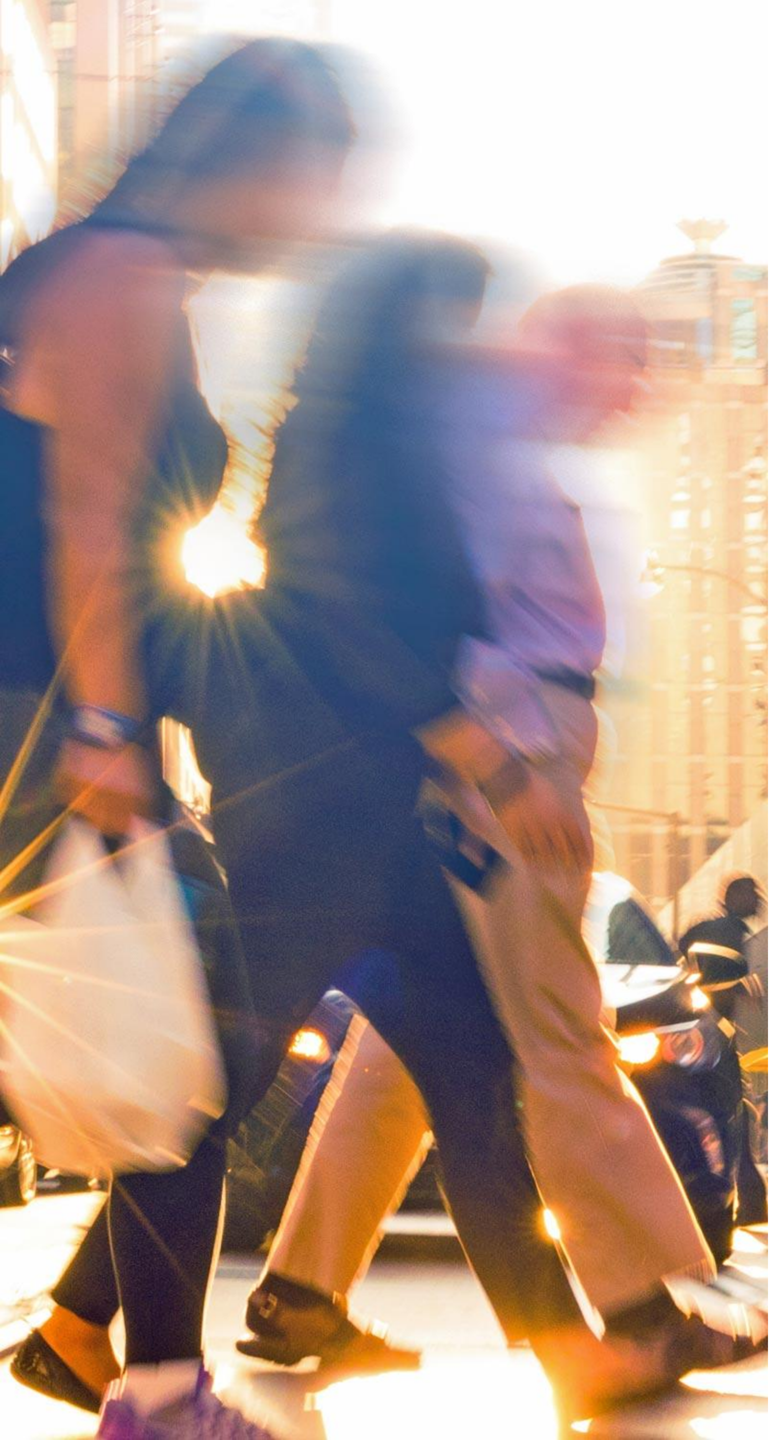

AI adoption at work: Which worker and occupation groups are most likely to be affected?

Arif Jetha PhD
Associate Scientific Director and Scientist
Director, Partnership on AI and Quality of work (PAIQ)

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WSIB Ontario | Workplace Safety and Insurance Board

WORK SAFE BC

SSHRC CRSH

Future Skills Centre | Centre des Compétences futures

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Research team and OHS partners

Research team

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Peter Smith, IWH

Viet Vu, The Dais

Partners

The Dais

Statistics Canada

Labour Market Information Council

Partnership on AI and the Quality of work (PAIQ)

To examine how the increasing use of AI will affect the quality of working lives in Canada and well-being of workers

Length: 7-year research and partnership project

Pan-Canadian team:
40 multidisciplinary researchers
34 partner organizations

3 Research clusters

Labour force analysis

Evidence observatory

Workplace-based studies

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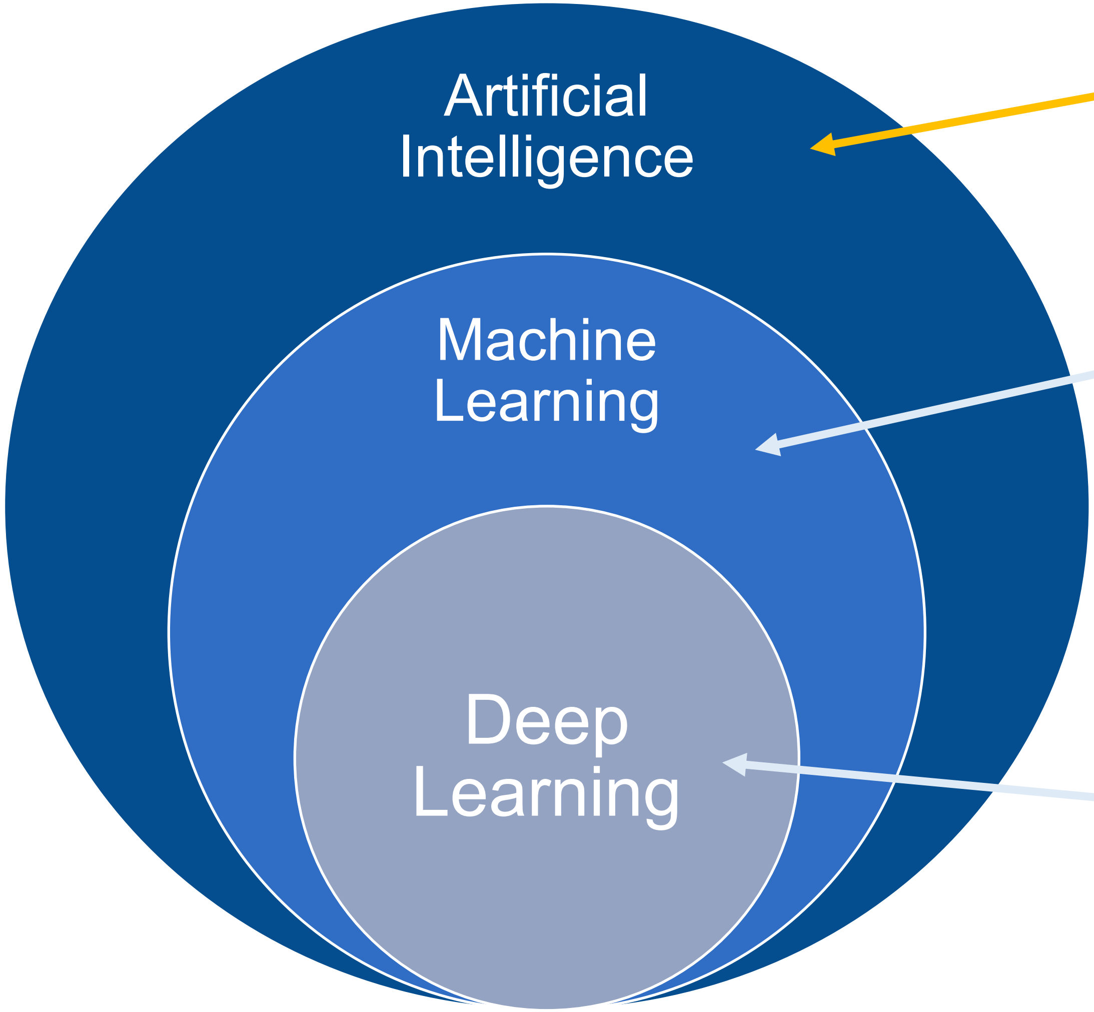
SSHRC CRSH

Partnership on AI and Quality of work

Background

AI at work

AI as a series of systems



Systems that solve problems traditionally requiring human intelligence

- Statistical algorithms to large amounts of data to detect patterns, make predictions, generate decisions, or optimize processes

- Fraud detection services (finance), image diagnostic tools (health care)

- Neural networks to simulate the complex decision-making power of the human brain

- Chatbot (sales), content writing (journalism), product defect inspection tools (manufacturing)

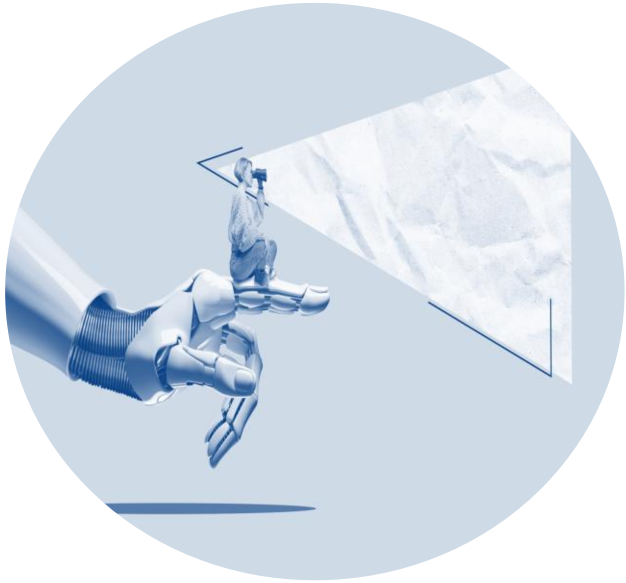
~12% of Canadian companies report adopting AI to produce goods or deliver services

Source: Statistics Canada

61% of Canadian workers us AI tools at work

Source: KPMG Canada

AI at work



Augment

Automate

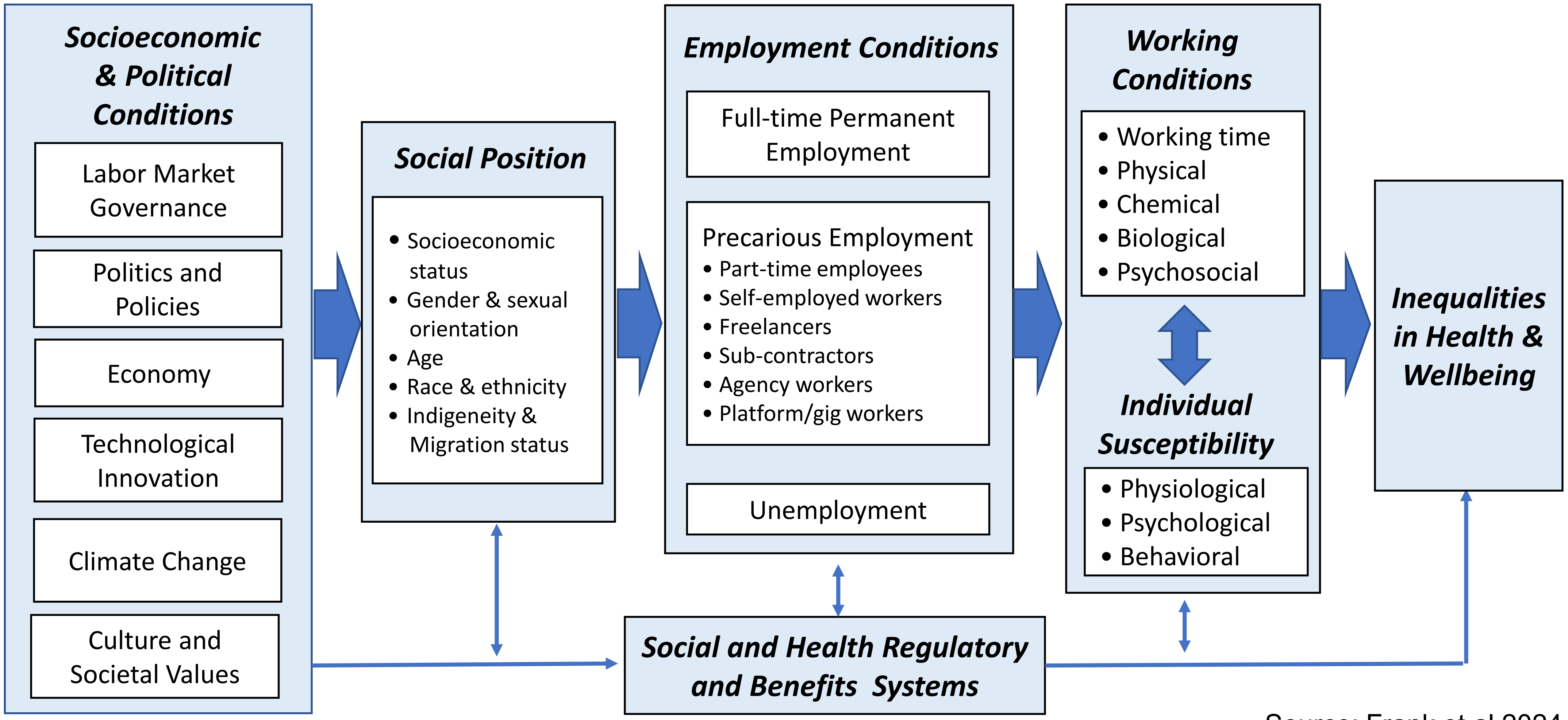
Optimize

Reorganize

Background

Unpacking labour market patterns using a social determinants of health framework

Conceptual framework of social determinants influencing work, health, and wellbeing



Source: Frank et al 2024

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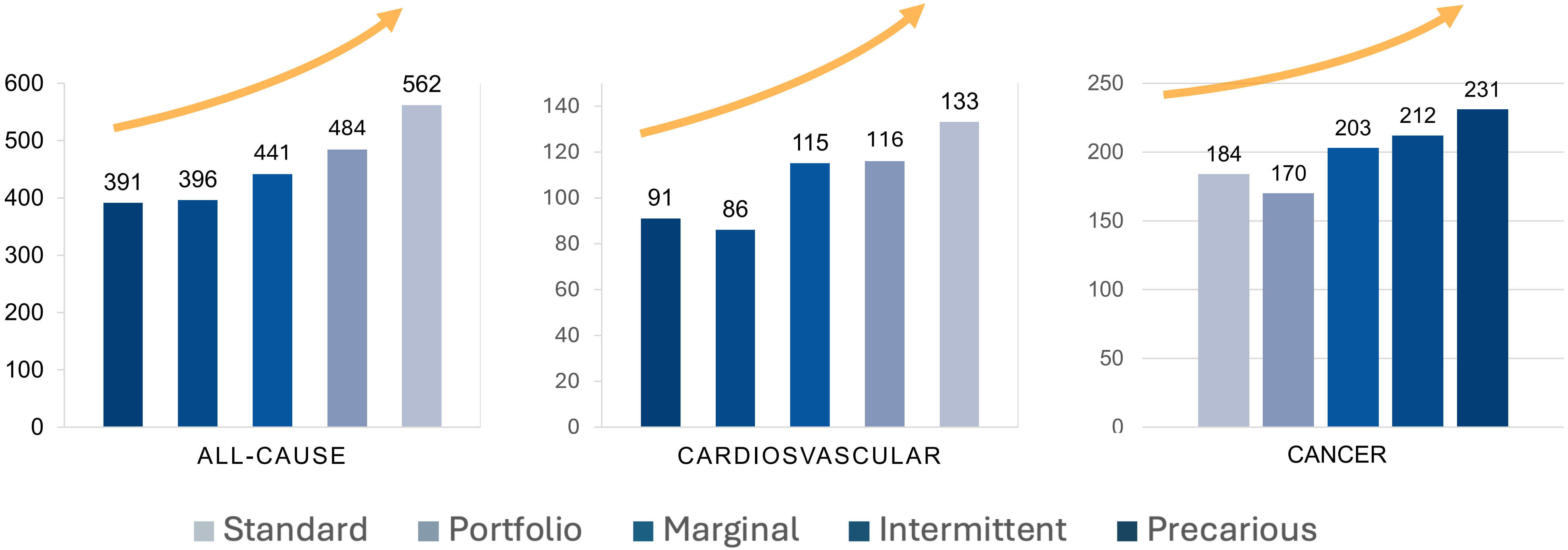
Workers in lower quality employment experienced higher rates of all-cause and cause-specific mortality

AGE-STANDARDIZED MORTALITY RATES (PER 100,000)



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Source: Shahidi et al., 2025; Slide acknowledgement: FV Shahidi

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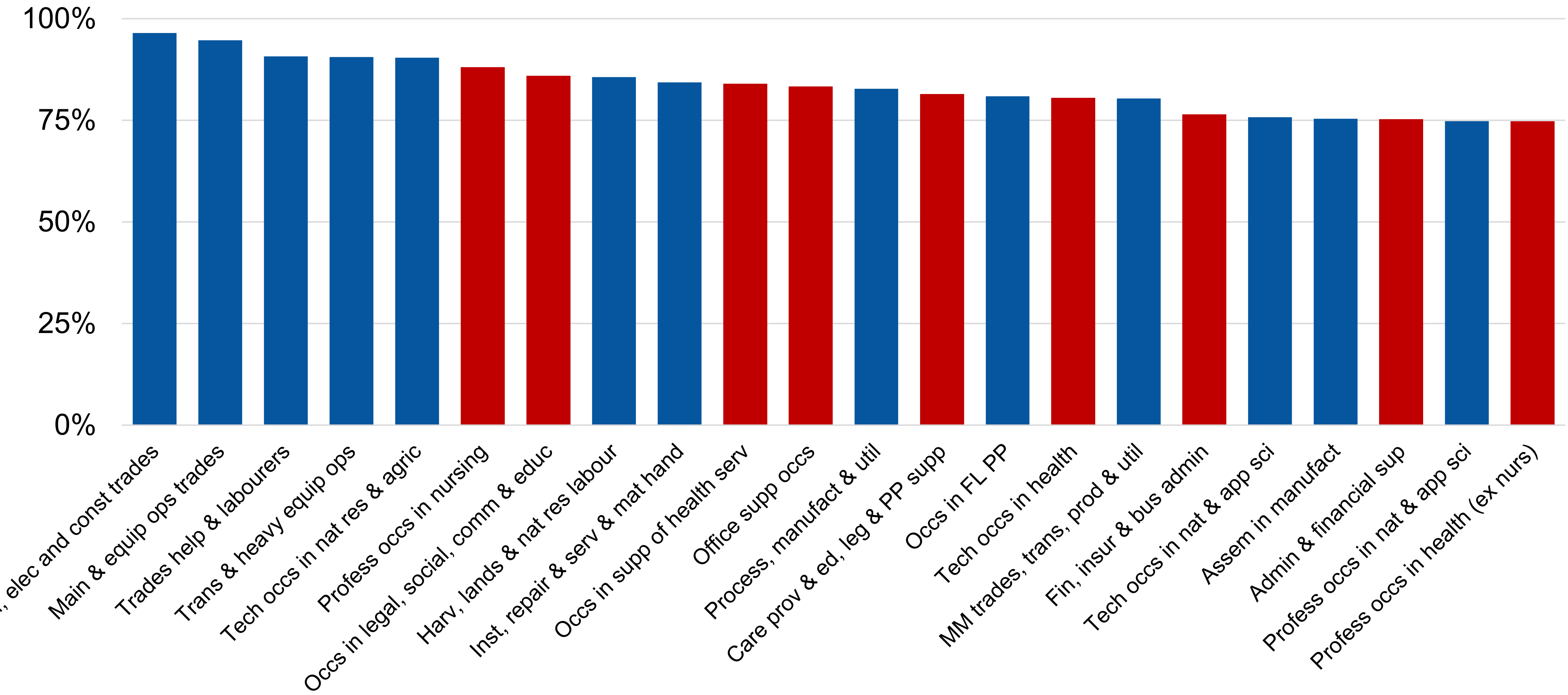
Gender divisions in Canada's labour market (gendered occupations with 75% or more women/men)



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Source: Labour Force Survey; Acknowledgement: P Smith

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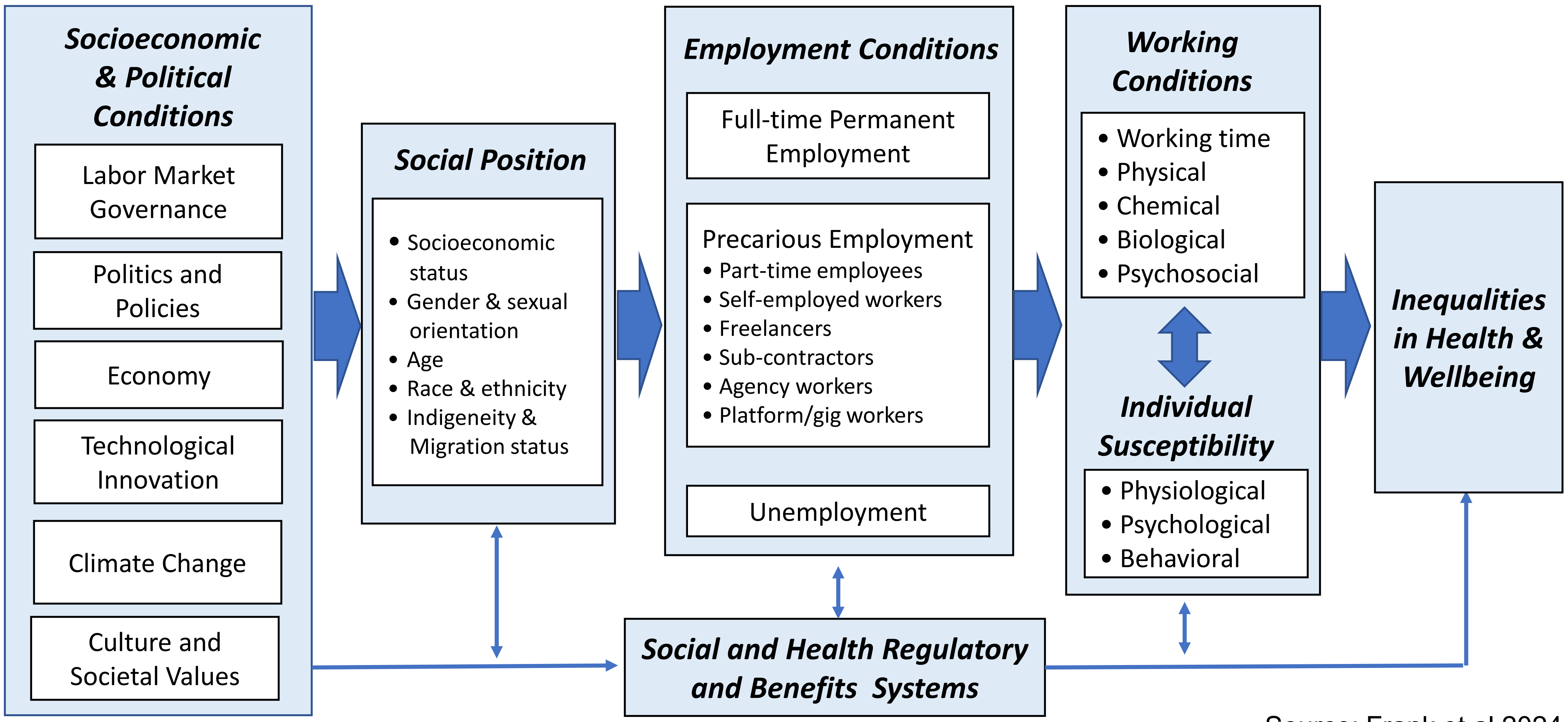
Women have been less likely to benefit from productivity gains related to new digital technologies

Source: European Institute for Gender Equality

Conceptual framework of social determinants influencing work, health, and wellbeing



Source: Frank et al 2024

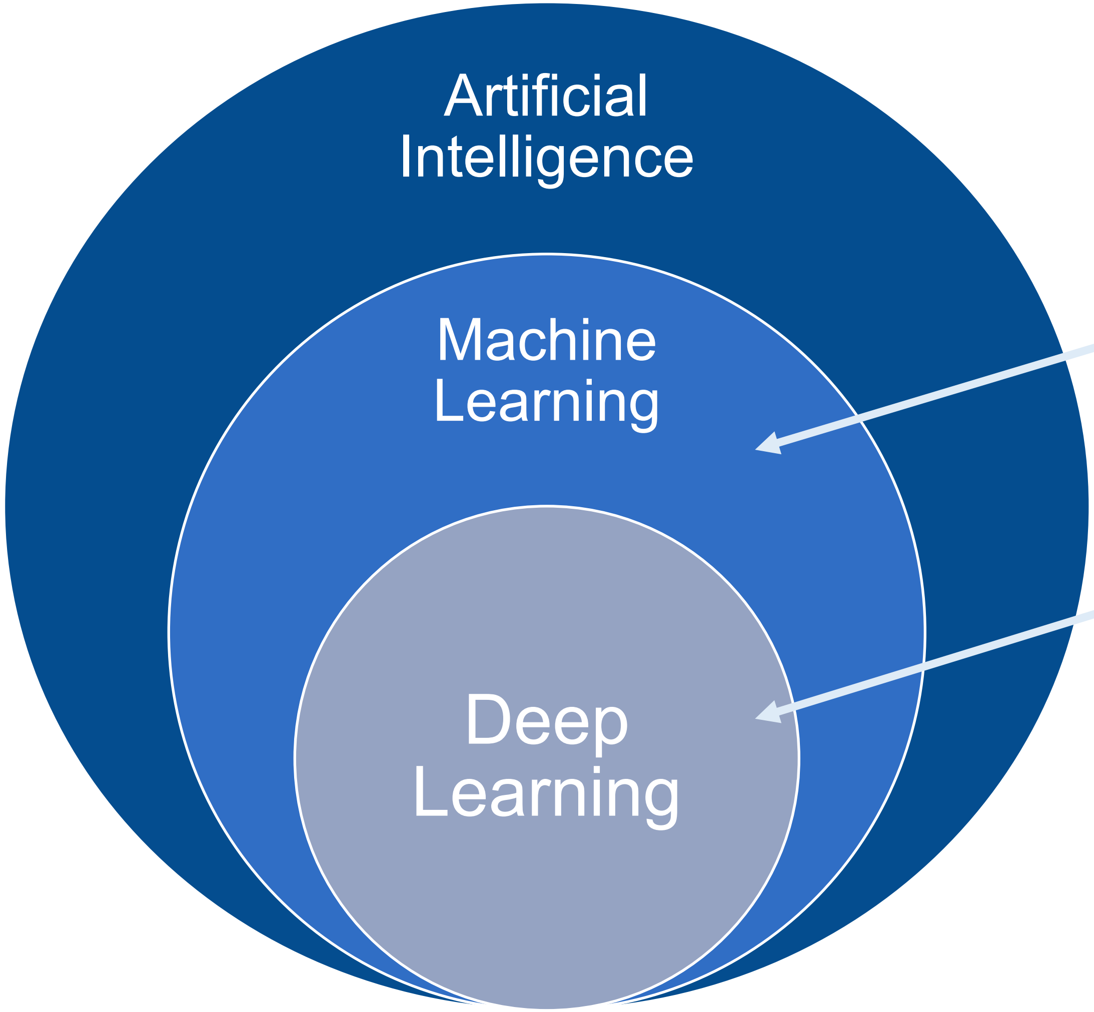
Aims and Objectives

To examine how AI impacts Canadian workers and occupations

1. Explore the role of measures of occupational AI exposure as a proxy to determine AI impact in the labour market
2. Examine the differential impact of AI according to worker (gender) and occupational characteristics (precarious work)
3. Draw from a social determinants of health framework to identify and interpret findings

Analytical approach

Measures of AI exposure



To estimate how susceptible occupations are to being performed AI technologies

Suitability for Machine Learning

- Measures how easily job tasks can be learned by machine learning
- Brynjolfsson, Mitchell, Rock (2018)

Large language model exposure

- Text-, code-, and image-generation can impact job tasks
- Eloundou, Manning, Mishken, Rock (2024)

Occupations are bundles of job tasks (*what*) and work activities (*how*)

- Technology can impact workers in specific tasks rather than whole occupations
- Applied to studies of computerization, automation, AI
- Job tasks captured in US O*Net

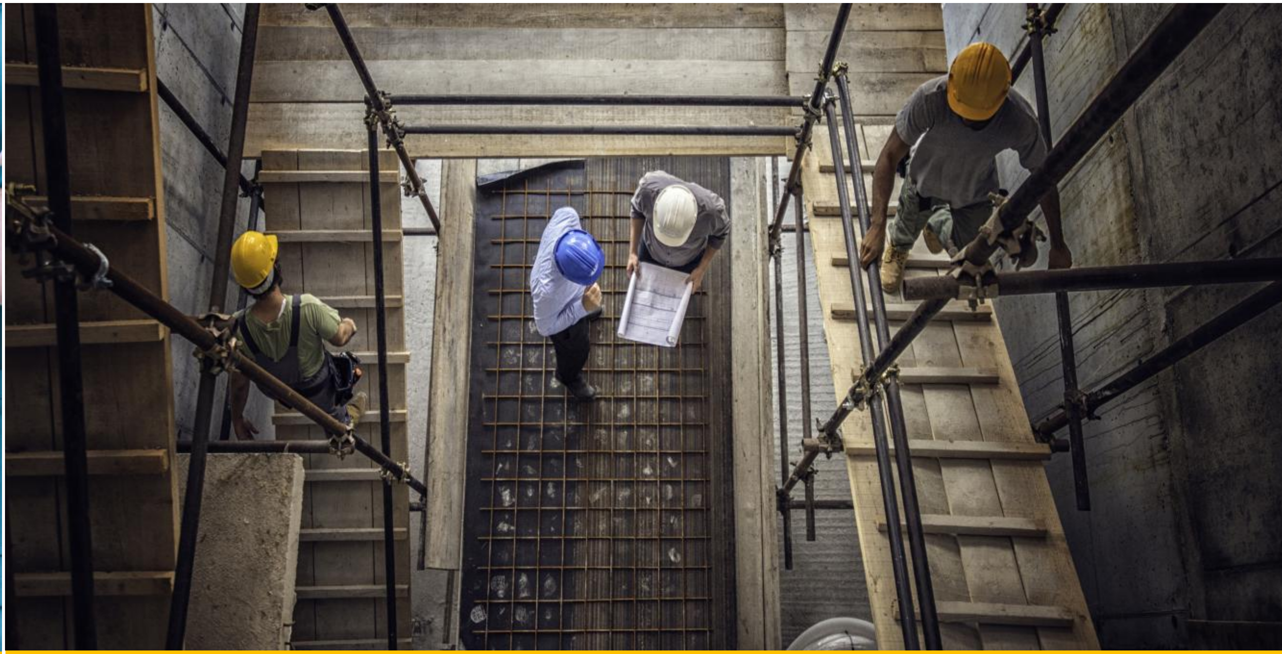
Source: Autor, Levy, & Murnane, R. J. (2003)

Internal medicine physician
O*Net: 29-1216.00

19 Job tasks

- Analyze results or examination information to diagnose
- Treat internal disorders
- Prescribe medication, therapy, and other medical care

Construction labourer
O*Net: 47-2061.00



27 Job tasks

- Clean, or repair machinery, equipment, or tools
- Signal equipment operators to move machinery
- Unload materials, distribute them to appropriate locations

Data source: Canada’s Labour Force Survey

- Nationally-representative
- Cross-sectional monthly survey of the household population
- ~100,000 respondents
- Built using probability sampling
- **O*NET codes cross-walked to National Occupation Classification Codes**

Source: Statistics Canada

Study 1
Worker differences in occupational exposure to machine learning

Source: Jetha et al., 2025

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

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ABSTRACT

Introduction: Machine learning (ML), an artificial intelligence (AI) subfield, is increasingly used by Canadian workplaces. Concerningly, the impact of ML may be inequitable and contribute to social and health inequities in the working population. The aim of this study is to estimate the number of workers in occupations with high, medium, and low ML exposure and describe differences in exposure according to occupational and worker sociodemographic factors.
Methods: Canadian occupations were scored according to the extent to which they were made up of job tasks that could be performed by ML. Eight years of data from Canada's Labour Force Survey were pooled and the number of Canadians in occupations with high, medium, or low exposure to ML were estimated. The relationship between hourly wages, educational attainment, and job skill, training and experience requirements, and ML exposure was examined using multinomial models that were stratified by gender.
Results: Approximately 5.7 million Canadians are working in occupations characterized by high ML exposure. Women workers and workers with a college or bachelor's degree and in occupations with lower job skills requirements made up a greater proportion of workers in occupations with high ML exposure. Multinomial models indicated gender differences in the relationship between independent variables and ML exposure. Among men, higher educational attainment and hourly wages were associated with high occupational ML exposure. However, among women, higher educational attainment and hourly wages were associated with low occupational ML exposure.
Conclusion: ML exposure is segmented according to occupational and worker sociodemographic characteristics and has the potential to widen inequities in the working population. ML may have a gendered effect and disproportionately impact certain groups of women when compared to men. We provide a critical evidence base to inform strategic responses that ensure inclusion in a working world where ML is commonplace.

1. Introduction

Industrialized labor market contexts are increasingly shaped by inequity which are known to influence disparities in the health and quality of life of workers (Frank et al., 2023). The rapid adoption of artificial intelligence (AI) has the potential to drive innovation and raise productivity. AI can also contribute to the polarization of the labor market. To date, most studies on the impact of AI focus on aggregate labor market outcomes. There is a lack of descriptive research which examines how the technology may differentially impact workers according to occupational or sociodemographic characteristics. Such research allows researchers and policymakers to identify groups of workers who may be most or least likely to be affected by the technology, and who may benefit from direct policy and programmatic support. We use a novel application of an existing analytical approach and national labor force data to estimate the number of Canadian workers in

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Measure 1: Suitability for machine learning (SML)

- Extent to which actions and outputs for a specific job task can be learned by a machine
- Rubric evaluated the criteria required for machine learning to be used to perform a job task
- Average SML scores for job tasks were calculated
- Occupation-level SML scores were then produced by taking the weighted average, by importance, of the job tasks

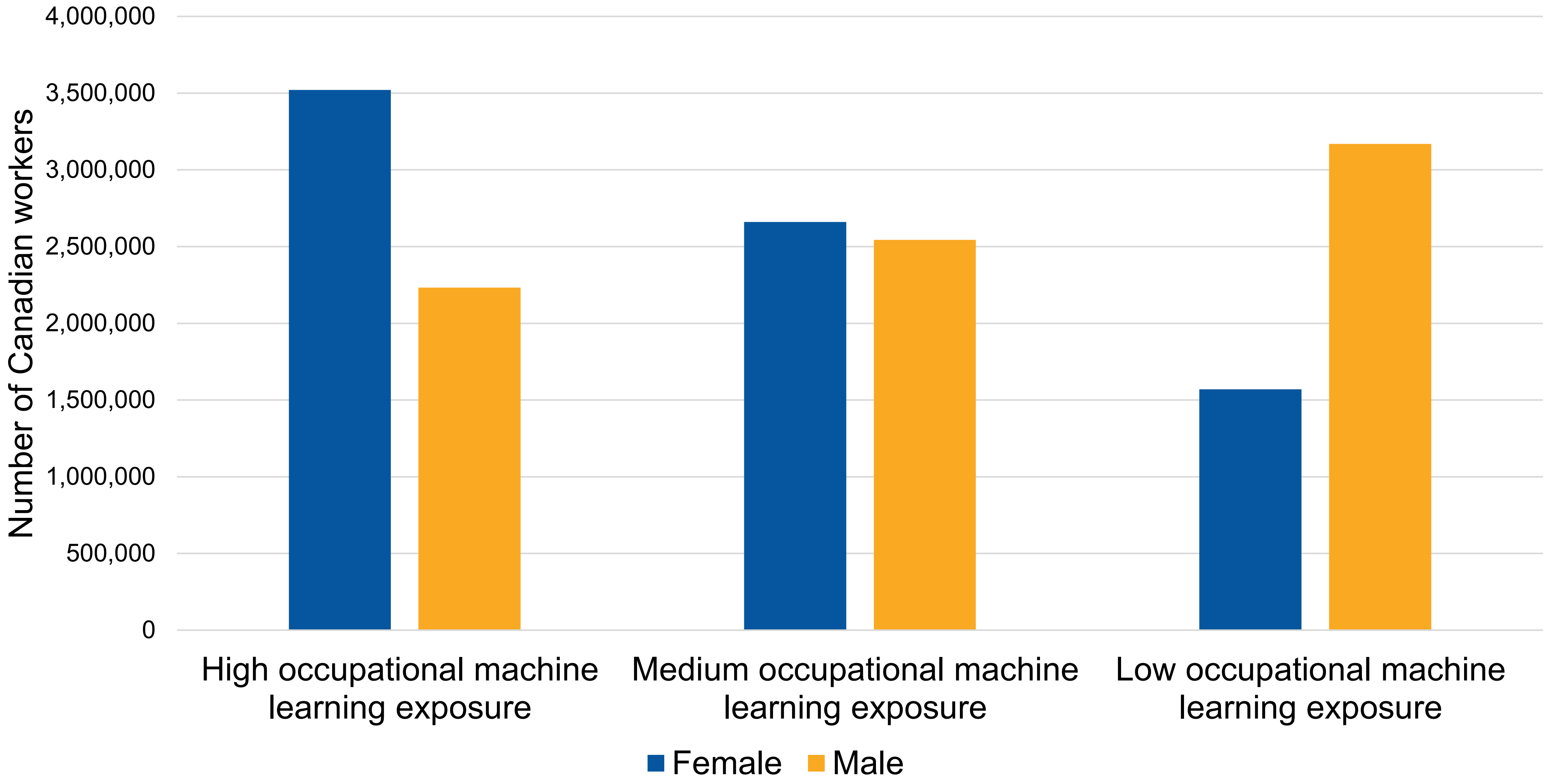
Source: Brynjolfsson, Mitchell, Rock, 2018

Canadian occupations with high and low machine learning exposure

Highest ML Occupations Top 33.3 percentile of SML values
Records management technicians
Travel counsellors
Patternmakers
Human resources and recruitment officers
Customer services representatives - financial institutions
Accounting and related clerks
Railway traffic controllers and marine traffic regulators
Transportation route and crew schedulers
Shippers and receivers
Executive assistants

Lowest ML Occupations **Bottom 33.3 percentile of SML values**
Police officers
Massage therapists
Other support occupations in personal services
Advertising, marketing and public relations managers
Traditional Chinese medicine practitioners and acupuncturists
Other practitioners of natural healing
Plasterers, drywall installers and finishers and lathers
Dancers
Athletes

Machine learning exposure and gender



Source: Jetha et al., 2025

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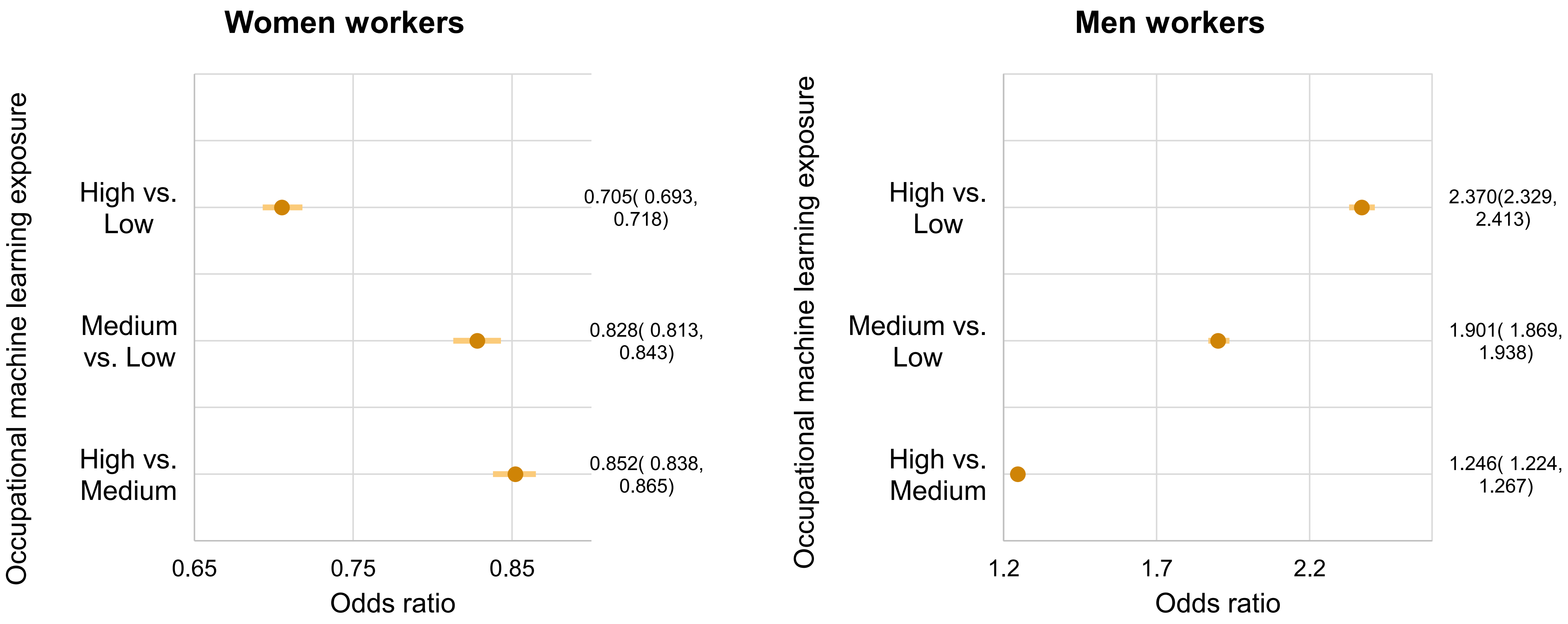
Machine learning exposure among workers with highest level of educational attainment



Notes: Reference category lowest educational attainment (≤ Some post-secondary education);
Model adjusted for age, immigration status, province, industry, unionization, job permanency, work hours

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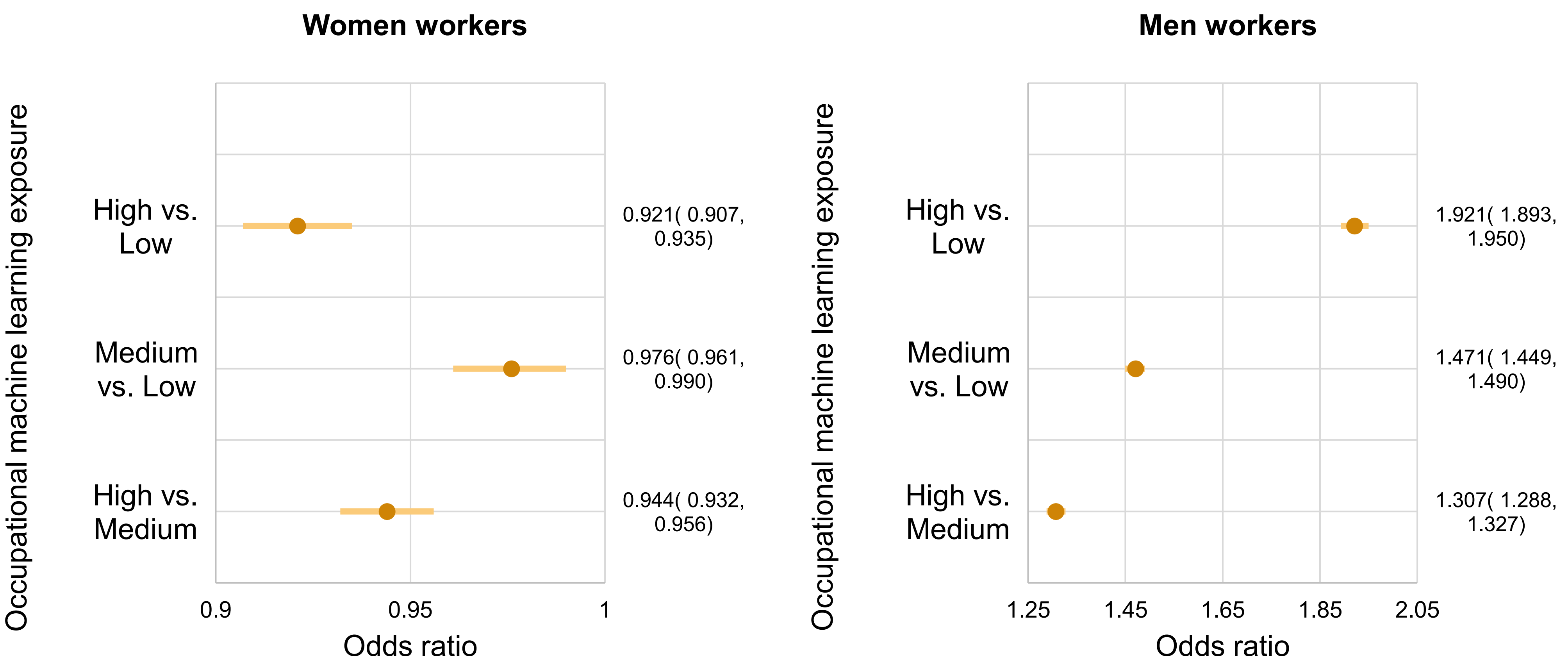
Machine learning exposure: Highest hourly earners and gender



Reference category: ≤ 25th percentile of hourly wages (Quartile 1)
Model adjusted for age, immigration status, province, industry, unionization, job permanency, work hours

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Study 2

Differences in occupational large language model exposure and precarious work

Source: Jetha et al., In progress

Measure 2: Large language model (LLM) exposure measure

- Rubric to examine the extent to which LLMs could reduce the time required for a human to complete a job task by at least 50% while preserving or improving job task quality
- Accounts for the partial requirement of additional software on top of an LLM to realize the 50%-time savings
- Rubric was applied to job tasks in O*Net
- Aggregate score were produced at the occupational level

Source: Eloundou, Manning, Mishken, Rock (2024)

Canadian occupations with high and low LLM exposure

High LLM exposure occupations	Low LLM exposure occupations
Translators, terminologists and interpreters	Foundry workers
Legal administrative assistants	Railway yard and track maintenance workers
Computer systems developers and programmers	Boilermakers
Software developers and programmers	Ironworkers
Authors and writers (except technical)	Athletes
Technical writers	Electrical power line and cable workers
Executive assistants	Bricklayers
Other customer and information services representatives	Concrete finishers
Web developers and programmers	Roofers and shingles
Translators, terminologists and interpreters	Oil and gas drilling, servicing and related labourers

Measuring precarious work in Canada's Labour Force Survey

Precarious work item

- Temporary employment
- Low wages (≤ 2/3 of the median wage)
- Irregular work hours
- Involuntary part-time work

Occupations grouped into quartiles

- Q1: Lowest prevalence of exposure
- Q4: Highest prevalence of exposure

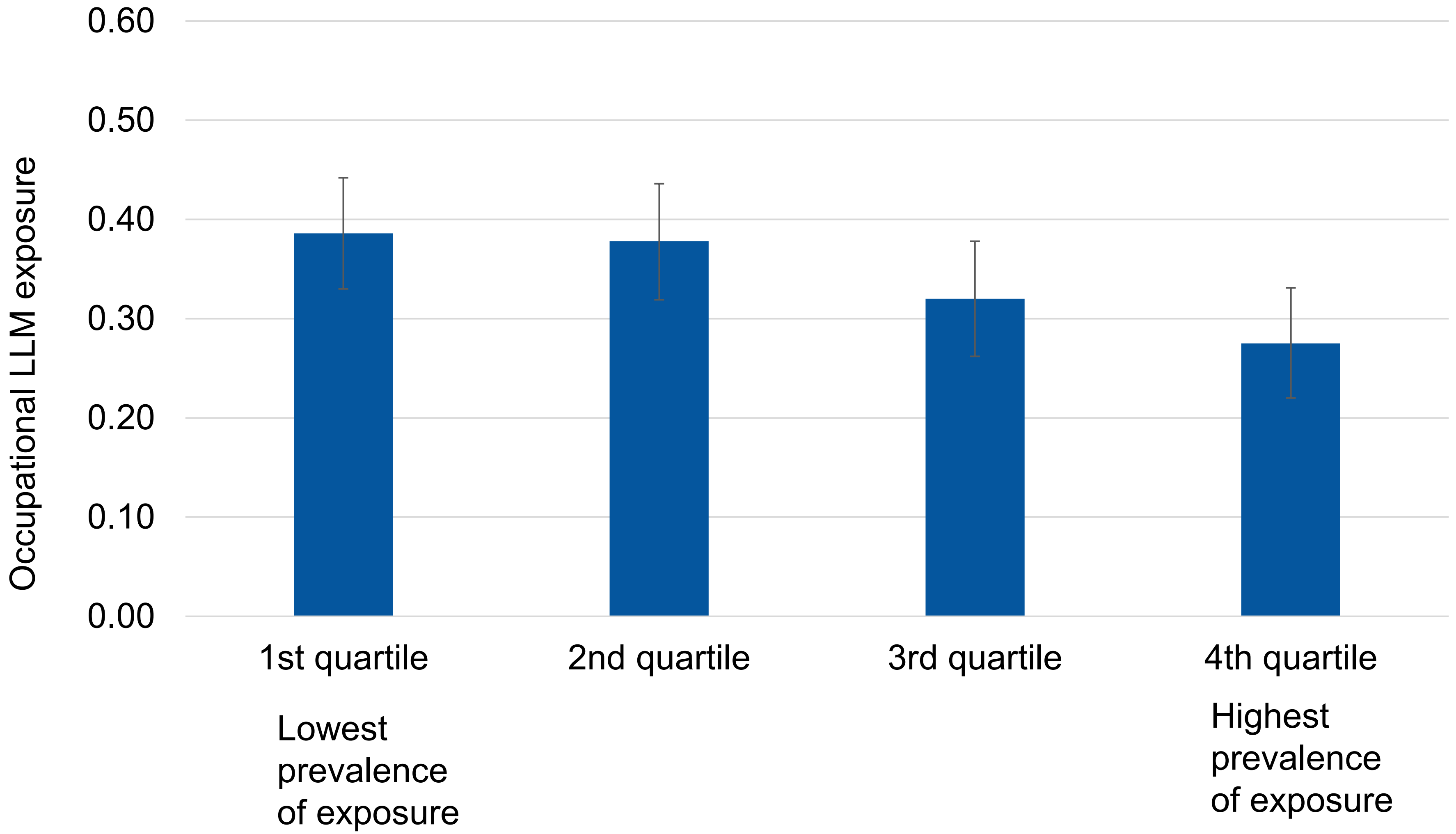
Multi-dimensional precarious work index

times an occupation assigned to Q4

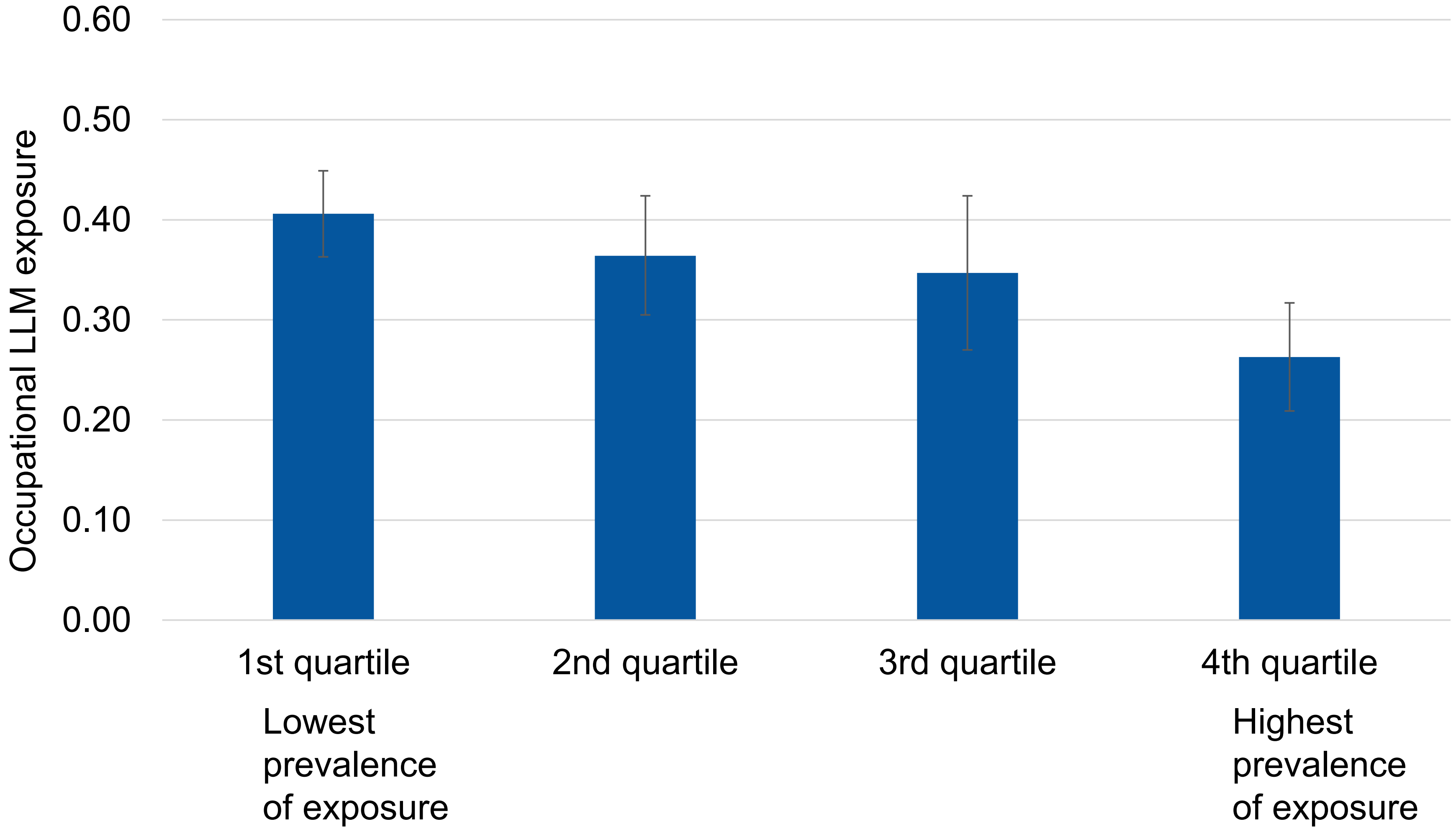
- low: 0
- moderate: 1
- high: 2
- very high: ≥ 3

Source: Shahidi et al, 2024

Occupational LLM exposure and temporary employment



Occupational LLM exposure and low wage



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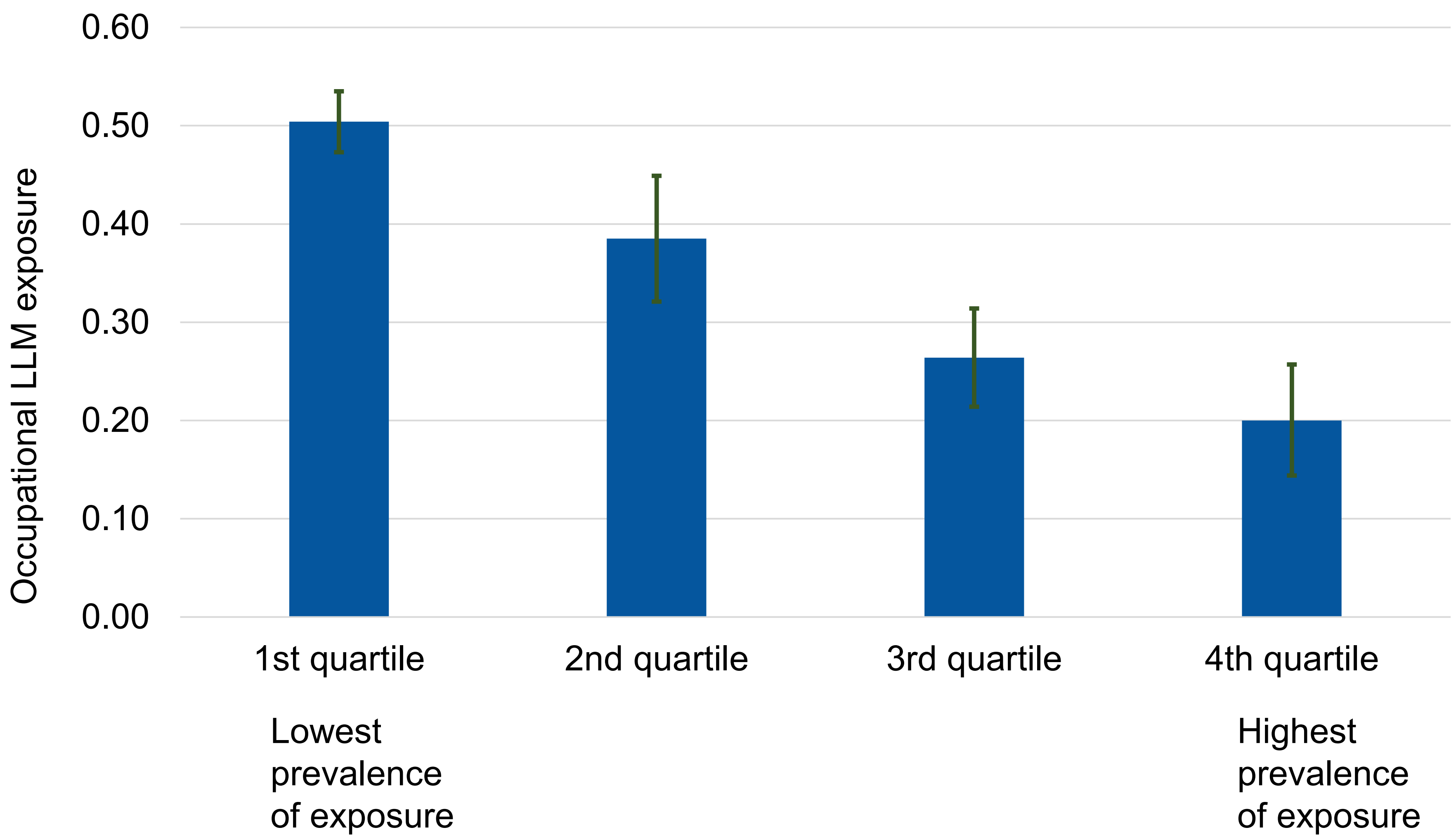
Occupational LLM exposure and irregular work hours



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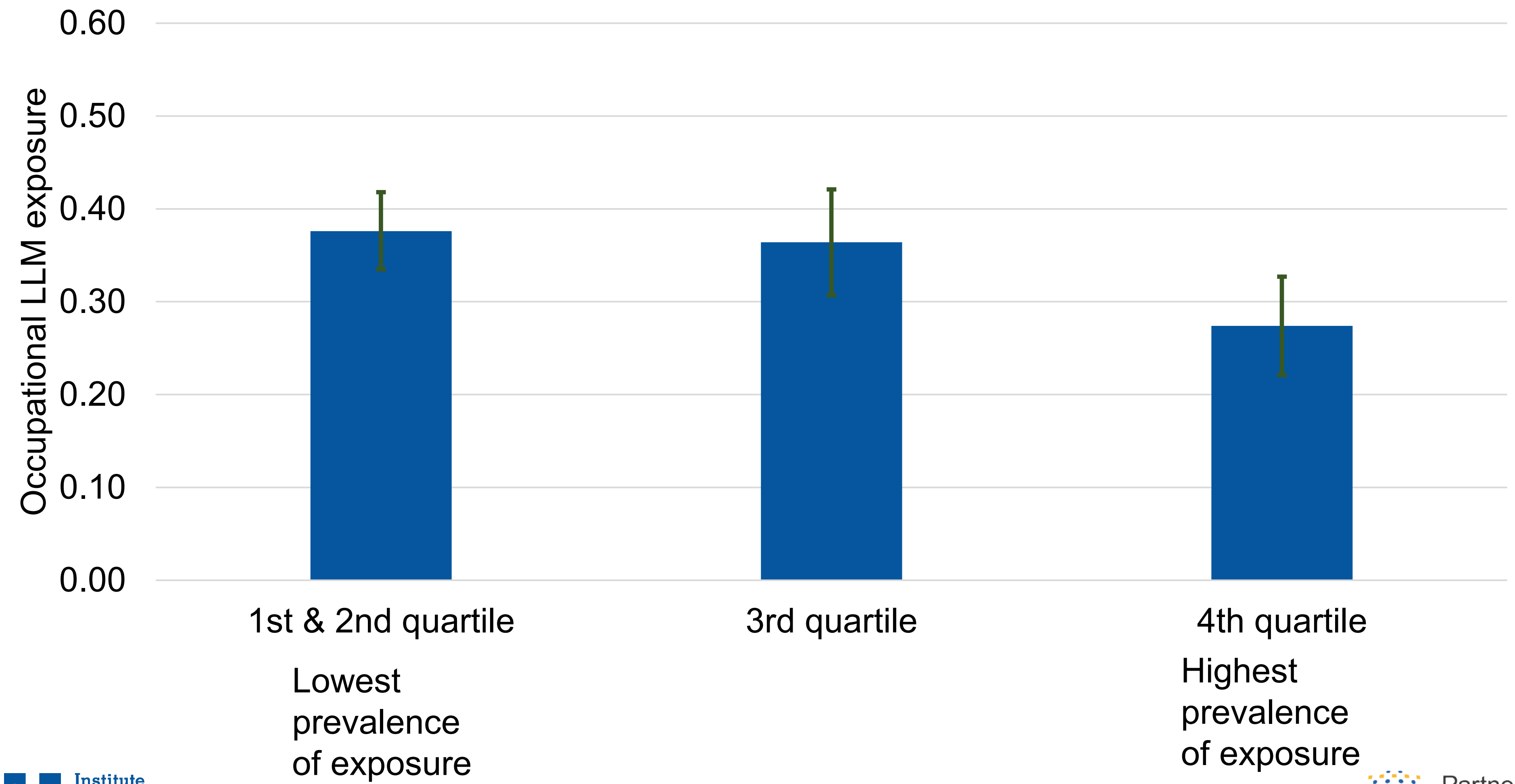
Occupational LLM exposure and involuntary part-time work



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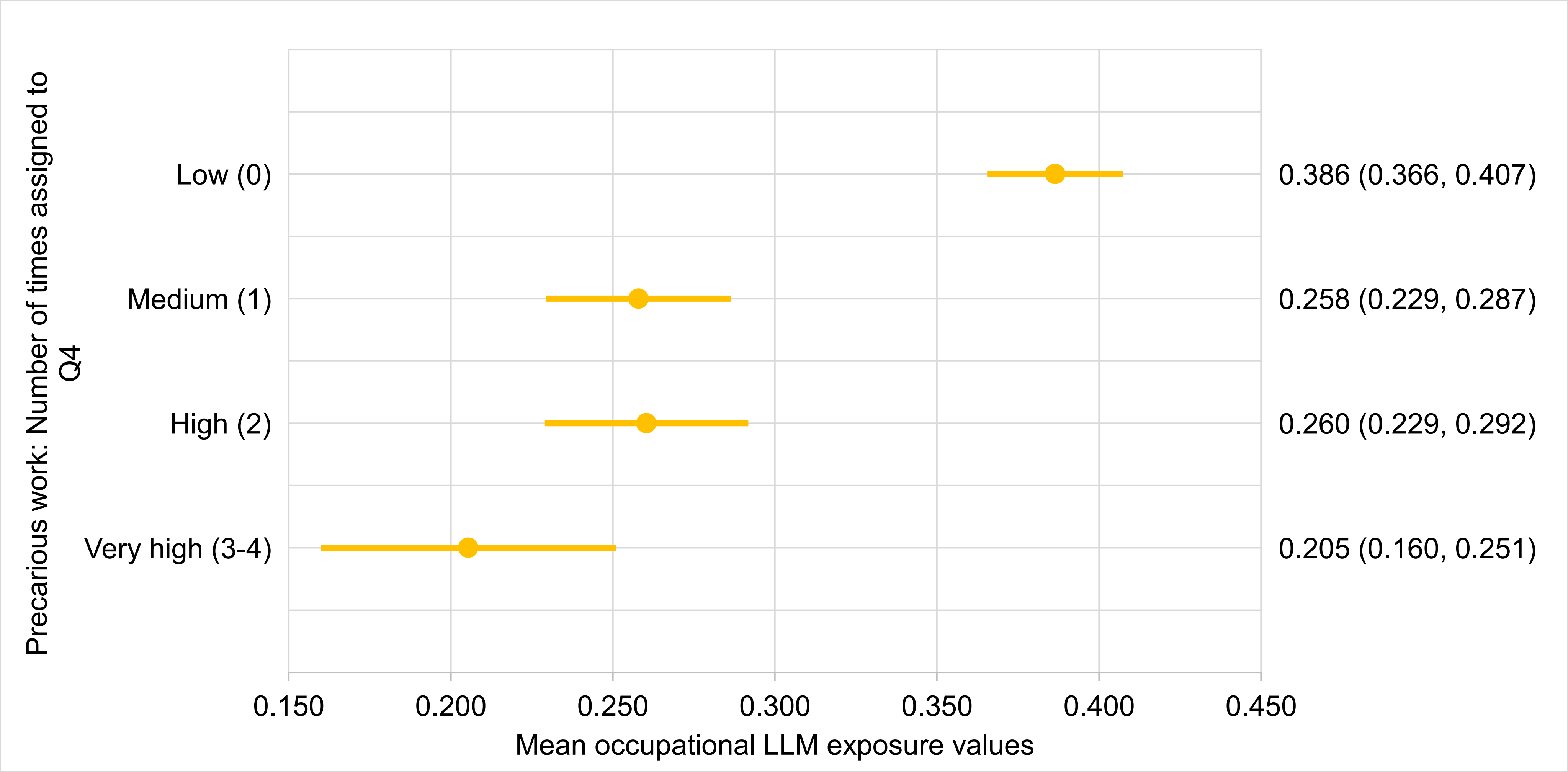
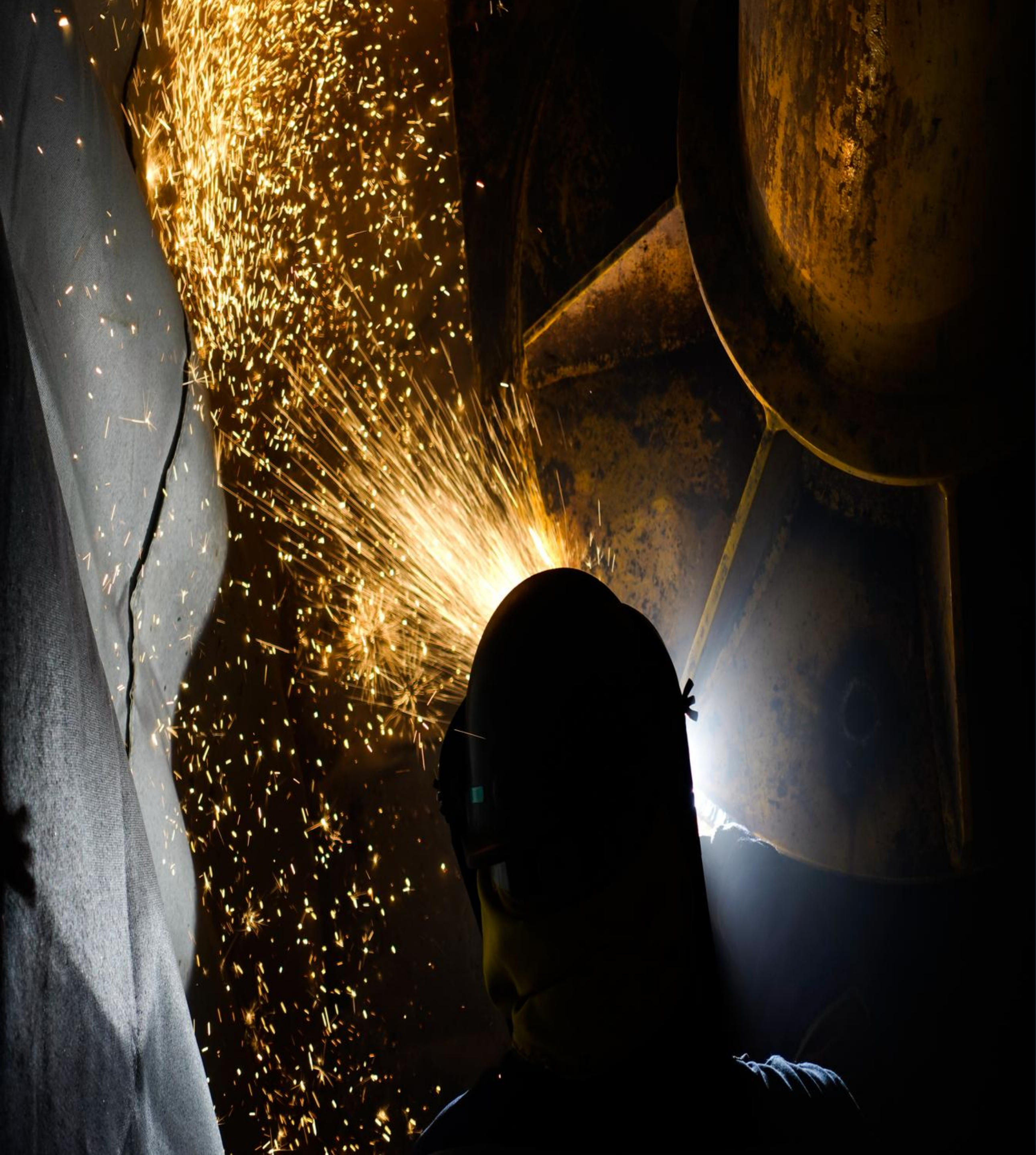
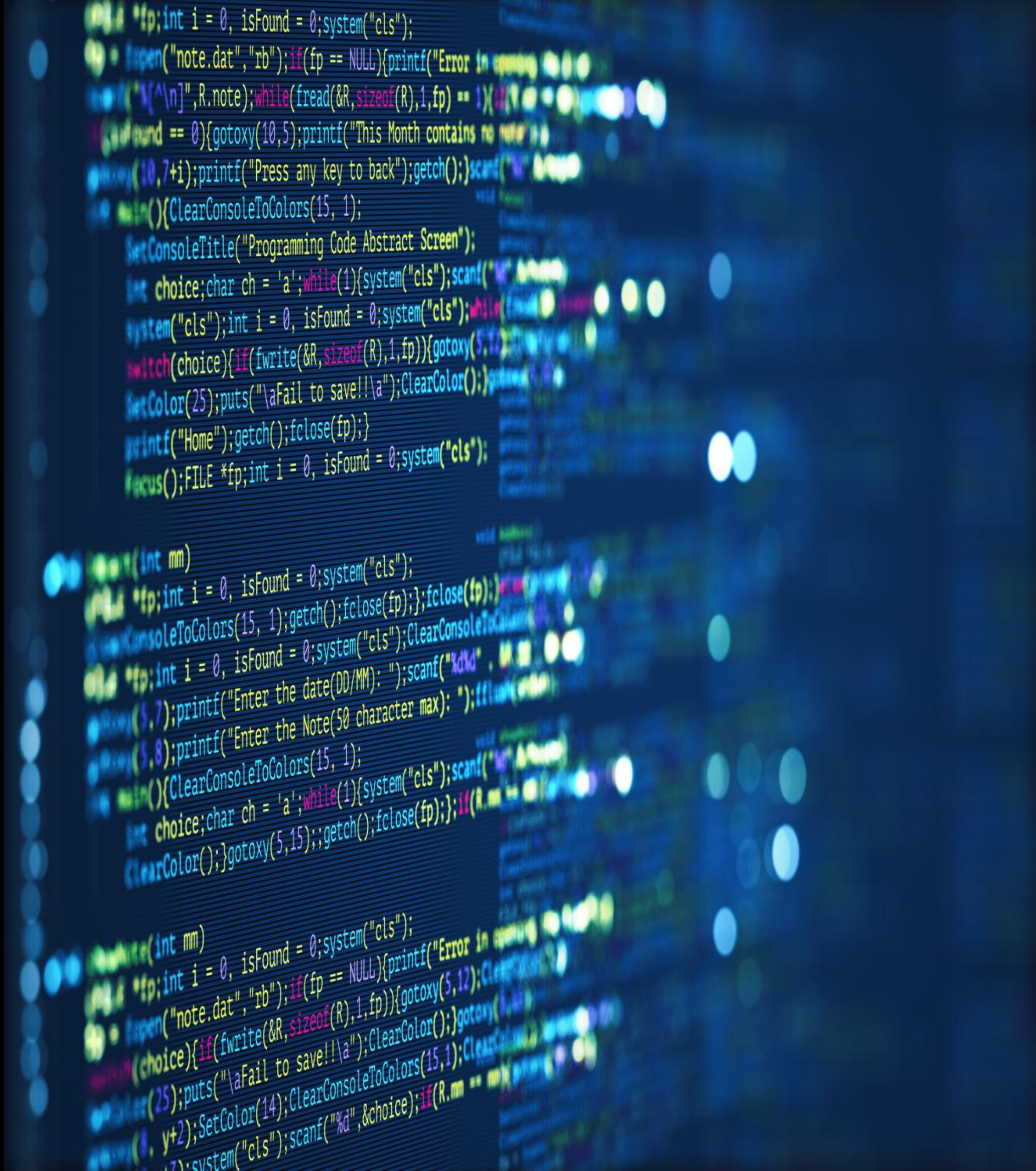
Multidimensional precarious work index and occupational LLM exposure



Note: model adjusted to gender, age group, educational attainment, industry (goods-producing or service-producing) and provincial composition.




*fp;int i = 0, isFound = 0;system("cls");
("note.dat","rb");if(fp == NULL){printf("Error in
",R.note);while(fread(&R,sizeof(R),1,fp) == 1
== 0){gotoxy(10,5);printf("This Month contains no
(10,7+i);printf("Press any key to back");getch();
(){ClearConsoleToColors(15, 1);
SetConsoleTitle("Programming Code Abstract Screen");
int choice;char ch = 'a';while(1){system("cls");
system("cls");int i = 0, isFound = 0;system("cls");
(choice){if(fwrite(&R,sizeof(R),1,fp)){gotoxy(
SetColor(25);puts("\aFail to save!!\a");ClearColor();
printf("Home");getch();fclose(fp);}
FILE *fp;int i = 0, isFound = 0;system("cls");
(int mm)
*fp;int i = 0, isFound = 0;system("cls");
*fp;int i = 0, isFound = 0;system("cls");
(int mm)
*fp;int i = 0, isFound = 0;system("cls");
("note.dat","rb");if(fp == NULL){printf("Error in
(choice){if(fwrite(&R,sizeof(R),1,fp)){gotoxy(5,12);
(25);puts("\aFail to save!!\a");ClearColor();}
y+2);SetColor(14);ClearConsoleToColors(15,1);
system("cls");scanf("%d",&choice);if(R.mm ==

Take away points

Take away messages

- Proxy measures of AI exposure can be valuable starting point to target future research
- Impact of AI on the labour market will not be uniform
- Primary research is required to expand on the experiences of workers in occupations with high and low exposure
- Research is needed on the health and equity implications of AI across workers from different social positions

Thank you

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ArifJetha

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