Appendix A: Construction of Indices

The construction of the AI Occupational Exposure score (AIOE) is based on a similar methodology created within the American context by Felten, Raj and Seamans (2021).[1] They use the Standard Occupational Classification (SOC) codes as defined by the U.S. Bureau of Labor Statistics.[2] A set of 10 applications for which AI is most applicable were determined by the international non-profit digital rights group Electronic Frontier Foundation (EFF), who tracks the progress of scientific development and progress in the technologies since 2010. The identified applications, originally listed and defined in Felten et al. (2021), are shown below in Table A1.

Table A1: Applications of AI included in the construction of AIOE scores

AI application	Definition
Abstract strategy games	At a high level, the decision making ability to play abstract games involving sometimes complex strategy and reasoning ability, such as chess, go, or checkers.
Real-time video games	The ability to play a variety of real-time video games of increasing complexity at a high level.
Image recognition	The determination of what objects are present in a still image.
Visual question answering	The recognition of events, relationships, and context from a still image.
Image generation	The creation of complex images.
Reading comprehension	The ability to answer simple reasoning questions based on an understanding of text.
Language modelling	The ability to model, predict, or mimic human language.
Translation	The translation of words or text from one language into another.
Speech recognition	The translation of words or text from one language into another.
Instrumental track recognition	The translation of words or text from one language into another.

Subsequently, each application was linked to a set of 52 O*NET[3] work abilities, with a matrix detailing each work ability's relatedness to an application. As each occupation has related scores detailing the importance and prevalence for each work ability as defined by O*NET, a weighted level-ability exposure score can be constructed which aggregates across all abilities. This provides an index which compares relative AI exposure for occupations.

While the original Felten et al (2021) paper used O*NET work abilities scores by occupation for version 24.3, we use the most recent O*NET version released at the time of analysis, which was the 28.3 release in May 2024. Subsequently, to construct the scores in the Canadian context, American SOC occupations were crosswalked over to Canadian National Occupational Classification (NOC) codes using a crosswalk produced by the Brookfield Institute for Innovation + Entrepreneurship (now incorporated into The Dais).[4] This was expanded to include SOC occupations as defined by O*NET,[5] which allowed us to connect close to 99 percent of the Canadian labour force with an AIOE score.

In addition to exposure, we overlay a score on how well an AI technology complements or works alongside workers to provide improvements on tasks. This is based on a methodology by the IMF,[6] which takes into account work contexts for occupations as defined by O*NET.[7] Similar to the AIOE score, we use work context scores from the most recent O*NET release at the time of writing (Version 28.3 released in May 2024). In addition, in alignment with how we derived AIOE scores in the NOC context, we first created complementarity scores for SOC occupations as defined by O*NET, then used the Brookfield Institute crosswalk to assign scores for Canadian NOC occupations.

Work contexts could include interpersonal contexts (e.g. how much human interaction is an occupation expected to have, and in what ways?), physical work conditions (e.g. conditions that a worker in an occupation would be expected to perform their work in, potential physical hazards, etc.), and other structural characteristics (e.g. whether the work is routine or challenging, criticality of the position, pace of the job, etc.). In addition, job zones of occupations are included, which describe the level of preparation required for an occupation in terms of on-the-job training, education, and experience. Table A2 outlines the work contexts that are included as inputs to derive the complementarity score (which is also outlined in more detail from pages 10 to 12 in the original IMF report). As understood in the original IMF methodology, the occupational contexts in which AI is expected to perform are important in supporting an understanding of their risks and opportunities. In particular, this could inform which occupations have a higher potential for task or job replacement, and where AI technologies could perform at a higher degree of efficiency and accuracy with mitigated risks associated with error.

Table A2: Work contexts included in the construction of complementarity scores

Context group	Work context
Communication	Face-to-face interactions
	Public speaking
Responsibility	Responsibility for outcomes
	Responsibility for others' health
Physical conditions	Exposure to outdoor environments
	Physical proximity to others
Criticality	Consequence of error
	Freedom of decisions
	Frequency of decisions
Routine	Degree of automation
	Unstructured versus structured work
Skills	Job Zones[8]

Each work context for each occupation is measured on a scale of 0 to 100. An arithmetic mean is first calculated between inputs within a context group (giving us six different means). Another arithmetic mean is then calculated again using the means of all six context groups, which gives us a complementarity score for each occupation. The automation input in the routine context group is inverted, as a higher degree of automation signifies lower complementarity).

Appendix B: Concordance with Statistics Canada Methodology

In Mehdi and Morissette (2024),[9] a similar application of AI exposure and complementarity scores were applied to Canadian occupations. The difference in the assignment of occupations to quadrants stems from a difference in how the American Standard Occupational Classification (SOC) was applied to the Canadian National Occupational Classification context (NOC). In this report, a crosswalk produced by the Brookfield Institute for Innovation + Entrepreneurship[10] (now incorporated into The Dais) was applied to translate American occupations to Canadian occupations. This allows for the conversion of 2018 SOC occupations to 2021 NOC occupations. Statistics Canada used a crosswalk that converted 2018 SOC occupations to 2016 NOC occupations, then from 2016 NOC occupations to 2021 NOC occupations.[11] [12] For comparison, their exposure-complementarity graph can be found in the results section of their report.

Statistics Canada's crosswalk captures around 90 percent of the labour force in 2021,[13] with 470 occupations represented. This is compared to the 506 occupations represented in our analysis, which represents close to 99 percent of the labour force in 2021. Given this slight difference in methodology, 30 occupations were sorted in a different quadrant in our analysis compared to Statistics Canada's analysis. In addition, the proportion of the labour market in each quadrant according to the 2021 Canadian Census employment counts are shown below in Table B1.

Table B1: Percentage of labour force employment by Statistics Canada quadrant assignments (2021 Canadian Census)

Quadrant	Number of workers included in quadrant[14]	Share of total labour force (2021)
High exposure - High complementarity	4,543,040	24.8%
High exposure - Low complementarity	4,599,750	25.1%
Low exposure	7,333,200	40.0%

To ensure the robustness of our analysis, the unique skills analysis was applied to job postings using Statistics Canada's quadrant assignments for occupations. As Statistics Canada analyzed occupations through the lens of High Exposure-High Complementarity, High Exposure-Low Complementarity, and Low Exposure quadrants, we inferred Low Exposure-Low Complementarity and Low Exposure-High Complementarity quadrant assignments based on the output of scores, which were provided to us by the authors of the Statistics Canada report. We find no significant differences in skills trends using these quadrant assignments. The top 10 unique skills in each quadrant using the Statistics Canada quadrant assignments are shown below in Tables B2 to B5.

Table B2: High Exposure-High Complementarity unique skills with Statistics Canada quadrant assignments

Skill	Share of skills listed in job postings in the quadrant	Share of skills listed across all job postings	Share of job postings in quadrant with this skill	Share of job postings across all quadrants with this skill
Planning	3.4%	1.6%	25.9%	11.6%
Patient care	2.0%	0.9%	15.1%	6.5%
Coaching	0.8%	0.3%	6.1%	1.9%
Leadership	4.4%	2.4%	33.8%	17.3%
Critical thinking	0.9%	0.4%	7.0%	2.8%
Teaching and training	1.9%	1.1%	14.8%	7.7%
Budgeting	1.4%	0.8%	10.8%	5.6%
Problem solving	2.5%	1.7%	19.4%	12.3%
Advanced Cardiac Life Support (ACLS)	0.3%	0.1%	2.3%	0.6%
Project management	1.1%	0.7%	8.3%	5.0%

Table B3: High Exposure-Low Complementarity unique skills with Statistics Canada quadrant assignments

Skill	Share of skills listed in job postings in the quadrant	Share of skills listed across all job postings	Share of job postings in quadrant with this skill	Share of job postings across all quadrants with this skill
Accounting	1.6%	0.7%	13.4%	5.0%
Microsoft Excel	2.4%	1.3%	19.4%	9.3%
Office administration	1.0%	0.4%	7.9%	2.9%
Information filing	0.7%	0.2%	5.6%	1.7%
Microsoft Word	2.0%	1.1%	16.6%	8%
Microsoft Office	2.3%	1.4%	19.1%	9.7%
Filing systems	0.6%	0.2%	5.1%	1.6%
Data analysis	0.9%	0.5%	7.8%	3.3%
Sales	1.3%	0.7%	10.4%	4.9%
Proofreading	0.5%	0.2%	4.4%	1.4%

Table B4: Low Exposure-Low Complementarity unique skills with Statistics Canada quadrant assignments

Skill	Share of skills listed in job postings in the quadrant	Share of skills listed across all job postings	Share of job postings in quadrant with this skill	Share of job postings across all quadrants with this skill
Kitchen cleaning	2.2%	0.5%	12.3%	3.6%
Cleaning	3.4%	0.9%	18.7%	6.2%
Cooking / meal preparation	3.0%	0.8%	16.4%	5.7%
Kitchen inspection	0.8%	0.2%	4.7%	1.3%
Kitchen management	1.0%	0.2%	5.3%	1.7%
Handling heavy loads	3.4%	1.3%	18.6%	9.6%
Food menus planning	0.7%	0.2%	4.1%	1.3%
Loading and unloading	1.2%	0.4%	6.6%	3.2%
Forklift operation	0.9%	0.3%	4.9%	2.1%
Hand-eye co-ordination	0.7%	0.2%	3.7%	1.5%

Table B5: Low Exposure-High Complementarity unique skills with Statistics Canada quadrant assignments

Skill	Share of skills listed in job postings in the quadrant	Share of skills listed across all job postings	Share of job postings in quadrant with this skill	Share of job postings across all quadrants with this skill
Food quality control	1.7%	0.2%	12%	1.7%
Estimating	1.5%	0.2%	10.5%	1.6%
Repairs / Corrective maintenance	3.1%	0.8%	22.3%	5.4%
Work scheduling	2.4%	0.6%	17.4%	4.1%
Truck driving	1.6%	0.4%	11.1%	2.6%
Mechanical skills	1.1%	0.3%	7.6%	1.8%
Blueprint reading	1.3%	0.4%	9.2%	2.5%
Inspection of vehicles	0.9%	0.2%	6.2%	1.4%
Preventive maintenance	1.0%	0.3%	7.5%	2.0%
Machinery/ equipment repairs	1.1%	0.3%	7.5%	2.1%

In addition, we applied the Statistics Canada quadrant assignments to track occupational firm demand and wages to see whether there are significant differences. Figures B1, B2 and B3 below show that the trends remained the same as our original analysis using our quadrant assignments.

Figure B1

Job postings for occupations by Statistics Canada exposure-complementarity quadrant and month

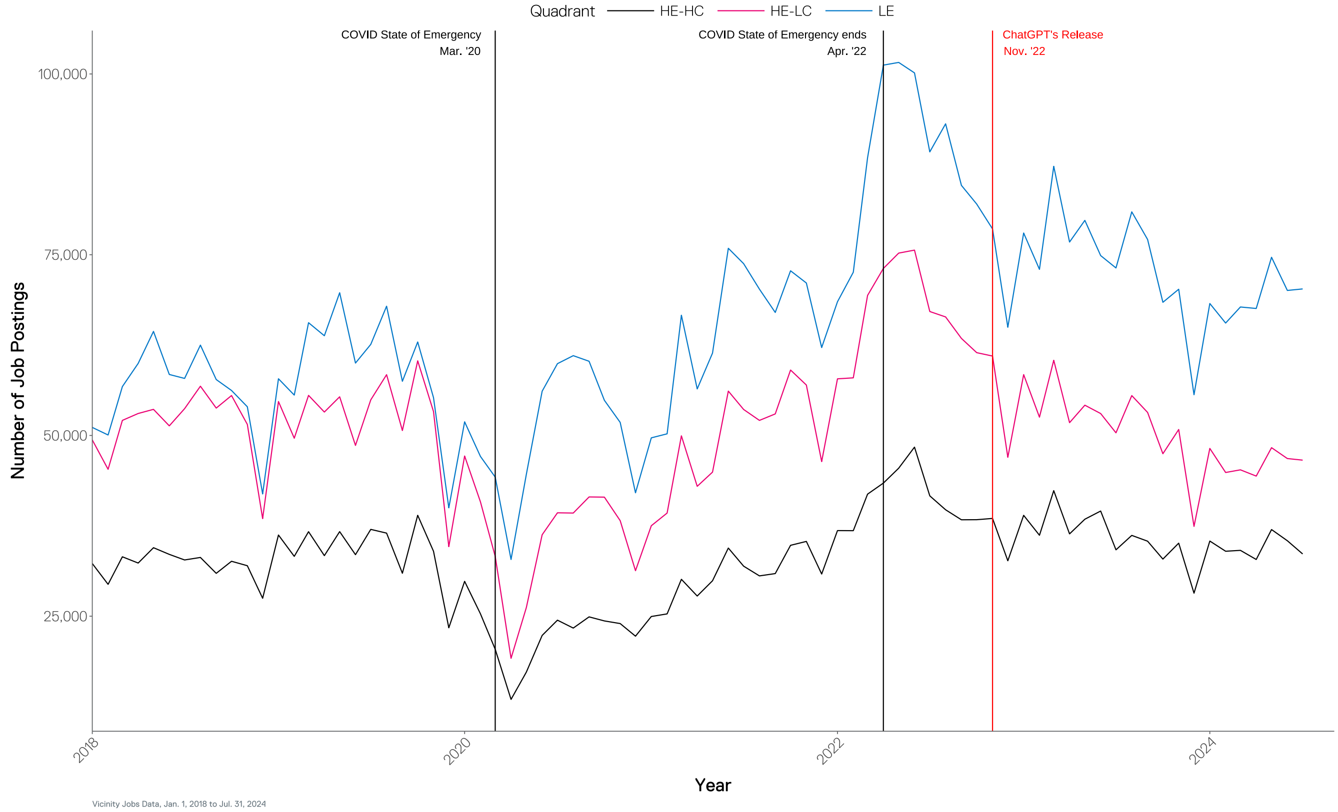


Figure B2

Job postings for occupations by Statistics Canada exposure-complementarity quadrant and month (indexed to January 2018)

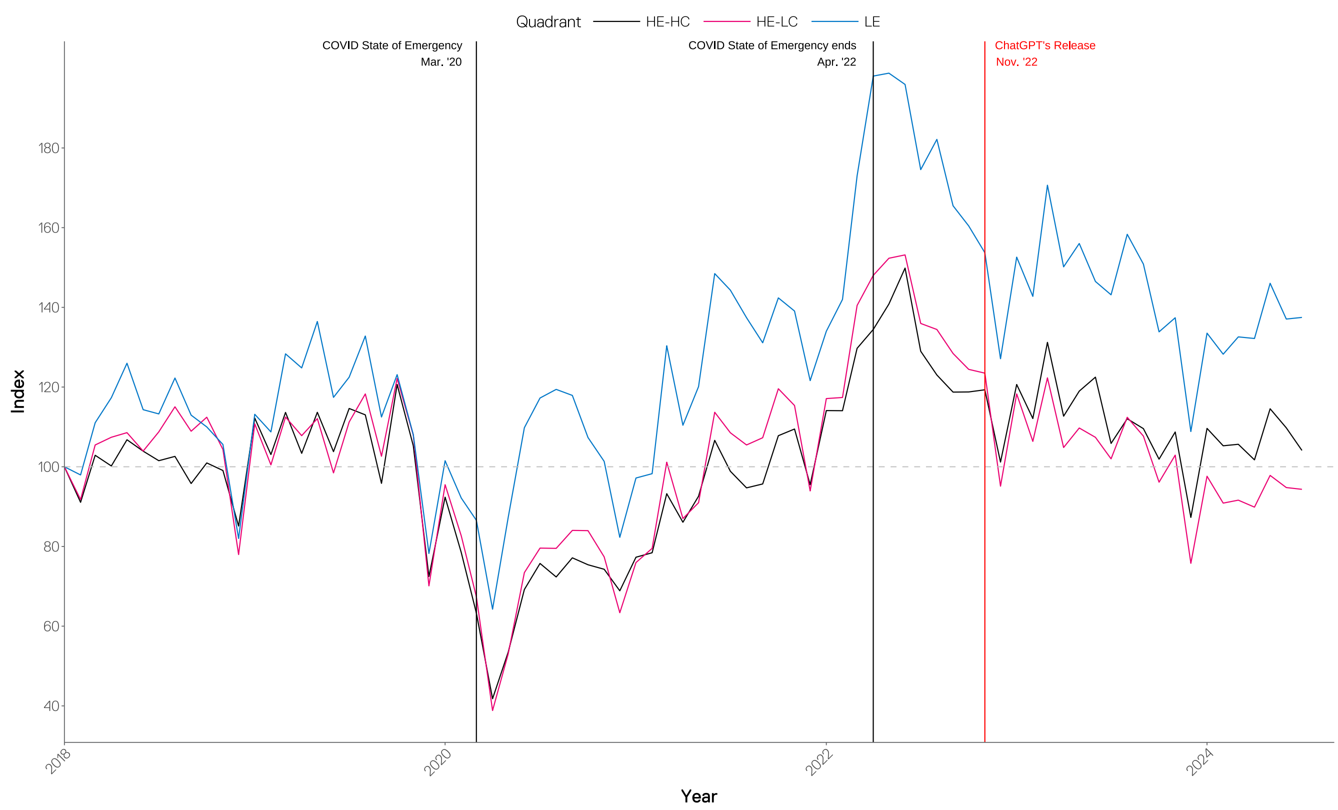
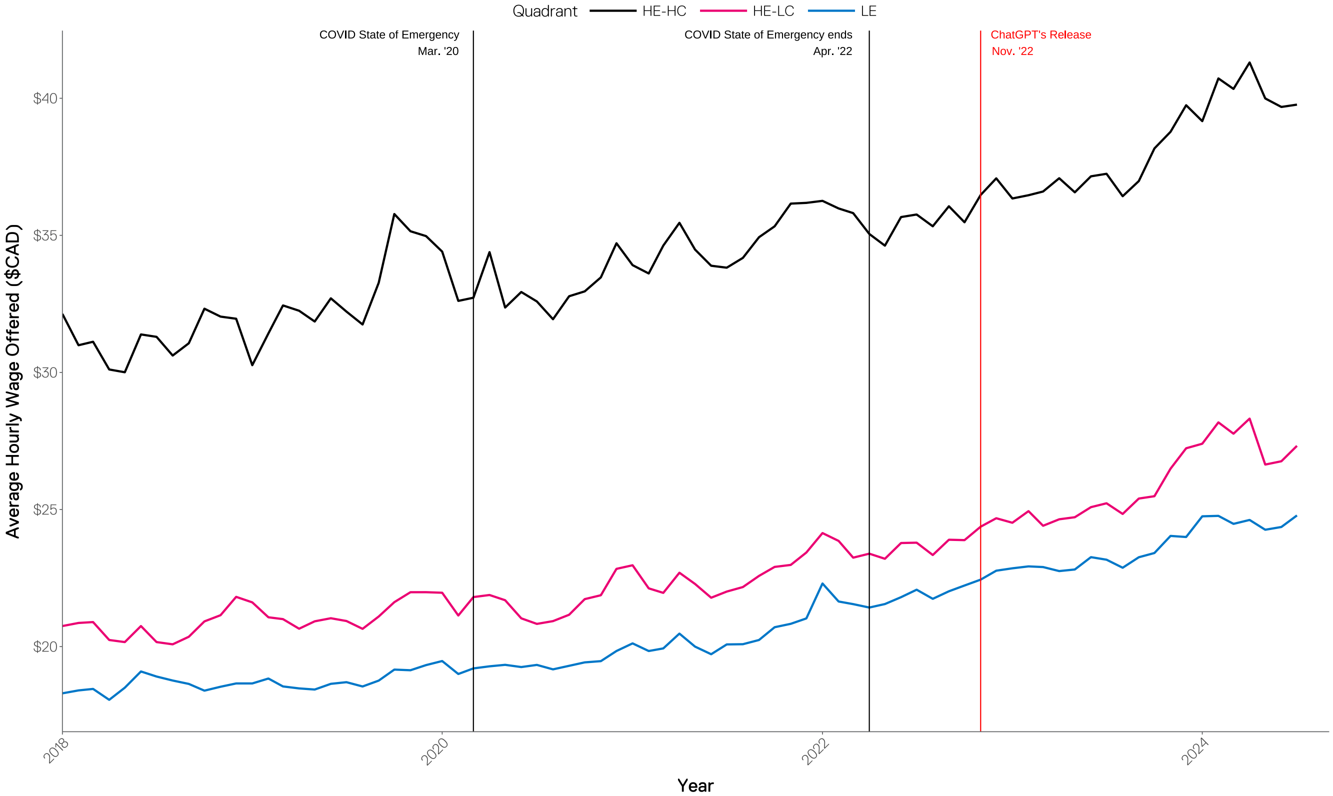


Figure B3

Monthly average hourly wage offered in job postings for occupations by Statistics Canada exposure-complementarity quadrant



Vicinity Jobs Data, Jan. 1, 2018 to Jul. 31, 2024

Appendix C: TF-IDF Methodology

The unique skills analysis leverages an adjusted term frequency-inverse document frequency (TF-IDF) framework to identify skills featured in a quadrant to a greater degree than the other three. This methodology is commonly used in natural language processing to analyze documents of text; in the context of skills analysis, the components used for classification are used in the following ways:

1. The term frequency (TF) component calculates the percentage of appearances for each skill *t* out of total appearances across all skills *j* and all job postings in a quadrant *q*. For example, if the skill Teamwork appears 500 times in job postings out of 10,000 skills appearances contained across all job postings in the High Exposure - High Complementarity quadrant, the term frequency would be five percent. Each quadrant would have an individual calculation of term frequency for each skill. This gives us a sense of how common a skill is demanded for jobs in a quadrant, agnostic of its prevalence in other quadrants.

$$TF_{t,q} = \left(\frac{n_t}{\sum_{t=1}^{j_q} n_{t,q}} \right)$$

2. The inverse document frequency (IDF) component calculates the degree to which a skill *t* is unique or uncommon across job postings. As an example, imagine that there are 100,000 skills that appear across all job postings in all quadrants (represented as *N* in the equation). Say the skill Teamwork appears 90,000 times (represented as *DF* in the equation) across all job postings in all quadrants, whereas the skill Leadership appears 10,000 times. This means that Leadership skills are more uniquely demanded across the labour market (10 percent of all jobs demand this skill) relative to Teamwork skills, which is contained in 90 percent of all job postings.

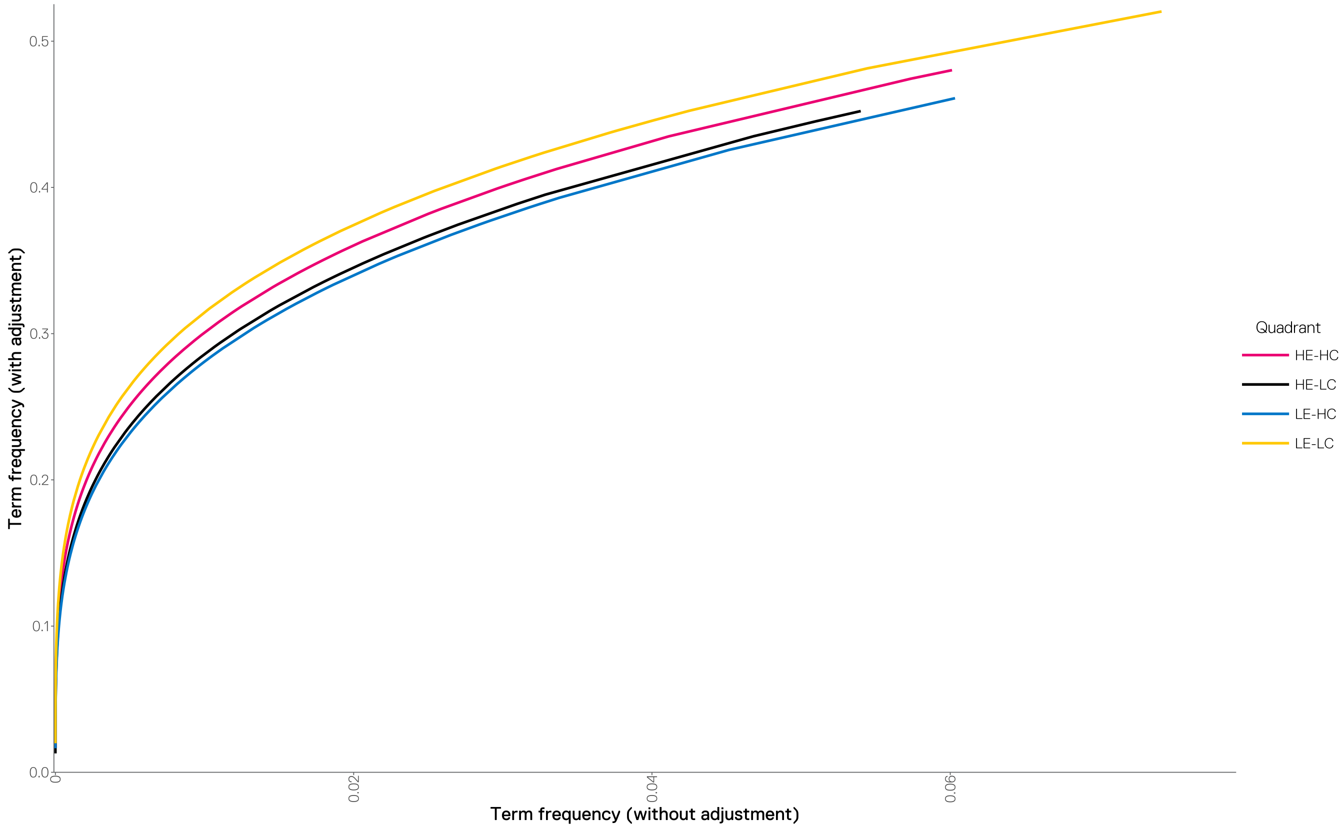
$$IDF_t = log\left(\frac{N}{DF_t}\right)$$

   The IDF component amplifies the term frequency component; if a skill features prominently in a quadrant (high TF) which does not appear that frequently in other quadrants (low DF), then this skill would be assessed as being more uniquely demanded for job postings in this quadrant.

A notable departure of our methodology from a conventional TF-IDF concerns the weight of the term frequency component. Given the wide distribution of term frequencies for skills (ranging from seven percent to less than 0.0001 percent for some skills), the impact of the IDF component for skills with smaller term frequencies would be significantly reduced. An adjustment value *m* reduces the distance between skill term frequencies which sets the 50th percentile skill in a quadrant equal to the midpoint value between the minimum and maximum term frequency in a quadrant, with distances between other skills scaled to fit this distribution (see Figure C1).

Figure C1

Term frequency score adjustment by quadrant



Note: term frequencies vary by quadrant due to differences in median values.

The resulting TF-IDF applied to each skill-quadrant pair is as follows:

$$TDIDF_{t,q} = \left(\frac{n_t}{\sum_{t=1}^{j_q} n_{t,q}} \right)^{m_q} log\left(\frac{N}{DF_t}\right)$$

$$\text{with } m_q = \frac{log(\frac{(maxTF_q + minTF_q)}{2})}{log(medianskillTF_q)}$$

The adjustment values for each quadrant are shown in Table C1.

Table C1: Adjustment values by quadrant

Quadrant	Adjustment value (*m*)
HE-HC	0.261
HE-LC	0.272
LE-LC	0.251
LE-HC	0.276

The comparison between the share of skills in the job postings in a quadrant compared to the share of skills across all job postings and quadrants is detailed below.

Table C2: Share of unique skills in High Exposure-High Complementarity quadrant

Skill	Share of skills listed in job postings in the quadrant	Share of skills listed across all job postings
Planning	3.1%	1.6%
Coaching	0.8%	0.3%
Patient care	1.7%	0.9%
Leadership	4.1%	2.4%
Critical thinking	0.8%	0.4%
Sales	1.2%	0.7%
Problem solving	2.5%	1.7%
Budgeting	1.2%	0.8%
Advanced Cardiac Life Support (ACLS)	0.3%	0.1%

Table C3: Share of unique skills in the High Exposure-Low Complementarity quadrant

Skill	Share of skills listed in job postings in the quadrant	Share of skills listed across all job postings
Accounting	1.5%	0.7%
Microsoft Excel	2.2%	1.3%
Data analysis	1.0%	0.5%
Microsoft Word	1.9%	1.1%
Microsoft Office	2.2%	1.4%
Office administration	0.9%	0.4%
Information filing	0.6%	0.2%
Reports preparation	1.5%	0.9%
Filing systems	0.6%	0.2%
Proofreading	0.5%	0.2%

Table C4: Share of unique skills in the Low Exposure-Low Complementarity quadrant

Skill	Share of skills listed in job postings in the quadrant	Share of skills listed across all job postings
Kitchen cleaning	1.9%	0.5%
Cleaning	2.9%	0.9%
Cooking / meal preparation	2.5%	0.8%
Truck driving	1.3%	0.4%
Handling heavy loads	3.3%	1.3%
Kitchen inspection	0.7%	0.2%
Kitchen management	0.8%	0.2%
Loading and unloading	1.2%	0.4%
Inspection of vehicles	0.7%	0.2%
Forklift operation	0.9%	0.3%

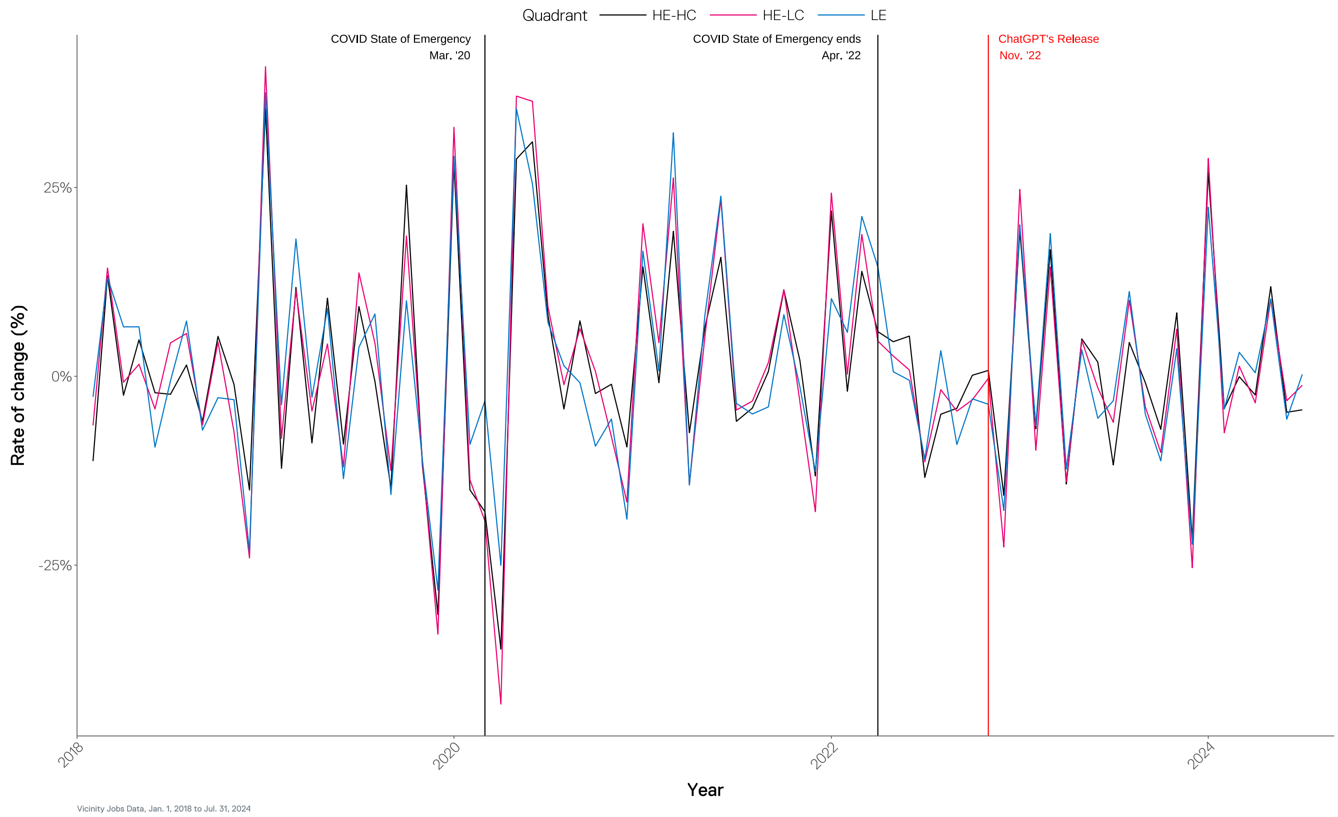
Table C5: Share of unique skills in the Low Exposure-High Complementarity quadrant

Skill	Share of skills listed in job postings in the quadrant	Share of skills listed across all job postings
Food quality control	1.8%	0.2%
Estimating	1.6%	0.2%
Repairs / Corrective maintenance	2.8%	0.8%
Mechanical skills	1.3%	0.3%
Work scheduling	2.3%	0.6%
Machinery/equipment repairs	1.1%	0.3%
Scaffolding	0.6%	0.1%
Mechanical repairs	0.4%	0.1%
Electrical repairs	0.4%	0.1%
Preventive maintenance	0.9%	0.3%

Appendix D: Additional Robustness Analysis

Assessing the rate of change in job postings by quadrant from month to month, trends remained relatively consistent across quadrants over time, as seen in Figure D1.

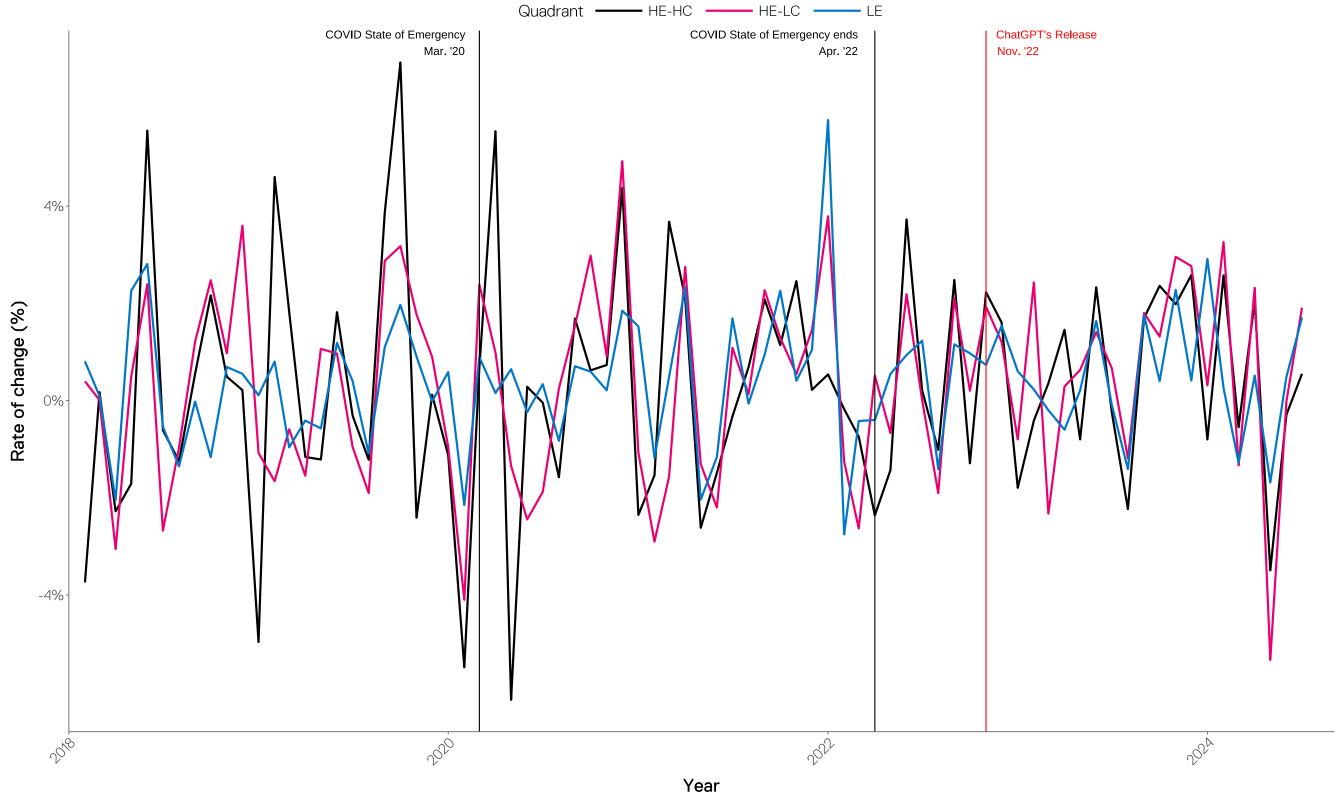
Figure D1
Rate of change for job postings demand for occupations by exposure-complementarity quadrant



Assessing the rate of change for average wages per quadrant and month, trends are consistent across quadrants for the most part across time, with the HE-HC quadrant generally having higher variance (especially towards the start of the COVID-19 pandemic). This is shown in Figure D2.

Figure D2

Rate of change of monthly average hourly wage offered in job postings for occupations by exposure-complementarity quadrant



Vicinity Jobs Data, Jan. 1, 2018 to Jul. 31, 2024

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[2] The full list of SOC occupations defined by the U.S. Bureau of Labor Statistics can be found here: https://www.bls.gov/oes/current/oes_stru.htm.

[3] O*NET is a database providing information on occupations in the US as it relates to areas such as knowledge, work activities and contexts, skills, and occupational outlook. https://www.onetcenter.org/overview.html

[4] More information about the crosswalk is available at https://dais.ca/reports/crosswalk-blog-post/.

[5] O*NET expands on the list of SOC occupations as outlined by the Bureau of Labor Statistics found here: https://www.bls.gov/soc/. A full list of O*NET occupations can be found here: https://www.onetonline.org/find/all.

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[12] Statistics Canada, Correspondence Table: National Occupational Classification (NOC) 2016 V1.3 to National Occupational Classification (NOC) 2021 V1.0. based on GSIM, https://www.statcan.gc.ca/en/statistical-programs/document/noc2016v1_3-noc2021v1_0.

[13] This calculation is based on a total of 18,339,455 employment income recipients in Statistics Canada's 2021 Census aged 15 and above, compared to a base of 13,589,900 employed individuals aged 18 to 64 in May 2021 presented in Statistics Canada's report.

[14] ibid.