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ARTIFICIAL INTELLIGENCE AND THE CHANGING DEMAND FOR SKILLS IN CANADA

THE INCREASING IMPORTANCE OF SOCIAL SKILLS

OECD ARTIFICIAL INTELLIGENCE PAPERS
May 2024 **No. 17**

OECD
BETTER POLICIES FOR BETTER LIVES

Artificial intelligence and the changing demand for skills in Canada: The increasing importance of social skills

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Most workers who will be exposed to artificial intelligence (AI) will not require specialised AI skills (e.g. machine learning, natural language processing, etc.). Even so, AI will change the tasks these workers do, and the skills they require. This report provides first estimates for Canada on the effect of artificial intelligence on the demand for skills in jobs that do not require specialised AI skills. The results show that the skills most demanded in occupations highly exposed to AI are management, communication and digital skills. These include skills in budgeting, accounting, written communication, as well as competencies in basic word processing and spreadsheet software. The results also show that, in Canada, demand for social and language skills have increased the most over the past decade in occupations highly exposed to AI. Using a panel of establishments confirms the increasing demand for social and language skills, as well as rising demand for production and physical skills, which may be complementary to AI. However, the establishment panel also finds evidence of decreasing demand for business, management and digital skills in establishments more exposed to AI.

Keywords: Artificial Intelligence, Skills, Canada.

JEL Codes: J24, J23, J63.

Acknowledgements

This report was written by Andrew Green under the supervision of Stijn Broecke. The report also benefitted from helpful comments on earlier drafts provided by Anne Saint-Martin, Anna Milanez, Marguerita Lane and Alexandre Georgieff. The OECD Secretariat would like to thank the Department of Employment and Social Development Canada for supporting this report, and is particularly grateful to Erwin Gomez Gomez and Rosemary Cockshutt, whose co-ordination and comments were invaluable in the production of the report. Many thanks are also due to Andrea Bassanini for providing an ISCO to SOC crosswalk, Julie Lassébie for sharing the ONET+ classification, Francesca Borgonovi for furnishing an ESCO to ONET crosswalk, and Satoshi Araki for providing support with the employer cleaning programmes.

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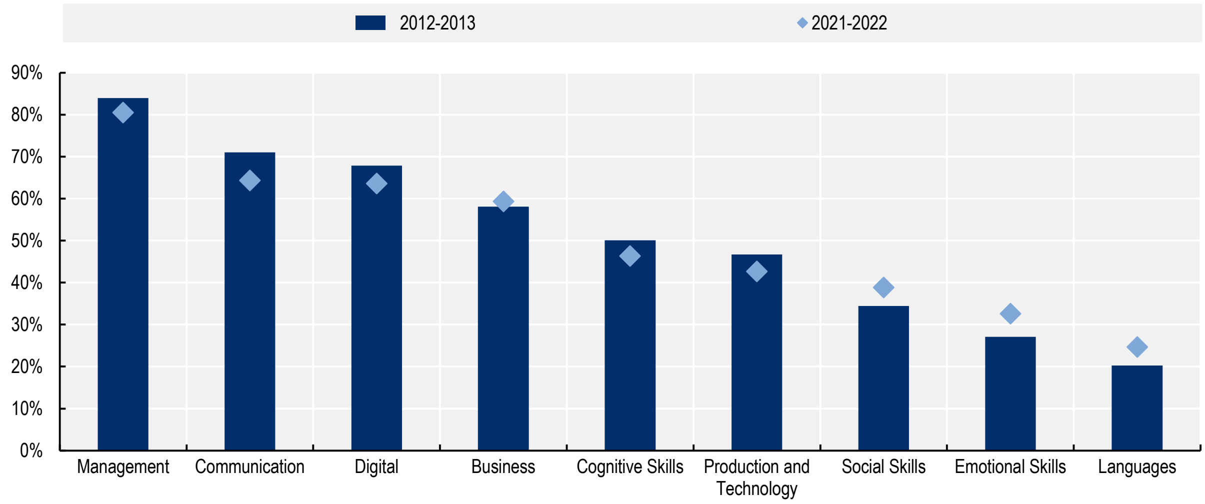
Artificial Intelligence (AI) is changing how workers perform their jobs and what skills they require. For example, a Canadian insurer implemented an AI tool that uses historical data to predict when a customer is likely to escalate a service issue. Sales agents previously conducted spot checks on a random selection of dossiers to review customer accounts for potential issues. The work required both analytical and financial skills to identify issues, but also social and communication skills to effectively reach out to customers. After the introduction of the AI technology, agents were given a priority list of account issues, which the AI technology had already identified. The job of a sales agent changed to emphasise greater customer interaction with less time needed to analyse dossiers (Milanez, 2023[1]).

This report provides representative estimates of the changing skill demand for occupations exposed to AI using online job vacancies in Canada between 2012 and 2022. There is little research on the changing skill demands for workers who will work with AI but do not have or require AI skills. Yet understanding how AI will change skill demands for this majority of workers is important for how skills policies, training agencies, career guidance and public employment services adapt their offerings in the future.

In Canada, a little over 1.1 million vacancies are highly exposed to AI representing over 30% of vacancies overall. The most demanded skills in occupations with high AI exposure are management, communication and digital skills (Figure 1). The most frequently demanded management and digital skills include general project management, budgeting, accounting and competencies with basic word processing and spreadsheet software. Communication skills refer to all forms of communication but concentrate heavily on written and oral communication. On average in 2021 and 2022 in Canada, 80% of vacancies in high AI exposure occupations demanded at least one management skill and 64% demanded at least one digital or communication skill.

Figure 1. The most demanded skills in occupations with high AI exposure are management, communication and digital skills, but social, emotional and language skills have seen the greatest increase in demand

Share of vacancies demanding at least one skill from ONET+ skill groupings in 2012-13 and 2021-22 in Canada, high-exposure occupations



Note: The share is defined as the share of vacancies in the high exposure tercile demanding at least one of the skills from each ONET+ skill grouping. AI exposure is defined by the occupation of each vacancy according Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the mean. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

In high-exposure occupations, the skill groupings that experienced the largest increase in demand over the past decade in Canada are language and social skills. The share of vacancies demanding at least one skill from each of these groupings increased by over 4 percentage points among high-exposure occupations between 2012-13 and 2021-22. This translates to over 200 000 more vacancies demanding at least one language skill, and 300 000 additional vacancies demanding at least one social skill. The most frequently demanded social skills include teamwork, collaboration, managing stakeholders, negotiation and team building. In Canada, language skills capture demand for speaking either English or French, and frequently, both languages.

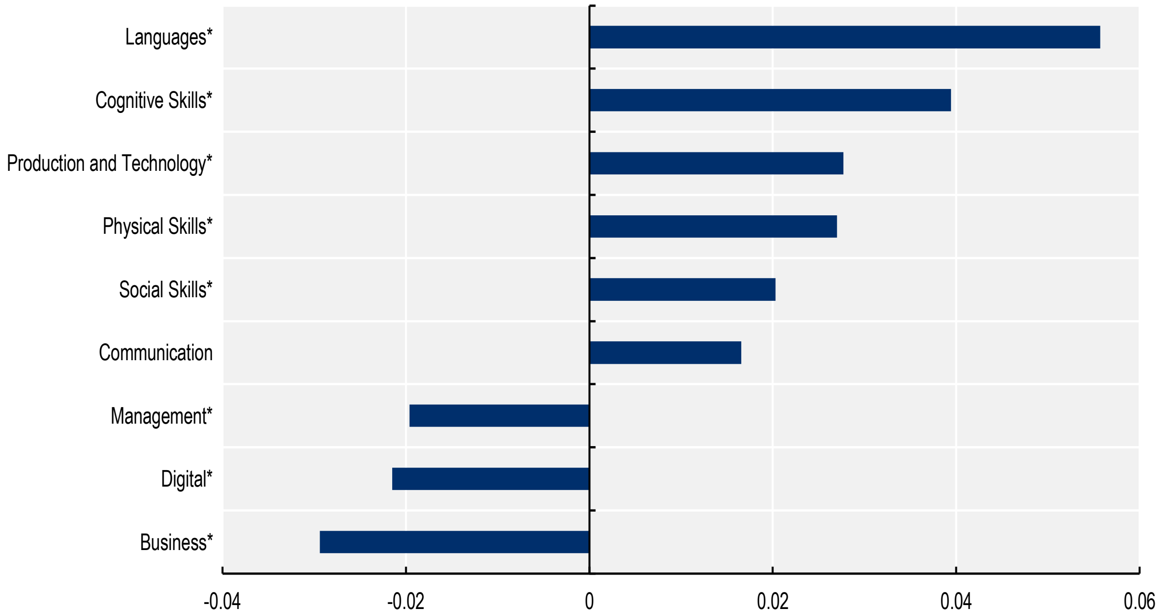
The report also looks at the demand for skills in establishments more exposed to AI, which allows for better identification of the causal effect of AI on skills demand. This analysis confirms the increasing demand for language and social skills in establishments more exposed to AI (Figure 2). The share of vacancies demanding language skills in an establishment with high AI exposure is 5 percentage points greater than in a moderately exposed establishment. For social skills, the increase in demand is 2 percentage points for highly exposed establishments compared to those that are moderately exposed. The magnitudes of these demand changes are small amounting to one more vacancy demanding at least one of these skills over the preceding decade. However, should AI adoption increase, it may foretell greater demand for these skills going forward.

The analysis at the establishment level also allows one to capture changes in demand for skills that have little overlap with AI's capabilities. Returning to the previous example of the Canadian insurer, the adoption of the AI tool should lead to greater productivity and cost savings for the firm. If the firm passes along these savings to customers, this may lead to greater demand for their insurance products. The firm may respond to the greater demand by hiring more sales agents thereby increasing demand for social and communication skills. However, they may also need to increase demand for auto damage appraisers, for example. These workers appraise vehicle damage to determine repair costs for insurance companies.

They require skills related to the repair and maintenance of vehicles, which are more typical of auto mechanics and other blue-collar occupations with little AI exposure.

Figure 2. More exposed establishments also demand more social and communication skills in Canada

Percentage point change in demand for skill groupings from establishment-level AI exposure in Canada, by ONET+ skill grouping



Note: Bars are regression coefficients of establishment-level AI exposure on changes in share of vacancies demanding at least one skill from a grouping. They are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base (2012-13) and end years (2021-22) when comparing a moderately exposed establishment to a highly exposed establishment (a one standard deviation increase). Stars indicate the skill groupings where the regression coefficient is significant at the 95% confidence level. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[2]) weighted by the establishment's base year occupation shares. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

This report also provides evidence that AI adoption may increase the demand for some of these blue-collar skills, which are not as exposed to AI. For example, compared to a moderately exposed establishment, a highly exposed establishment increases demand for skills related to production and technology, and physical skills by 2 percentage points. The most frequently demanded skills in the production and technology grouping are repair, cleaning, troubleshooting and quality assurance and control. For physical skills they are heavy lifting and manual dexterity. These results on production and technology and physical skills were particularly strong in Canada compared to the other OECD countries analysed in the report.

At the same time, the demand for management, digital and business skills may be falling in establishments more exposed to AI. For each skill grouping, moving from a moderately to a highly exposed establishment results in a two-percentage point decrease in demand for at least one skill from each grouping. These are some of the most demanded skills in high-exposure occupations, and one may be tempted to conclude that AI will render these skills obsolete. However, the magnitudes of these results are small, and as of writing, they do not portend seismic shifts in skill demand. Just as with the sales agents in the Canadian insurance company, the introduction of AI did not obviate the need for digital and analytical skills; the sales agents still needed to understand what problems the AI tool had identified. Rather, the introduction of AI de-emphasised cognitive and financial skills, and heightened the importance of social and communication skills.

1 Introduction

Artificial Intelligence (AI) adoption is changing how workers perform their jobs and how work is organised. For example, a Canadian insurer implemented an AI tool that uses historical data to predict when a customer is likely to escalate a service issue. Sales agents previously conducted spot checks to review customer accounts for potential issues. After the introduction of the AI technology, agents were given a priority list of account issues to solve pre-emptively reducing the need for the agents to identify the issues themselves (Milanez, 2023[1]).

This reorganisation of tasks due to AI will often result in changing demand for skills. In the previous example, the implementation of the AI tool suggests that sales agents may need fewer analytical skills to discern customer problems from a randomly selected dossier, and instead they may emphasise social skills to effectively reach-out to customers pre-emptively. Another set of changing skill demands concerns workers with AI skills defined as those with the knowledge and competencies to actively develop and maintain AI models. Despite relatively high demand for these skills in Canada (Borgonovi et al., 2023[4]), workers with these skills are only a tiny share of overall employment or labour demand (Green and Lamby, 2023[5]). The flurry of recent research on their employment prospects and wages of these workers do not represent a majority of workers in OECD labour markets who, like the sales agents in the above example, will likely work with AI in their jobs without requiring any skills or even knowledge of how the AI systems function. Yet understanding how AI will change skill demands for the majority of workers is important for how skills policies, training agencies, career guidance and public employment services adapt their offerings in the future.

This report helps fill this knowledge gap by providing representative estimates of the changing skill demand for occupations exposed to AI, but who do not possess or need AI skills in Canada. To measure changing skill demands, this report uses online job vacancies, and their associated skill demands, between 2012-13 and 2021-22. The data come from Lightcast which contain the quasi-universe of online job vacancies complete with descriptions of the key skills and competencies required. The Lightcast data is combined with data on AI exposure from Felten, Raj and Seamans (2021[2]) who use information on basic AI advances collected from the Electronic Frontier Foundation's AI measurement project as well as crowd-sourced opinions of basic skills that overlap with the AI advances to calculate a relative ranking of occupational exposure to AI. Actual AI use in occupations or establishments are not available in the Lightcast data. The AI exposure measures, therefore, proxy for AI use. To provide greater context to the results from Canada, where appropriate, the results are compared with 9 other OECD countries.[1]

The analysis finds that in Canada, the broad skill groupings of management, communication and digital skills are the most demanded skills in occupations most exposed to AI. These groupings include skills in project management, budgeting, accounting and competencies with basic word processing and spreadsheet software. Currently, 80% of high AI exposure occupations in Canada contain at least one management skill and 64% contain at least one skill belonging to the digital or communication skill groupings, respectively. High exposure AI occupations – defined as occupations with an exposure measure at least one standard deviation above the mean – are concentrated in high-pay occupations

[1] The countries are Austria, Belgium, Canada, Czechia, France, Germany, the Netherlands, Sweden, the United Kingdom and the United States.

requiring higher than average education such as: genetic counsellors, financial examiners and budget analysts. The most demanded occupations among high-exposure occupations in Canada are secretaries and administrative assistants and software developers and programmers. In 2021-22, 1.1 million vacancies representing over 30% of vacancies are found in occupations highly exposed to AI.

For high-exposure occupations, social and language skills have experienced the largest increases in demand over the past decade. The share of vacancies demanding at least one skill from the language and social skill groupings increased by over 4 percentage points, respectively, between 2012-13 and 2021-22. The most frequently demanded social skills include teamwork, collaboration, managing stakeholders, negotiation and team building. In Canada, language skills capture demand for speaking either English or French, or bilingual competency.

To better identify the effect of AI exposure on skill demands, this report also builds a panel of establishments. In this panel, establishment-level AI exposure is calculated from an establishment's occupational composition in the base year (2012-13) which is used to identify changes in skill demand between the base and end years (2021-22). This produces a shift-share design (Borusyak, Hull and Jaravel, 2021[6]) which identifies the effect of AI exposure by assuming that advances in AI's ability to perform various tasks contemporaneously performed by labour are uncorrelated with unobserved establishment characteristics. The empirical design allows one to compare changing skill demands in establishments that share the same industry and local labour market (among other characteristics), but which differ only in their AI exposure in the base year while plausibly eliminating omitted variable bias.

The results from this panel of establishments provide further evidence for the increasing demand for language and social skills in establishments more exposed to AI. A one standard deviation increase in establishment AI exposure leads to a five-percentage point increase in the share of vacancies demanding any language skill, and a two-percentage point increase in the share of vacancies demanding social skills. A one standard deviation increase is equivalent to an establishment moving from moderately to highly exposed to AI. As the example makes clear, although the results are robust, the effects are small, and they should be interpreted as capturing relative demand between observationally similar establishments.

Demand also increased in the skill groupings production and technology and physical skills. These results are particularly strong in Canada compared to similar OECD countries. The skill groupings production and technology and physical skills are found disproportionately in low-exposure occupations and include skills such as maintenance, repair, forklift driving and more fundamental skills such as dexterity, heavy lifting and range of motion. This provides some suggestive evidence of the types of skills that may see increased demand due to complementarities with AI in production. For example, an establishment that does home renovations and employs construction workers may also employ architects that provide integrated in-house design services. The adoption of an AI application may allow the establishment to provide the design services at a lower cost, which increases demand for their services overall, allowing them to employ more construction workers than before.

The results from this panel of establishments also reveal that demand for management, business process, and digital skills appears to be declining in establishments more exposed to AI. For management, digital, and business process skills, an establishment with high AI exposure reduced the share of vacancies demanding any of these skills by between two and 3 percentage points compared to a moderately exposed establishment. This is equivalent to an establishment posting one fewer vacancy requiring these skills in 2021-22 compared to 2012-13. The results for these skill groupings are consistent and robust across countries. Business process skills primarily include administrative and clerical tasks as well as skills related to sales and marketing.

This report complements recent OECD work on changing demand for skills due to AI, and adult learning systems in Canada. The most recent OECD Employment Outlook focused on AI and labour markets, and documented some of the skill needs due to AI (OECD, 2023[7]). These included AI skills for those that will develop and maintain AI systems, but also digital, cognitive and transversal skills such as creativity and teamwork. This report accords with this analysis by showing that communication and teamwork will be important for those exposed to AI in Canada, but it also finds less evidence for the growing importance of digital skills (Lassébie, 2023[8]). Canada's adult learning system performs well in two areas: alignment of training with labour market needs, and coverage (the share of adults and employers who participate in job-related training). Canada has also recently advanced the Future Skills council and the Future Skills Centre to advise and prepare workers and government agencies on emerging skill needs and how to prepare workers for the future labour market (OECD, 2020[9]). This report fits into these initiatives, by giving first estimates of the changing skill needs for occupations exposed to AI.

This report also highlights the increasing demand for social skills. Deming and Kahn (2018[10]) show that cognitive skill and social skill requirements in job ads positively predict occupational wage differences across local labour markets in the United States from 2010-15. This largely predates AI adoption, and the authors interpret this finding as higher demand for these skills – particularly in tandem.[2] This report finds supporting evidence for the increasing importance of social and cognitive skills in Canada due to AI exposure.

The report is organised as follows. Section 2 describes the various datasets and classification systems used to construct the data. Section 3 provides descriptive evidence on broad skill changes in Canada at the occupation level stratified by AI exposure, and section 4 provides evidence for the effects of AI exposure on the demand for various sets of skills at the establishment-level using quasi-random variation in ex-ante exposure to AI tasks.

[2] See Deming (2017[39]) for further evidence using survey data from the United States.

2 Measuring AI exposure and skills in job vacancies

2.1. Measuring AI exposure with advances in the capabilities of artificial intelligence

One of the core challenges of measuring changing skill demands due to AI is to find a direct measure of AI use on the job. Recent studies that focus on a specific AI application adopted by a subset of workers in a particular firm, or experimental approaches focusing on one AI application, provide credible evidence of the effects of AI exposure – including changing skill demands – on those workers (Peng et al., 2023[11]; Noy and Zhang, 2023[12]; Brynjolfsson, Li and Raymond, 2023[13]). However, these studies lack the external validity to make statements about changing skill demand from AI generally. More general case studies and surveys of workers and firms analysing AI use in the workplace provide a more representative picture of the effects of AI adoption, but these are often limited to certain industries, and they lack plausibly exogenous assignment of AI applications. There are also an increasing number of official government surveys of AI use by firms, but these are not usually detailed enough to ascertain which workers are using AI, nor can they easily capture changing skill demands.[3]

This report uses advances in the capabilities of AI and compares them to the tasks performed in jobs as a proxy for AI exposure. The measure of AI exposure used in this chapter comes from Felten, Raj and Seamans, (2021[2]) who measure progress in AI applications from the Electronic Frontier Foundation's AI Progress Measurement project and connect it to abilities from O*NET using crowd-sourced assessments of the connection between applications and abilities. The measured exposure of each task to AI is then aggregated to the occupation (industry or local labour market, respectively) level to derive measures of exposure. The measure is relative, with mean zero and unit variance, and it is defined for over 700 SOC-10 occupations.

This measure of AI exposure has some important advantages compared to other measures of AI exposure. The measure is theoretically ambiguous with respect to whether the overlap between progress in AI and the abilities required in a job means "risk of displacement", or "complementary". Second, this measure is applicable in a wide variety of settings including the universe of job vacancies used as the primary data source in this report (below). Finally, and perhaps most importantly, measures of AI exposure can be used with an empirical design that allows for plausibly exogenous variation in AI exposure (Section 4), and this measure in particular has been previously shown to correlate with vacancies demanding AI skills in the

[3] They have, however, other advantages given their representativeness and the availability of other firm-level information (including e.g. the presence of ICT specialists or the provision of ICT training), which allow for the possibility to investigate the links between the use of AI by firms, their productivity, and the role of complementary assets. See Calvino and Fontanelli (2023[34]) who focus on 11 countries based on a common statistical code executed in a decentralised manner on official firm-level surveys.

United States (Acemoglu et al., 2022[14]). This provides an important source of external validity that this measure of AI exposure is correlated with firm-level AI activity.[4]

Other approaches to measuring AI exposure that have been used in the literature do not capture workers without AI skills or are less suited for cross-country comparative analysis. One popular method for identifying AI exposure uses job postings and their associated skill demands for workers with AI skills to infer AI adoption by firm, occupation or industry (Alekseeva et al., 2021[15]; Squicciarini and Nachtigall, 2021[16]; Calvino et al., 2022[17]; Manca, 2023[18]; Green and Lamby, 2023[5]).[5] However, this method misses firms who adopt AI but do not develop or service it in-house, or workers whose abilities overlap with AI advances but who do not need AI skills.[6] Finally, the release of generative AI models to the public has induced a wave of new AI exposure measures (Briggs and Kodnani, 2023[19]; Eloundou et al., 2023[20]; Felten, Raj and Seamans, 2023[21]; Pizzinelli et al., 2023[22]). It remains an open question how strongly these measures correlate with actual AI adoption or activity.[7]

2.1.1. High-skill occupations are the most exposed to artificial intelligence

High-skill, high-wage occupations are the most exposed to artificial intelligence. Table 2.1 shows the occupations that are the most and least exposed to artificial intelligence. Genetic counsellors, financial examiners and actuaries are the three occupations with the highest AI exposure. These are occupations that require cognitive skills that cannot be automated with a discrete set of instructions, but for which artificial intelligence excels (Green, 2023[23]). In contrast, the least exposed occupations rely mostly on non-routine physical skills and include dancers, fitness trainers, as well as helpers to painters, plasterers and stucco masons.[8]

[4] Acemoglu et al., (2022[14]) experiment with other measures of AI exposure including Brynjolfsson, Mitchell and Rock, (2018[31]) who apply a rubric for evaluating task potential for machine learning to tasks in O*NET, and Webb (2020[32]) measures AI progress from patents and connects this to O*NET as well. However, they do not find that these measures of AI exposure are as strongly correlated with an establishment's AI activity as measured by the number of vacancies with AI skills.

[5] Calvino et al. (2022[17]) also combine job postings with other data sources that allow identifying different types of AI adopters, focusing on the UK. These include AI-related Intellectual Property Rights and information on AI-related activities mentioned on company websites.

[6] See Georgieff and Hyee, (2021[33]) for a thorough discussion of the relative merits of the various approaches to measuring AI exposure including which effects of AI on tasks each approach can recover.

[7] Felten, Raj and Seamans (2023[21]) update their original AI exposure measure, used in this report, to account for generative AI. The two measures are almost perfectly correlated which provides some evidence that the AI exposure measures used in this report are capturing many of the basic advances underlying newer generative AI applications.

[8] The exposure measure of Felten, Raj and Seamans (2021[2]) focuses on software applications using AI, and will therefore not capture instances of AI combining with other technologies – robots, for example – which would likely disproportionately affect blue-collar workers.

Table 2.1. High-skilled occupations are the most exposed to artificial intelligence

Top 5 highest and lowest occupations by AI exposure

Occupations Most Exposed to AI			Occupations Least Exposed to AI	
Genetic Counselors (29-9092)	1.53		Dancers (27-2031)	-2.67
Financial Examiners (13-2061)	1.53		Fitness Trainers and Aerobics Instructors (39-9031)	-2.11
Actuaries (15-2011)	1.52		Helpers (37-3014)	-2.04
Purchasing Agents (13-1023)	1.51		Reinforcing Iron and Rebar Workers (47-2171)	-1.97
Budget Analysts (13-2031)	1.50		Pressers, Textile, Garment, and Related Materials (51-6021)	-1.95

Note: 2010 SOC occupation codes are in parentheses. The exposure measure is scaled such that the unweighted occupation average is zero with unit variance. Purchasing agents exclude those working in wholesale or retail trades and farm products. Helpers includes those helping painters, paperhangers, plasterers, and stucco masons.
Source: Felten, Raj and Seamans (2021[2]).

This report uses these exposure measures as a proxy for AI use in an occupation or an establishment in two different ways. First, at the occupation level, the report looks at differences in changing skill demand between low, moderate and high-exposure occupations over time (Section 3). Next, the report examines changing skill demand at the establishment level, and measures AI exposure by taking the weighted average of AI exposure of the occupations of posted vacancies by the establishment in the base year, and then comparing changing skill demand between observationally similar establishments (same local labour market, and industry) which differ only in their extent of exposure to AI (Section 4). The rest of this section describes in detail the construction of these two samples and provides some basic descriptive statistics.

2.2. Capturing skill demands from the universe of online job vacancies

In addition to AI exposure, this report measures skill demands by occupation using a dataset of the universe of online job vacancies from the firm Lightcast. Lightcast collects job postings from over 50 000 online job boards and company websites. It then deduplicates, standardises and disseminates the job postings in machine-readable form. The database includes information on location, sector, occupation, required skills and education of job postings across an expanding list of countries. The use of Lightcast data for academic research has proliferated in recent years, and at least for the United States, has become a widely accepted and representative dataset for the analysis of various aspects of labour demand (Modestino, Shoag and Ballance, 2016[24]; Deming and Kahn, 2018[10]; Hershbein and Kahn, 2018[25]; Borgonovi et al., 2023[4]). For many other OECD countries, including Canada, the Lightcast data is representative of aggregate variables at the occupational level (Cammeraat and Squicciarini, 2021[26]; Araki et al., 2022[27]).

The advantage of the Lightcast data for this report is that, for each vacancy, Lightcast lists the skills demanded for the job. Lightcast pulls skills information directly from the vacancy standardising the spelling and concepts. Depending on the database and type of taxonomy used, Lightcast's online vacancy information provides more than 32 000 unique skills. The breadth and depth of detail classifying skills in quasi-real time – it allows for within-occupation variation in skills – is one of the advantages of the Lightcast vacancy data.[9]

[9] See OECD (2021[35]) for a further discussion of the advantages of using vacancy posting data with skills demanded compared to more traditional sources of skills in occupations such as O*NET and ESCO.

Lightcast data does, however, have some limitations. Not all jobs are posted online. The data will therefore miss jobs that are advertised word to mouth, as well as occupations and industries that rely on more informal networks for hiring. Lightcast data will therefore somewhat oversample high-skilled jobs that have a higher probability of being posted online (Carnevale, Jayasundera and Repnikov, 2014[28]).[10] This will likely result in an overestimate of vacancies or firms with high AI exposure as these occupations tend to be overwhelmingly high-pay, high-skilled and are more likely to be posted online.[11] For the analysis that follows, this may result in an underestimation of any (potential) complementarities between AI and skills demanded in low exposure occupations.

2.2.1. Sample construction

This report uses Lightcast data from Canada and 9 other OECD countries for comparison. In the Lightcast data, the occupational distribution of vacancies in the 10 countries have been previously shown to be representative of the occupation-employment distribution using labour force surveys (Araki et al., 2022[27]). In addition, they all exhibit some evidence of demanding workers with AI skills, which is a proxy for AI use. The countries include Canada, the United States, the United Kingdom, Austria, Belgium, France, Germany, the Netherlands, Sweden and the Czech Republic (hereafter 'Czechia'). Lightcast organises the countries into separate databases with two parallel taxonomies for classifying skills. Canada, the United States and the United Kingdom receive Lightcast's own taxonomy, and the rest of the countries in the sample use ESCO, a skill taxonomy developed by the European Union. The rest of the sample construction consists of harmonising firm names and time periods within countries and the different occupation classifications and skill groupings across countries.

The report harmonises the occupation classification to SOC-10. The Felten, Raj and Seamans (2021[2]) measure of AI exposure as well as Canada, the United Kingdom and the United States already use SOC-2010 to classify occupations.[12] The remaining seven countries use the ISCO-08 classification which is the standard international classification for occupations. This report crosswalks ISCO-08 to SOC-10 using a recently developed employment-weighted crosswalk and a simple imputation procedure (Bassanini, Garnero and Puymoyen, Forthcoming[29]).[13]

The empirical analysis relies on changes over time in skill demand from a base year to the most recent year for which data is available. For Canada, the United States and the United Kingdom, the analysis compares base years of 2012-13 pooling all valid vacancies in these years. For the other countries, the base years are 2018-19 with the differences between the two databases solely accounted for by data availability. The end years for all countries are pooled years 2021-22. For all analyses to follow, the measure of skill demand is the share of vacancies demanding a skill from a particular skill grouping.

[10] This is particularly true in Canada, although the bias appears relatively small – see Tsvetkova et al. (2024[41]).

[11] They may also underestimate vacancies for occupations or positions where headhunting or informal networks are more valuable for filling vacancies.

[12] There are some SOC-10 occupations, which appear in the Lightcast data for which no AI exposure measure exists. These are almost always miscellaneous categories where Lightcast cannot precisely allocate the vacancy. For all these cases, a vacancy with a missing AI exposure measure is assigned an unweighted average of AI exposure of all occupations two levels up (four-digit SOC-10) in the SOC-10 hierarchy.

[13] The imputation procedure uses the employment-weighted crosswalk – with employment weights specific to each country – as a posterior probability distribution over the set of possible SOC-10 occupations for each ISCO occupation. For each vacancy classified into an ISCO-08 occupation, a single SOC-10 occupation is drawn randomly from the associated distribution to allocate it a SOC-10 occupation. This procedure is similar in spirit to Rubin (1987[36]), but only drawing one occupation instead of multiple. There is therefore only one implicate and all estimates to follow will not consider this additional source of variance.

Skills for each vacancy are harmonised into an adapted O*NET+ classification. There are over 30 000 skills across the various countries and, to facilitate their use, the skills are grouped hierarchically. Canada, the United Kingdom and the United States have skills grouped according to Lightcast's own skill taxonomy which has a heavy industry focus, and most importantly, does not map all or even most skills into the taxonomy. This report regroups skills into an adapted O*NET classification, which relies on natural language processing to map skills into lightly modified ONET groups (see Box 2.1). Skills in the remaining countries are grouped according to the ESCO classification system used in the European Union. This report uses an existing crosswalk to map skills from ESCO Level 3 to O*NET Level 3, and then allocates O*NET Level 3 into the adapted O*NET classification (see Annex B for a full description of the O*NET+ classification). For all analysis to follow, this report uses both the ONET+ and Lightcast taxonomies although preference is given to ONET+ both due to greater cross-country comparability, and because it covers almost all skills in the database.

Box 2.1. Mapping Lightcast skills to uniform O*NET+ groupings

There are over 30 000 distinct skills reported by Lightcast across the various countries they cover, and researchers have sought various techniques to reduce the dimensionality of this set of skills for policy analysis. Some researchers have resulted to simply using education or experience (Deming and Kahn, 2018[10]) or lists of specific skills they have manually curated (Alekseeva et al., 2021[15]). Lightcast has its own skill taxonomy classifying the approximately 17 000 distinct skill keywords into hundreds of "clusters" and 28 "families". However, the taxonomy tends to reflect industry categories rather than actual skills, and it is used exclusively in Canada as well as a few anglophone countries while European countries have their skills classified using ESCO. In addition, the Lightcast taxonomy does not allocate every, or even most, skills to a cluster or family. For example, over 45% of skills, and a little over 38% of skills weighted by frequency, are not assigned a cluster or family in the Canadian data for 2022. The most frequently demanded unassigned skills include social, cognitive and communication skills such as teamwork, writing, research and creativity.

This report uses an approach to group the skill information contained in Lightcast from Lassébie et a. (2021[3]). It does so by classifying the approximately 17 000 different skills appearing in Lightcast data for Australia, Canada, New Zealand, Singapore, the United Kingdom and the United States into a pre-existing skill taxonomy based on the skill's meaning or definition. Instead of a manual classification, the approach uses a semi-supervised machine learning algorithm that produces an automatic classification of skills into the taxonomy's broader categories. The approach builds on BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art algorithm published by researchers at Google AI Language, which is trained on a large corpus of text to "understand" the English language. The model is further trained for the classification of skills keywords. The approach classifies the changing list of Lightcast skills into a taxonomy that is stable over time. This stability in structure and the mutually exclusive nature of the taxonomy's categories are especially important to simplify empirical analysis.

The skills are classified into a taxonomy based on O*NET that the authors call O*NET+. O*NET is a publicly available online database that, for each occupation, provides definition and main characteristics, including the skills, knowledge and abilities required to perform the job. It is organised under a clear hierarchical structure and has been validated by labour market and education experts and it additionally finds wide use among policy makers and statistical agencies. The final taxonomy maps over 17 000 skills into 60 categories and 16 broad categories. The taxonomy adheres closely to O*NET, but it is augmented in cases where O*NET is not sufficiently detailed, for example, digital skills. The similar structure to O*NET allows one to hand-classify ESCO Level 3 skills into O*NET+ categories which is what this report does to harmonise the skills in the seven European countries. Annex B provides a summary of the taxonomy.

Source: Lassébie et al. (2021[3]).

Finally, section 4 examines changing skill demand at the establishment level which is defined as the combination of employer name and local labour market geography. Firms are defined as all vacancies within a country that have the same employer's name.[14] Ideally, one would define establishments using identifiers for actual establishments such as an exact address, but that is not available in the Lightcast

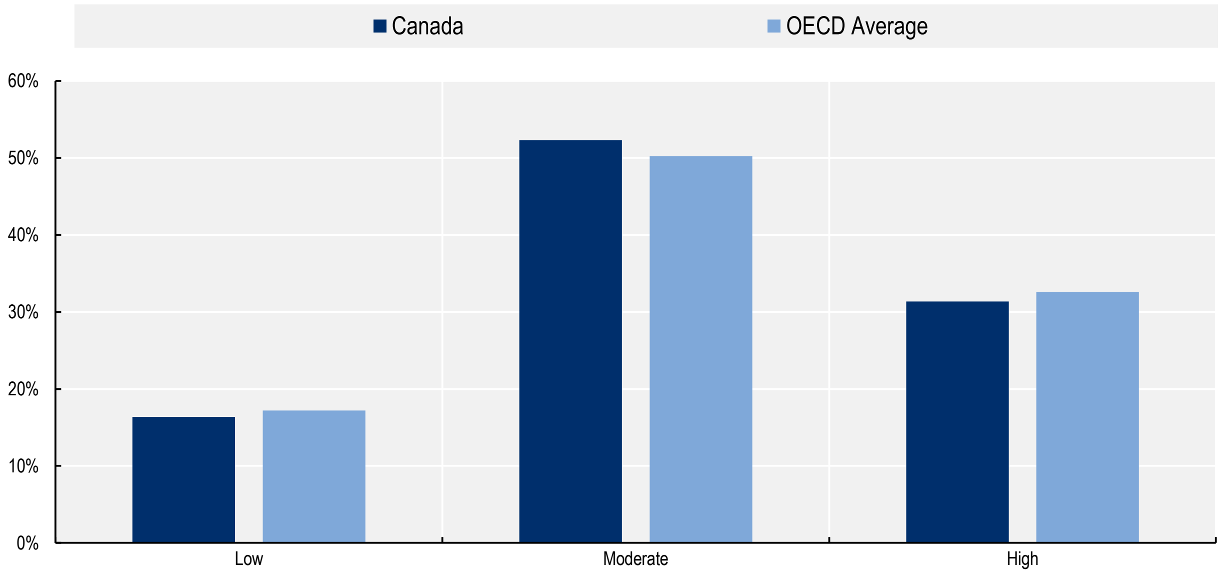
[14] Employer names are standardised and cleaned to handle certain common suffixes such as "inc." or "gmbh". Vacancies posted to job boards are included in the occupation sample but excluded from the establishment sample. To identify job boards, this report follows the same procedure outlined in Araki et al. (2022[27]).

data. Following Acemoglu et al. (2022[14]), this report uses the local labour market as a proxy, which is defined by TL2 regions. TL2 regions are designed for cross-country comparability while still respecting existing geographic entities. For example, in the United States, TL2 regions are analogous to states, and in Canada, they are provinces. The analysis in section 4, therefore, allows for the comparison of different establishments within the same region.[15]

2.3. Slightly less than one-third of vacancies in Canada are highly exposed to AI

The share of vacancies with high AI exposure in Canada is slightly lower than the OECD average. The share of vacancies with high AI exposure is just over 31% in Canada compared to one-third of vacancies across the OECD countries in the sample (Figure 2.1). Recall that AI exposure is taken from Felten, Raj and Seamans (2021[2]), who normalise their measure to have a mean of zero and variance of one. High exposure in this report is defined as all vacancies whose occupation has an AI exposure measure one standard deviation greater than the mean.

Figure 2.1. The share of vacancies by exposure to artificial intelligence, 2021-22



Note: AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average, and low-exposure occupations have an exposure measure less than one standard deviation less than the average. Moderate exposure occupations have an exposure measure within one standard deviation of the average. Average is an unweighted cross-country average and includes Canada.
Source: OECD analysis of Lightcast data and Felten, Raj and Seamans (2021[2]).

A little less than 52% of vacancies in Canada have moderate AI exposure and more than 16% have low AI exposure. On average in the sample, 50% of vacancies have moderate AI exposure (defined as occupational exposure within one standard deviation of the mean), and 17% have low AI exposure (defined as one standard deviation less than the mean). Shares of vacancies with moderate and low AI exposure exhibit more cross-country variance than those of high AI exposure.

[15] This is a coarser definition of a labour market than found in the literature, but it allows for large enough sample sizes in smaller countries while retaining harmonised cross-country definitions.

Low exposure vacancies have grown the fastest over the period observed. Both high and moderate AI exposure vacancies have grown by over 300% between the base and end years, while low exposure occupations have grown by over 400% on average across countries in the sample. One should use caution when interpreting these numbers as the base and end years vary across countries, and a portion of this growth is likely due to Lightcast improving the breadth of their vacancy sampling over time. However, this report focuses primarily on occupations with high AI exposure which disproportionately require higher education and are more likely to be listed online. High exposure occupations, therefore, are unlikely to be disproportionately represented in new sources of Lightcast coverage.

2.3.1. In Canada, the high-exposure occupations with the highest demand are administrative and clerical occupations, and software developers

Secretaries, administrative assistants as well as software programmers comprise the largest share of vacancies in high-exposure occupations in Canada. Secretaries and administrative assistants make up about 3% of vacancies and software developers about 2.4%. The top five most demanded occupations among high-exposure occupations make up a little less than a third of all vacancies in the high-exposure group (Table 2.2).

Table 2.2. The most demanded occupations by AI exposure group in Canada, 2021-22

High AI exposure			Low AI exposure	
Occupation	Share		Occupation	Share
Secretaries and Administrative Assistants (43-6010)	3.0%		Laborers and Material Movers (53-7060)	2.4%
Software Developers and Programmers (15-1130)	2.4%		Driver/Sales Workers and Truck Drivers (53-3030)	2.3%
Marketing and Sales Managers (11-2020)	1.8%		Building Cleaning Workers (37-2010)	1.8%
Bookkeeping, Accounting, and Auditing Clerks (43-3030)	1.3%		Maintenance and Repair Workers (49-9070)	1.0%
Human Resources Workers (13-1070)	1.2%		Construction Laborers (47-2060)	0.9%

Note: Share is the share of *all* vacancies. SOC-10 code displayed in parentheses. High-exposure occupations have an exposure measure at least one standard deviation greater than the average, and low-exposure occupations have an exposure measure less than one standard deviation less than the average. High AI exposure additionally omits “Miscellaneous Computer Occupations (15-1190)” for clarity, which contains 1.9% of vacancies.
Source: OECD analysis of Lightcast data and Felten, Raj and Seamans (2021[2]).

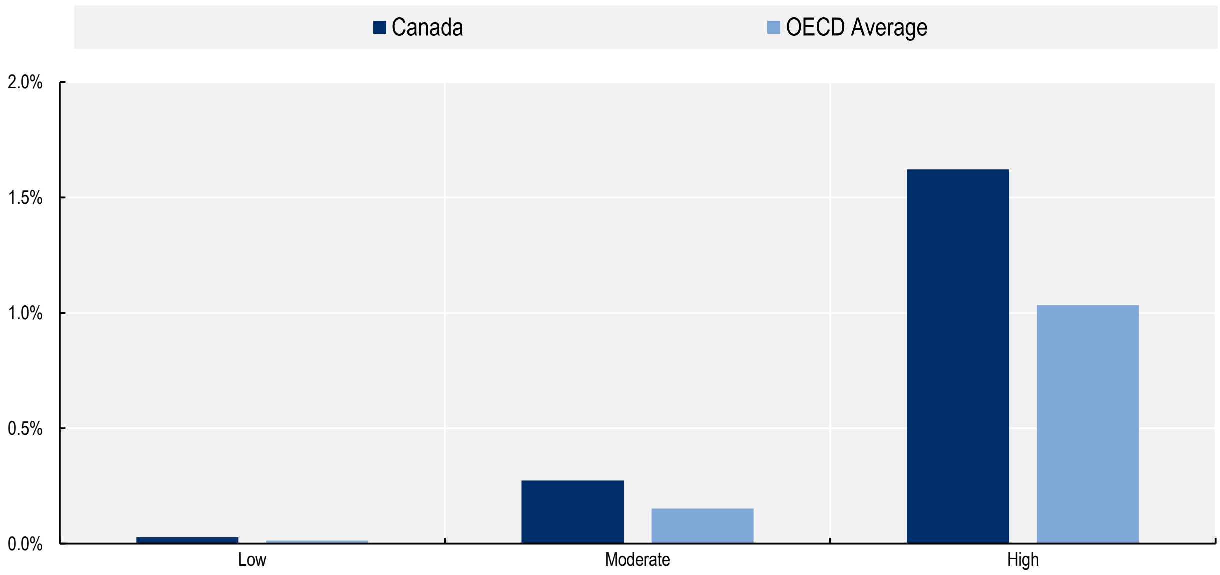
2.3.2. AI skills are concentrated in high exposure occupations

The final step before presenting results on changing skill demands involves removing vacancies demanding AI skills. This report concerns changing skill demands for workers exposed to AI, but who do not have (or need) AI skills. Workers with AI skills comprise workers with skills in computer programming and statistics who have high levels of education (Green and Lamby, 2023[5]). Demand for these skills has grown briskly over the past decade and resulted in substantial wage premiums for those with AI skills (Alekseeva et al., 2021[15]; Borgonovi et al., 2023[4]). Leaving these vacancies in the final sample risks conflating demand for specialised AI skills with the typical experience that one might expect for the majority of workers exposed to AI.

Vacancies demanding AI skills are disproportionately found in occupations with high AI exposure. Figure 2.2 shows the share of vacancies that demand AI skills stratified by AI exposure tercile. Over 1.5% of vacancies demand AI skills among high-exposure occupations compared to less than 0.5% among occupations with moderate AI exposure.[16] There are virtually no vacancies demanding AI skills among vacancies with low AI exposure. These patterns are not surprising because vacancies demanding AI skills are concentrated in occupations such as computer programmers and statisticians which have high AI exposure.

These figures reinforce the point that vacancies demanding AI skills represent a tiny portion of labour demand or employment overall. By removing these vacancies from the sample, the analysis can better isolate changing skill demands for positions that are likely to use AI without the need for AI skills, which is the representative case for most workers.

Figure 2.2. The share of vacancies demanding AI skills by exposure to artificial intelligence, 2021-22



Note: Share is defined as the share of vacancies demanding AI skills by exposure tercile. AI exposure is defined by the occupation of each vacancy according Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the mean occupational exposure, and low-exposure occupations have an exposure measure less than one standard deviation less than the mean. Moderate exposure occupations have an exposure measure within one standard deviation of the mean. Average is an unweighted cross-country average and includes Canada. Vacancies demanding AI skills are classified using a Naïve Bayes classifier trained separately for each country on vacancies demanding "machine learning".
Source: OECD analysis of Lightcast data and Felten, Raj and Seamans (2021[2]).

[16] Vacancies demanding AI skills are classified using a Naïve Bayes classifier trained separately for each country on vacancies demanding "machine learning". See Green and Lamby (2023[5]) for a description of the procedure.

3 Occupational skill demand and AI exposure in Canada

This section gives an overview of the skills most demanded in occupations with high AI exposure as well as how these skill demands have changed over the sample period. The analysis groups occupations by high, moderate and low AI exposure, and examines changes over time using a large cross-section of vacancies.

3.1. Management, communication and digital skills are the most demanded skills in occupations with high AI exposure

Skills in management, business as well as digital skills are the most demanded in occupations with high AI exposure. Table 3.1 shows the most demanded skill groupings – measured by the share of vacancies demanding at least one skill from that grouping – across intensity of AI exposure in the end period, 2021-22 in Canada. The skills groupings are from the ONET+ taxonomy. Resource management is by far the most demanded skill grouping with 80% of high AI exposure vacancies demanding at least one skill from this grouping. Communication and digital skills are the next most demanded occupations with 64% of vacancies in the highest exposed occupations demanding skills from these groupings. Resource Management contains skills pertaining to general project management and administration as well as accounting and budgeting skills. Communication skills includes many skills related to writing as well as verbal or oral communication. In Canada, the most frequent skills under the digital grouping can be neatly summarised as facility with Microsoft Office. The top skill groupings (also business process and cognitive skills) are suggestive of white-collar office work that might be colloquially described as “routine” but are difficult to codify in a deterministic way. These are the types of skills where current AI applications excel.

Moderate and low exposure occupations also have strong demand for many of these same skill groupings, but at much lower rates. The top three demanded skill groupings for moderately exposed occupations are: resource management, business processes and production and technology. For occupations with low AI exposure the top grouping is production and technology, joined by resource management and physical skills. Production and technology includes the subgroupings installation and maintenance, quality assurance and production processes. Some of the most frequent skills include repair, cleaning, cooking and forklift operation. With these notable exceptions, the most demanded skills are relatively similar across AI exposure groupings, but moderate and especially low exposure occupations have a more dispersed skill demands as measured by the share of vacancies demanding skills in different categories.

Table 3.1. The skill groups in highest demand by intensity of AI exposure, 2021-22

Share of vacancies in Canada demanding at least one skill from ONET+ skill groups by intensity of AI exposure, 2021-22

High AI exposure			Moderate AI exposure			Low AI exposure	
Skill group	*Share*		*Skill group*	*Share*		*Skill group*	*Share*
Resource Management	80%		Resource Management	66%		Production and Technology	80%
Communication	64%		Business Processes	55%		Resource Management	40%
Digital	64%		Production and Technology	52%		Physical Skills	33%
Business Processes	59%		Communication	51%		Communication	30%
Cognitive Skills	46%		Digital	35%		Languages	29%

Note: Share is defined as the share of vacancies in each exposure grouping demanding at least one of the skills from each skill grouping pooled over the years 2021 and 2022. AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Low AI exposure occupations have an exposure measure at most one standard deviation less than the average with moderate exposure occupations in between. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

The Lightcast skill taxonomy confirms that digital, finance and business skills are the most demanded among high-exposed occupations. Table 3.2 shows the share of vacancies demanding at least one skill from the Lightcast skill cluster family groupings. The most demanded skills for high-exposure occupations come from the information technology family where 53% of high-exposure vacancies demand at least one skill. The next most demanded families are business and finance with 49% and 37%, respectively. Just as with the ONET+ grouping, information technology can be succinctly summarised as demand for competence with Microsoft Office as well as computer programming. The most frequent skills demanded under the business family include general management and business administration. The most frequently demanded skills in the finance family are accounting and budgeting.

Table 3.2. The Lightcast skill groupings find that programming and financial skills are the most demanded in high-exposure occupations

Share of vacancies in Canada demanding at least one skill from Lightcast skill cluster families by intensity of AI exposure, 2021-22

High AI exposure			Moderate AI exposure			Low AI exposure	
Skill group	*Share*		*Skill group*	*Share*		*Skill group*	*Share*
Information Technology	53%		Business	33%		Maintenance, Repair, and Installation	33%
Business	49%		Customer and Client Support	31%		Supply Chain and Logistics	27%
Finance	37%		Health Care	29%		Health Care	23%
Administration	30%		Sales	28%		Architecture and Construction	21%
Customer and Client Support	22%		Administration	26%		Manufacturing and Production	18%

Note: Share is defined as the share of vacancies in each exposure grouping demanding at least one of the skills from each skill cluster family pooled over the years 2021 and 2022. AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Low AI exposure occupations have an exposure measure at most one standard deviation less than the average with moderate exposure occupations in between. Skill cluster families are defined by Lightcast.
Source: OECD analysis of Lightcast data, and Felten, Raj and Seamans (2021[2]).

The most demanded skills in the low-exposure tercile are again quite similar to those found in the ONET+ taxonomy. The most demanded skills among vacancies with low AI exposure are maintenance, repair, and installation (maintenance); supply chain and logistics (logistics); and healthcare. The maintenance family is demanded by 33% of vacancies in the low-exposure tercile, and the logistics family is demanded by 27% of vacancies. The most frequently demanded skills in maintenance are plumbing, power tools and painting. For logistics, they are inventory management, forklift operation and procurement.

As the results show, the two taxonomies are capturing similar skills among exposure terciles, but they do differ mostly due to their construction. The Lightcast taxonomy shows lower shares of skills demanded in each skill category compared to the ONET+ skill groupings. This is because Lightcast divides families into 28 families compared to 16 for ONET+. This will simply mechanically reduce the share of vacancies that demand at least one skill from any family. For example, the ONET+ taxonomy groups management, administration, finance and accounting skills under Resource Management, while these skills are dispersed over three different categories in Lightcast. As mentioned previously, the other key difference is that the Lightcast taxonomy does not group all skills into a family. In Canada in 2022, 45% of skills are not allocated to a family, which reduces to 38% when one weights the results by frequency. This will also reduce the share of vacancies demanding any skill from a family. The rest of this section looks at changing skill demand over time for high-exposure vacancies. To account for the shortcomings of the Lightcast taxonomy, and for better cross-country comparisons, the results will focus more on the ONET+ taxonomy.

3.2. For high-exposure occupations, demand for emotional, social and language skills have increased the most over the past decade

Demand for emotional, social and language skills have increased the most over the past decade among high-exposure occupations. Emotional skills (attitudes),[17] social skills and language skills have seen the largest increases in demand of 5, 4 and 4 percentage points, respectively (Figure 3.1). Emotional skills include skills such as self-management/rigour, motivation and adaptability. Language skills are almost exclusively the ability to speak French or English, or both. The skill grouping medicine saw the largest increase in demand (9 percentage points), however, this increase was almost entirely due to the rapid increase in demand for skills related to administering vaccinations. It seems more likely this is a consequence of the vaccination campaigns related to the COVID-19 pandemic and not to any underlying effect of AI.

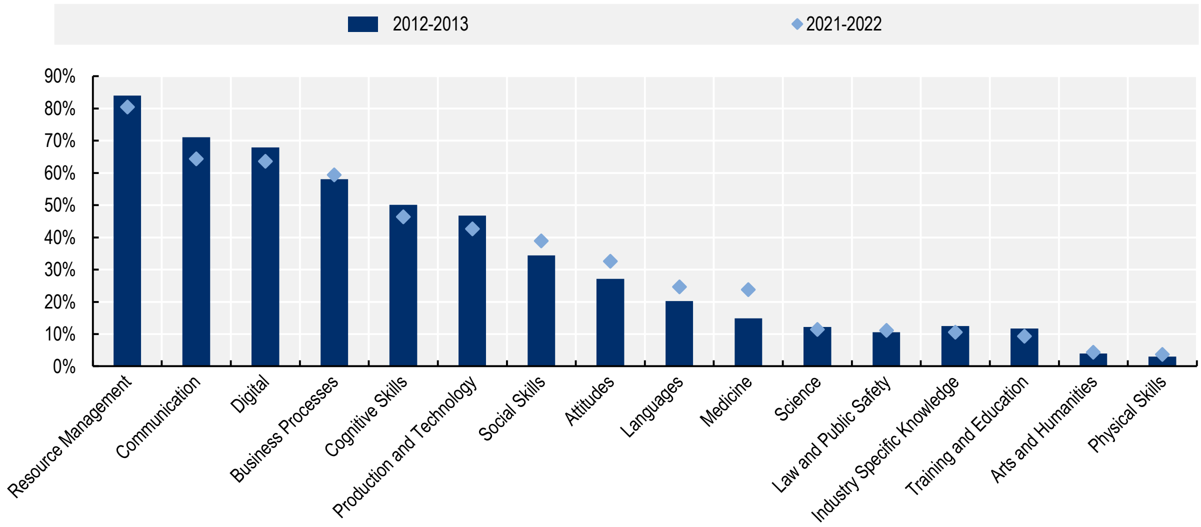
In contrast, the most demanded skills among high-exposure occupations have declined the most in Canada over the past decade. Communication and digital skills declined the most with reductions in demand of over 6 and 4 percentage points, respectively. Cognitive skills and resource management skills also declined by over 3 percentage points.

Demand for communication, digital and cognitive skills fell more in low-exposure occupations compared to high-exposure occupations. Demand for communication and cognitive skills fell by over 20 percentage points and demand for digital skills fell by 10 percentage points (Annex Table A A.1). The skill groupings that experienced the largest increases in demand in high-exposure occupations also saw diverging trends compared to low-exposure occupations. In low-exposure occupations, demand for social skills fell by over 2 percentage points compared to an increase of 4 percentage points in high-exposure occupations. For language skills, demand in low-exposure occupations fell by 10 percentage points compared to an increase of 4 percentage points in high-exposure occupations.

[17] The skills classified under the category Attitudes in the ONET+ taxonomy overlap closely with what are commonly referred to as emotional skills (OECD, 2015[40]). For clarity, this report uses the category Attitudes and emotional skills interchangeably.

Figure 3.1. Among high-exposure occupations, emotional and social skills have seen some of the largest increases in demand

Share of vacancies demanding at least one skill from ONET+ skill groupings in 2012-13 and 2021-22 in Canada, high-exposure occupations



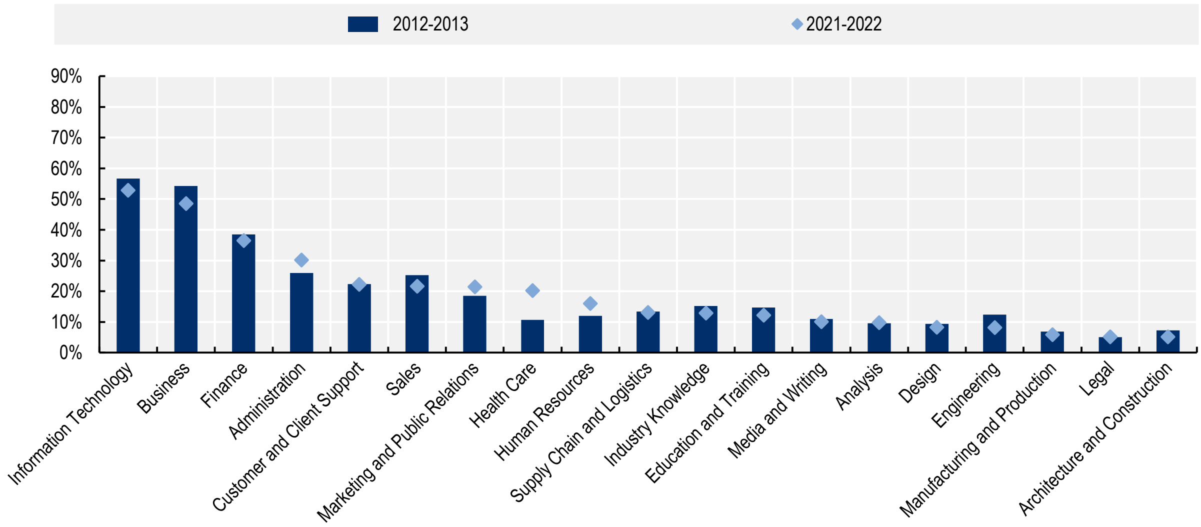
Note: Share is defined as the share of vacancies in high exposure grouping demanding at least one of the skills from each ONET+ skill grouping. AI exposure is defined by the occupation of each vacancy according Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

Using the Lightcast skill cluster families, the results for high-exposure occupations mostly mirror those using the ONET+ grouping when examining the skills experiencing the greatest reductions in demand. Demand for skills related to business, engineering and information technology decreased by 6, 4 and 4 percentage points, respectively, over the past decade in Canada (Figure 3.2). The most frequently demanded business skills relate to various types of staff and project management and the skill family is roughly analogous to the ONET+ grouping resource management. Similarly, information technology is roughly analogous to digital skills in the ONET+ groupings.

The two skill taxonomies differ when examining the skill families that have increased the most among high-exposure occupations in Canada. For the Lightcast taxonomy, the skill families administration, human resources and marketing saw the largest increases in demand of about 4 percentage points each. Administration includes the skills scheduling, data entry and record keeping. Recall that using the ONET+ taxonomy, the largest increase in demand was for social, emotional and language skills. This discrepancy is largely due to the Lightcast taxonomy's lack of coverage for "soft skills" that do not fit neatly into industry classifications. For example, some of the most frequently demanded skills that are not classified in the Lightcast taxonomy are communication skills, teamwork/collaboration, English and detail-oriented. These skills are classified as communication, social skills, languages and emotional skills in the ONET+ taxonomy, respectively.

Figure 3.2. Demand for administrative skills has increased the most among high-exposure occupations

Share of vacancies demanding at least one skill from Lightcast skill cluster families in 2012-13 and 2021-22 in Canada, high-exposure occupations



Note: Share is defined as the share of vacancies in high exposure grouping demanding at least one of the skills from each Lightcast skill cluster family. AI exposure is defined by the occupation of each vacancy according Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average.
Source: OECD analysis of Lightcast data, and Felten, Raj and Seamans (2021[2]).

The remainder of this section explores these skill changes in more depth. The main skill groupings provide a nice starting point for understanding changing skill demands, but they lack the specificity to understand changing skill demands at a practical level. The analysis breaks out the changes for the social and emotional skill groupings that have seen the largest changes in demand by a selection of their sub-groupings that have also experienced large changes in demand. In addition, the analysis shows these changes by country.

3.3. Co-ordination and self-rigour are among the social and emotional skills that have increased in demand

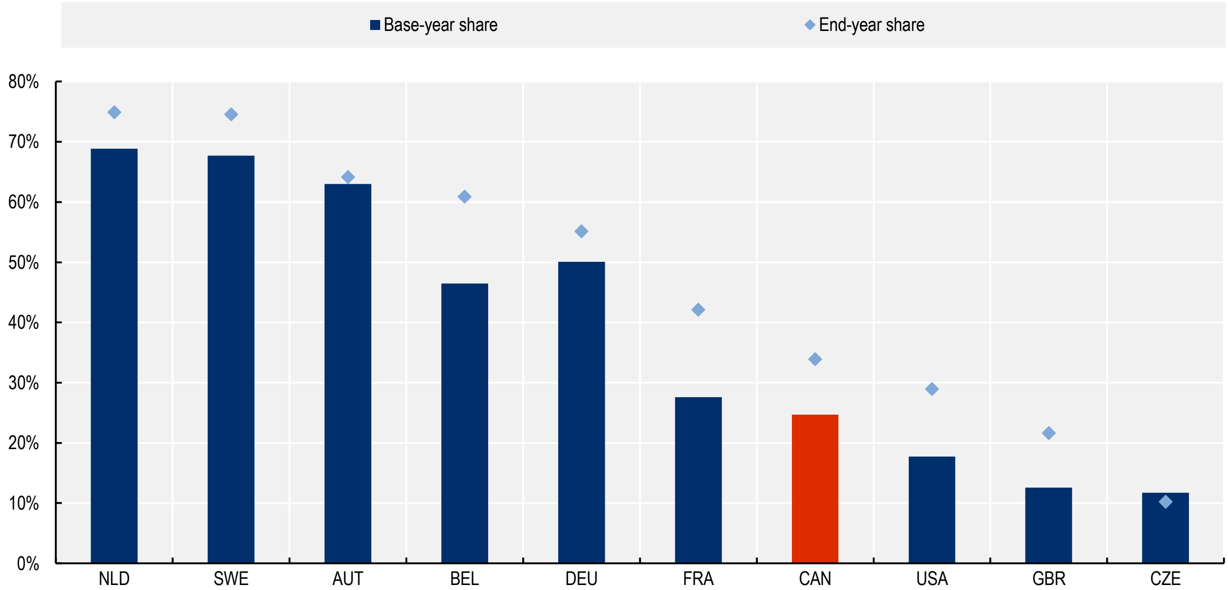
Co-ordination skills are the fastest growing subcomponent in the social skills category across countries and especially in Canada. The share of vacancies demanding co-ordination skills in Canada increased from 25% to 34% among high-exposure occupations over the past decade (Figure 3.3). The most demanded co-ordination skills are “work in teams”, “teamwork” and “collaboration”. On average across countries in the sample, the share of vacancies demanding co-ordination skills increased from 39% to 47% between the base and end years. Only Czechia experienced a modest decline in the demand for co-ordination skills. In contrast, every other country in the sample saw demand rise for these skills with the largest increases experienced in the United States, Canada and the United Kingdom.[18] In Canada,

[18] As noted previously, the crosswalk from the Lightcast taxonomy to ONET+ differ by country. Canada, the United Kingdom and the United States use the crosswalk of Lassébie et al. (2021[3]) and the remaining countries use an ESCO to ONET crosswalk adapted to ONET+. This sometimes results in Canada, the United Kingdom and the

co-ordination skills were the only sub-group of social skills to register an increase in demand over the past decade (Figure A A.1).

Figure 3.3. Demand for co-ordination skills has increased the most among rising demand for social skills

The share of high AI exposure vacancies demanding co-ordination skills in the base and end year by country



Note: Countries sorted by end-year values. Co-ordination skills are a subgroup of Social Skills in the merged ONET+ skill groupings from Lassébie et al. (2021[3]). Share is defined as the share of vacancies in the high exposure tercile demanding at least one of the skills from the co-ordination skill grouping in each country. The base year is pooled 2012-13 for the United States, Canada, the United Kingdom, and 2018-19 for France, Germany, Belgium, Sweden, the Netherlands, Austria and Czechia. The end years are pooled 2021 and 2022. AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]) for Canada, the United States and the United Kingdom. The remaining countries mapped using a crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

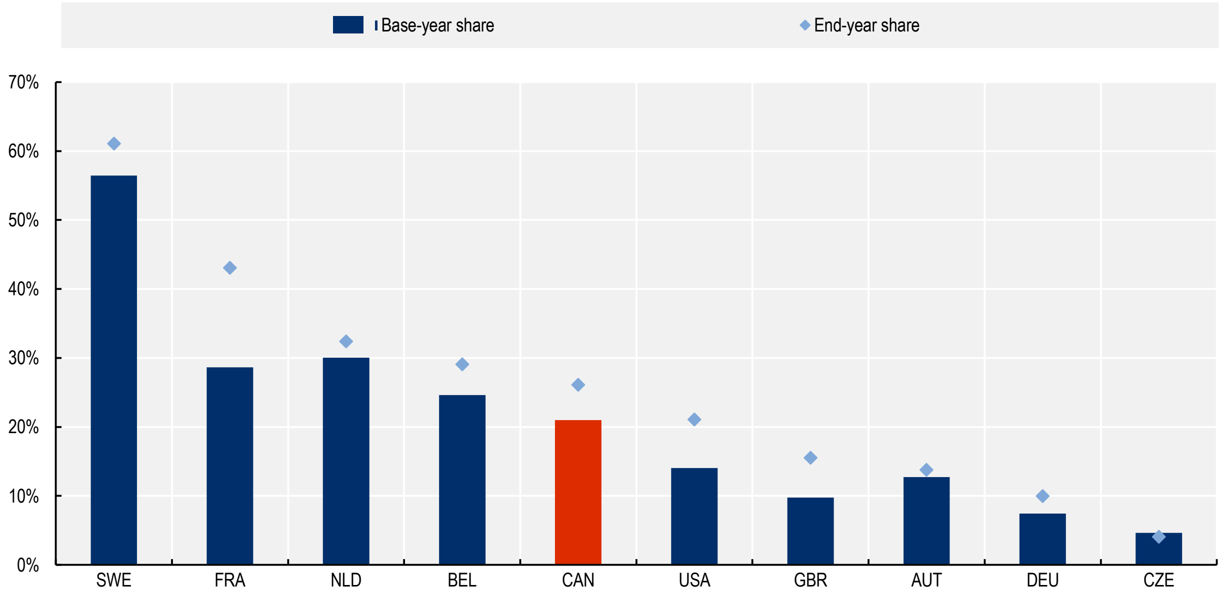
Among emotional skills, the sub-group defined as self-management or rigour has seen this largest increase in demand in Canada. These skills are a sub-group of the emotional (attitudes) skill grouping. Between 2012-13 and 2021-22 the share of vacancies demanding any skills in this sub-group increased from 21% to 26% among high-exposure occupations (Figure 3.4). Skills such as detail-oriented and self-starter are the most frequently demanded skills in this sub-group. In addition to self-management or rigour, the sub-grouping motivation and commitment also saw increased demand (Figure A A.2).

Compared to other countries in the sample, the increase in demand for self-management skills in Canada is roughly average. The share of high-exposure vacancies demanding these skills increased from 21% to 26% (coincidentally, the same as in Canada) between the base and end years on average across countries in the sample. The largest percentage point increases were found in France and the United States. Czechia was the only country that experienced a decline in vacancies demanding self-management skills.

United States having systematically lower levels of skill demand for some sub-groupings. The changes within countries over time, however, are often similar, and the regression analysis in section 4 is done by country ensuring that these cross-country differences do not matter for the regression analysis.

Figure 3.4. Demand for self-management and rigour has increased the most among rising demand for emotional skills

The share of high AI exposure vacancies demanding self-management/rigour skills in the base and end year by country



Note: Countries sorted by end-year values. Self-management/rigour skills are a subgroup of Attitudes (emotional skills) in the merged ONET+ skill groupings from Lassébie et al. (2021[3]). Share is defined as the share of vacancies in the high exposure tercile demanding at least one of the skills from the self-management/rigour skill grouping in each country. The base year is pooled 2012-13 for the United States, Canada, the United Kingdom, and 2018-19 for France, Germany, Belgium, Sweden, the Netherlands, Austria and Czechia. The end years are pooled 2021 and 2022. AI exposure is defined by the occupation of a vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]) for Canada, the United Kingdom and the United States. The remaining countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

4 Changing skill demands due to establishment-level AI exposure

This section analyses changing skill demand from AI exposure at the establishment level. AI adoption is currently low, and the available evidence suggests that, at least outside of specific experiments or case studies, it has not yet had large effects on employment, productivity or wages (Green, 2023[23]; Green, Salvi del Pero and Verhagen, 2023[30]). It seems unlikely, therefore, that the broad changes in skill demand documented in the previous section are exclusively, or even mostly, due to AI penetrating the workplace. For example, the previous section found that skills related to healthcare or medicine have seen increasing demand among high-skill occupations but, upon closer inspection, this is almost entirely due to increased demand for administering vaccines due to the COVID-19 pandemic. This section examines changing skill demand with a panel of establishments and employs an empirical design that can more precisely isolate the effects of AI on skill demand from other confounding factors.

The first step to moving from an analysis of the cross-section of vacancies to aggregating them to the establishment level is defining an establishment. As explained earlier (Section 2), the Lightcast data does not contain explicit establishment identifiers. This report follows Acemoglu et al. (2022[14]) and defines an establishment in Lightcast as the combination of an employer name and local labour market geography (TL2 regions; provinces in Canada). Demand for skills is fundamentally about demand from establishments, and moving to the establishment-level allows the analysis to capture potential complementarities in production.

4.1. Comparing similar establishments who differ only in their exposure to AI

The empirical design uses an establishment's underlying AI exposure in the base year as an instrument for changes in skill demand over time.[19] The underlying AI exposure is computed by taking a weighted average of occupational AI exposure in an establishment in the base year with the weights determined by the same establishment's occupational share of posted vacancies. The empirical design leverages the fact that skill demand is measured at the establishment level, but AI exposure is computed at the level of occupation. This unlocks a "shift-share" empirical design, which assumes that the base-year AI exposure is uncorrelated with contemporaneous advances in AI's capabilities (Borusyak, Hull and Jaravel, 2021[6]).[20] Establishments choose their optimal mix of occupations (skills) to maximise current and expected future

[19] Ideally, this would be an instrument for actual establishment-level AI adoption, but this is unobserved in Lightcast data. The empirical set-up proceeds as simply a "first-stage". All results follow from this set-up without loss of generality.

[20] Note that unlike Goldsmith-Pinkham, Sorkin and Swift (2020[37]) who require vacancy shares to be exogenous, consistency in Borusyak, Hull and Jaravel (2021[6]) requires the exogeneity of the shocks while allowing the shares to be potentially correlated with unobserved establishment characteristics, and that the exposure measure incorporates many sufficiently independent shocks.

profits (or equivalently to minimise costs).[21] The assumption is that, in the base year, establishments' chosen occupational mix is made independently of concomitant advances in AI technologies that are being developed in other firms or university research laboratories. This is a reasonable assumption as the average large retailer is unlikely to be kept abreast of working papers in AI research labs, for example. Moreover, to the extent establishments are knowledgeable of recent progress in AI, it is often many years before such advances can be made into commercially available applications if they ever are at all.

This research design has two practical implications for the sample and the measurement of AI exposure. First, the empirical design limits the analysis to establishments that were operating in the base year. If vacancies cannot be assigned to an establishment in the base year, either because their establishment did not exist then, or the vacancy contained missing geographic identifiers or firm names, they are dropped from the analysis. One downside to this approach is that it will miss skill demand in new establishments that are created due to advances in AI. In addition, it is important to emphasise that an establishment need only to exist in the base year to be included in the sample. It can fail to appear in the end-year, which implies that it ceased to exist at some point in the intervening years, or it has zero observed labour demand in the end year, rendering all counts and shares zero.[22]

The second implication of the empirical design is that it necessitates an establishment-level AI exposure measure. For an establishment operating in the base year in a particular country, the AI exposure of that establishment, AI_e, is defined by the following equation:

$$AI_e = \sum_o s_{o,e} \, AI_o$$

The variable $s_{o,e}$ is the share of vacancies of occupation *o* demanded in establishment *e* in the base year. AI_o is the AI exposure of occupation *o*. The establishment-level AI exposure measure is simply a weighted average of AI exposure defined by the mix of occupations demanded in the establishment during the base year. The establishment-level AI exposure measures are standardised to be mean zero with unit variance which allows one to interpret the corresponding regression coefficients as the change for a one standard deviation increase in establishment-level AI exposure. One can roughly interpret a one standard deviation change in establishment-level AI exposure as the difference between a moderately exposed and a highly exposed establishment.

The main estimating equation is presented below and estimated separately for each country.

$$\Delta y_{e,s} = \beta AI_e + \boldsymbol{x}_{\boldsymbol{e}}'\boldsymbol{\gamma} + \epsilon_e$$

The dependent variable, $\Delta y_{e,s}$, captures the change in the outcome variable between the end year and the base year for an establishment. For measuring changes in skill demand, this is simply the difference in shares of vacancies demanding at least one skill from a given skill grouping, *s*, between the end and base years in an establishment, *e*.

The parameter of interest, β, is the effect of AI exposure on the difference in shares and $\boldsymbol{x}_{\boldsymbol{e}}'\boldsymbol{\gamma}$ is a vector of controls. The controls include indicator variables for TL2 region and industry,[23] as well as the

[21] With the Lightcast data, one only observes vacancies and not the employed occupation mix. This empirical design therefore requires the additional assumption that the distribution of an establishment's posted vacancies approximate its employed occupation distribution.

[22] The theoretical justification for keeping the sample as an unbalanced panel is that high AI exposure may not only weaken labour and skill demand, but it may do so with such intensity that the establishment shuts down. All results in this section are robust to running the analysis on a balanced panel, however.

[23] Industry is defined by the 2-digit industry code as specified in Lightcast for each country. For the United States and Canada this is NAICS, for the United Kingdom, SIC, and for the remaining countries ISIC. Because industry is included only as controls and the specifications are always estimated within each country separately, industry was not cross

establishment's vacancy-size decile as measured by vacancies in the base year. The error term is denoted by ϵ_e. All regressions are estimated using ordinary least squares weighted to the base year size of establishments. Standard errors are clustered at the firm (employer name) level. The specification identifies the effect of AI exposure on outcomes by comparing observationally similar establishments (conditional on labour market, industry and establishment size), but which differ only in their base year AI exposure, which by assumption is orthogonal to all other unobserved forces that may affect labour or skill demand.[24] Finally, given the limitations of the Lightcast taxonomy as well as the findings in the previous section that both the Lightcast and ONET+ taxonomies are capturing similar trends, the rest of this section will analyse results using the ONET+ taxonomy. However, the same results for Canada are also available using the Lightcast taxonomy and produce qualitatively similar results (Figure A A.3).

4.2. Establishments more exposed to AI are associated with increasing demand for language and social skills, as well as skills most often associated with production workers

In Canada, AI exposure is associated with increased demand for cognitive and language skills (Figure 4.1). A one standard deviation increase in establishment level AI exposure leads to an increase in demand for language skills by 6 percentage points, and for cognitive skills by 4 percentage points. Language skills in Canada include the requirement of English, French, or both languages in a vacancy listing. Digging further into cognitive skills, the most frequently demanded skills in this grouping are problem solving, research, creativity and analytical skills.

There is also evidence in Canada that AI exposure may be producing positive complementarities raising demand for skills most commonly found in occupations with little AI exposure. The skill groupings production and technology and physical skills each saw 3 percentage point increases in the share of vacancies demanding any of the skills in these two groupings for a one standard deviation increase in establishment level AI exposure. These skills can be summarised as typically indicative of blue-collar occupations and include maintenance, repair, forklift driving and more fundamental skills such as dexterity, heavy lifting and range of motion. These are the types of skills that are possibly complementary in production to AI. For example, if a logistics warehouse can use AI to reduce the costs of routing shipments, they may be able to lower their costs and see increased demand – possibly necessitating greater demand for forklift drivers in the warehouse.

Social skills have also seen increased demand due to establishment-level AI exposure. A one standard deviation increase in establishment-level AI exposure results in a 2-percentage point increase in the share of vacancies requiring any social skills. Recall from the previous section that the grouping social skills was one of the skill groupings where demand increased the most among high-exposure occupations. This

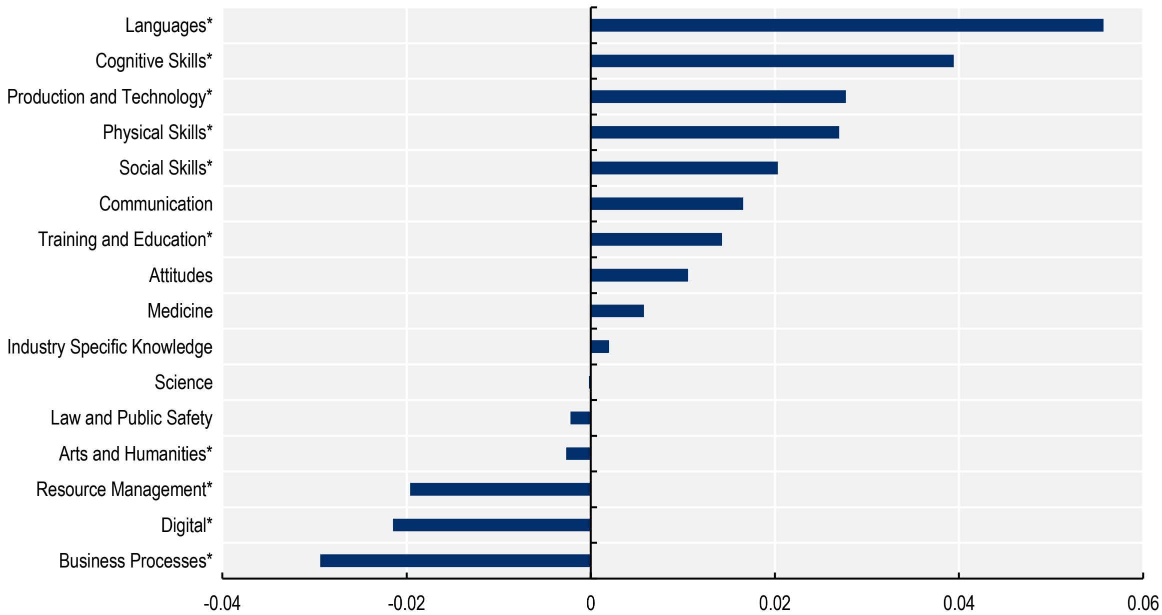
walked to a common classification. In addition, industry was not always available for all vacancies. However, if a common employer name was found, industry was assigned as the modal industry across vacancies with the same employer's name.

[24] More precisely, the shocks (exposure measures) are orthogonal, not necessarily the vacancy shares. Although the shocks to AI's capabilities are likely exogenous, it is possible that they are correlated with unobserved characteristics. For example, establishments in the information and technology sectors, or larger establishments may be more likely to be exposed. The added controls can account for some of these correlations, but likely not all. To account for this, the report builds an *expected* AI exposure measure by randomising exposure across occupations in 3 000 simulations and taking the expected establishment-level AI exposure as the average over these simulations for each establishment. The observed AI exposure measure is then recentred by subtracting the expected AI exposure measure – see Borusyak, Hull and Jaravel (2024[38]). This recentred AI exposure measure has little bearing on the results, and the observed AI exposure measure is therefore used throughout.

establishment-level analysis provides more evidence that this increase in demand is not spurious or linked to other trends correlated with occupation-level AI exposure.

Figure 4.1. Languages, cognitive skills and skills associated with production workers have seen increasing demand in establishments more exposed to AI

Regression coefficients for the percentage point change in demand for skill groupings from establishment-level AI exposure in Canada, by ONET+ skill grouping



Note: Bars are regression coefficients (β) of establishment-level AI exposure on changes in share of vacancies demanding at least one skill from a grouping. They are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base (2012-13) and end years (2021-22) for a one standard deviation increase in establishment-level AI exposure. Stars indicate the skill groupings where the regression coefficient is significant at the 95% confidence level. All regressions run separately for each skill grouping and include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[2]) weighted by the establishment's base year occupation shares. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

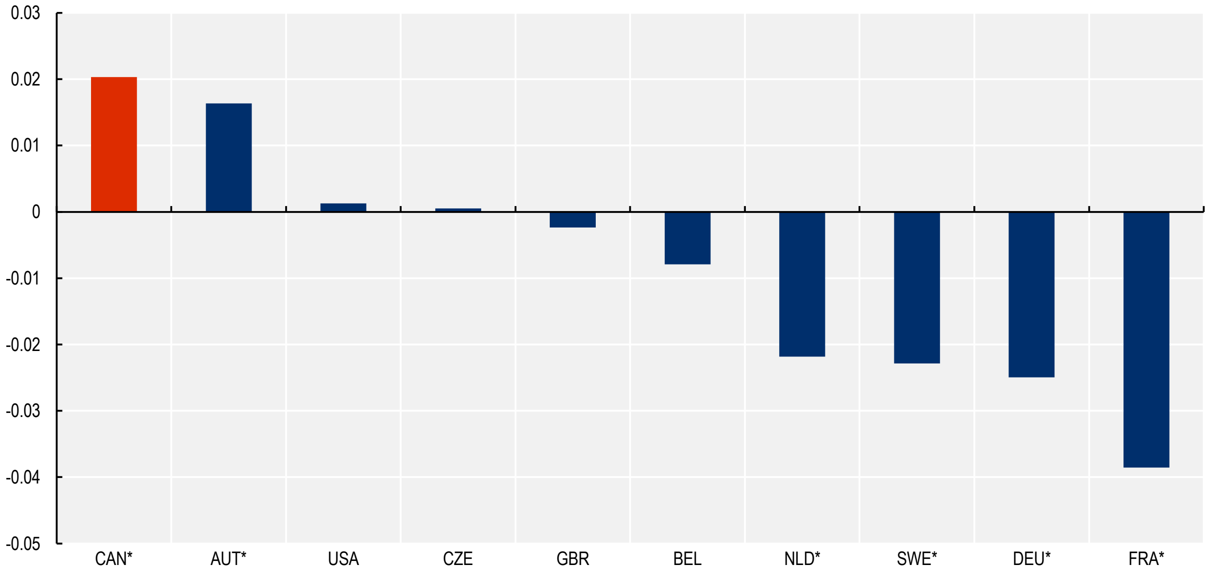
The skill groupings that experienced decreased demand are resource management, digital and business process skills. For each of these skill groupings, a one standard deviation increase in AI exposure results in a drop in the share of vacancies demanding at least one skill of the grouping by between 2 to 3 percentage points. Business process skills include sales, customer service, as well as administrative and record keeping tasks. Digital skills include basic computer programming, but the most frequently demanded skills are competencies with Microsoft Office applications. Resource management includes tasks and skills related to project management, budgeting, accounting and human resource management. These skills, competencies and tasks are often found in white-collar, office support work including finance and HR departments, and mid-level administrative tasks that require basic computer use. The rest of this section compares the results for Canada to other OECD countries for a selection of skill groupings.

4.3. When comparing Canada to other OECD countries, the increase in demand for social skills is particularly strong

The increasing demand for social skills among high-exposure occupations in Canada is confirmed by examining the cross-country establishment-level results. On average across countries in the sample, demand for social skills declined by less than 1 percentage point for a one standard deviation increase in AI exposure (Figure 4.2). In addition to Canada, Austria, Czechia and the United States also saw increasing demand for AI skills. Social skills were one of the skill groupings that experienced the largest increase in demand among high-exposure occupations (Section 3). The results of this section further reinforce the increasing importance of social skills with AI exposure.

Figure 4.2. Canada has the strongest positive association between higher AI exposure and increasing demand for social skills

Regression coefficients of the effect of AI exposure on the share of establishment vacancies demanding social skills

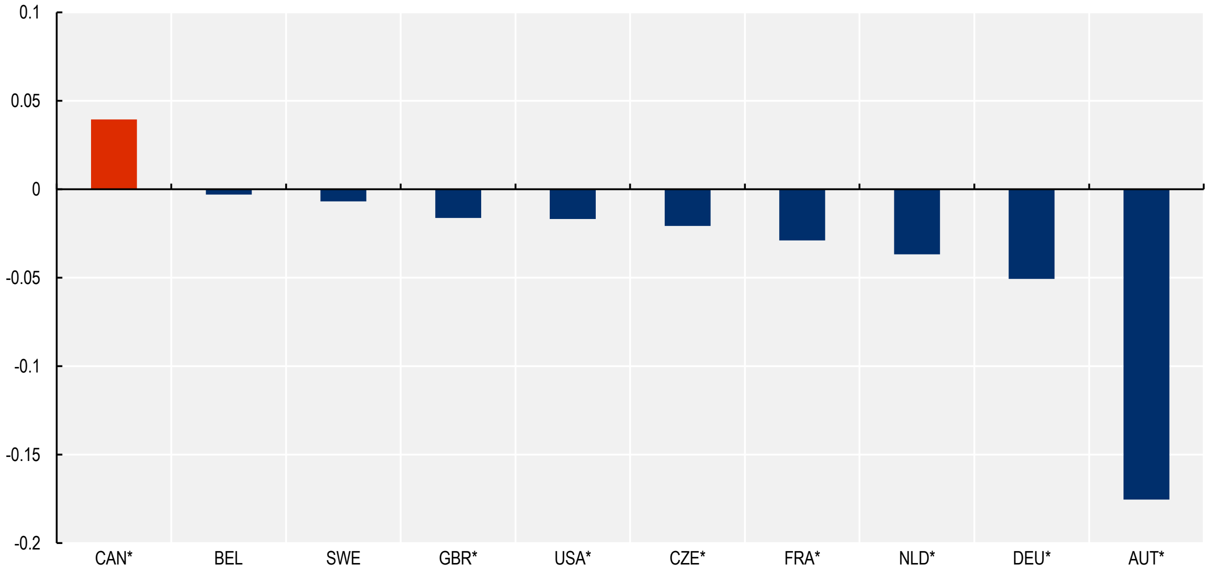


Note: Bars are the regression coefficient of establishment AI exposure (β) on the change in the share of vacancies demanding at least one skill from the social skills grouping, by country. They are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base and end years for a one standard deviation increase in establishment-level AI exposure. Stars indicate countries where regression coefficients are significant at the 95% confidence level. All regressions include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Base years are 2012-13 for Canada, the United Kingdom and the United States, and 2018-19 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-22. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[2]) weighted by the establishment's base year occupation shares. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]) for the United States, Canada and the United Kingdom. The remaining countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

In contrast, Canada is the only country in the sample where AI exposure is associated with increasing demand for cognitive skills at the establishment level. On average across countries in the sample, demand for cognitive skills declined by a little over 3 percentage points for a one standard deviation increase in AI exposure (Figure 4.3). Except for Canada and Austria, the estimates are relatively similar for all countries in the sample. Austria experienced the largest decline in demand and the magnitude of the decline may be an outlier. The results provide some additional context for Canada that the increase in demand for cognitive skills should be viewed with caution.[25]

Figure 4.3. Canada is the only country to have higher demand for cognitive skills associated with higher AI exposure

Regression coefficients of the effect of AI exposure on the share of establishment vacancies demanding cognitive skills



Note: Bars are the regression coefficient of establishment AI exposure (β) on the change in the share of vacancies demanding at least one skill from the cognitive skills grouping, by country. They are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base and end years for a one standard deviation increase in establishment-level AI exposure. Stars indicate countries where regression coefficients are significant at the 95% confidence level. All regressions include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Base years are 2012-13 for Canada, the United Kingdom and the United States, and 2018-19 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-22. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[2]) weighted by the establishment's base year occupation shares. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]) for the United States, Canada and the United Kingdom. The remaining countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

4.4. Increasing demand for production and physical skills is found across countries, and is especially strong in Canada

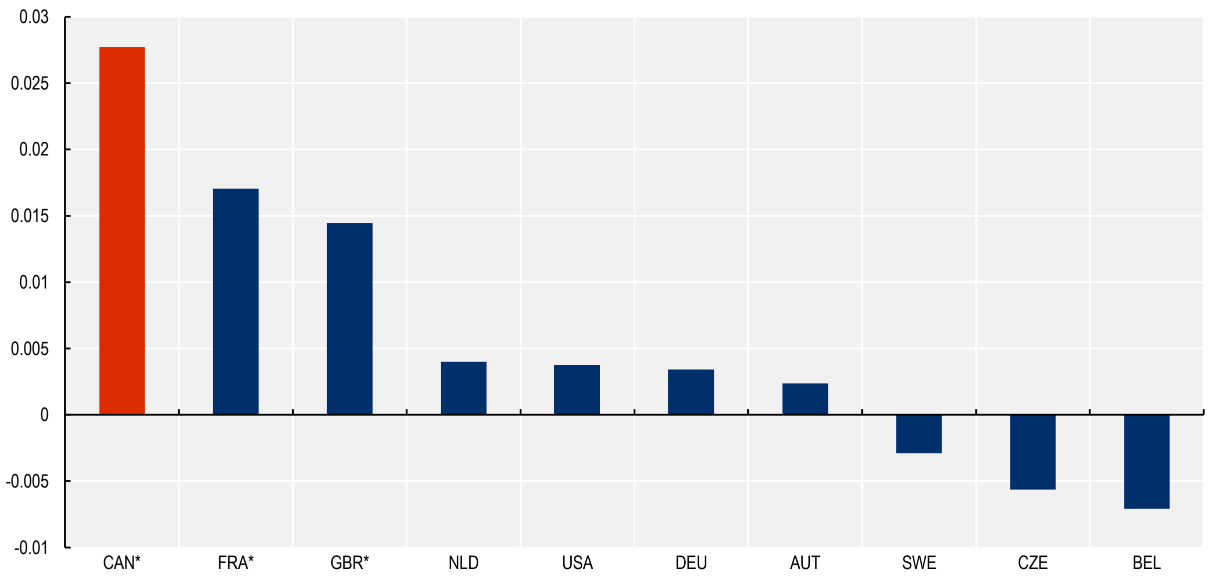
Establishment-level AI exposure is associated with increasing demand for production and physical skills in Canada, which is consistent with results from other countries. On average across countries in the sample, demand for production and technology skills increased by about half a percentage point for a one standard deviation increase in establishment-level AI exposure (Figure 4.4). In seven out of ten countries in the sample, higher establishment-level AI exposure is associated with increasing production and technology skills. The strongest positive association was found in Canada at over 2 percentage points. Recall that

[25] This may be partially due to changes in the sample composition between the occupation and establishment samples. For example, the share of vacancies demanding cognitive skills in the occupation sample decreased by 11 percentage points (Table A A.1), but it decreased by 5 percentage points in the establishment sample (Table A A.2).

production and technology skills include competencies and skills such as repair, cleaning and cooking. Similar results also obtain for physical skills (Table A A.3) in which there is also a strong positive association in Canada. Physical skills include manual dexterity and heavy lifting. These are skills often associated with lower-skill production jobs, and this suggests that AI exposure may be having a strong complementary effect on demand for these skills, with the effect particularly pronounced in Canada.

Figure 4.4. Greater demand for production and technology skills signals potential complementarities with AI

Regression coefficients of the effect of AI exposure on the share of establishment vacancies demanding production and technology skills



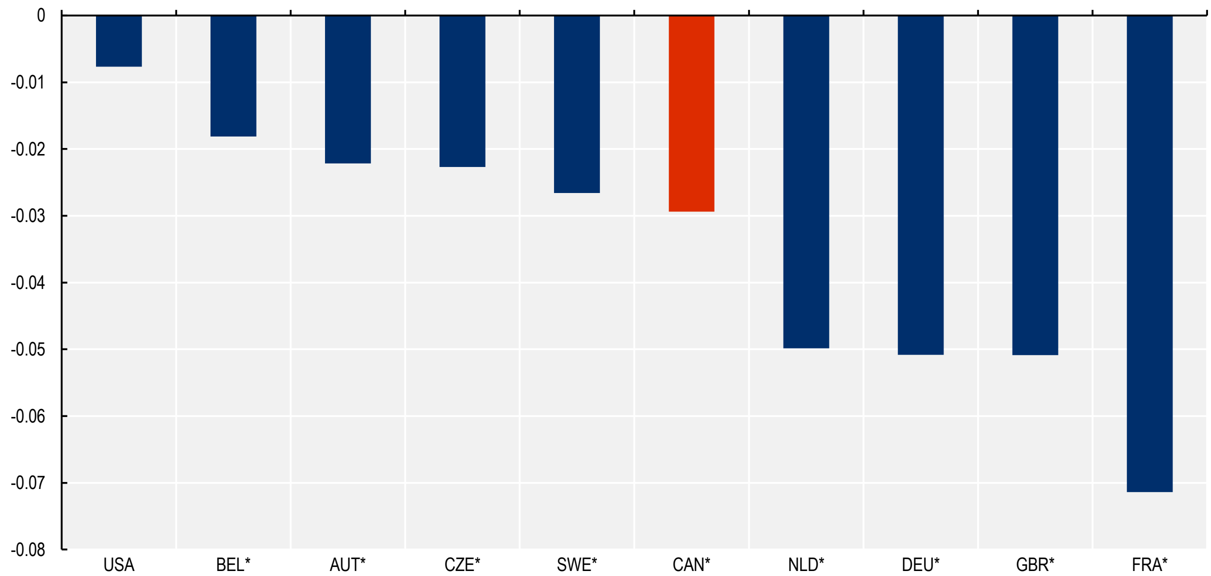
Note: Bars are the regression coefficient of establishment AI exposure (β) on the change in the share of vacancies demanding at least one skill from the production and technology grouping, by country. They are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base and end years for a one standard deviation increase in establishment-level AI exposure. Stars indicate countries where regression coefficients are significant at the 95% confidence level. All regressions include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Base years are 2012-13 for Canada, the United Kingdom and the United States, and 2018-19 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-22. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[2]) weighted by the establishment's base year occupation shares. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]) for the United States, Canada and the United Kingdom. Th remaining countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

4.5. The decline in demand for business, clerical and management skills is consistent across countries

Business process skills have seen a reduction in demand in establishments more exposed to AI. On average across countries in the sample, demand for business process skills declined by 3.5 percentage points for a one standard deviation increase in AI exposure (Figure 4.5). For Canada, the decline was slightly less than 3 percentage points. All countries in the sample saw a decline in business process skills, and in all but the United States are the estimates statistically significant from zero. France saw the largest reduction in demand. Business Process skills include clerical and administrative tasks along with sales and customer service. The magnitudes of the decline in skill demand for the other skill groupings that saw establishment-level drops in demand in Canada – resource management and digital skills – are relatively uniform across countries (Table A A.3). These results provide additional evidence that drops in demand for these skills are not unique to Canada.

Figure 4.5. As with every other country, higher establishment-level AI exposure is associated with declining demand for administrative and clerical skills in Canada

Regression coefficients of the effect of AI exposure on the share of establishment vacancies demanding business process skills



Note: Bars are the regression coefficient of establishment AI exposure (β) on the change in the share of vacancies demanding at least one skill from the business process skill grouping, by country. They are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base and end years for a one standard deviation increase in establishment-level AI exposure. Stars indicate countries where regression coefficients are significant at the 95% confidence level. All regressions include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Base years are 2012-13 for Canada, the United Kingdom and the United States, and 2018-19 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-22. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[2]) weighted by the establishment's base year occupation shares. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]) for the United States, Canada and the United Kingdom. The remaining countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

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Annex A. Additional tables and figures

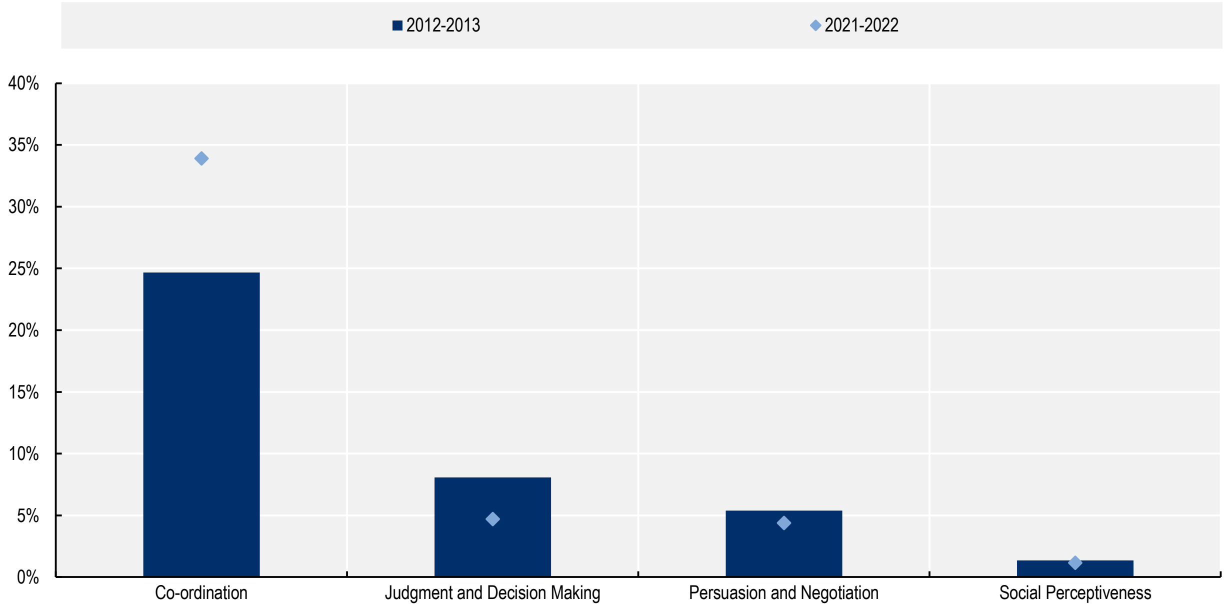
Table A A.1. Share of vacancies demanding at least one skill from each major grouping in occupation sample in Canada, 2012-13 (base) and 2021-22 (end)

	Overall			High-exposure			Low-exposure		
Skill	Base	End	Change	Base	End	Change	Base	End	Change
Arts and Humanities	2.9%	3.1%	0.1%	3.9%	4.4%	0.4%	1.1%	1.5%	0.4%
Attitudes	25.4%	29.5%	4.1%	27.1%	32.6%	5.4%	23.7%	26.6%	3.0%
Business Processes	55.2%	50.5%	-4.6%	58.1%	59.4%	1.3%	22.6%	20.6%	-2.0%
Cognitive Skills	42.6%	31.2%	-11.4%	50.1%	46.4%	-3.8%	32.1%	12.4%	-19.7%
Communication	64.9%	51.7%	-13.1%	71.1%	64.4%	-6.7%	51.5%	30.1%	-21.5%
Digital	52.3%	40.2%	-12.2%	67.9%	63.6%	-4.3%	22.3%	12.0%	-10.3%
Industry Specific Knowledge	15.1%	11.8%	-3.4%	12.5%	10.6%	-1.9%	6.2%	5.0%	-1.2%
Languages	24.1%	26.0%	2.0%	20.3%	24.6%	4.4%	38.9%	29.1%	-9.8%
Law and Public Safety	9.5%	8.2%	-1.3%	10.6%	11.2%	0.6%	7.4%	5.8%	-1.6%
Medicine	18.8%	26.4%	7.7%	14.8%	23.8%	8.9%	15.5%	20.8%	5.3%
Physical Skills	10.2%	14.3%	4.0%	3.0%	3.7%	0.7%	32.3%	33.0%	0.7%
Production and Technology	52.9%	53.8%	0.8%	46.7%	42.6%	-4.1%	79.4%	80.5%	1.1%
Resource Management	73.0%	66.1%	-6.9%	84.0%	80.5%	-3.5%	45.7%	39.5%	-6.2%
Science	10.2%	8.9%	-1.3%	12.2%	11.5%	-0.7%	6.2%	5.9%	-0.3%
Social Skills	31.8%	31.9%	0.1%	34.4%	38.9%	4.5%	24.8%	22.7%	-2.1%
Training and Education	11.2%	7.3%	-3.9%	11.7%	9.4%	-2.3%	9.0%	2.6%	-6.5%

Note: Occupation sample includes all vacancies including job boards. Base and end denote the share of vacancies demanding at least one skill from a grouping by base and end years, respectively. Base years are 2012-13. The end years are 2021-22. Change is computed as the simple percentage point difference of the base year subtracted from the end year. AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Low AI exposure occupations have an exposure measure at most one standard deviation less than the average. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

Figure A A.1. Demand for co-ordination skills has increased the most among rising demand for social skills

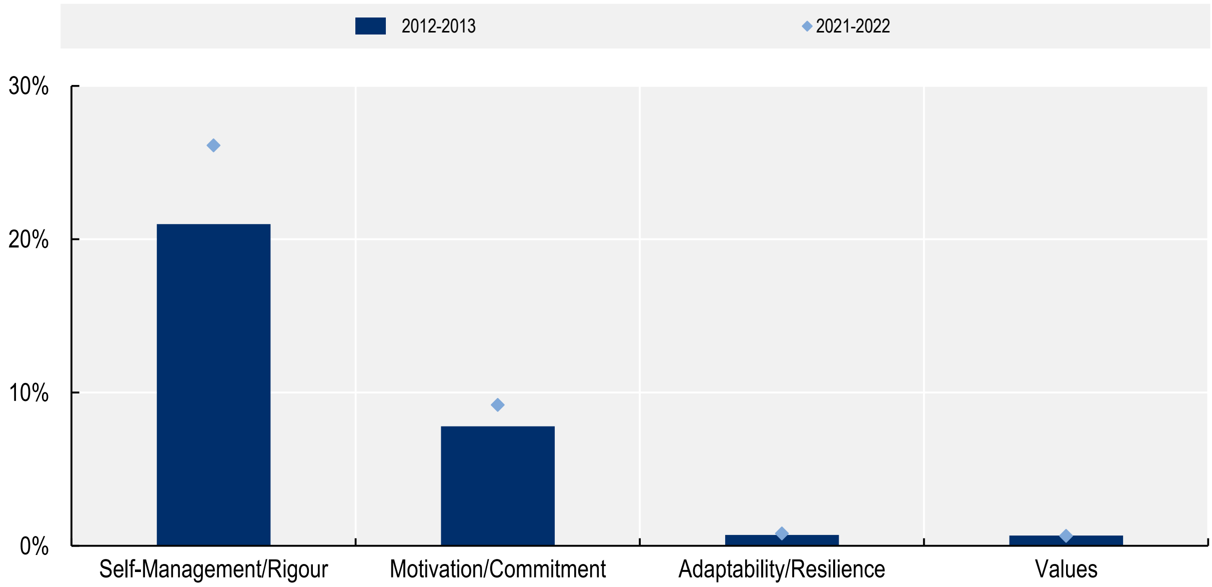
The share of high AI exposure vacancies demanding subsets of social skills in Canada over time



Note: Sub-groups sorted by shares in 2021-22. Share is defined as the share of vacancies in the high exposure tercile demanding at least one of the skills from the subgroups of social skills. AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Social skills groupings are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

Figure A A.2. Demand for self-management and motivation has increased the most among rising demand for emotional skills

The share of high AI exposure vacancies demanding subsets of emotional skills in Canada over time



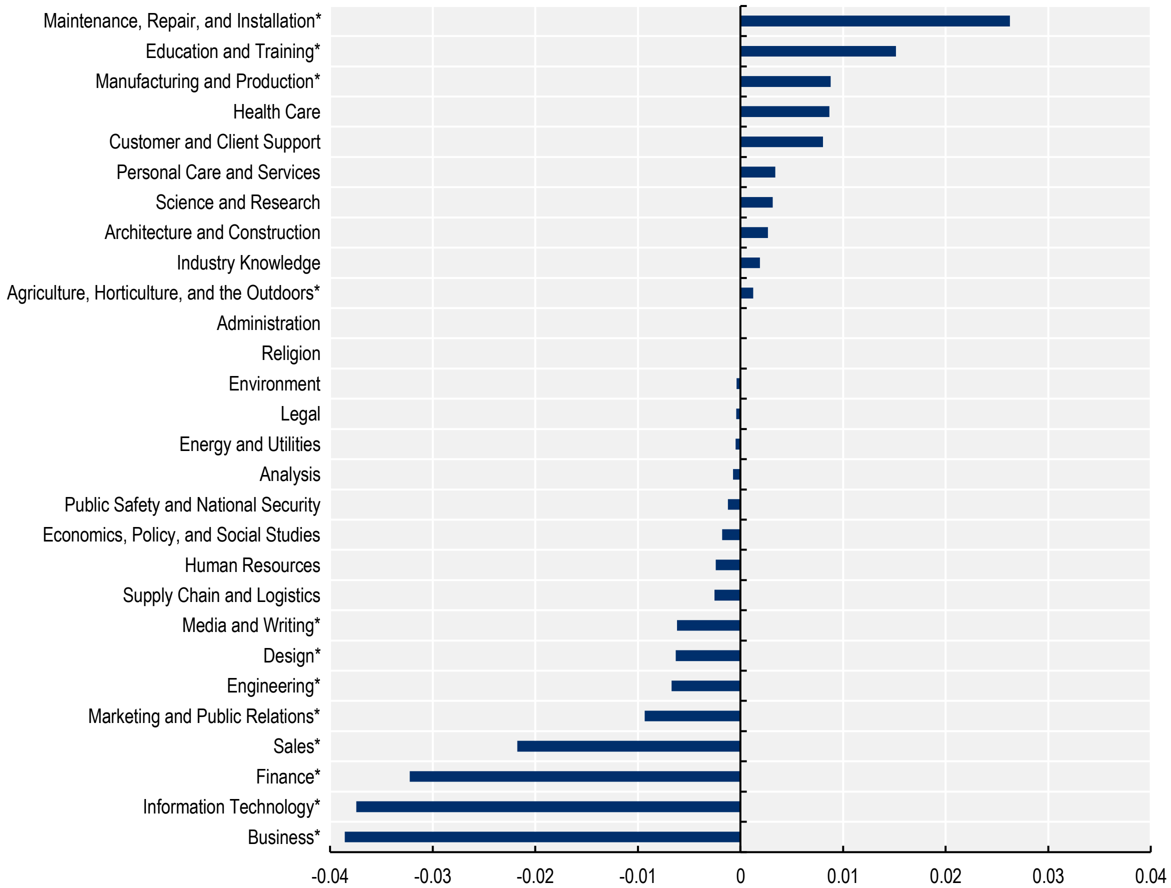
Note: Sub-groups sorted by shares in 2021-22. Share is defined as the share of vacancies in the high exposure tercile demanding at least one of the skills from the subgroups of Attitudes (emotional skills). AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Emotional skills are synonymous with the Attitudes groupings as defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

Table A A.2. Share of vacancies demanding at least one skill from each major grouping in establishment sample in Canada, 2012-13 (base) and 2021-22 (end)

	Overall			High-exposure			Low-exposure		
Skill	Base	End	Change	Base	End	Change	Base	End	Change
Arts and Humanities	2.8%	3.0%	0.2%	3.9%	4.2%	0.4%	0.9%	1.3%	0.5%
Attitudes	24.2%	25.3%	1.1%	26.2%	28.8%	2.7%	24.3%	23.7%	-0.7%
Business Processes	56.3%	51.7%	-4.6%	59.0%	56.3%	-2.6%	30.0%	28.5%	-1.4%
Cognitive Skills	41.8%	36.5%	-5.3%	50.8%	51.3%	0.5%	28.5%	16.3%	-12.2%
Communication	64.0%	52.5%	-11.5%	71.4%	64.4%	-7.0%	48.8%	31.1%	-17.7%
Digital	51.2%	42.8%	-8.4%	67.2%	63.8%	-3.4%	24.8%	15.5%	-9.3%
Industry Specific Knowledge	16.1%	13.1%	-2.9%	13.0%	12.0%	-1.0%	11.6%	7.3%	-4.4%
Languages	20.6%	19.5%	-1.1%	18.9%	20.6%	1.7%	29.3%	19.2%	-10.1%
Law and Public Safety	9.7%	9.3%	-0.5%	10.9%	11.8%	0.9%	7.1%	7.0%	-0.1%
Medicine	18.7%	26.6%	7.8%	14.8%	24.5%	9.6%	15.0%	21.1%	6.1%
Physical Skills	10.1%	12.4%	2.3%	2.9%	3.5%	0.6%	31.3%	31.3%	0.0%
Production and Technology	51.1%	48.8%	-2.3%	47.4%	45.2%	-2.2%	72.3%	67.3%	-5.0%
Resource Management	72.9%	67.6%	-5.3%	85.0%	81.1%	-3.9%	45.1%	42.8%	-2.2%
Science	10.2%	10.0%	-0.3%	12.6%	13.2%	0.6%	5.4%	5.6%	0.2%
Social Skills	31.4%	33.2%	1.7%	35.0%	42.4%	7.4%	22.4%	19.2%	-3.2%
Training and Education	9.9%	8.2%	-1.7%	10.4%	9.5%	-0.8%	7.1%	2.9%	-4.2%

Note: Establishment sample includes all vacancies with valid employer name and TL2 region and excludes job boards. Base and end denote the share of vacancies demanding at least one skill from a grouping by base and end years, respectively. Base years are 2012-13 and end years are 2021-22. Change is computed as the simple percentage point difference of the base year subtracted from the end year. AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[2]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. Low AI exposure occupations have an exposure measure at most one standard deviation less than the average. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]).
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

Figure A A.3. Regression coefficients for the percentage point change in demand for skill groupings from establishment-level AI exposure in Canada, by Lightcast skill grouping



Note: Bars are regression coefficients (β) of establishment-level AI exposure on changes in share of vacancies demanding at least one skill from a grouping. They are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base (2012-13) and end years (2021-22) for a one standard deviation increase in establishment-level AI exposure. Stars indicate the skill groupings where the regression coefficient is significant at the 95% confidence level. All regressions run separately for each skill grouping and include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[2]) weighted by the establishment's base year occupation shares. Skill groups are defined by Lightcast.
Source: OECD analysis of Lightcast data and Felten, Raj and Seamans (2021[2]).

Table A A.3. Regression coefficients for the percentage point change in demand for skill groupings and establishment-level AI exposure, by country and skill grouping

Skill	AUT	BEL	CAN	CZE	DEU	FRA	GBR	NLD	SWE	USA
Arts and Humanities	**-0.002**	0.000	**-0.003**	0.000	0.000	0.001	**-0.002**	**-0.002**	0.001	**-0.004**
Attitudes	**-0.031**	**-0.031**	0.011	0.004	**-0.023**	**-0.036**	**-0.010**	**-0.021**	**-0.019**	0.004
Business Processes	**-0.022**	**-0.018**	**-0.029**	**-0.023**	**-0.051**	**-0.071**	**-0.051**	**-0.050**	**-0.027**	-0.008
Cognitive Skills	**-0.175**	-0.003	**0.039**	**-0.021**	**-0.051**	**-0.029**	**-0.016**	**-0.037**	-0.007	**-0.017**
Communication	**-0.004**	0.006	0.017	**-0.013**	**-0.013**	**-0.007**	**-0.031**	**-0.014**	-0.003	**-0.017**
Digital	**-0.048**	**-0.023**	**-0.021**	-0.004	**-0.047**	**-0.029**	**-0.031**	**-0.051**	**-0.033**	**-0.034**
Industry Specific Knowledge	0.000	0.000	0.002	**0.000**	0.000	**0.000**	-0.001	0.000	**0.000**	0.005
Languages	**-0.026**	**-0.011**	**0.056**	**-0.012**	**-0.028**	**-0.025**	-0.002	**-0.026**	**0.015**	**0.013**
Law and Public Safety	-0.001	**0.006**	-0.002	**0.003**	0.000	**0.007**	-0.001	-0.001	0.001	**0.008**
Medicine	**0.016**	**-0.001**	0.006	**0.001**	**-0.015**	0.000	**-0.006**	**-0.003**	**0.016**	**0.011**
Physical Skills	**-0.009**	0.001	**0.027**	**-0.019**	-0.001	**0.007**	0.002	0.006	-0.001	0.013
Production and Technology	0.002	-0.007	**0.028**	-0.006	0.003	**0.017**	**0.014**	0.004	-0.003	0.004
Resource Management	**-0.034**	**-0.012**	**-0.020**	**-0.011**	**-0.057**	**-0.046**	**-0.045**	**-0.074**	**-0.020**	**-0.033**
Science	**0.004**	0.005	0.000	0.003	**0.004**	**0.004**	**-0.004**	**0.010**	0.002	-0.003
Social Skills	**0.016**	-0.008	**0.020**	0.000	**-0.025**	**-0.039**	-0.002	**-0.022**	**-0.023**	0.001
Training and Education	**-0.002**	**-0.001**	**0.014**	**0.008**	**-0.002**	0.001	**-0.007**	**-0.003**	0.000	-0.003
Number of Establishments	31 013	44 203	31 879	24 668	327 164	162 812	109 187	23 587	26 193	460 043

Note: Numbers in the table are regression coefficients on establishment-level AI exposure and they are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base and end years for a one standard deviation increase in establishment-level AI exposure. Figures in bold are significant at the 95% confidence level. All regressions run separately for each skill grouping and country and include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Base years are 2012-13 for Canada, the United Kingdom and the United States, and 2018-19 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-22. Establishment-level AI exposure is the average occupational AI-exposure in an establishment from Felten, Raj and Seamans (2021[2]) weighted by the establishment's base year occupation shares. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[3]) for the United States, Canada and the United Kingdom. The remaining countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[2]) and Lassébie et al. (2021[3]).

Annex B. O*NET+ combined ONET-ESCO classification

The O*NET+ taxonomy used in this report contains 17 501 skills as created by Lightcast grouped into 60 categories (Table A B.1). This is slightly more skills than reported in the working paper (17 331) from Lassébie et al. (2021[3]), which the authors attribute to a revision from updating the data through 2021. The working paper also reports 61 categories instead of the 60 in this report. The authors explain that this is due to dropping the category "Local Languages", which was small, and only denoted the use of the English language.

Despite these differences, the taxonomy used in this report is quite close to what is reported in the working paper. There are 292 skills per category in the taxonomy used in the report with the median category containing 107 skills. The working paper reports (over 61 categories) a mean of 289 and a median of 108. The distribution of skills per category is also quite close in the files compared to Figure 4 in the working paper (not reproduced here).

Table A B.1. The O*NET+ taxonomy

Broad Category	Category label
Arts and Humanities	Fine Arts
Arts and Humanities	History and Archaeology
Arts and Humanities	Philosophy and Theology
Attitudes	Adaptability/Resilience
Attitudes	Motivation/Commitment
Attitudes	Self-Management/Rigour
Attitudes	Values
Business Processes	Clerical
Business Processes	Customer And Personal Service
Business Processes	Sales and Marketing
Cognitive Skills	Learning
Cognitive Skills	Originality
Cognitive Skills	Quantitative Abilities
Cognitive Skills	Reasoning and Problem-Solving
Communication	Active Listening
Communication	Communications and Media
Communication	Reading Comprehension
Communication	Speaking
Communication	Writing
Digital	Computer Programming
Digital	Digital Content Creation
Digital	Digital Data Processing
Digital	ICT Safety, Networks and Servers
Digital	Office Tools and Collaboration Software
Digital	Web Development and Cloud Technologies
Industry Specific Knowledge	Industry Knowledge

Broad Category	Category label
Languages	Foreign Languages
Law and Public Safety	Law and government
Law and Public Safety	Public Safety and Security
Medicine	Medicine and Dentistry
Medicine	Psychology, Therapy, Counselling
Physical Skills	Auditory and Speech Abilities
Physical Skills	Physical Abilities
Physical Skills	Psychomotor Abilities
Physical Skills	Visual Abilities
Production and Technology	Building and Construction
Production and Technology	Design
Production and Technology	Engineering, Mechanics and Technology
Production and Technology	Equipment Selection
Production and Technology	Food Production
Production and Technology	Installation and Maintenance
Production and Technology	Production and Processing
Production and Technology	Quality Control Analysis
Production and Technology	Telecommunications
Production and Technology	Transportation
Resource Management	Administration and Management
Resource Management	Management of Financial Resources
Resource Management	Management of Material Resources
Resource Management	Management of Personnel Resources
Resource Management	Time Management
Science	Biology
Science	Chemistry
Science	Geography
Science	Physics
Science	Sociology and Anthropology
Social Skills	Coordination
Social Skills	Judgment and Decision Making
Social Skills	Persuasion and Negotiation
Social Skills	Social Perceptiveness
Training and Education	Training and Education

Note: Category denotes the major skill grouping and Category label are the sub-groupings associated with each category. Names and table are reproduced from Annex B (Table A B.1) in Lassébie et al. (2021[3]). The groupings used in this report are slightly different than what is presented in the associated working paper. It covers slightly more skills, which the authors attribute to updating the data through 2021. The working paper also reports 61 categories instead of the 60 in this table. The authors report that this is due to dropping the category “Local Languages”, which only captured a small number of skills, and only denoted the use of the English language. The working paper also lists the category “Work ethics” but this is not found in the underlying data. The category “Values” is the only category listed in the data, but it does not appear in the working paper. The description of categories in the working paper strongly suggests that these two are equivalent. The data used in this report keeps the label “Values” as found in the underlying data.
Source: Lassébie et al. (2021[3]).