to workers' socioeconomic (e.g., educational attainment, gender) and occupational characteristics (e.g., hourly wages, job skills, training and experience requirements).
3. Determining whether gender moderates the association between educational attainment, job skills, training and experience requirements, hourly wages, and machine learning exposure.

Summary of methodological approach

Eight years of Statistics Canada's Labour Force Survey (LFS) were pooled. 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 according to high machine learning exposure (top 10 per centile of SML scores) and low machine learning exposure (bottom 10 per centile 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.

Key findings

Overall, 1,902,050 Canadian workers were employed in occupations with high machine learning exposure where 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 with low machine learning exposure where 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 jobs with high job skills, 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 jobs with less job skills, 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. 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 is 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 not be neutral to workers; scholars anticipate significant impacts on the 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 impacts different types of jobs and workers. Such research is crucial for identifying 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 (ML) 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 across all industries, such as 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 recent 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 fully adopted AI[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, changes in technology 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 occupations are exposed to machine learning 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 significant job displacement due to workforce reduction or 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 high machine learning exposure, 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. This means that machine learning's learning abilities are constantly evolving, leading to changing impacts on both workers and workplaces [16]. 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. 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 vary across different occupations and groups of workers [29]. In Canada, as in many other developed countries, 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 increases in wages 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.

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 automotive technology than lawyers, which require post-graduate education and multiple years of training, and consist of cognitively demanding tasks (e.g., managing legal proceedings, 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 influence 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 ML[3]. Similarly, a study using Canadian census data from 2016 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 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].

Gender, education, wages, and susceptibility to automation may be interrelated[36,40]. US data suggest that men with lower education levels are more likely to work in jobs highly susceptible to automation and may face wage decreases as a result [34]. Conversely, the same study found 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 will worsen or lessen gender differences in the Canadian workforce remains uncertain.

Machine learning exposure and the job skills ecosystem in Canada

Objectives

Our study aims to examine 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 describe the potential impact of machine learning on Canadian occupations and different groups of workers. Our research has three main study objectives, which include:

1. Estimating the number of workers in occupations characterized by high or low machine learning exposure in Canada.
2. Examining how machine learning exposure differs according to workers' socioeconomic (e.g., educational attainment, gender) and occupational (e.g., job skill level requirements, hourly wages) characteristics.
3. Determining whether gender moderates the association between educational attainment, job skill requirements, hourly wages, and machine learning exposure.

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 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 cross-sectional monthly 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. Weighted monthly cycles were combined to produce annual estimates. Labour Force Survey waves 2020-2021 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 might significantly bias study results [42].

Suitability for Machine Learning measure to estimate occupational machine learning exposure

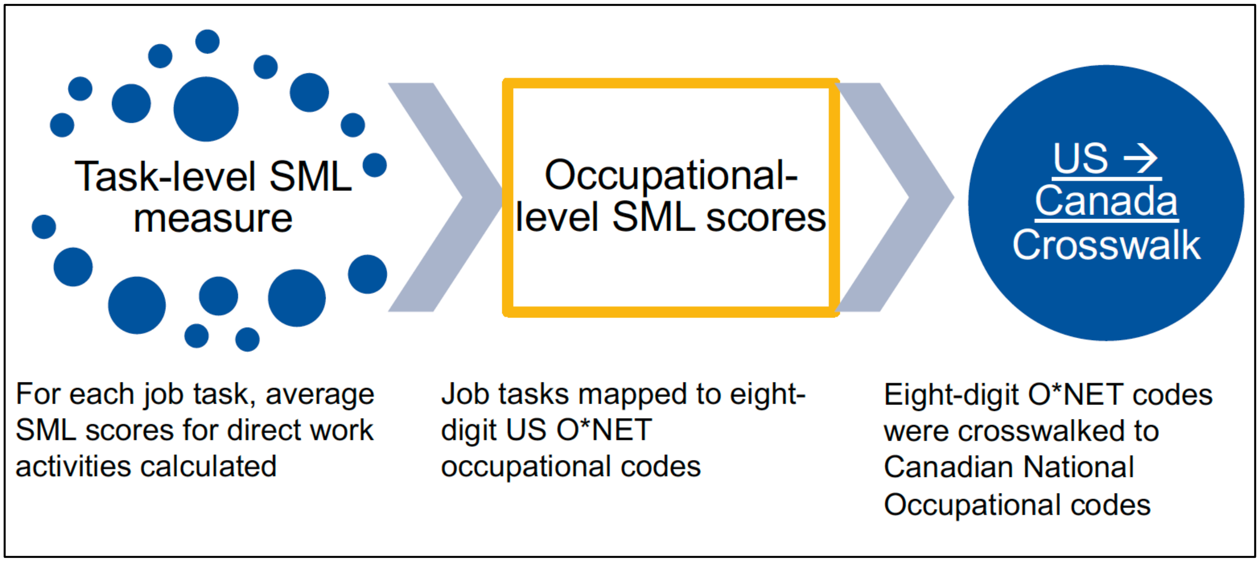
To measure occupational exposure to machine learning, we used the suitability for machine learning (SML) measure developed by Brynjolfsson and colleagues in the US. The SML estimates the extent to which actions and outputs for a specific job task can be learned by a machine. The SML measure offers detailed 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 [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. Based on the SML values, we categorized occupations as high machine learning exposure (top 10 percentile of SML scores, SML score ≥ 3.597) and low machine learning exposure (bottom 10 percentile of SML scores, SML score ≤ 3.351).

Outcome variables[1]

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.

[1] In research, an outcome variable is the focus of the study. The independent variable is the variable that is changed or controlled to study the effects on the dependent variable. In this study, the dependent variable is high or low exposure to machine learning. The independent variables are worker characteristics (such as gender and educational attainment) or work characteristics (such as hourly wages and job skill, training and experience requirements).

Independent variables

Gender: A one-item question in the Labour Force Survey asked the respondent, "What is your gender?" For this study, 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 Statistics Canada, 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).

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 produced weighted estimates of the number of workers in Canada in occupations with high machine learning exposure or low machine learning exposure. 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[2] regressions models were fitted to estimate odds of employment in high or low machine learning exposure occupations within 95% confidence intervals[3]. 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 or considered sociodemographic and work context covariates. Also, for each of these models, findings were examined separately for men and women to examine potential gender differences.

[2] Logistic regression is a statistical modeling method. It estimates the probability of an event occurring (e.g., high or low exposure to machine learning) when considering an independent variable. Multivariable logistic regression accounts for one or more independent variables while accounting for study covariates.

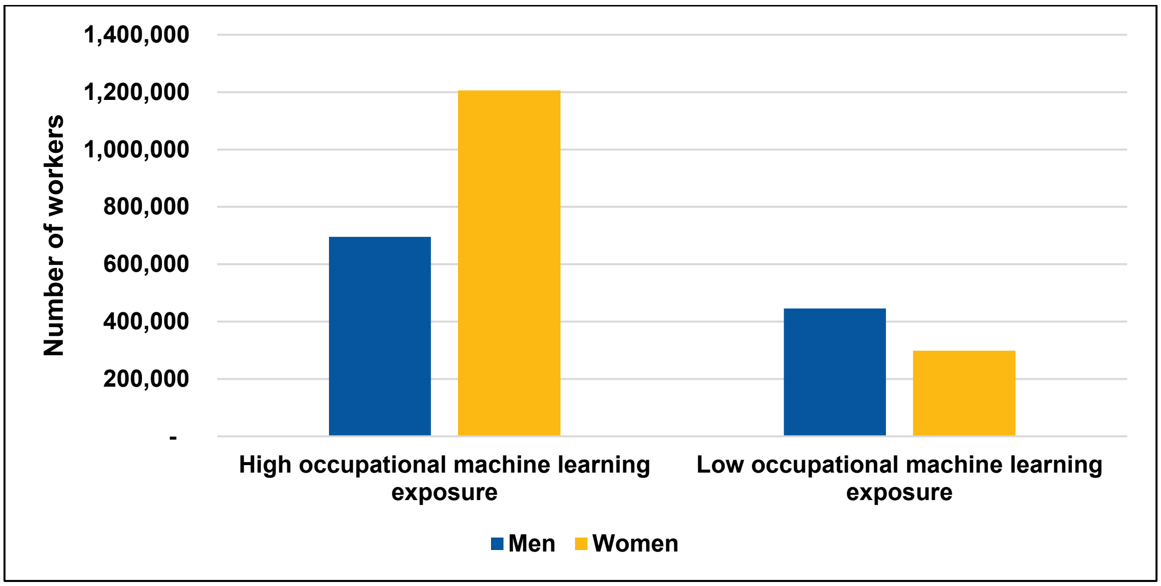
[3] Confidence intervals are a range of values, above and below a finding, in which the actual value is likely to fall. The confidence interval represents the accuracy or precision of an estimate.

Results

Overall, 1,902,050 Canadian workers were employed in occupations with high machine learning exposure where the greatest proportion of job tasks are suitable for machine learning. This figure represents 12 per cent of the Canadian workforce. In comparison, about 744,250 workers were employed in occupations with low machine learning exposure where a smaller proportion of job tasks are 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.

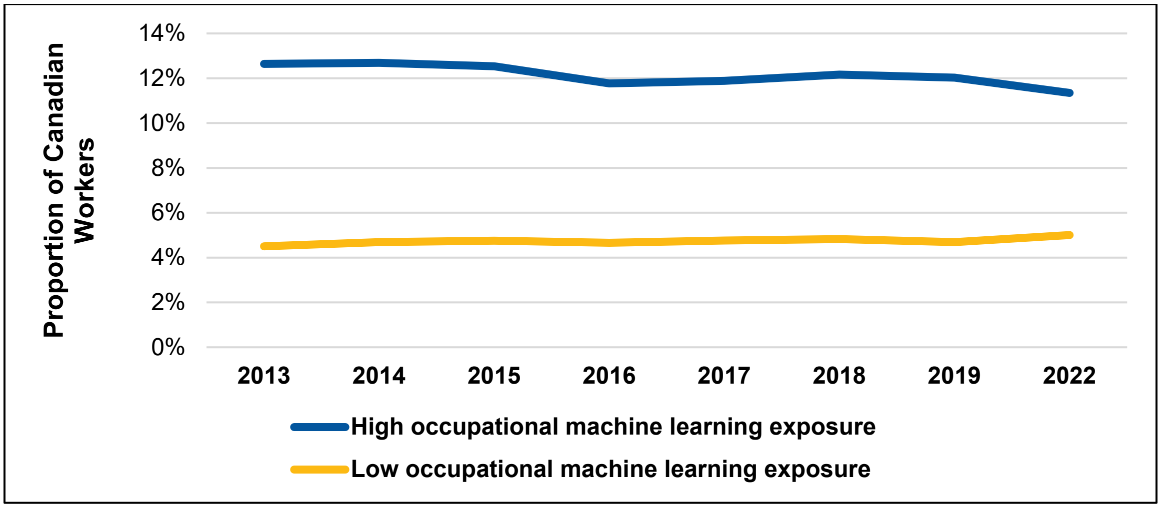
In occupations characterized by high machine learning exposure, women made up a larger proportion than men (63.4 per cent vs. 36.6 per cent). In contrast, in occupations characterized by low machine learning exposure, men outnumbered women (59.9 per cent vs. 40.1 per cent). (Figure 2).

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



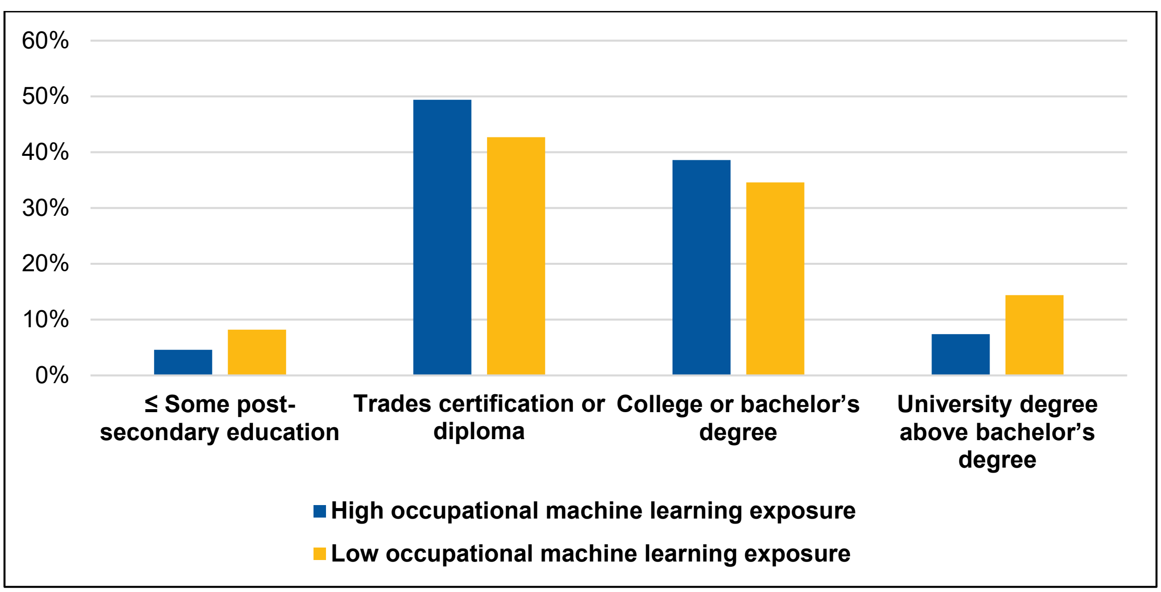
The proportion of Canadian workers in occupations characterized by high or low exposure to machine learning remained relatively unchanged over each wave of the survey (Figure 3). Data from each survey wave were combined for the remaining portions of the analysis presented in the next sections.

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.



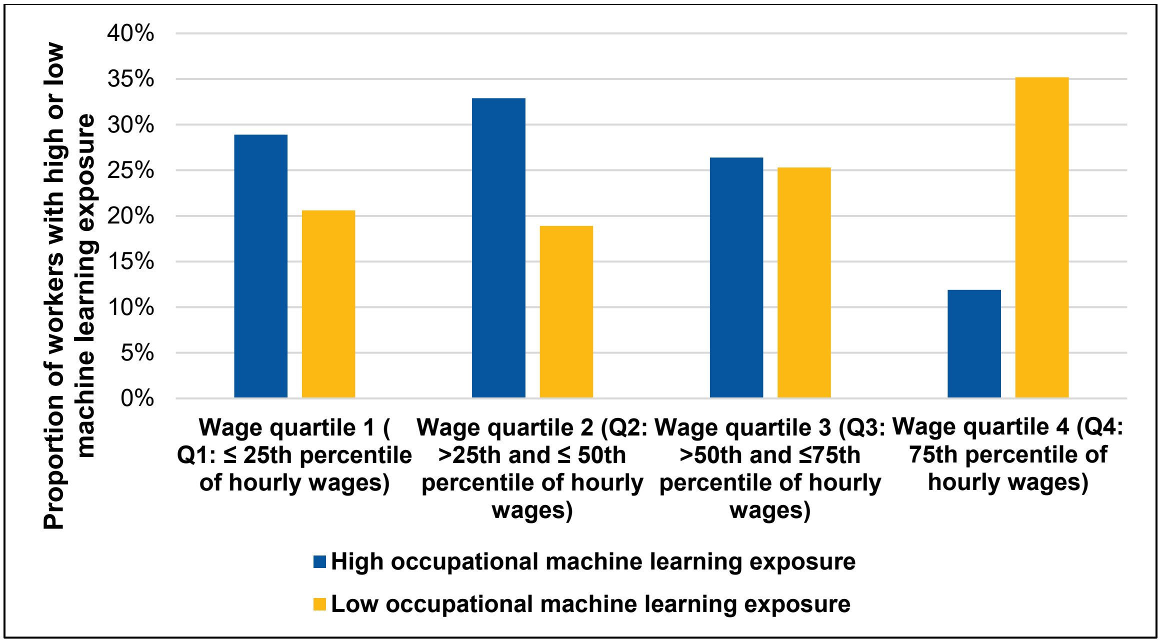
Next, using descriptive statistics, we illustrate how machine learning exposure differs according to educational attainment, hourly wages and job skills, training and experience. The proportion of workers in high and low exposure to machine learning also differed according to educational attainment. When compared to occupations with low exposure, occupations characterized by high exposure to machine learning had larger shares of workers with a trade's 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 smaller proportions 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. Proportion of Canadian workers in occupations with high and low exposure according to educational attainment



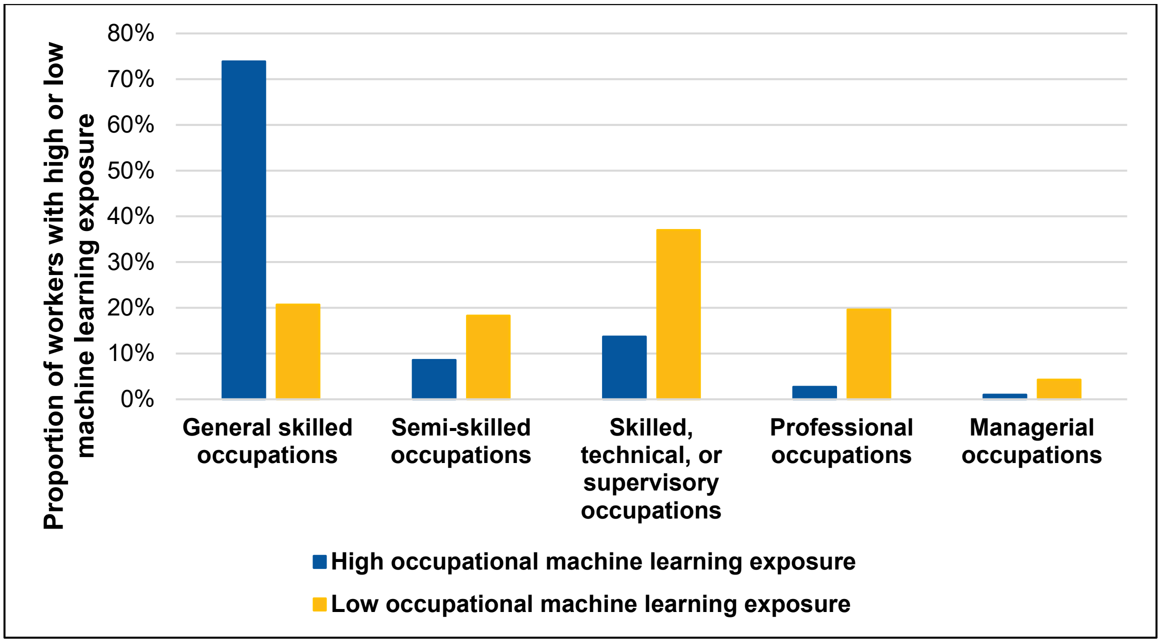
When compared to occupations with low exposure to machine learning, occupations with high exposure to machine learning were composed of a greater proportion of workers in the two lower-earning quartiles (21 per cent vs. 29 per cent of the lowest earning quartile; 19 per cent vs. 33 percent of earners 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. Proportion of Canadian workers in occupations with high and low machine learning exposure according to job skills, training, and experience requirements.



Models showing the association between the educational attainment, hourly wages and job skills, training and experience requirements and machine learning exposure 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.

For both women and men workers, greater educational attainment was associated with a lower odds of high occupational machine learning exposure 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.

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

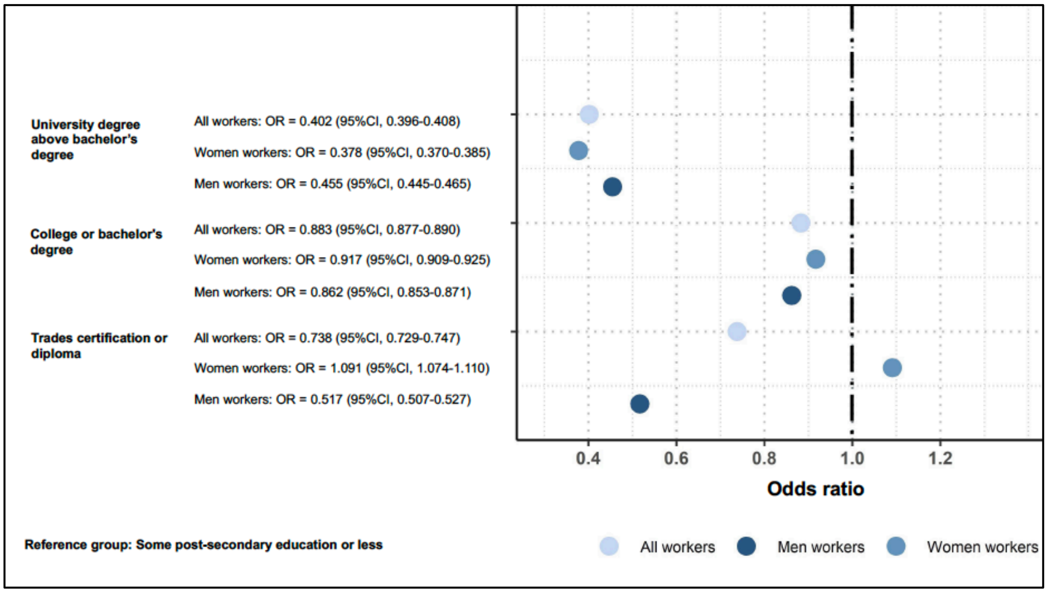
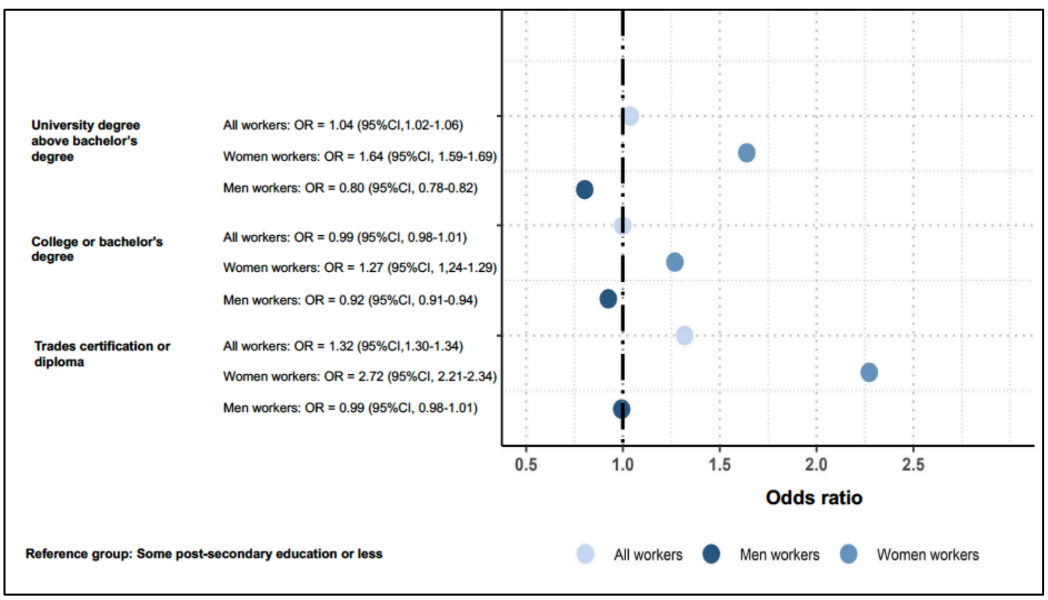


Figure 8. Summary of multivariable logistic regression model examining the association between educational attainment and low occupational machine learning exposure.



Among both women and men, the highest earners were less likely to make up the workers with high occupational machine learning exposure (Figure 9). They were more likely to make up the workers in low machine learning exposure occupations (Figure 10). Of note, 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). By contrast, women in the highest earning quartile are not more likely to have low machine learning.

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

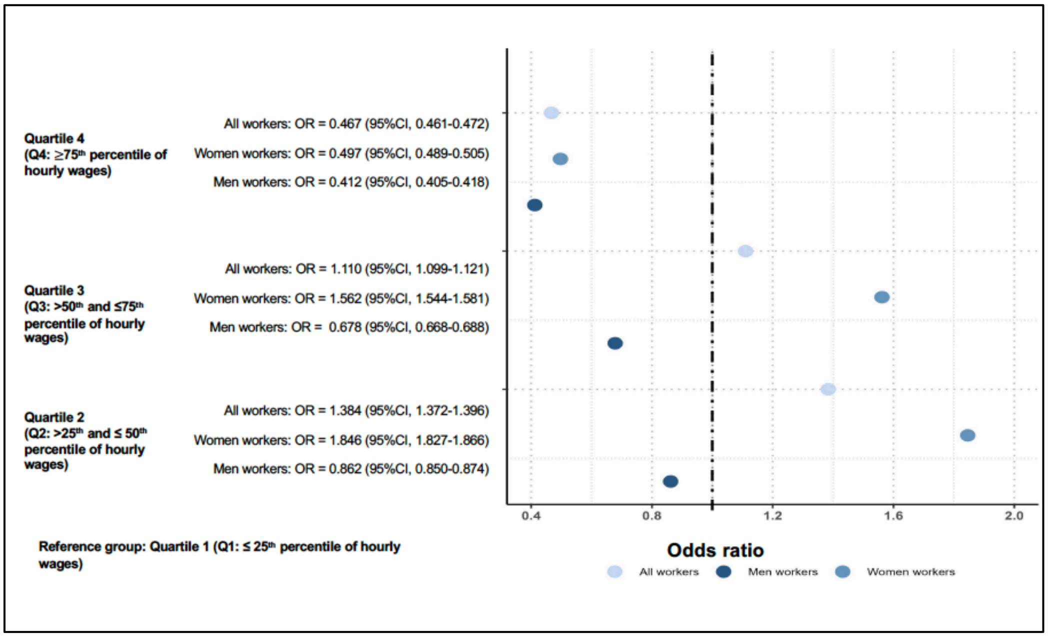
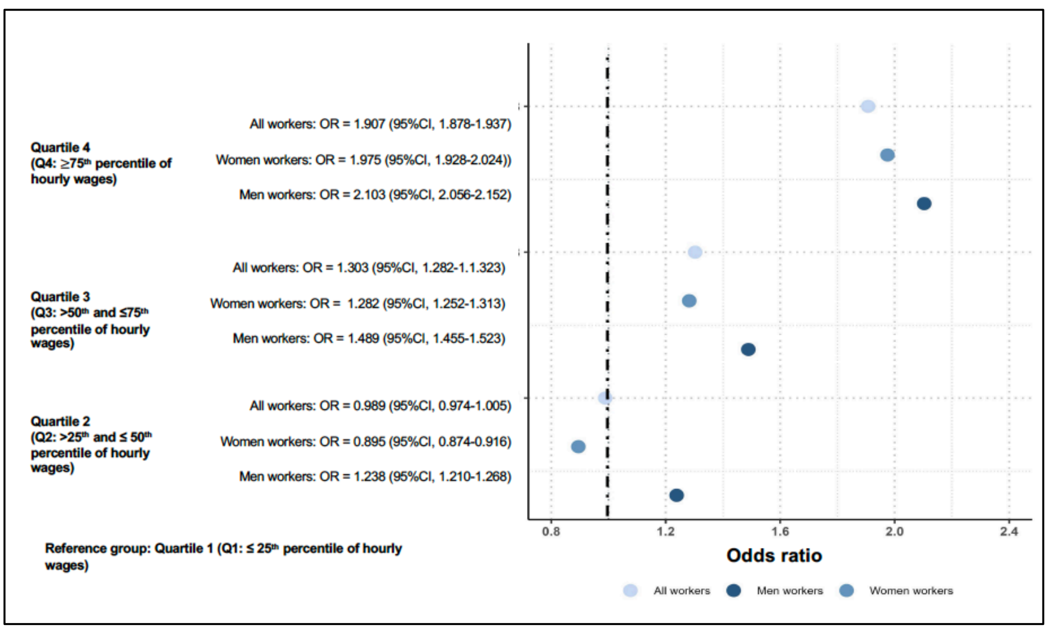


Figure 10. Summary of multivariable logistic regression model examining the relationship between hourly wages and low occupational machine learning exposure.



Finally, greater job skills, training and experience requirements were associated with a lower likelihood of high occupational exposure to machine learning (Figure 11) and 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 to have 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.

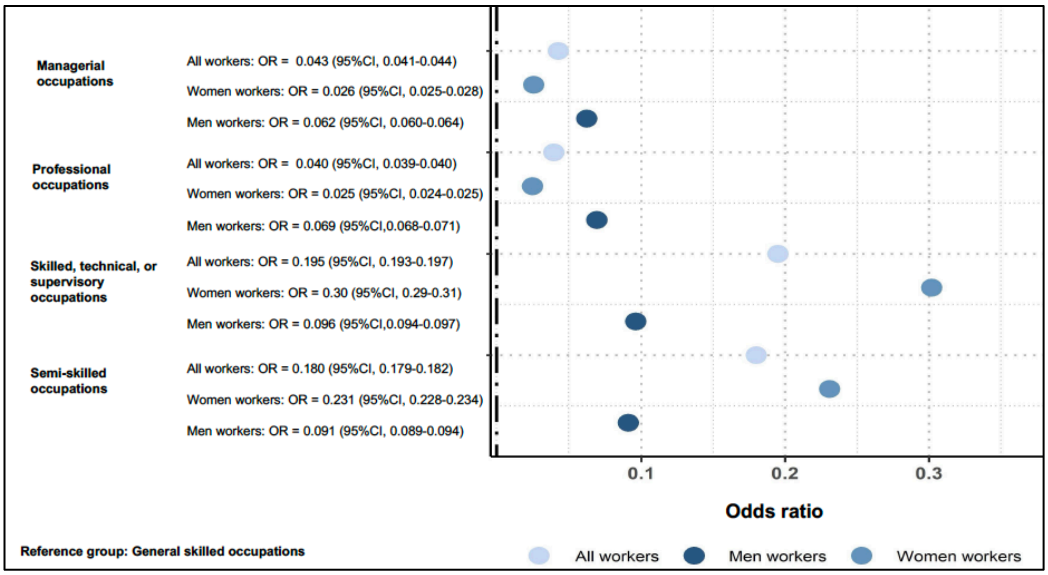
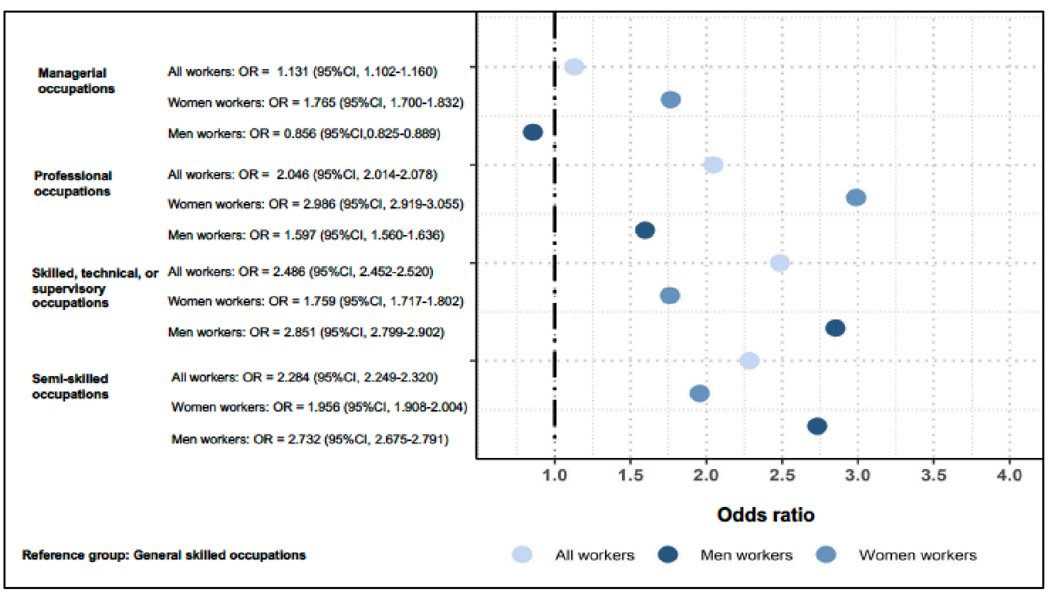


Figure 12. Summary of multivariable logistic regression model examining the relationship between occupational job skills, training and experience requirements and low occupational machine learning exposure.



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, potentially worsening existing workforce disparities. To our knowledge, our study stands out as one of the earliest attempts to provide an overview of machine learning exposure in different occupations across Canada's job market and how this exposure may vary according to a workers' sociodemographic and job-related characteristics. Like other technological transformations that have shaped Canada’s labour market, we show that 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. 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 machine learning exposure (i.e., those most suitable for machine learning tasks) and low machine learning exposure (i.e., those least suitable for machine learning tasks). Our analysis revealed that nearly two million Canadian workers are in high machine learning exposure occupations, 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. 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 are in line with previous automation trends, indicating 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]. However, machine learning might also improve working conditions by handling repetitive or hazardous tasks, thus benefiting certain groups [22,23]. Further research is necessary to delve into our findings and gain a deeper understanding of how machine learning can affect working conditions and various worker groups, both positively and negatively. This understanding will be crucial for developing targeted policy interventions and support measures.

Exposure to machine learning within Canadian occupations may exhibit gender-related patterns. Men and women often concentrate 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]. The implications of these findings could be interpreted in several ways. The job tasks that women workers perform and the job roles they hold may be at a greater risk of being substituted by machine learning. Alternatively, women may be more likely to benefit from machine learning including the technology’s ability to complement their tasks and contribute to productivity gains. Our findings may suggest that men may be shielded from job displacement 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 achievements and occupying managerial roles tended to have lower exposure to machine learning in their occupations. 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.

Our research has significant implications for policy-makers and workforce program planners. We demonstrate that nearly all Canadian occupations encompass bundles of tasks suitable and unsuitable for machine learning. Some economists propose potential benefits from firms segregating and reorganizing tasks based on their machine learning suitability [16]. For instance, 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. Our study's evidence can inform the design of job skills development programs in light of the AI revolution. Using our findings, there may be a necessity to target retraining 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 [51]. The importance of skill development may be especially pertinent for women in roles with heightened machine learning exposure [48].

Implications for the job skills ecosystem in Canada

Study strengths and limitations

Our study possesses several strengths and limitations. We employ 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 generate population-based estimates of machine learning exposure. Furthermore, we characterize 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 influence Canada's labour market and contribute to labour market segmentation. However, there are notable limitations. Our measurement focuses solely on the technical feasibility of machine learning and its task suitability [15,25]. We do not comment on the practical application of machine learning or its specific impacts on workers and job performance. Our findings also do 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 employ 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 does 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 most influenced by machine learning, showing that a significant portion 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 this technology. We highlight how machine learning exposure in occupations could contribute to labour market segmentation based on factors like educational attainment, wages, and job-specific skills and training requirements. Notably, the impact of machine learning on work experiences may vary based on gender, reflecting differences in educational levels and job skill, training and experience requirements between men and women. Further investigation is needed to fully examine how machine learning impacts 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.

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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

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
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.

Models	Outcome a: High occupational ML exposure[a]						Outcome b. Low Occupational ML exposure[b]					
	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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