Toronto Metropolitan University

the dais

AI Work Watch Tool Methodology

Labour Force Survey

For the AI Work Watch tool, we rely on the monthly Statistics Canada Labour Force Survey (LFS) public-use microdata. The LFS is a nationally representative household monthly survey that measures employment, unemployment, and overall labour force participation in Canada. In addition to these labour market indicators, the survey records participants' occupations, making it useful for measuring changes in Canada's occupational distribution over time.

We limit our analysis to employed respondents, as the objective is to measure changes in the occupational distribution of workers. Each respondent is weighted using the standard LFS weights to ensure that the resulting employment counts are representative of the overall Canadian labour force, rather than only the survey sample. Occupations are classified using the National Occupational Classification (NOC), Canada's standard system for organizing occupations based on the type of work performed and the skills, education, and training they require. Canada's occupational coding framework has gone through several revisions since the 1980s, meaning that occupation codes are not directly comparable across the entire timeframe.

Table A1. Concordance across the occupational classifications used in the dissimilarity index, 1985 to 2026.

SOC 1980 (1985-1987)	2001 National Occupational Classifications (1987-2005)	NOC at the 1-digit level (2006 onwards)
1 Managerial & administrative	1 Senior Management Occupations, 2 Other Management Occupations	01 - Management occupations
8 Clerical & related	3 Professional Occupations in Business & Finance, 4 Financial, Secretarial & Administrative Occupations, 5 Clerical Occupations incl. Supervisors	02 - Business, finance & administration
2 Natural sciences, engineering & math	6 Natural & Applied Sciences	03 - Natural & applied sciences
6 Medicine & health	7 Professional Occupations in Health, 8 Technical & Assisting Occupations in Health	04 - Health occupations
3 Social Science & related, 4 Religion, 5 Teaching & related	9 Social Science, Government Service & Religion, 10 Teachers & Professors, 16 Childcare & Home Support Workers	05 - Education, law, social, community & government
7 Artistic, literary, recreational	11 Occupations in Art, Culture, Recreation & Sport	06 - Art, culture, recreation & sport
9 Sales, 10 Service	12 Wholesale/Technical/Insurance/Real Estate Sales Specialists, 13 Retail Salespersons, Clerks, Cashiers, 14 Chefs, Cooks, Food & Beverage Service, 15 Protective Services, 17 Sales & Service n.e.c.	07 - Sales & service
18 Construction, 19 Transport equipment operating, 21 Other crafts, 20 Material handling	18 Contractors & Supervisors in Trades & Transportation, 19 Construction Trades, 20 Other Trades Occupations, 21 Transport & Equipment Operators, 22 Trades Helpers & Labourers	08 - Trades, transport & equipment operators
11 Farming, 12 Fishing, 13 Forestry, 14 Mining	23 Occupations Unique to Primary Industry	09 - Natural resources, agriculture & related production
15 Processing, 16 Machining, 17 Fabricating	24 Machine Operators & Assemblers, 25 Labourers in Processing, Manufacturing & Utilities	10 - Manufacturing & utilities

Additionally, the baseline for the Computers era required an adjustment due to a change in the occupational coding in the Labour Force Survey. The intended baseline was January 1984. However, in that month, individuals performing managerial tasks within sales, service, and other occupations were reassigned into the management category, artificially increasing the dissimilarity index to a significant degree (Usalcas & Kinack 2017). Because the dissimilarity index uses a 12-month moving average, this discontinuity affects the entire year of 1984. To address this, January 1985 is used as the baseline for the Computers era instead.

Exposure indices

AI exposure measures the likelihood of artificial intelligence (AI) applications impacting occupations. Different exposure metrics measure related, but distinct, concepts:

- **AI Occupational Exposure (AIOE)** measure was proposed by Felten, Raj & Seamans (2021), and was updated in Felten, Raj & Seamans (2023) to include large language models.
- The **Eloundou exposure metric** was first proposed in Eloundou et al. (2024), and combines human ratings and ratings generated by GPT-4, applied to Detailed Work Activities and occupational tasks as outlined in O*Net.

Target Measures

We first examine the validity of exposure metrics by correlating an occupation's theoretical AI exposure to actual AI use observed in survey data. This relationship is estimated across occupations, showing how well the indices rank occupations by use overall, though use within a given occupation varies widely (Humlum & Vestergaard 2025b).

The **Dissimilarity Index** provides a straightforward way to track how a labour force changes over time. Instead of looking at individual occupations, it compares the *overall distribution* of workers across occupations to a chosen baseline month. A one-point increase in the index means that an additional one per cent of workers would have to change occupations to restore the baseline mix.

Using Mehdi & Frenette's (2026) approach, we measure occupational change by comparing smoothed employment shares across occupations to a baseline month, adapting the Duncan & Duncan (1955) calculation (see Appendix A). To reduce sample noise due to one-off-events and sampling methods, we apply a 12-month moving average to the employment shares (3-month for the graduate comparison). To place the period after the release of ChatGPT in context, we also track dissimilarity across three earlier reference periods: 1985 to 1989, which covers the spread of personal computers; 1996 to 2002, which covers the mass adoption of the internet; and 2016 to 2019, a stable pre-pandemic period used as a benchmark for normal structural drift. Finally, the differences in the dissimilarity index between younger and older workers can be compared, to detect if the labour market for young people are changing faster than older workers.

The Canaries in the Coal Mine (Brynjolfsson, Chandar & Chen 2025) framework offers a complementary way to understand the influence of generative AI on the Canadian labour market. While the dissimilarity indexes track broad shifts in the occupational mix, the Canaries measure focus on exposure. It also allows us to decompose our analysis into the following age bands (that broadly proxies early career opportunities in the labour market): Youth (15-24), Early Career 1 (22–25), Early Career 2 (26–30), Developing (31–34), Mid-Career 1 (35–40), Mid-Career 2 (41–49), and Senior (50+). We use November 2022 as an employment baseline, corresponding to the public release of ChatGPT. As with the dissimilarity index, we apply a 12-month moving average to our data.