OECD publishing

ARTIFICIAL INTELLIGENCE AND THE CHANGING DEMAND FOR SKILLS IN THE LABOUR MARKET

OECD ARTIFICIAL INTELLIGENCE PAPERS

April 2024 **No. 14**

OECD
BETTER POLICIES FOR BETTER LIVES

Artificial intelligence and the changing demand for skills in the labour market

Andrew Green

Most workers who will be exposed to artificial intelligence (AI) will not require specialised AI skills (e.g. machine learning, natural language processing, etc.) to work with AI. Even so, AI will change the tasks these workers do, and the skills they require. This report provides first estimates for the effect of artificial intelligence (AI) 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 and business skills. These include skills in general project management, finance, administration and clerical tasks. The results also show that there have been increases over time in the demand for these skills in occupations highly exposed to AI. For example, the share of vacancies in these occupations that demand at least one emotional, cognitive or digital skill has increased by 8 percentage points. However, using a panel of establishments (which induces plausibly exogenous variation in AI exposure), the report finds evidence that the demand for these skills is beginning to fall in establishments most exposed to AI.

Keywords: Artificial Intelligence, Skills, Labour Demand.

JEL Codes: J24, J23, J63.

Résumé

La plupart des salariés qui seront exposés à l'intelligence artificielle (IA) n'auront pas besoin de compétences spécialisées en IA (telles que l'apprentissage automatique, le traitement du langage naturel, etc.). Néanmoins, l'IA modifiera les tâches de ces salariés et les compétences qu'elles requièrent. Ce rapport fournit les premières estimations de l'effet de l'intelligence artificielle (IA) sur la demande de compétences dans les emplois qui ne nécessitent pas de compétences spécialisées en IA. Les résultats montrent que les compétences les plus demandées dans les professions fortement exposées à l'IA sont les compétences en gestion et en commerce. Il s'agit notamment de compétences en matière de gestion de projets, de finances, d'administration et de travail de bureau. Les résultats montrent également que la demande de ces compétences dans les professions fortement exposées à l'IA a fortement augmenté au fil du temps. Par exemple, la part des postes vacants dans ces professions qui exigent au moins une compétence émotionnelle, cognitive ou numérique a augmenté de 8 points de pourcentage. Toutefois, en utilisant un panel d'établissements (qui induit une variation exogène plausible de l'exposition à l'IA), le rapport constate que la demande de ces compétences commence à diminuer dans les établissements les plus exposés à l'IA.

Abstract

Die meisten Beschäftigten, die in ihrem Arbeitsalltag mit künstlicher Intelligenz (KI) konfrontiert sind, benötigen keine spezialisierten KI-Kompetenzen (z. B. im Bereich maschinelles Lernen oder maschinelle Sprachverarbeitung). Allerdings verändert KI die Aufgaben, die sie zu erledigen haben, und die Kompetenzanforderungen, denen sie gerecht werden müssen. Diese Studie liefert erste Schätzungen zum Effekt von KI auf den Kompetenzbedarf in Beschäftigungen, die keine spezialisierten KI-Kompetenzen erfordern. Sie zeigt, dass die am stärksten nachgefragten Kompetenzen in Berufen mit hohem KI-Potenzial Managementfähigkeiten und kaufmännische Kompetenzen sind. Dazu gehören Kompetenzen in den Bereichen Projektmanagement, Finanzen, Verwaltung und Sachbearbeitung. Die Ergebnisse zeigen auch, dass die Nachfrage nach diesen Kompetenzen in Berufen mit hohem KI-Potenzial im Zeitverlauf erheblich gestiegen ist. So hat beispielsweise der Anteil der Stellenausschreibungen für diese Berufe, in denen mindestens eine emotionale, kognitive oder digitale Kompetenz verlangt wird, um 8 Prozentpunkte zugenommen. Bei Verwendung eines Betriebspanels (was die Berücksichtigung plausibel exogener Variationen des KI-Potenzials ermöglicht) finden sich allerdings Belege dafür, dass die Nachfrage nach diesen Kompetenzen in Betrieben mit besonders hohem KI-Potenzial zu sinken beginnt.

Acknowledgements

This publication contributes to the OECD's Artificial Intelligence in Work, Innovation, Productivity and Skills (AI-WIPS) programme, which provides policymakers with new evidence and analysis to keep abreast of the fast-evolving changes in AI capabilities and diffusion and their implications for the world of work. The programme aims to help ensure that adoption of AI in the world of work is effective, beneficial to all, people-centred and accepted by the population at large. AI-WIPS is supported by the German Federal Ministry of Labour and Social Affairs (BMAS) and will complement the work of the German AI Observatory in the Ministry's Policy Lab Digital, Work & Society. For more information, visit https://oecd.ai/work-innovation-productivity-skills and https://denkfabrik-bmas.de/.

The report was carried out under the supervision of Stijn Broecke (Team Lead for the Future of Work) and Mark Keese (Head of the Skills and Employability Division). The report also benefitted from helpful comments from colleagues from the Directorate for Employment, Labour and Social Affairs specifically Stijn Broecke, Anne Saint-Martin, Anna Milanez, Marguerita Lane, Alexandre Georgieff and Fabio Manca, as well as Ricardo Espinoza, and colleagues from the Directorate for Science, Technology and Innovation and the Directorate for Education and Skills. Many thanks are also due to Andrea Bassanini for providing an employment-weighted ISCO to SOC crosswalk, Francesca Borgonovi for furnishing an ESCO to ONET crosswalk, and Satoshi Araki for providing support with the employer cleaning programs.

Federal Ministry
of Labour and Social Affairs

Table of contents

FIGURES

TABLES

Executive summary

Artificial intelligence (AI) adoption by firms is changing how workers perform their jobs and how work is organised. This reorganisation of tasks will result in changing demand for skills. For example, firms will demand more workers with AI skills, i.e. workers with the knowledge and competencies to actively develop and maintain AI models. However, despite the recent popular interest and policy research on workers with AI skills, these workers represent only a tiny share of overall employment.

Most workers who will work with AI are unlikely to need any AI skills or even knowledge of how AI systems function. Comparatively little research has looked at how AI will change the skills demanded from these workers. This report provides representative estimates of the changing skill demand for occupations exposed to AI, but who do not possess or need AI skills, using online job vacancies across 10 OECD countries over the past decade.

The most demanded skills in occupations with high AI exposure are management, business processes and social skills. Management and business processes contain skills such as project management, budgeting and accounting, administration, clerical tasks and customer support. On average across the 10 OECD countries in the sample, 72% of vacancies in high AI exposure occupations demand at least one management skill and 67% demand at least one business processes skill. Social, emotional and digital skills are also highly demanded with over 50% of vacancies in high-exposure occupations demanding at least one skill from these skill groupings. High-exposure occupations comprise a third of all vacancies in OECD countries in the sample.

The share of vacancies demanding at least one skill from each of these groupings has increased by over five percentage points among high-exposure occupations over the period analysed. Among these high-exposure occupations, the share of vacancies demanding at least one cognitive, emotional or digital skill increased by eight percentage points on average across countries in the sample. For social skills, demand increased by over 6 percentage points, while it increased by over 5 percentage points for business process and management skills.

At the same time, the report finds evidence that the demand for these skills may be falling in establishments more exposed to AI. Using a sample of establishments that better identifies the causal effect of AI exposure, there is evidence of decreasing demand for cognitive, digital, as well as business process and resource management skills in establishments more exposed to AI. To a lesser extent, emotional and communication skills also experienced decreased demand. The magnitudes of these demand changes are small, and they should be viewed in the context of rising demand for these skills overall. However, should AI adoption increase, these results may foretell how skill demand due to AI will evolve.

The report also provides some evidence that AI adoption may increase the demand for some blue-collar skills, possibly through a productivity effect that results in higher demand and spills over to other workers at the establishment. For example, the report finds that higher establishment AI exposure is associated with increased establishment demand for skills related to production and technology, and physical skills.

Synthèse

L'adoption de l'intelligence artificielle (IA) par les entreprises modifie la façon dont les travailleurs effectuent leurs tâches et l'organisation du travail. Cette réorganisation des tâches entraînera une évolution de la demande de compétences. Par exemple, les entreprises demanderont davantage de travailleurs possédant des compétences en IA, c'est-à-dire des travailleurs ayant les connaissances et les compétences nécessaires pour développer et entretenir activement des modèles d'IA. Toutefois, malgré l'intérêt récent de la population et des recherches en politique pour les salariés ayant des compétences en IA, ceux-ci ne représentent qu'une part infime de l'emploi global.

La plupart des salariés qui travailleront avec l'IA n'auront probablement pas besoin de compétences en IA, ni même de connaissances sur le fonctionnement des systèmes d'IA. Relativement peu d'études se sont penchées sur la manière dont l'IA modifiera les compétences exigées de ces salariés. Ce rapport fournit des estimations représentatives de l'évolution de la demande de compétences pour les professions exposées à l'IA, mais qui ne présentent pas ou n'ont pas besoin de compétences en IA, en utilisant les offres d'emploi en ligne dans 10 pays de l'OCDE au cours de la dernière décennie.

Les compétences les plus demandées dans les professions fortement exposées à l'IA sont la gestion, les techniques commerciales et les compétences sociales. La gestion et les techniques commerciales comprennent des compétences telles que la gestion de projet, la budgétisation et la comptabilité, l'administration, le travail de bureau et l'assistance à la clientèle. En moyenne, dans les 10 pays de l'OCDE faisant partie de l'échantillon, 72 % des postes vacants dans les professions à forte exposition à l'IA exigent au moins une compétence en gestion et 67 % au moins une compétence en techniques commerciales. Les compétences sociales, émotionnelles et numériques sont également très demandées, plus de 50 % des postes vacants dans les professions à forte exposition exigeant au moins une compétence de ces groupes. Les professions à forte exposition représentent un tiers de toutes les offres d'emploi dans les pays de l'OCDE faisant partie de l'échantillon.

La part des postes vacants exigeant au moins une compétence de chacun de ces groupes a augmenté de plus de cinq points de pourcentage parmi les professions à forte exposition au cours de la période analysée. Parmi ces professions très exposées, la part des postes vacants exigeant au moins une compétence cognitive, émotionnelle ou numérique a augmenté de huit points de pourcentage en moyenne dans les pays de l'échantillon. Pour les compétences sociales, la demande a augmenté de plus de 6 points de pourcentage, tandis qu'elle a augmenté de plus de 5 points de pourcentage pour les compétences en matière de techniques commerciales et de gestion.

Dans le même temps, le rapport montre que la demande de ces compétences pourrait diminuer dans les établissements plus exposés à l'IA. En utilisant un échantillon d'établissements qui identifie mieux l'effet causal de l'exposition à l'IA, on constate une baisse de la demande de compétences cognitives et numériques, ainsi que de compétences en techniques commerciales et en gestion des ressources dans les établissements les plus exposés à l'IA. Dans une moindre mesure, les compétences émotionnelles et de communication ont également fait l'objet d'une baisse de la demande. L'ampleur de ces variations de la demande est faible, et il convient de les replacer dans le contexte d'une demande croissante pour ces compétences en général. Toutefois, si l'adoption de l'IA s'intensifie, ces résultats peuvent présager de l'évolution de la demande de compétences liée à l'IA.

Le rapport fournit également des éléments indiquant que l'adoption de l'IA peut accroître la demande de certaines compétences possédés par les ouvriers, éventuellement par le biais d'un effet de productivité qui se traduit par une demande accrue et se répercute sur d'autres travailleurs de l'entreprise. Par exemple, le rapport constate qu'une plus grande exposition des établissements à l'IA est associée à une demande accrue de compétences liées à la production et à la technologie, ainsi qu'à des compétences physiques.

Zusammenfassung

Wenn KI in Unternehmen eingeführt wird, hat dies Auswirkungen darauf, wie die Beschäftigten ihren Tätigkeiten nachgehen und wie ihre Arbeit organisiert wird. Durch diese Umorganisation ändert sich die Kompetenznachfrage. So wächst beispielsweise die Nachfrage der Unternehmen nach Arbeitskräften mit KI-Kompetenzen, d. h. Personen, die über die nötigen Kenntnisse und Fähigkeiten verfügen, um aktiv KI-Modelle zu entwickeln und zu pflegen. Trotz des jüngsten öffentlichen Interesses an KI und verschiedener politikorientierter Studien zu Beschäftigten mit KI-Kompetenzen ist deren Anteil an der Gesamtbeschäftigung jedoch weiterhin sehr gering.

Die meisten Beschäftigten, die mit KI arbeiten, werden vermutlich keine KI-Kompetenzen benötigen und wahrscheinlich auch nicht wissen müssen, wie KI-Systeme funktionieren. Bislang wurden nur vergleichsweise wenige Studien dazu angestellt, welchen Einfluss KI auf die Kompetenzen hat, die von diesen Beschäftigten verlangt werden. Der vorliegende Bericht enthält repräsentative Schätzungen zur Veränderung des Kompetenzbedarfs in Berufen mit KI-Potenzial, in denen die Beschäftigten aber nicht über KI-Kompetenzen verfügen bzw. keine KI-Kompetenzen benötigen. Ausgangsbasis dafür sind Online-Stellenausschreibungen aus den letzten zehn Jahren aus zehn OECD-Ländern.

In Berufen mit hohem KI-Potenzial am stärksten nachgefragt sind Managementkompetenzen, kaufmännische Kompetenzen und soziale Kompetenzen. Management- und kaufmännische Kompetenzen umfassen Projektmanagement, Finanzplanung und Buchhaltung, Verwaltung, Sachbearbeitung und Kundendienst. Im Durchschnitt der zehn in der Stichprobe enthaltenen OECD-Länder verlangen 72 % der Stellenausschreibungen für Berufe mit hohem KI-Potenzial mindestens eine Managementkompetenz und 67 % mindestens eine kaufmännische Kompetenz. Soziale, emotionale und digitale Kompetenzen werden ebenfalls stark nachgefragt. Über 50 % der Stellenausschreibungen für Berufe mit hohem KI-Potenzial verlangen mindestens eine Kompetenz dieser Art. Ein Drittel der in der Stichprobe insgesamt berücksichtigten Stellenausschreibungen betrifft Berufe mit hohem KI-Potenzial.

Im betrachteten Zeitraum ist der Anteil der Stellenausschreibungen für Berufe mit hohem KI-Potenzial, die mindestens eine Kompetenz aus den oben genannten Bereichen erfordern, um mehr als 5 Prozentpunkte gestiegen. Der Anteil derjenigen, die mindestens eine kognitive, emotionale oder digitale Kompetenz erfordern, ist im Durchschnitt der in der Stichprobe erfassten Länder um 8 Prozentpunkte gestiegen. Die Nachfrage nach sozialen Kompetenzen wuchs um über 6 Prozentpunkte und die nach kaufmännischen und Managementkompetenzen um über 5 Prozentpunkte.

Zugleich gibt es aber auch Anzeichen für einen möglichen Rückgang der Nachfrage nach diesen Kompetenzen in Unternehmen mit höherem KI-Potenzial. Ein Betriebspanel, das die Kausaleffekte des KI-Potenzials besser erkennen lässt, liefert Anhaltspunkte dafür, dass die Nachfrage nach kognitiven, digitalen, kaufmännischen und ressourcenmanagementbezogenen Kompetenzen in Unternehmen mit höherem KI-Potenzial abnimmt. Auch die Nachfrage nach emotionalen und kommunikationsbezogenen Kompetenzen scheint zurückzugehen, allerdings in geringerem Umfang. Diese Nachfrageveränderungen sind klein und sollten im Kontext einer insgesamt steigenden Nachfrage nach diesen Kompetenzen gesehen werden. Dennoch könnten diese Ergebnisse Rückschlüsse auf die weitere Entwicklung der Kompetenznachfrage im Fall einer stärkeren KI-Nutzung zulassen.

Die Studie liefert zudem Anhaltspunkte dafür, dass mit einer zunehmenden KI-Nutzung die Nachfrage nach bestimmten Kompetenzen aus dem Bereich der manuellen Berufe steigen könnte. Grund dafür ist möglicherweise ein Produktivitätseffekt, der die Nachfrage erhöht und auf andere Beschäftigte im Unternehmen ausstrahlt. So wird in der Studie beispielsweise festgestellt, dass ein höheres KI-Potenzial auf Betriebsebene mit einer höheren betrieblichen Nachfrage nach Kompetenzen aus dem Bereich Produktion und Technologie sowie körperlichen Fähigkeiten einhergeht.

1 Introduction

AI adoption is changing how workers perform their jobs and how work is organised. For example, an auto manufacturer can now implement an image processing tool for quality assurance purposes. The AI tool captures an image of a vehicle body and assesses whether its dimensions meet production standards. Before the introduction of the technology, workers inspected a random sample of vehicle bodies, taking measurements manually. Now, the technology alerts workers to potential non-conformities by displaying text on an output screen ("Attention! Possible deviation!"), and workers inspect and measure only these flagged instances (Milanez, 2023[1]).

This reorganisation of tasks due to AI will often result in changing demand for skills. The most obvious 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. However, workers with these skills are only a tiny share of overall employment or labour demand (Green and Lamby, 2023[2]). Despite the flurry of recent research on their employment prospects and wages, these workers do not represent a majority of workers in OECD labour markets who, like the autoworkers 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.

There is comparatively 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 the majority of workers is important for how skills policies, training agencies, 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 vacancies exposed to AI, but that do not possess or need AI skills. To measure changing skill demand, this report uses online job vacancies across 10 OECD countries[1] and their associated skill demands. 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[3]) 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 is not available in the Lightcast data. The AI exposure measures, therefore, proxy for AI use, and the report provides evidence to support this assumption.

The analysis finds that the broad skill groupings of management and business skills are the most demanded skills in occupations most exposed to AI. These groupings include skills in general project management, finance, administration, clerical tasks, and customer support. On average across the 10 OECD countries in the sample, 72% of high AI exposure vacancies contain at least one management skill and 67% contain at least one skill belonging to the business processes skill grouping. High exposure AI occupations are defined as occupations with an exposure measure at least one standard deviation above the mean, and they comprise about one third of vacancies in OECD countries in the sample. They are concentrated in high-pay occupations requiring higher than average education such as: genetic

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

counsellors, financial examiners and budget analysts. Other broad skill groupings that are highly demanded in these occupations include: digital, emotional[2] and social skills.

For high-exposure occupations, some of the most demanded skill groupings have also experienced the largest increases in demand over time. The share of vacancies demanding at least one skill from the emotional, cognitive and digital skills groupings increased by 8 percentage points, respectively, between the base and end years of the analysis. Cognitive skills include the sub-groupings “originality” and “reasoning and problem-solving”, among others. The other two skill groupings that have seen the largest increases among high-exposure occupations are social and language skills (7 and 8 percentage points, respectively). These changes are relatively similar for both high- and low-exposed occupations suggesting that AI exposure is only one of many trends shaping skill demand.

To better identify the effect of AI exposure on skill demands, this report also builds a panel of establishments by country. In this panel, establishment-level AI exposure is calculated from an establishment’s occupational composition in the base year which is used to identify changes in skill demand between the base and end years. This produces a shift-share design (Borusyak, Hull and Jaravel, 2021[4]) 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 reveal that demand for management, business process, cognitive and digital skills appears to be declining in establishments more exposed to AI. Emotional skills and communication skills also experienced decreased demand. For business process, digital, cognitive and management skills, a one standard deviation increase in establishment AI exposure leads to over a three percentage point decline in the share of vacancies demanding any of these skills. A one standard deviation increase is equivalent to moving from a moderately to a highly exposed establishment. Alternatively, it is the difference in AI exposure of a nail salon staffed primarily with manicurists and a law office that mostly employs legal secretaries and clerks. 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 in the context of growing skill demand for most of these skills in the aggregate.

Demand increased slightly for some skill groupings, such as production and technology and physical skills. These skill groupings 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.[3] However, these increasing skill demands were quite modest with substantial cross-country heterogeneity.

Although this paper is primarily concerned with skills, the establishment-level analysis also produces estimates of changing labour demand due to AI exposure. At the establishment level, increasing AI exposure is associated with modestly higher vacancy posting, although with substantial cross-country heterogeneity. A one standard deviation increase in AI exposure corresponds to a 3% increase in vacancy

[2] Within the taxonomy for skills used in this report, emotional skills most often fall under the category “Attitudes” which reflects what one often considers “soft-skills” such as self-motivation, and independence. This report uses the skill grouping “Attitudes” interchangeably with emotional skills.

[3] 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.

posting at the establishment level, on average, across countries in the sample. This is consistent with the literature that associates AI exposure with only modest changes in employment (Green, 2023[5]). However, the increased labour demand concentrates among low-exposure occupations making it unlikely that it will compensate for the decreased demand of skills found primarily in high-exposure occupations. Finally, higher AI exposure is also associated with higher vacancy posting for positions requiring AI skills. Just as with labour demand overall, there is cross-country heterogeneity in the results. The strongest evidence comes from countries with high shares of vacancies demanding AI skills. This also serves as evidence that the exposure shift-share instrument is relevant for detecting AI activity within establishments.

This analysis fits into a few different literatures, and is closest to work using vacancy data to study the effect of AI on skills.[4] The report is most similar to Acemoglu et al. (2022[6]) who use the same Lightcast data and the same empirical design to examine changes in the labour market due to AI exposure in the United States. The authors build an establishment-level data set and use various measures of AI exposure to proxy AI adoption, but their main specifications adopt the Felten, Raj and Seamans (2021[3]) measure (as in this report), showing that it correlates best with measures of AI activity. The focus of their paper is on labour demand and employment, but using Lightcast's own skill classification system, they show that the largest skill *changes* due to AI exposure concentrate in groups similar to those found in this paper, such as: information technology, finance, business and analysis.[5] The present report differs from Acemoglu et al. (2022[6]) by using measures of directly interpretable skill demand, as well as a uniform taxonomy of skills that captures all skills in the database.

The results of this paper are the first to connect changing skill demands in aggregate, representative data, to advances in AI's capabilities in basic office, computer programming and customer service tasks. Peng et al. (2023[7]) run an experiment where programmers were incentivised to complete a coding task as quickly as possible. A randomly selected treated group had access to CoPilot, a generative AI programme that suggests code and functions in real time depending on the context. The study finds that developers in the treated group completed the programming task over 50% faster than those in the control group. Noy and Zhang (2023[8]) assigned business professionals two writing tasks, and only suggested ChatGPT (an AI application) between the first and second tasks to a randomly selected subset of participants. They find that business professionals using ChatGPT performed writing tasks in less time and produced output of higher quality than those working unaided. Brynjolfsson, Li and Raymond (2023[9]) find that a generative AI application, which makes real-time suggestions for how customer support workers should answer calls, increases productivity by 14% defined as the number of calls resolved in an hour. The application was introduced gradually over time to allow the researchers to compare workers using the application to those who did not yet have access.

This paper also fits into the wider literature of studies using Lightcast data to examine the various determinants of changing skill demand. Using Lightcast data from the United States, Hershbein and Kahn (2018[10]) show that vacancies demanding routine, cognitive skills such as those found in clerical and administrative occupations demanded more skills, and employment in these positions grew modestly after the great recession. The authors attribute these findings to the complementarity of these occupations to capital investments in technologies that automate routine tasks. This report finds that AI may now be putting these same clerical and administrative skills under direct threat of automation leading to diminishing demand for these skills. Deming and Kahn (2018[11]) 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 2010-2015. This largely predates AI adoption, and the authors interpret this finding as higher demand

[4] Most of this research has focused on demand for AI skills – see Alekseeva et al. (2021[12]), Squicciarini and Nachtigall (2021[13]), Manca (2023[15]), and Borgonovi et al. (2023[21]).

[5] The authors' use an aggregate skill change measure and stratify their results conditional on the direction of skill changes (positive or negative). The results are therefore hard to interpret, and less useful for policy analysis.

for these skills – particularly in tandem.[6] This report finds that, although demand for cognitive skills is still increasing in the aggregate, on the margin, exposure to AI is putting downward pressure on demand for these skills.[7] This report finds less evidence, however, for the effect of AI exposure on demand for social skills.

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 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.

[6] See Deming (2017[47]) for further evidence using survey data from the United States.

[7] See Deming (2021[37]) for a model of why demand for decision-making – a part of cognitive skills – on the job may have increased over the past few decades, and why (implicitly, not explicitly stated in the paper) AI may reverse this trend and devalue decision-making as a skill.

2 Measuring AI exposure and skills in job vacancies

2.1. Measuring AI exposure from 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[7]; Noy and Zhang, 2023[8]; Brynjolfsson, Li and Raymond, 2023[9]). 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.[8]

This paper 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[3]) who measure progress in AI applications from the Electronic Frontier Foundation's AI Progress Measurement project (from 2010 to 2015), 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 paper (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 posting vacancies demanding AI skills

[8] 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[38]) who focus on 11 countries based on a common statistical code executed in a decentralised manner on official firm-level surveys.

in the United States (Acemoglu et al., 2022[6]). This provides an important source of external validity that this measure of AI exposure is correlated with establishment-level AI activity.[9]

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[12]; Squicciarini and Nachtigall, 2021[13]; Calvino et al., 2022[14]; Manca, 2023[15]; Green and Lamby, 2023[2]).[10] However, this method misses firms who adopt AI but do not develop or service it in-house, or demand for workers whose abilities overlap with AI advances but who do not need AI skills.[11] Finally, the release of generative AI models to the public has induced a wave of new AI exposure measures (Briggs and Kodnani, 2023[16]; Eloundou et al., 2023[17]; Felten, Raj and Seamans, 2023[18]; Pizzinelli et al., 2023[19]). However, none of these measures have been previously shown to correlate with actual AI adoption or activity.[12]

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 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[5]). 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.[13]

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

[9] Acemoglu et al., (2022[6]) experiment with other measures of AI exposure including Brynjolfsson, Mitchell and Rock, (2018[34]) who apply a rubric for evaluating task potential for machine learning to tasks in O*NET, and Webb (2020[35]) 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 demanding AI skills.

[10] Calvino et al. (2022[14]) 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.

[11] See Georgieff and Hyee, (2021[36]) 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.

[12] Felten, Raj and Seamans (2023[18]) update their original AI exposure measure, used in this report, to account for generative AI. The two measures are almost perfectly correlated.

[13] The exposure measure of Felten, Raj and Seamans (2021[3]) 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.

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[3]).

This paper 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 paper looks at differences in changing skill demand between low, moderate and high-exposure occupations over time (section 3). Next, the paper examines changing skill demand at the establishment level, and measures AI exposure by taking the average AI exposure of occupations employed by the establishment in a 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[20]; Deming and Kahn, 2018[11]; Hershbein and Kahn, 2018[10]; Borgonovi et al., 2023[21]). For many other OECD countries, the Lightcast data is representative of aggregate variables at the occupational level (Cammeraat and Squicciarini, 2021[22]; Araki et al., 2022[23]).

The advantage of the Lightcast data for this report is that, for each vacancy, Lightcast lists the skills, tasks and competencies demanded for the job. Lightcast pulls this 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 and it is unmatched for cross-country analysis of changing skill demands.[14]

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[24]). 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.[15] For the analysis that follows, this may result in an underestimation of any (potential) complementarities between AI and skills demanded in low exposure occupations.

[14] See OECD (2021[39]) 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.

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

2.2.1. Sample construction

This report uses Lightcast data from 10 OECD countries. 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[23]). In addition, they all exhibit some evidence of demanding workers with AI skills, which is a proxy for AI use. The countries include English-speaking countries (Canada, the United Kingdom and the United States) and continental European countries (Austria, Belgium, the Czech Republic [hereafter 'Czechia'], France, Germany, the Netherlands and Sweden,). Lightcast organises the countries into separate databases (henceforth "English-speaking" and "European countries" databases) with two parallel taxonomies for classifying skills. The rest of the sample construction consists of harmonising employer 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[3]) measure of AI exposure, and the English-speaking countries in the Lightcast data already use SOC-2010 to classify occupations.[16] The European countries use the ISCO-08 classification which is the standard international classification. 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[25]).[17]

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 English-speaking countries, the analysis compares base years of 2012-2013 pooling all valid vacancies in these years. For European countries, the base years are 2018-2019 with the differences between the two databases solely accounted for by data availability. The end years for all countries are pooled years 2021-2022. For all analyses to follow, the measure of skill demand is the share of vacancies demanding at least one skill from a particular grouping.

Skills for each vacancy are grouped into a harmonised O*NET-ESCO classification. There are over 30 000 skills across the various countries and, to facilitate their use, the skills are grouped hierarchically. The English-speaking countries have skills grouped according to Lightcast's own skill classification which has a heavy industry focus, and most importantly, does not map all or even most skills into the taxonomy. This report regroups skills in English-speaking countries into an adapted O*NET classification (O*NET+), which relies on natural language processing to map skills into lightly modified ONET groups (see Box 2.1). Skills in European countries are grouped according to the ESCO classification system used in the European Union. This paper uses an existing crosswalk to map skills between ESCO level 3 and O*NET level 3, and then allocates O*NET level 3 into the adapted O*NET classification (see Annex C for a full description of the O*NET+ classification).

---

[16] 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.

[17] 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[40]), 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.

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[11]) or lists of specific skills they have manually curated (Alekseeva et al., 2021[12]). 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 skills, and it is used exclusively in English-speaking countries while non-English speaking 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 50% of skills, and a little over 30% of skills weighted by frequency, are not assigned a cluster or family in the United States data for 2022.

This report uses an approach to group the skill information contained in Lightcast from Lassébie et a. (2021[26]). 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 policymakers 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 non-English speaking countries. Annex C provides a summary of the taxonomy.

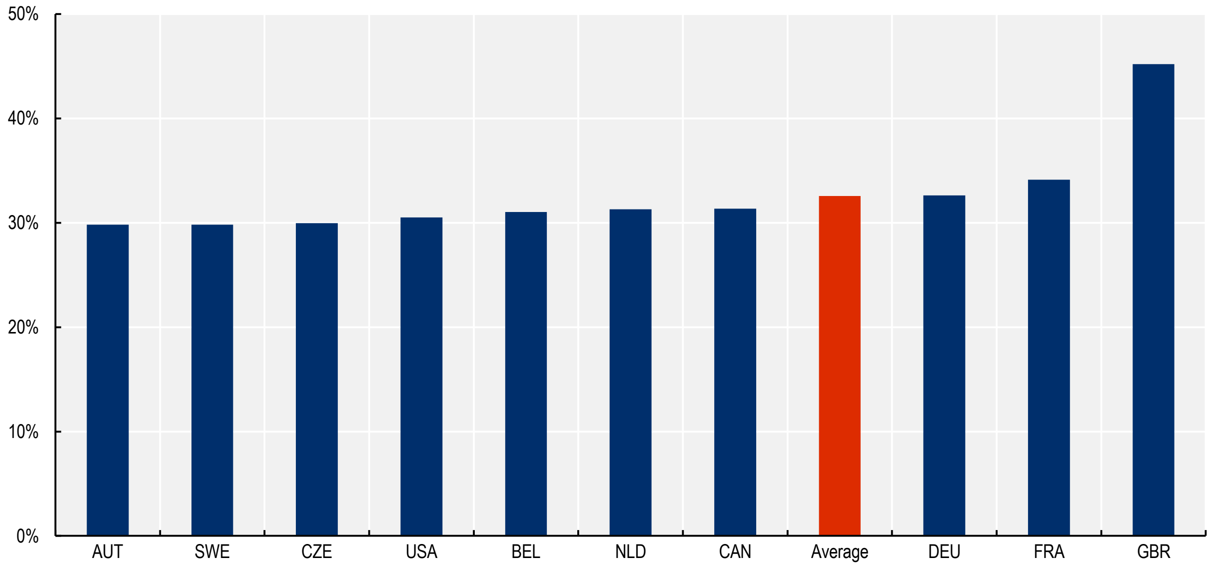
Source: Lassébie et al. (2021[26]).

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.[18] Ideally, one would define establishments using identifiers for actual establishments such as an exact address, but that is not available in the Lightcast data. Following Acemoglu et al. (2022[6]), 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 (OECD, 2022[27]). 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.[19]

2.3. Almost a third of vacancies have high AI exposure

Across the 10 OECD countries in the sample, about one third of vacancies have high AI exposure (Figure 2.1). Recall that AI exposure is taken from Felten, Raj and Seamans (2021[3]), who normalise their measure to have a mean of zero and variance of one. High exposure in this paper is defined as all vacancies whose occupation has an AI exposure measure one standard deviation greater than the mean. There is a little variation across countries with the lowest share of high-exposure vacancies found in Austria (31%) and the highest share in the United Kingdom (45%).[20]

Figure 2.1. The share of vacancies with high exposure to artificial intelligence, 2021-2022



[18] 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[23]).

[19] 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.

[20] The United Kingdom may be an outlier because occupations grouped under "professionals" are particularly overrepresented in Lightcast data, and they also tend to have higher than average AI exposure – see Cammeraat and Squicciarini (2021[22]).

Note: Share is defined as the share of vacancies with high AI exposure over all vacancies in the sample by country. Average is an unweighted cross-country average. AI exposure is defined by the occupation of each vacancy according to Felten, Raj and Seamans (2021[3]). 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[3]).

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. The United Kingdom has the lowest shares of vacancies with low (9%) or moderate AI exposure (46%). The highest shares of vacancies with low AI exposure are found in Belgium (22%), and the highest shares of moderate exposure are found in the United States (58%).

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.

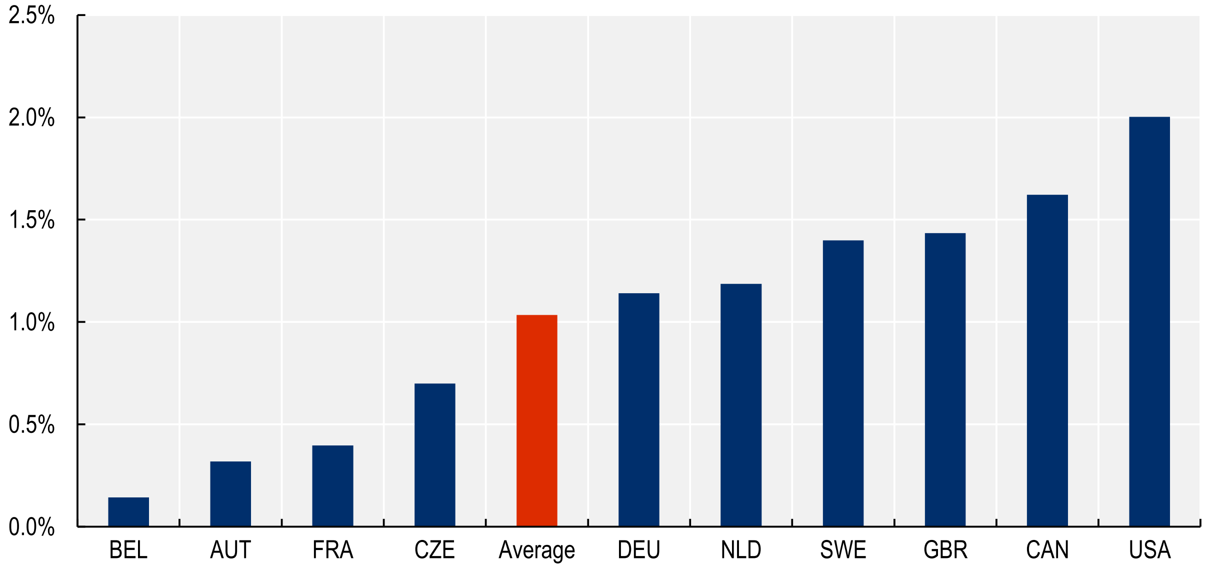
2.3.1. Vacancies with AI skills are concentrated in high exposure occupations

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[2]). 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[12]; Borgonovi et al., 2023[21]). Workers with AI skills are disproportionately found in occupations with high AI exposure (Figure 2.2).[21] In contrast, vacancies with moderate or low AI exposure contain almost no workers with AI skills. By removing these workers from the sample, the analysis can better isolate changing skill demands for workers who are likely to use AI without the need for AI skills from those who will be engaged in its development and maintenance and who do need such skills.[22]

[21] Vacancies demanding AI skills are classified using a Naïve Bayes classifier trained separately for each country on vacancies demanding “machine learning”. See Annex B for a description of the procedure.

[22] The share of vacancies demanding AI skills is so small that their inclusion does not affect the results that follow.

Figure 2.2. The share of vacancies demanding AI skills among vacancies with high exposure to artificial intelligence, 2021-2022



Note: Share is defined as the share of vacancies demanding AI skills and which have high AI exposure over all vacancies with high AI exposure by country. Average is an unweighted cross-country average. AI exposure is defined by the occupation of each vacancy according Felten, Raj and Seamans (2021[3]). High-exposure occupations have an exposure measure at least one standard deviation greater than the average. 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[3]).

3 Changes in occupational skill demand from AI exposure

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 and business skills are the most demanded skills in occupations with high AI exposure

Skills in management and business are the most demanded in occupations with high AI exposure. Table 2.1 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, 2021-2022. The share of vacancies demanding the skill groupings is calculated as an unweighted average across countries in the sample. Resource management, business processes and attitudes (emotional skills) are the three most demanded occupations with 72%, 67% and 63% of vacancies in the highest exposed occupations demanding skills from these groupings. Resource Management contains skills pertaining to human resource management and general project management and administration as well as accounting and budgeting skills. Business processes includes clerical skills and skills in customer service and sales. Many of these skill groupings (resource management, business processes and digital 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.

Not all skill groupings obviously overlap with the current capabilities of AI. Attitudes, or emotional skills, for example, seek things such as "self-starters", "energetic", and "detail oriented". Some of the most common skills listed under the grouping social skills are "teamwork/collaboration", "negotiation" and "stakeholder management". These groupings are examples of social (social skills) and emotional (attitudes) skills, or "soft" skills. These skills have come into focus for their association with higher educational achievement, and the development of cognitive skills such as literacy, numeracy and problem solving. They also correlate with positive health and social outcomes later in life (OECD, 2015[28]). These skills do not directly overlap with AI's current capabilities, but their association with a range of cognitive skills suggests that they may be complementary to AI, and therefore may be affected by changing skill demand due to AI exposure.

Table 3.1. The skill groups in highest demand by intensity of AI exposure, 2021-2022

Share of vacancies demanding at least one skill from a skill group 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	0.72		Attitudes	0.56		Production and Technology	0.51
Business Processes	0.67		Social Skills	0.51		Attitudes	0.51
Attitudes	0.63		Resource Management	0.50		Social Skills	0.39
Social Skills	0.59		Business Processes	0.48		Resource Management	0.24
Digital	0.58		Production and Technology	0.39		Cognitive Skills	0.24

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[3]). 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[26]) for the United States, Canada and the United Kingdom. European OECD countries mapped using crosswalk from ESCO to ONET+. The countries included in the average are Austria, Belgium, Canada, Czechia, France, Germany the Netherlands, Sweden, the United Kingdom and the United States.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

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: attitudes, social skills and resource management. For occupations with low AI exposure the top grouping is production and technology, joined by attitudes and social skills. Production and technology includes the subgroupings installation and maintenance, quality assurance and production processes. With these notable exceptions, the most demanded skills are relatively similar across AI exposure groupings, but moderate and especially low exposure occupations have more dispersed skill demands as measured by the share of vacancies demanding skills in different categories.

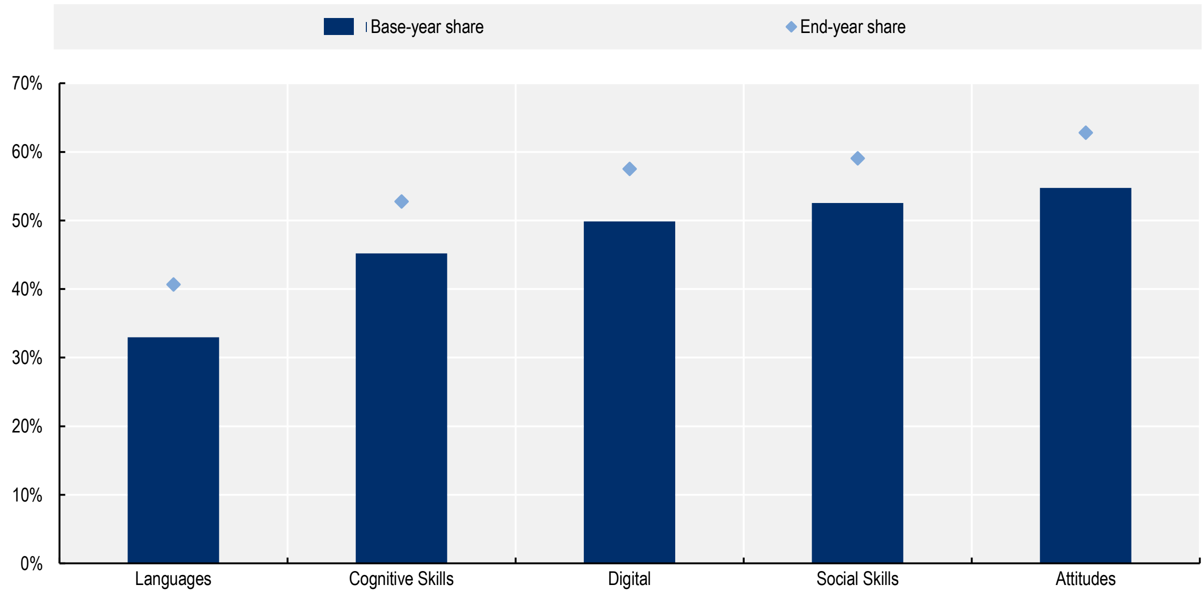
3.2. For high-exposure occupations, the most demanded skill groupings have also seen the largest increases in demand over time

The most demanded skills in high-exposure occupations have also seen some of the largest increases in demand over time. Attitudes, social skills and digital skills are all some of the most demanded skills for high exposure occupations in 2021 and 2022 and they have also seen the largest increases in demand of 8, 7 and 7 percentage points, respectively (Figure 3.1). The other two skill groupings that have seen the largest increases are cognitive and language skills, which are the sixth and seventh most demanded skills among high-exposure occupations – see Annex Table A A.1. They have each increased by 8 percentage points. Cognitive skills include the sub-groupings originality as well as reasoning and problem-solving, among others. Language skills are almost exclusively the ability to speak foreign languages, and in particular, English. Business process skills and management skills, the most demanded skills among high-exposure occupations, have also increased by over five percentage points among high-exposure occupations.

These trends are similar for all vacancies as well as vacancies with low AI exposure. Attitudes (emotional skills), cognitive skills, languages and digital skills increased the most among vacancies overall which includes vacancies with moderate and low AI exposure. The magnitudes of the changes are similar as well although slightly less than among high-exposure occupations. Attitudes, cognitive and digital skills experienced the largest percentage point increase among low-exposure occupations as well, but the changes are about half as large compared to high-exposure occupations – see Annex Table A A.1. The relative similarity of changing skill demands across the distribution of AI exposure suggests that AI exposure is only one of the many possible trends driving changes in skill demand.

Figure 3.1. The most demanded skills for high exposure occupations have also seen some of the largest increases in demand

The skill groups with the largest increases in demand in high exposure occupations over time



Note: Share is defined as the share of vacancies in high exposure grouping demanding at least one of the skills from each skill grouping in each country. Datapoints are the unweighted average across countries. The countries included are the United States, Canada, the United Kingdom (English-speaking countries), and France, Germany, Belgium, Sweden, the Netherlands, Austria and Czechia (European countries). The base years for English-speaking countries are pooled 2012-2013, and pooled 2018-2019 for European countries. The end years are pooled 2021 and 2022. AI exposure is defined by the occupation of each vacancy according Felten, Raj and Seamans (2021[3]). 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[26]) for the United States, Canada and the United Kingdom. European OECD countries mapped using crosswalk from ESCO to ONET+. The countries included in the average are Austria, Belgium, Canada, Czechia, France, Germany the Netherlands, Sweden, the United Kingdom and the United States.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

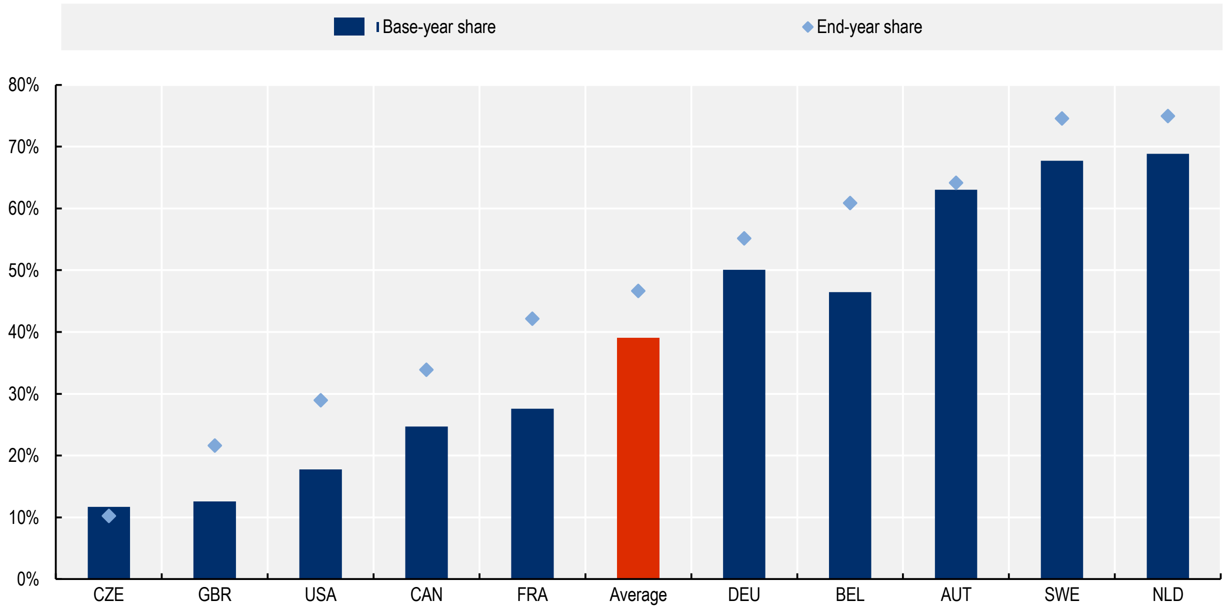
The rest of this section explores these skill changes in more depth. The main skill groupings provide a nice starting point for understanding changing skill demands, but they lack the specificity to understand changing skill demands at a practical level. The analysis breaks out the changes for a selection of the 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. Skills requiring collaboration with colleagues, originality, and experience with basic office tools have seen the largest rise in demand in occupations highly exposed to AI

Co-ordination skills are the fastest growing subcomponent in the social skills category. By far 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 (Figure 3.2). Only Czechia experienced a modest decline in the demand for coordination 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.[23]

Figure 3.2. Demand for co-ordination skills has increased in high exposure occupations in almost all countries

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



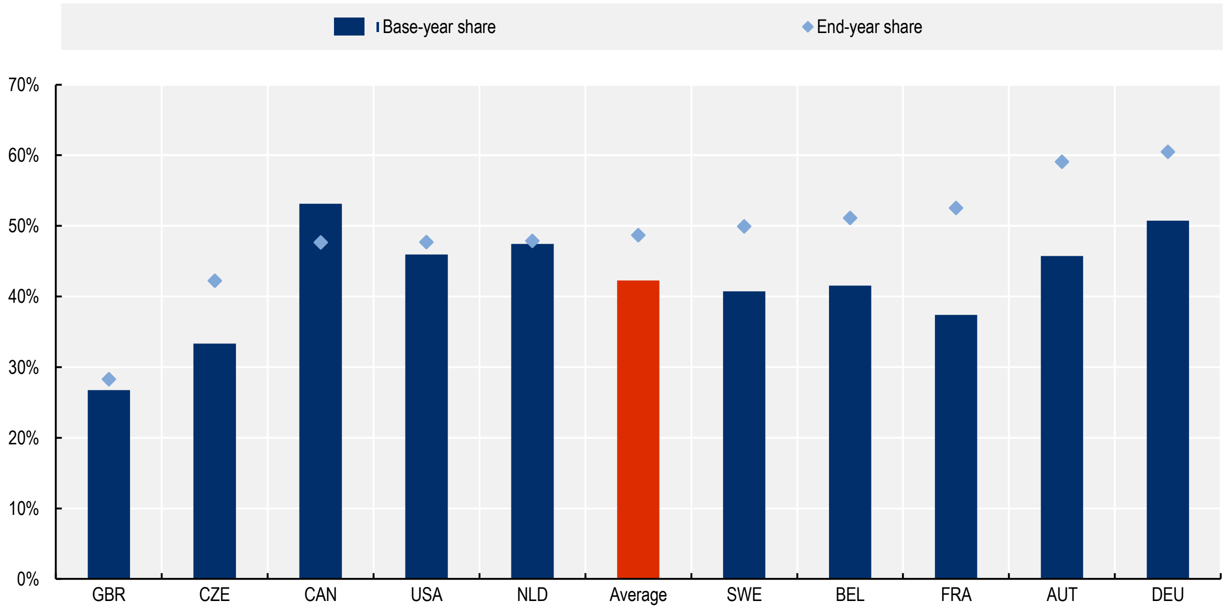
Note: Countries sorted by end-year values. Co-ordination skills are a subgroup of Social Skills in the merged ONET+ skill groupings from Lassébie et al. (2021[26]). Share is defined as the share of vacancies in the high exposure tercile demanding at least one of the skills from the co-ordination skill grouping in each country. The base year is pooled 2012-2013 for the United States, Canada, the United Kingdom (English-speaking countries), and 2018-2019 for France, Germany, Belgium, Sweden, the Netherlands, Austria and Czechia (European countries). 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[3]). 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[26]) for the English-speaking countries. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

[23] As noted previously, the crosswalk from the Lightcast taxonomy to ONET+ differ by country. The English-speaking countries use the crosswalk of Lassébie et al. (2021[26]) and the European countries use an ESCO to ONET crosswalk adapted to ONET+. This sometimes results in Canada, the United Kingdom and the 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.

There has also been an increase in demand for skills pertaining to the use of office tools and collaboration software. These skills are a sub-group of the digital skills category, and they can be easily summarised as demand for experience with Microsoft Word and Microsoft Excel. On average, the share of high-exposure vacancies demanding these skills increased from 42% to 49% between the base and end years (Figure 3.3). The largest percentage point increases were found in France, Austria and Belgium. Canada was the only country that experienced a decline in vacancies demanding office tools and collaboration software.

Figure 3.3. There has been an increase in demand for skills pertaining to the use of office tools and collaboration software

The share of high AI exposure vacancies demanding office tools and collaboration software in the base and end year by country

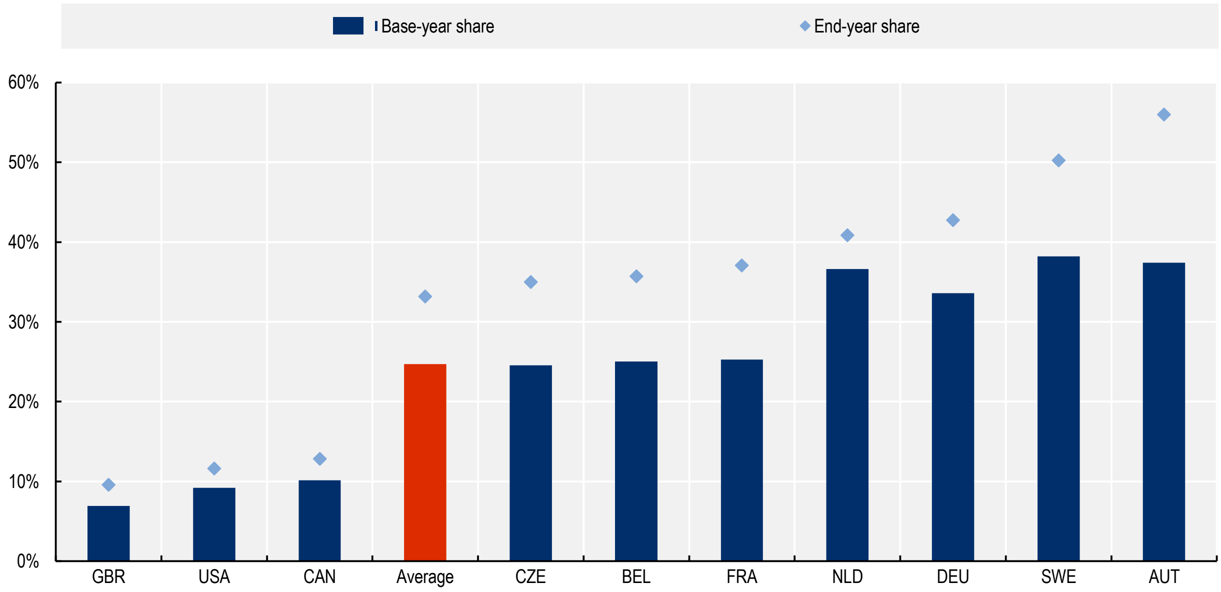


Note: Countries sorted by end-year values. Office tools and collaboration software skills are a subgroup of Digital skills in the merged ONET+ skill groupings from Lassébie et al. (2021[26]). Share is defined as the share of vacancies in the high exposure tercile demanding at least one of the skills from the co-ordination skill grouping in each country. The base year is pooled 2012-2013 for the United States, Canada, the United Kingdom (English-speaking countries), and 2018-2019 for France, Germany, Belgium, Sweden, the Netherlands, Austria and Czechia (European countries). 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[3]). 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[26]) for the English-speaking countries. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

Originality constitutes the sub-grouping of cognitive skills that has seen the greatest increase in demand. Originally comprises “creativity” and “developing new ideas”. On average, the share of high exposure vacancies demanding skills pertaining to originality has increased from 25% to 33% between the base and end years (Figure 3.4). The largest increases occurred in Sweden, France and Belgium. The English-speaking countries, in contrast, have seen the smallest increases. No countries in the sample saw a decrease in demand for these skills.

Figure 3.4. Demand has increased for skills pertaining to originality

The share of high AI exposure vacancies skills related to originality in the base and end year by country



Note: Countries sorted by end-year values. Originality is a subgroup of Cognitive skills in the merged ONET+ skill groupings from Lassébie et al. (2021[26]). 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 2012-2013 for the United States, Canada, the United Kingdom (English-speaking countries), and 2018-2019 for France, Germany, Belgium, Sweden, the Netherlands, Austria and Czechia (European countries). 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[3]). 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[26]) for the English-speaking countries. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

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[5]; Green, Salvi del Pero and Verhagen, 2023[29]). It seems unlikely, therefore, that the broad changes in skill demand documented in the previous section are exclusively due to AI penetrating the workplace. There are many other factors, uncontrolled for in that analysis, which could have driven the results presented.[24] 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[6]) and defines an establishment in Lightcast as the combination of an employer name and local labour market geography (TL2 region in this analysis). Demand for skills is fundamentally about demand from establishments, and moving to the establishment-level allows the analysis to capture potential complementarities in production. In addition, the combination of establishment-level skill demand and occupation-level AI exposure allows one to introduce quasi-random variation in AI exposure which can allow for more precise identification of the effect of AI exposure.

The establishment-level file produces a similar distribution of skill demand in the base and end years and replicates the same changes over time as the occupational sample. Annex Table A A.2 presents the levels and changes in the share of vacancies demanding a major skill grouping averaged over countries. Annex Table A A.1 presents the same information for the occupational sample. In general, levels of skill demand are slightly less in the establishment sample, but changes are of the same sign and of similar magnitude to the occupation sample overall, and for high- and low-exposure occupations, respectively. The results give one confidence that, although the samples differ, they are fundamentally capturing a similar sample of vacancies, and the results that follow are not due to changes in sample composition.

[24] For example, industry or macroeconomic shocks, declining employment in occupations composed of routine tasks due to automation, and national skills policies around digitalisation.

4.1. A better approach is to compare similar establishments which 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.[25] 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. This design-based empirical strategy 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[4]).[26]

There are two main assumptions that support this empirical strategy. The first assumption, relevancy, assumes that establishments that are more exposed to AI are more likely to adopt AI. The AI exposure measure captures, by definition, the overlap between AI's capabilities and tasks performed in the labour market. More exposed establishments should, therefore, find more uses for AI and be more likely to adopt AI at the margin. Although AI adoption is not observed in Lightcast data, this report provides some evidence for this assumption below. The second assumption (exclusion restriction) 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 employer 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 needs 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.[27]

[25] 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, and evidence for the relevancy of the exposure measure to predict establishment-level AI activity is presented below.

[26] Note that unlike Goldsmith-Pinkham, Sorkin and Swift (2020[41]) who require vacancy shares to be exogenous, consistency in Borusyak, Hull and Jaravel (2021[4]) 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.

[27] 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.

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.[28] 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. This is equivalent to moving from a moderately exposed establishment to 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,[29] as well as the 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 separately by country 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 shocks that may affect labour or skill demand.[30]

[28] Ideally, one would use the *employed* occupation mix of an establishment rather than its posted vacancies. 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 approximates its employed occupation distribution.

[29] 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 European countries ISIC. Because industry is included only as controls and the specifications are always estimated within each country separately, industry was not cross 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.

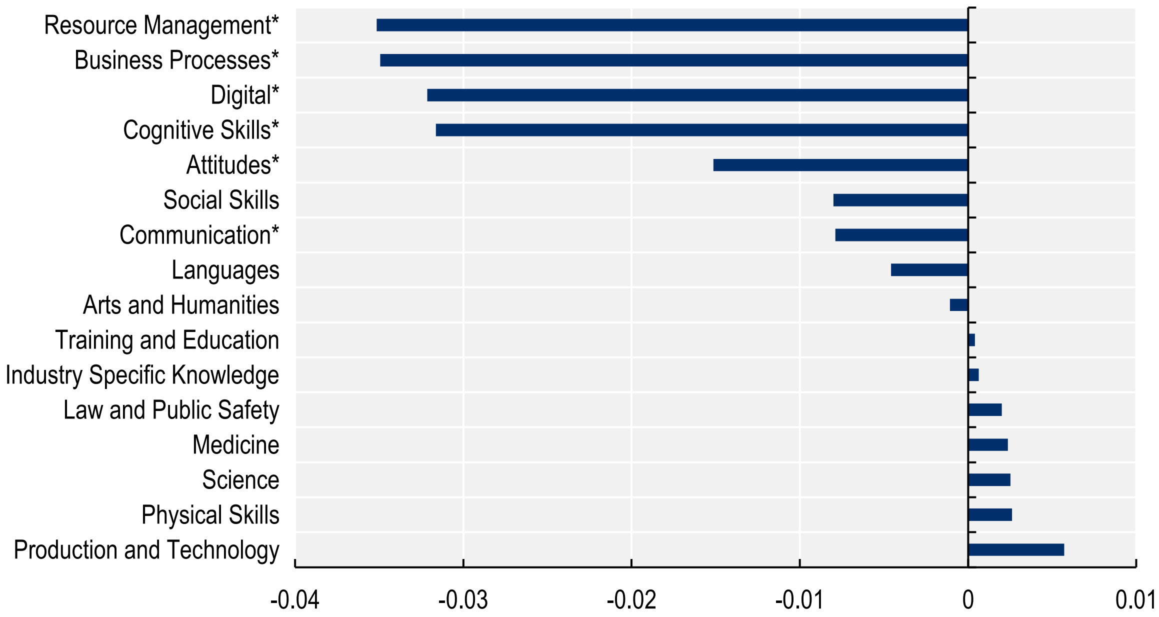
[30] More precisely, the shocks (exposure measures) are orthogonal, not necessarily the vacancy shares. Although the shocks to AI's capabilities are assumed exogenous, it is possible that they are correlated with unobserved establishment characteristics. For example, establishments in the information 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 remedy 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[42]). This recentred AI exposure measure has little bearing on the results, and the observed AI exposure measure is therefore used throughout.

4.2. Establishments more exposed to AI are associated with declining demand for general office software, business and management skills

At the establishment level, AI exposure is associated with declining demand for general skills commonly used in office settings. The strongest results, which were consistent across countries, pointed to decreasing demand for cognitive skills, digital skills, business processes and resource management skills (Figure 4.1). Digging further into these categories, the results point to drops in demand for general office skills such word processing and spreadsheet software, basic computer programming skills, as well as administrative and clerical tasks and basic project management skills.

Attitudes and communication skills also saw drops in demand due to AI exposure. Recall that the attitudes grouping is roughly equivalent to emotional skills and includes such skills as “independence” and “self-motivated”. It is not obvious why AI exposure would put downward pressure on these skills, but emotional skills are correlated with cognitive skills (OECD, 2015[28]). The downward pressure on emotional skills may simply be a downstream consequence of AI replacing demand for cognitive skills. The effect of AI exposure on communication skills is much clearer. After general communication skills, some of the most demanded skills in the communication grouping are “writing” and “writing communication”. The rise of generative AI applications has demonstrated that these skills may no longer be as heavily demanded by employers as before (Noy and Zhang, 2023[8]).

Figure 4.1. Country average of regression coefficients for the percentage point change in demand for skill groupings from establishment-level AI exposure, by skill grouping



Note: Bars are unweighted cross-country average regression coefficients (β) of establishment-level AI exposure in each 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 the skill groupings where at least 7 of 10 countries in the average have i) regression coefficients that are the same sign as the cross-country average and ii) those regression coefficients 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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[3]) 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[26]) for the United States, Canada and the United Kingdom. European countries mapped using a crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

There were some skill groupings that experienced modest increases in demand, including: production and technology and physical skills. 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. However, these increasing skill demands were more modest with substantial cross-country heterogeneity.

The skill groupings that experienced decreases in demand concentrate in occupations most exposed to AI. If AI exposure is putting downward pressure on skills disproportionately found in high-exposure occupations, one should expect the results to concentrate among these high-exposure occupations within an establishment. Annex Table A A.4 shows the results of the same regressions at the establishment level, but it changes the dependent variable to be the share of vacancies demanding at least one skill of a grouping among high- and low-exposure vacancies within that establishment, respectively. The results show that the cross-country average of regression coefficients remain the same or strengthen among high-exposure occupations, but mostly disappear within low-exposure occupations. The results provide further evidence that AI exposure is picking up real changes in skill demand. The rest of this section discusses in more depth the four skill groupings which saw the largest decreases in demand due to AI exposure.

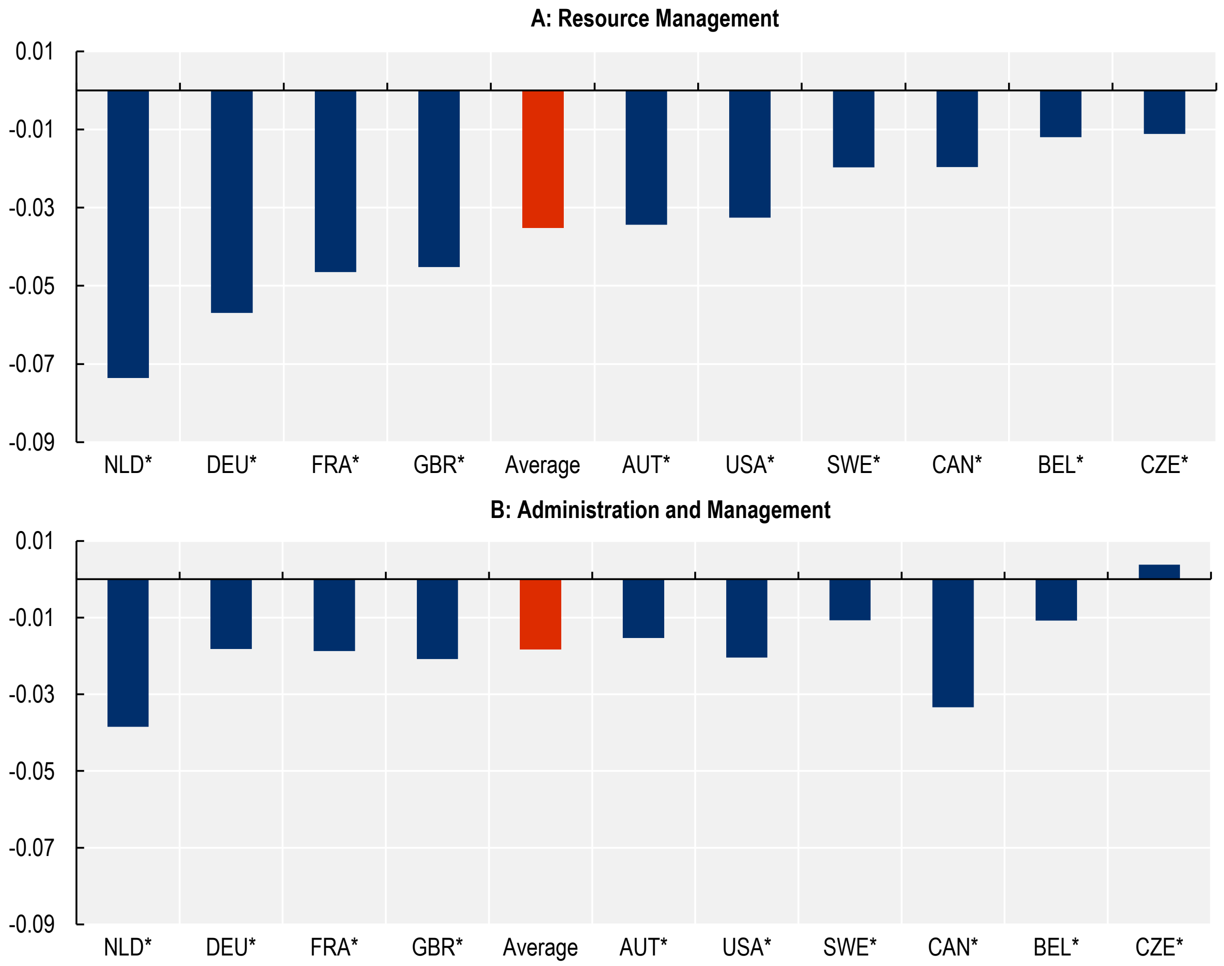
4.2.1. AI exposure is associated with declining demand for general management and clerical skills

Establishment-level AI exposure is associated with decreased demand for management skills. On average across countries in the sample demand for management skills declined by under 4 percentage points for a one standard deviation increase in AI exposure (Figure 4.2, Panel A). All countries in the sample are associated with a decline in management skills, and all are statistically significant from zero. Resource management includes human resource management, financial management, among others. Some of the most frequently demanded skills in financial management include budgeting and accounting. Recall that it was one of the most demanded skill groupings among highly exposed occupations.

Panel B in Figure 4.2 shows the results for the subgrouping administration and management. On average, the share of vacancies demanding at least one skill in this subgrouping declined by a little under 2 percentage points. Apart from Czechia, all countries experienced significant declines with the most notable being Canada which had one of the smallest declines for the main skill grouping of resource management and one of the largest declines for this subgrouping. What is notable about this subgrouping is that the most frequently appearing skills are general office administration and project management, skills that are more closely associated with lower-level office and general business duties than with higher-level management positions. One should be nuanced when interpreting these results, however. More basic management and administration skills appear to be less demanded in more exposed establishments, which is consistent with some of the other results in this report including declining demand with general office software. However, other research has indicated that management skills combined with AI skills are some of the most in-demand skills in the labour market (Alekseeva et al., 2021[12]; Borgonovi et al., 2023[21]).

Figure 4.2. AI exposure reduces establishment-level demand for management skills

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



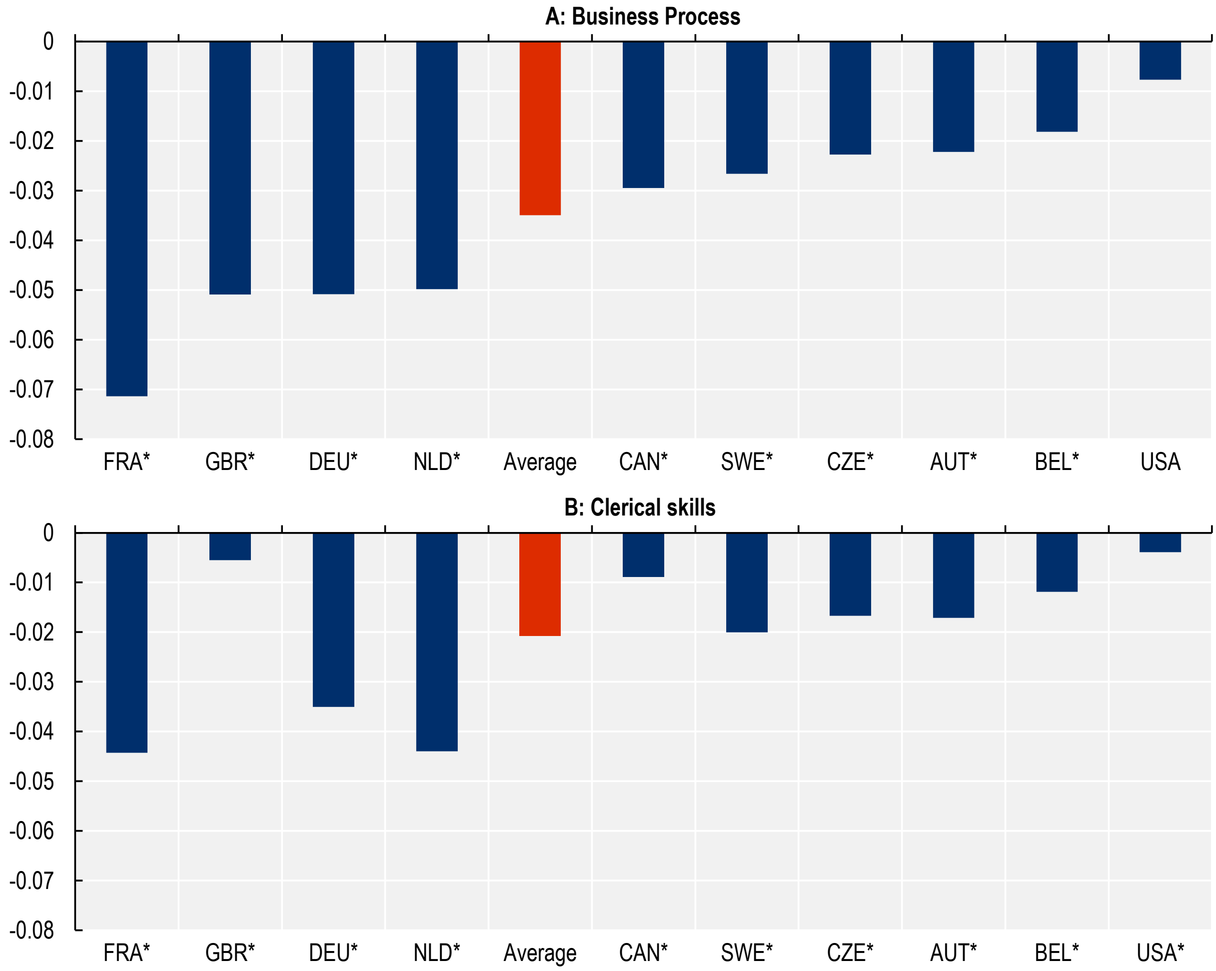
Note: Panel A presents the regression coefficients of establishment AI exposure (β) on the change in the share of vacancies demanding at least one skill from the resource management skill grouping, by country, and panel B plots coefficients from the same specification but using the change in the share of vacancies demanding at least one skill from the administration and management sub-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 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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[3]) 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[26]) for the United States, Canada and the United Kingdom. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

Business process skills have also seen a reduction in demand from 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 4.3, Panel A). All countries in the sample have seen 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.

Skills and tasks that can be roughly described as clerical tasks were the sub-group of skills that saw the largest reduction in demand. Demand for clerical skills declined by slightly more than 2 percentage points for a one standard deviation increase in establishment-level AI exposure (Figure 4.3, Panel B). Just as with the business process group, all countries saw a decline in demand for clerical skills with the drop in the United Kingdom much smaller than what one would expect from the reduction in business skills overall. The most frequently demanded skills in clerical tasks are administrative support and record keeping, and this subgrouping includes the use of general office tools as well.

Figure 4.3. AI exposure reduces establishment-level demand for general business skills

Regression coefficients of the effect of AI exposure on the share of establishment vacancies demanding business process skills and clerical skills, respectively



Note: Panel A presents the regression coefficients 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, and panel B plots coefficients from the same specification but using the change in the share of vacancies demanding at least one skill from the clerical skills sub-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 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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[3]) 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[26]) for the United States, Canada and the United Kingdom. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26])l.

4.2.2. AI exposure is also associated with declining demand for originality and basic computer programming skills

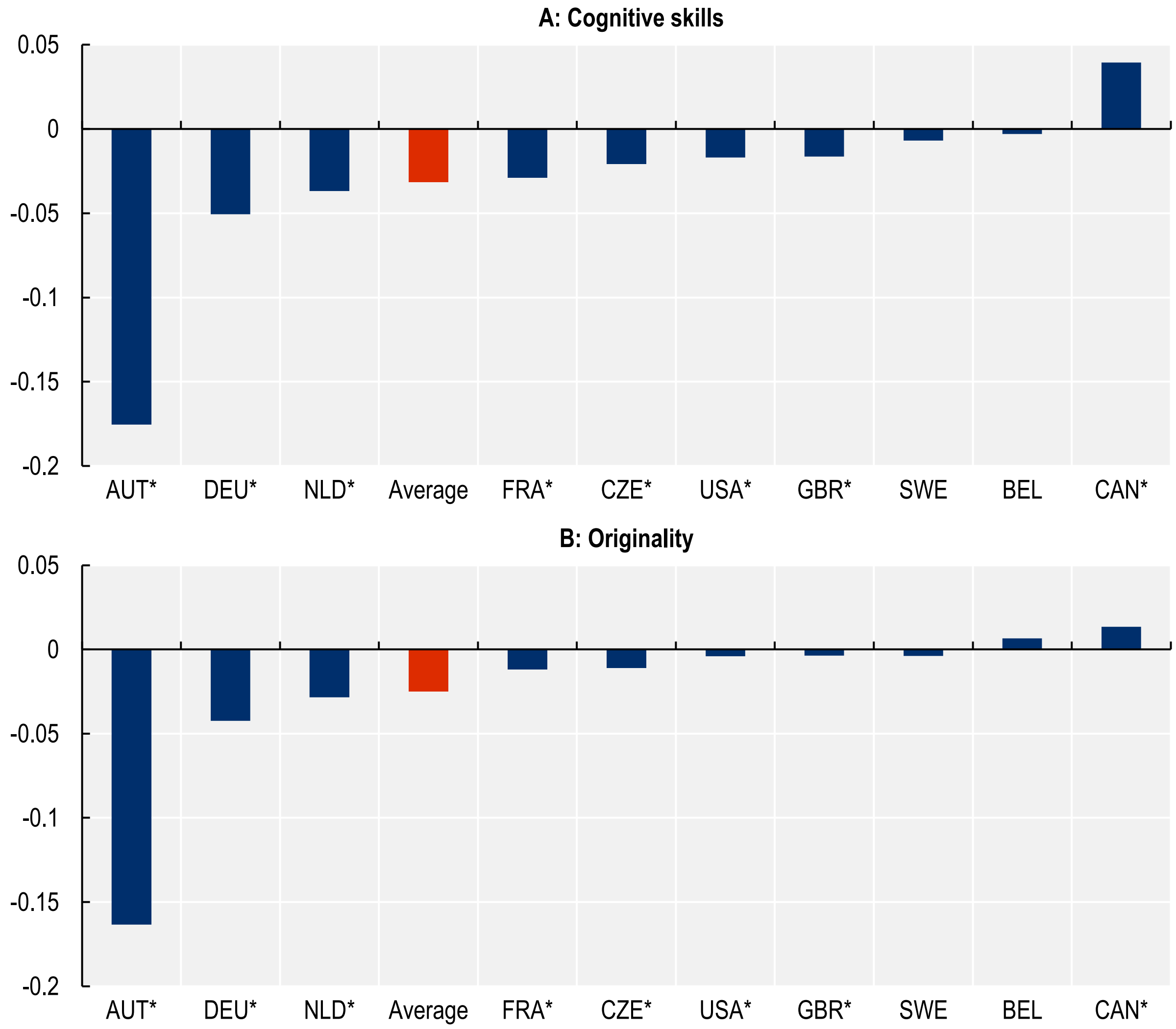
AI exposure is associated with a decline in demand for cognitive skills at the establishment level. On average across countries in the sample demand for cognitive skills declined by a little over 3 percentage points for a one standard deviation increase in AI exposure (Figure 4.4, Panel A). The estimates are relatively similar for all countries in the sample with the exception of Austria, which experienced the largest decline in demand, and Canada, which was the one country that experienced an increase in demand for cognitive skills. Recall that this was one of the skill groupings where demand increased when examining highly exposed occupations in the cross-section (section 2). The results provide some evidence that analysing AI exposure in broad cross-sections without controlling for confounding factors may miss some emerging trends.

Panel B in Figure 4.4 shows the results for the subgrouping originality, which was the sub-group of cognitive skills associated with the largest decline in demand in the establishment sample. On average, the share of vacancies posting skills grouped in the originality sub-grouping declined by under 3 percentage points. The differences in country-level estimates almost perfectly mirror those of the main grouping although somewhat attenuated.

It may seem surprising that originality or creativity would be less demanded with greater exposure to AI. These are skills that are not at first glance associated with AI's capabilities. However, many new discoveries rely on finding a new piece of information or missing element that had been previously overlooked (McCaffrey and Spector, 2017[30]). Machine learning may already be replacing humans in finding these overlooked elements, or simply generating new ideas at a higher rate and with higher average quality than humans (Girotra et al., 2023[31]). "What feels like inspiration is actually the output of a data analysis run by the human brain" (Ludwig and Mullainathan, 2024[32]).

Figure 4.4. AI exposure reduces establishment-level demand for cognitive skills, in particular originality

Regression coefficients of the effect of AI exposure on the share of establishment vacancies demanding cognitive skills and originality, respectively



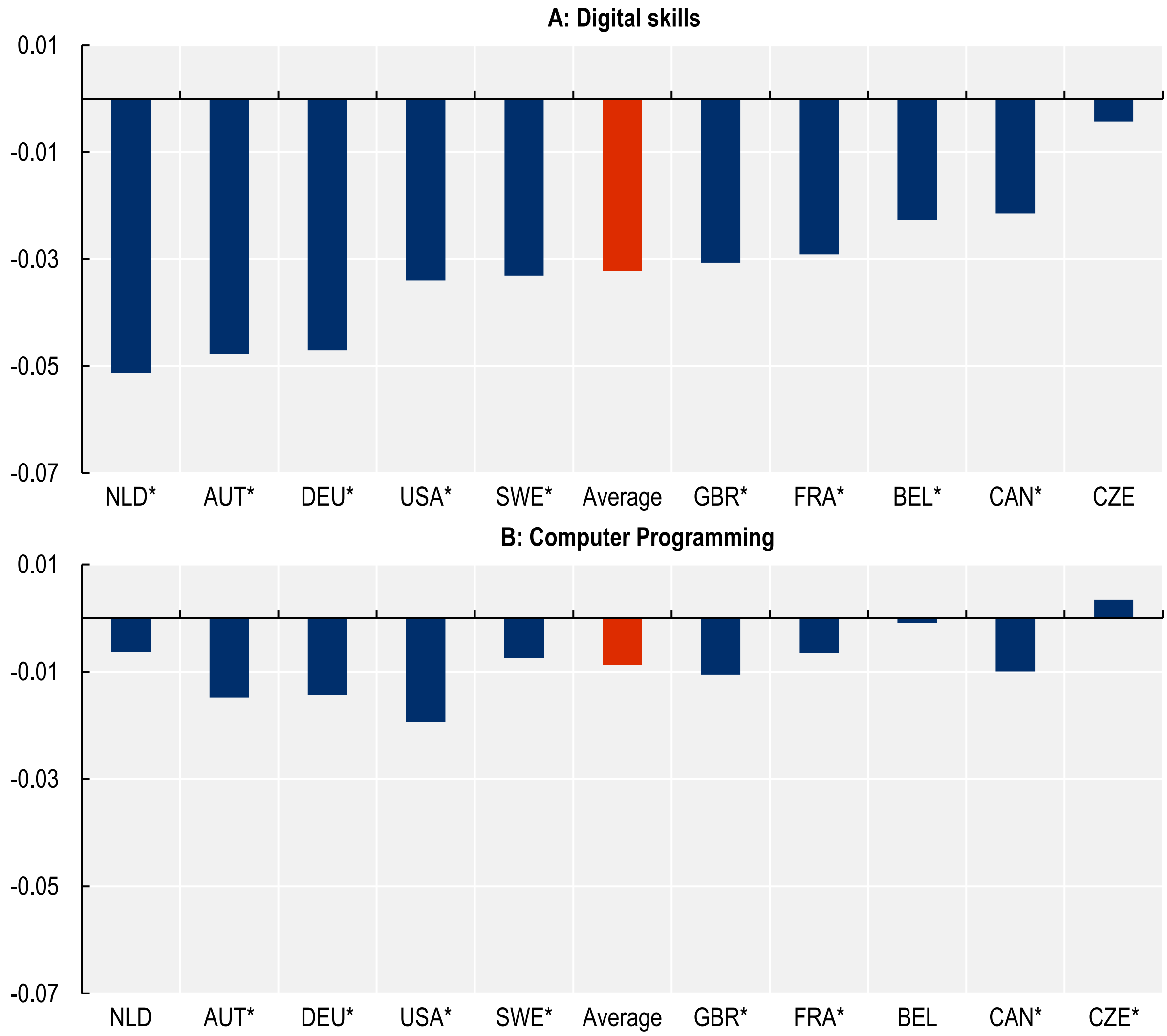
Note: Panel A presents the regression coefficient of establishment AI exposure (β) on the change in the share of vacancies demanding at least one skill from the cognitive skills grouping, by country, and panel B plots coefficients from the same specification but using the change in the share of vacancies demanding at least one skill from the originality sub-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 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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[3]) 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[26]) for the United States, Canada and the United Kingdom. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

AI exposure is also associated with a decline in demand for digital skills. On average across countries in the sample, demand for digital skills declined by over 3 percentage points for a one standard deviation increase in AI exposure (Figure 4.5, Panel A). All countries in the sample are associated with a decline in digital skills, and all are statistically significant from zero except for Czechia. Digital skills include the sub-groupings computer programming, collaboration software and office tools, and ICT network management. All sub-groupings of digital skills saw a decline in demand including collaboration software and office tools which was one of the sub-groupings that experienced one of the largest increases in demand in the cross-section (above).

Panel B in Figure 4.5 shows the results for the subgrouping computer programming, which was the sub-group of digital skills associated with one of the largest declines in skill demand. On average, the share of vacancies posting skills grouped in the computer programming sub-grouping declined by a little under one percentage point for a one standard deviation increase in establishment-level AI exposure. Apart from Czechia, all countries saw declines with the greatest decrease coming from the United States. Some of the most frequently demanded skills listed under computer programming include general knowledge of scripting languages and computer programming such as using python, as well as database management including SQL and SAP. Recent research suggests that AI can greatly aid in the speed and efficacy of basic computer programming (Peng et al., 2023[7]), so a decline in demand for these skills is not necessarily unexpected.

Figure 4.5. AI exposure reduces establishment-level demand for digital skills, in particular computer programming

Regression coefficients of the effect of AI exposure on the share of establishment vacancies demanding digital skills and computer programming, respectively



Note: Panel A presents the regression coefficient of establishment AI exposure (β) on the change in the share of vacancies demanding at least one skill from the digital skills grouping, by country, and panel B plots coefficients from the same specification but using the change in the share of vacancies demanding at least one skill from computer programming sub-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 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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[3]) 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[26]) for the United States, Canada and the United Kingdom. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

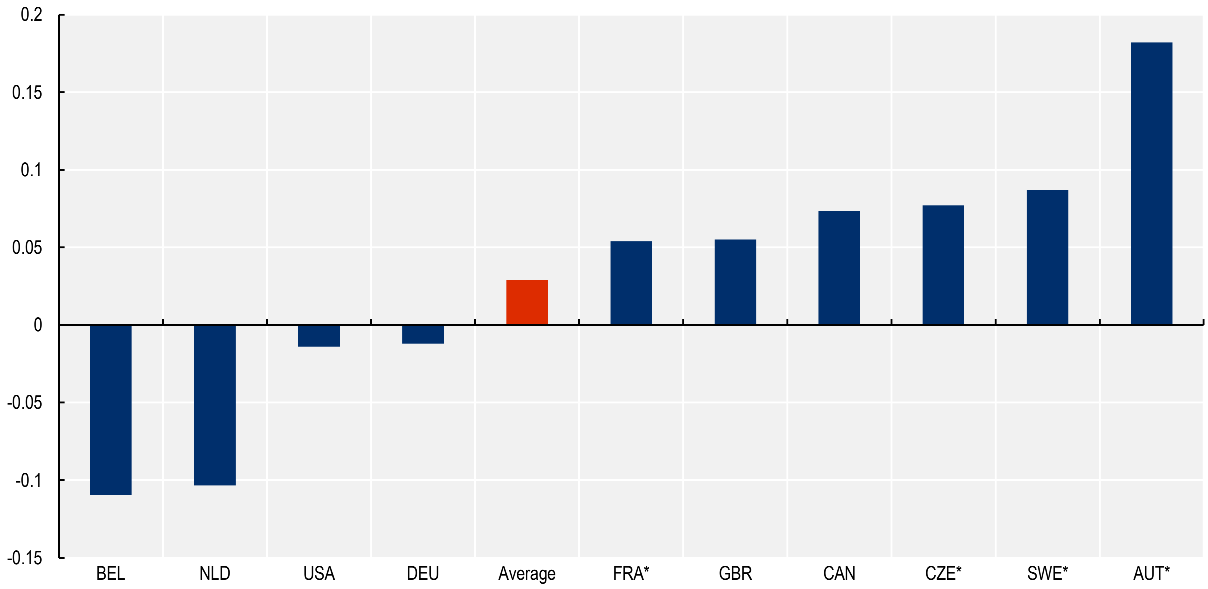
The results of the preceding establishment-level analysis on skills are consistent with current models of productivity, technological change and the labour market. In these models, establishments can reduce costs by adopting new technologies which make certain tasks done by humans redundant. Establishments will therefore demand less of these tasks or skills, and jobs or occupations dense in these tasks or skills may experience drops in labour demand. In jobs or occupations with little exposure, demand can grow for these occupations and the skills that go with them if the costs savings are sufficiently large that they lead to overall increases in product demand at an establishment (Acemoglu and Restrepo, 2018[33]; Acemoglu et al., 2022[6]). The rest of this section reinforces the internal validity of the preceding results on skills by testing the implications of this model for overall vacancy demand. In addition, the report analyses the effect of AI exposure on demand for vacancies demanding AI skills – excluded from the rest of this report – as a test for the validity of AI exposure as an instrument for AI adoption.

4.3. AI exposure is associated with modest increases in overall vacancy posting as well as vacancy postings demanding AI skills

Establishment-level AI exposure is associated with a modest increase in vacancy posting. Figure 4.6 depicts the regression coefficients of establishment AI exposure on the change in vacancy postings estimated separately by country. Stars over country labels indicate that the estimates are significantly different from zero using 95% confidence intervals. For these specifications, the analysis uses the difference in the inverse hyperbolic sine of the count of vacancies in an establishment, which is frequently used in place of logarithms as the former is well defined at zero.[31] The unweighted cross-country average coefficient is 0.03 which implies that a one standard deviation increase in AI exposure corresponds with a 3% increase in vacancy posting. Six of the ten countries in the sample saw an increase in vacancy posting of which four were statistically significant: Austria, Sweden, Czechia and France. In contrast, none of the four countries that experienced a decrease in vacancy posting is significantly different from zero.

Figure 4.6. There is modest evidence that establishment AI exposure increases labour demand

Regression coefficients of the effect of AI exposure on establishment vacancy change



[31] Defined as $\ln(x + \sqrt{x^2 + 1})$.

Note: This figure plots the regression coefficient of establishment AI exposure (β) on the change in vacancy posting at the establishment by country. They are interpreted as the percentage change in the number of vacancies demanded in an establishment 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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[3]) weighted by the establishment's base year occupation shares.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]).

The results from the association of AI exposure and overall labour demand are generally consistent with the related literature. The consensus of current studies is that AI appears to be associated with small increases in labour demand (Green, 2023[5]). This is consistent with the results in Figure 4.6. One exception is Acemoglu et al. (2022[6]) who study labour and skill demand in the United States, and whose empirical design is followed in this study. The authors find a decrease in vacancy posting associated with AI exposure in specifications similar to those found in this report. This report can replicate both the sign of their coefficient for the United States and the estimate is within an order of magnitude. Considering that this report uses a slightly different time period for the analysis, as well as higher levels of aggregation for the local geography and industry – necessary for comparable cross-country analysis – the similarity of these point estimates are encouraging for the validity of the results.[32]

When one looks at changing labour demand by occupational skill exposure, the results provide additional evidence for the validity of the results on skill demand. Consistent with the results on skills, which find that the main skill changes were concentrated among high-exposure occupations, the results for labour demand show that across countries, high-exposed occupations saw a decrease in vacancy postings compared to an increase for low-exposed vacancies. For a one standard deviation increase in establishment-level AI exposure, vacancy postings for high-exposure occupations declined by a little less than 20% and they increased for low-exposure occupations by over 20% (Figure A A.1). Every country in the sample had results consistent with the averages, and in nine out of 10 countries, results were statistically significant. The magnitudes are large, however, and should be interpreted with caution.[33] More important are the sign and significance of the results, which are robust.[34]

Finally, AI exposure also correlates with increased establishment-level demand for vacancies demanding AI skills which speaks to the relevance of AI exposure as an instrument. Vacancies demanding AI skills have been excluded from the preceding analysis consistent with the goals of this report. However, this report uses AI exposure as a proxy for AI adoption, and one should therefore expect demand for workers with AI skills to be positively correlated with actual AI adoption. The association between AI exposure and posting vacancies for AI skills, therefore, is a good check for the validity of the AI exposure measure as an instrument. Figure 4.7 depicts the estimates for the association of AI exposure with posting vacancies demanding AI skills. On average across countries, the association is positive.

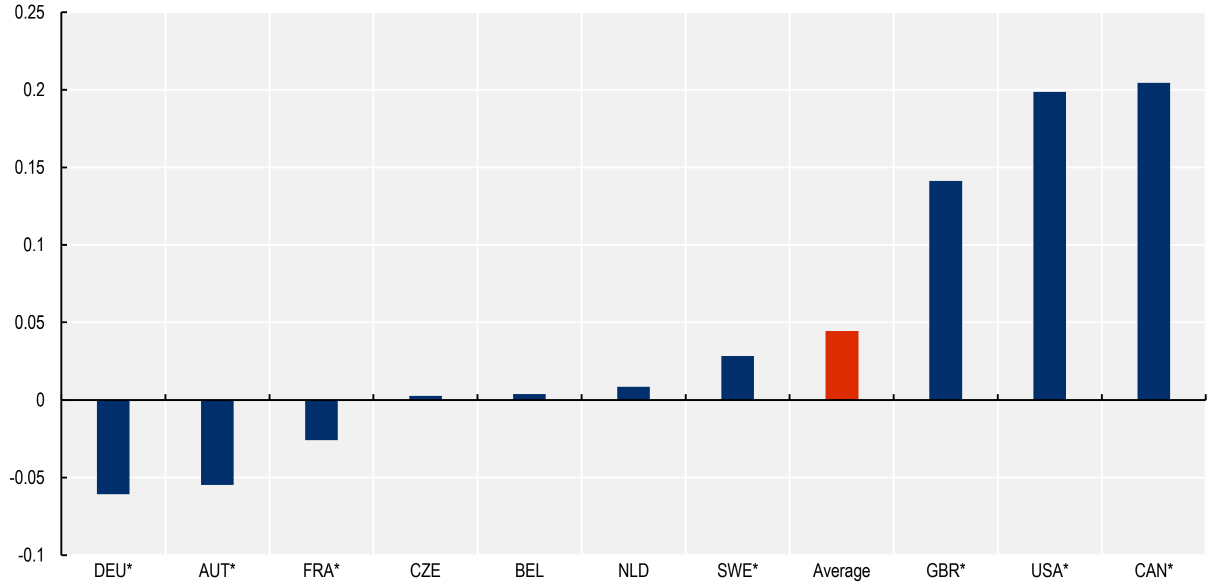
[32] There are other subtle differences including the inclusion of the Information sector which is dropped from Acemoglu et al. (2022[6]).

[33] Despite its popularity in the economics literature, recent research indicates that differences in the inverse hyperbolic sine function are not scale invariant, and can there produce artificially large estimates (Chen and Roth, 2023[43]).

[34] Due to the limitations of the inverse hyperbolic sine (IHS) function as a measure of relative change, this report ran the same specifications using the difference in vacancies for high-exposure (low-exposure) vacancies divided by the geometric mean of all vacancies in the same establishment in the base and end years. This measure, long used in the calculation of establishment-level labour market and enterprise statistics (Davis and Haltiwanger, 1992[45]), is bound by -2 and 2, symmetric, and always defined at zero in this empirical design (base year vacancy posting must be strictly positive to be included in the sample). The results show attenuated magnitudes compared to IHS differences as these results implicitly scale the changes by overall establishment size changes, but the signs of the coefficients and country-level patterns hold. See also Törnqvist, Vartia and Vartia (1985[44]).

Figure 4.7. Establishments more exposed to AI hire more workers with AI skills

Regression coefficients of AI exposure regressed on the change in share of vacancies demanding AI skills, by country



Note: This figure plots the regression coefficient of establishment AI exposure (β) on the percentage change in the number of vacancies demanding AI skills by country. They are interpreted as the percentage change in the number of vacancies demanding AI skills in an establishment 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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure from Felten, Raj and Seamans (2021[3]) weighted by the establishment's base year occupation shares.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]).

The positive association between AI exposure and posting vacancies demanding AI skills is consistent with the existing literature, and strongest among countries with a high incidence of vacancies demanding AI skills. Just as with overall vacancy posting, the parameter estimate for the United States matches the positive sign found in Acemoglu et al. (2022[6]), although in the most similar specification, the parameter estimate in this report is about double what they report. The estimates in Figure 4.7 contain sizeable cross-country heterogeneity, but it is notable that in countries with the highest incidence of vacancies demanding AI skills (Figure 2.2), the association is strongly positive and significant. The simplest explanation for this is that where there is enough power to detect the association between demand for AI skills and AI exposure, the estimates are positive and statistically significant.[35]

[35] Another potential explanation rests on the observation that the countries with the strongest positive results also have relatively weak employment protection legislation (EPL). In these countries, increasing AI exposure is more likely to be accompanied by hiring workers with AI skills (as opposed to contracting for these tasks) because establishments can more easily let these workers go if initial experiments with AI do not lead to substantial productivity gains. This would be consistent with current theories of AI adoption – see Brynjolfsson, Rock and Syverson (2021[46]).

References

Acemoglu, D. et al. (2022), “Artificial Intelligence and Jobs: Evidence from Online Vacancies”, *Journal of Labor Economics*, Vol. 40/S1, pp. S293-S340, https://doi.org/10.1086/718327. [6]

Acemoglu, D. and P. Restrepo (2018), “The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment”, *American Economic Review*, Vol. 108/6, pp. 1488-1542, https://doi.org/10.1257/aer.20160696. [33]

Alekseeva, L. et al. (2021), “The demand for AI skills in the labor market”, *Labour Economics*, Vol. 71, p. 102002, https://doi.org/10.1016/j.labeco.2021.102002. [12]

Araki, S. et al. (2022), “Monopsony and concentration in the labour market”, in *OECD Employment Outlook 2022: Building Back More Inclusive Labour Markets*, OECD Publishing, Paris, https://doi.org/10.1787/0ecab874-en. [23]

Bassanini, A., A. Garnero and A. Puymoyen (forthcoming), *OECD Employment Outlook 2024. Draft Chapter 2: The jobs that will make the net-zero transition: who holds them and are they good?*, OECD Publishing. [25]

Borgonovi, F. et al. (2023), “Emerging trends in AI skill demand across 14 OECD countries”, *OECD Artificial Intelligence Papers*, No. 2, OECD Publishing, Paris, https://doi.org/10.1787/7c691b9a-en. [21]

Borusyak, K., P. Hull and X. Jaravel (2024), “Design-based identification with formula instruments: A review”, *The Econometrics Journal*, https://doi.org/10.1093/ectj/utae003. [42]

Briggs, J. and D. Kodnani (2023), *The Potentially Large Effects of Artificial Intelligence on Economic Growth*, Goldman Sachs Economics Research. [16]

Brynjolfsson, E., D. Li and L. Raymond (2023), *Generative AI at Work*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w31161. [9]

Brynjolfsson, E., T. Mitchell and D. Rock (2018), “What Can Machines Learn and What Does It Mean for Occupations and the Economy?”, *AEA Papers and Proceedings*, Vol. 108, pp. 43-47, https://doi.org/10.1257/pandp.20181019. [34]

Brynjolfsson, E., D. Rock and C. Syverson (2021), “The Productivity J-Curve: How Intangibles Complement General Purpose Technologies”, *American Economic Journal: Macroeconomics*, Vol. 13/1, pp. 333-372, https://doi.org/10.1257/mac.20180386. [46]

Calvino, F. and L. Fontanelli (2023), “A portrait of AI adopters across countries: Firm characteristics, assets’ complementarities and productivity”, *OECD Science, Technology and Industry Working Papers*, No. 2023/02, OECD Publishing, Paris, https://doi.org/10.1787/0fb79bb9-en. [38]

Calvino, F. et al. (2022), “Identifying and characterising AI adopters: A novel approach based on big data”, *OECD Science, Technology and Industry Working Papers*, No. 2022/06, OECD Publishing, Paris, https://doi.org/10.1787/154981d7-en. [14]

Cammeraat, E. and M. Squicciarini (2021), "Burning Glass Technologies' data use in policy-relevant analysis: An occupation-level assessment", *OECD Science, Technology and Industry Working Papers*, No. 2021/05, OECD Publishing, Paris, https://doi.org/10.1787/cd75c3e7-en. [22]

Carnevale, A., T. Jayasundera and D. Repnikov (2014), *Understanding Online Job Ads Data: A Technical Report*, Georgetown University, Center on Education and the Workforce, https://cew.georgetown.edu/wp-content/uploads/2014/11/OCLM.Tech_.Web_.pdf. [24]

Chen, J. and J. Roth (2023), "Logs with Zeros? Some Problems and Solutions", *The Quarterly Journal of Economics*, https://doi.org/10.1093/qje/qjad054. [43]

Davis, S. and J. Haltiwanger (1992), "Gross Job Creation, Gross Job Destruction, and Employment Reallocation", *The Quarterly Journal of Economics*, Vol. 107/3, pp. 819-863, https://doi.org/10.2307/2118365. [45]

Deming, D. (2021), *The Growing Importance of Decision-Making on the Job*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w28733. [37]

Deming, D. (2017), "The Growing Importance of Social Skills in the Labor Market*", *The Quarterly Journal of Economics*, Vol. 132/4, pp. 1593-1640, https://doi.org/10.1093/qje/qjx022. [47]

Deming, D. and L. Kahn (2018), "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals", *Journal of Labor Economics*, Vol. 36/S1, pp. S337-S369, https://doi.org/10.1086/694106. [11]

Eloundou, T. et al. (2023), "GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models". [17]

Felten, E., M. Raj and R. Seamans (2023), "How will Language Modelers like ChatGPT Affect Occupations and Industries?", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4375268. [18]

Felten, E., M. Raj and R. Seamans (2021), "Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses", *Strategic Management Journal*, Vol. 42/12, pp. 2195-2217, https://doi.org/10.1002/smj.3286. [3]

Georgieff, A. and R. Hyee (2021), "Artificial intelligence and employment : New cross-country evidence", *OECD Social, Employment and Migration Working Papers*, No. 265, OECD Publishing, Paris, https://doi.org/10.1787/c2c1d276-en. [36]

Girotra, K. et al. (2023), "Ideas are Dimes a Dozen: Large Language Models for Idea Generation in Innovation", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4526071. [31]

Goldsmith-Pinkham, P., I. Sorkin and H. Swift (2020), "Bartik Instruments: What, When, Why, and How", *American Economic Review*, Vol. 110/8, pp. 2586-2624, https://doi.org/10.1257/aer.20181047. [41]

Green, A. (2023), "Artificial intelligence and jobs: No signs of slowing labour demand (yet)", in *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris, https://doi.org/10.1787/9c86de40-en. [5]

Green, A. and L. Lamby (2023), “The supply, demand and characteristics of the AI workforce across OECD countries”, *OECD Social, Employment and Migration Working Papers*, No. 287, OECD Publishing, Paris, https://doi.org/10.1787/bb17314a-en. [2]

Green, A., A. Salvi del Pero and A. Verhagen (2023), “Artificial intelligence, job quality and inclusiveness”, in *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris, https://doi.org/10.1787/99c4c123-en. [29]

Hershbein, B. and L. Kahn (2018), “Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings”, *American Economic Review*, Vol. 108/7, pp. 1737-1772, https://doi.org/10.1257/aer.20161570. [10]

Krueger, D. (ed.) (2021), “Quasi-Experimental Shift-Share Research Designs”, *The Review of Economic Studies*, Vol. 89/1, pp. 181-213, https://doi.org/10.1093/restud/rdab030. [4]

Lassébie, J. et al. (2021), “Speaking the same language: A machine learning approach to classify skills in Burning Glass Technologies data”, *OECD Social, Employment and Migration Working Papers*, No. 263, OECD Publishing, Paris, https://doi.org/10.1787/adb03746-en. [26]

Ludwig, J. and S. Mullainathan (2024), “Machine Learning as a Tool for Hypothesis Generation”, *The Quarterly Journal of Economics*, https://doi.org/10.1093/qje/qjad055. [32]

Manca, F. (2023), “Six questions about the demand for artificial intelligence skills in labour markets”, *OECD Social, Employment and Migration Working Papers*, No. 286, OECD Publishing, Paris, https://doi.org/10.1787/ac1bebf0-en. [15]

McCaffrey, T. and L. Spector (2017), “An approach to human–machine collaboration in innovation”, *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, Vol. 32/1, pp. 1-15, https://doi.org/10.1017/s0890060416000524. [30]

Milanez, A. (2023), “The impact of AI on the workplace: Evidence from OECD case studies of AI implementation”, *OECD Social, Employment and Migration Working Papers*, No. 289, OECD Publishing, Paris, https://doi.org/10.1787/2247ce58-en. [1]

Modestino, A., D. Shoag and J. Ballance (2016), “Downskilling: changes in employer skill requirements over the business cycle”, *Labour Economics*, Vol. 41, pp. 333-347, https://doi.org/10.1016/j.labeco.2016.05.010. [20]

Noy, S. and W. Zhang (2023), “Experimental evidence on the productivity effects of generative artificial intelligence”, *Science*, Vol. 381/6654, pp. 187-192, https://doi.org/10.1126/science.adh2586. [8]

OECD (2022), *OECD Territorial grids*, https://www.oecd.org/cfe/regionaldevelopment/territorial-grid.pdf. [27]

OECD (2021), “Navigating skill demands in turbulent times”, in *OECD Skills Outlook 2021: Learning for Life*, OECD Publishing, Paris, https://doi.org/10.1787/01a857c7-en. [39]

OECD (2015), *Skills for Social Progress: The Power of Social and Emotional Skills*, OECD Skills Studies, OECD Publishing, Paris, https://doi.org/10.1787/9789264226159-en. [28]

Peng, S. et al. (2023), “The Impact of AI on Developer Productivity: Evidence from GitHub Copilot”, https://arxiv.org/abs/2302.06590v1. [7]

Pizzinelli, C. et al. (2023), “Labor Market Exposure to AI: Cross-country Differences and Distributional Implications”, *IMF Working Paper Series*, No. 2023/216, International Monetary Fund, Washington, D.C., https://www.imf.org/en/Publications/WP/Issues/2023/10/04/Labor-Market-Exposure-to-AI-Cross-country-Differences-and-Distributional-Implications-539656. [19]

Rubin, D. (1987), *Multiple Imputation for Nonresponse in Surveys*, Wiley, https://doi.org/10.1002/9780470316696. [40]

Squicciarini, M. and H. Nachtigall (2021), “Demand for AI skills in jobs: Evidence from online job postings”, *OECD Science, Technology and Industry Working Papers*, No. 2021/03, OECD Publishing, Paris, https://doi.org/10.1787/3ed32d94-en. [13]

Törnqvist, L., P. Vartia and Y. Vartia (1985), “How Should Relative Changes be Measured?”, *The American Statistician*, Vol. 39/1, pp. 43-46, https://doi.org/10.1080/00031305.1985.10479385. [44]

Webb, M. (2020), “The Impact of Artificial Intelligence on the Labor Market”, Stanford University, https://www.michaelwebb.co/webb_ai.pdf. [35]

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

Skill	Overall			High-exposure			Low-exposure		
	Base	End	Change	Base	End	Change	Base	End	Change
Arts and Humanities	1.2%	1.3%	0.12%	1.6%	1.8%	0.21%	0.6%	0.8%	0.22%
Attitudes	50.3%	57.9%	7.55%	54.7%	62.8%	8.04%	42.5%	51.0%	8.41%
Business Processes	52.0%	55.2%	3.25%	61.8%	67.3%	5.50%	15.5%	19.3%	3.79%
Cognitive Skills	36.1%	43.1%	7.01%	45.2%	52.8%	7.55%	14.3%	23.7%	9.37%
Communication	24.9%	25.9%	0.96%	29.0%	31.3%	2.29%	10.3%	9.0%	-1.30%
Digital	38.7%	44.5%	5.77%	49.9%	57.5%	7.64%	9.7%	18.4%	8.69%
Industry Specific Knowledge	5.3%	4.1%	-1.19%	4.7%	4.0%	-0.76%	2.5%	1.9%	-0.58%
Languages	29.5%	35.5%	6.08%	33.0%	40.6%	7.67%	19.6%	22.5%	2.83%
Law and Public Safety	4.1%	5.6%	1.52%	4.7%	6.9%	2.22%	3.4%	3.3%	-0.06%
Medicine	10.3%	12.9%	2.59%	7.7%	10.5%	2.89%	5.9%	6.9%	0.96%
Physical Skills	13.3%	16.0%	2.70%	7.1%	8.9%	1.81%	19.7%	22.4%	2.68%
Production and Technology	35.5%	40.3%	4.80%	29.8%	35.1%	5.33%	49.9%	51.0%	1.13%
Resource Management	54.6%	58.1%	3.42%	66.6%	71.7%	5.04%	20.2%	24.0%	3.83%
Science	6.6%	8.6%	2.02%	5.3%	7.8%	2.45%	5.5%	7.0%	1.48%
Social Skills	48.6%	52.8%	4.26%	52.5%	59.1%	6.51%	37.1%	38.8%	1.72%
Training and Education	4.5%	4.5%	-0.01%	4.1%	4.1%	-0.02%	2.1%	1.5%	-0.58%

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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. All shares reflect unweighted averages across countries. 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[3]). 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[26]) for the United States, Canada and the United Kingdom. European OECD countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26])

Table A A.2. Share of vacancies demanding at least one skill from each major grouping in establishment sample

Skill	Overall			High-exposure			Low-exposure		
	Base	End	Change	Base	End	Change	Base	End	Change
Arts and Humanities	1.1%	1.2%	0.1%	1.7%	1.6%	0.0%	0.5%	0.6%	0.2%
Attitudes	43.6%	51.3%	7.6%	50.3%	57.2%	6.9%	34.1%	43.5%	9.4%
Business Processes	41.3%	46.5%	5.2%	56.6%	62.3%	5.7%	14.6%	19.4%	4.8%
Cognitive Skills	29.7%	37.7%	8.0%	43.3%	50.8%	7.5%	11.6%	20.1%	8.6%
Communication	21.4%	22.0%	0.6%	28.1%	29.6%	1.6%	10.0%	8.8%	-1.3%
Digital	29.2%	36.6%	7.5%	46.6%	53.6%	7.0%	8.7%	16.1%	7.4%
Industry Specific Knowledge	4.8%	3.3%	-1.6%	4.5%	2.9%	-1.7%	3.5%	2.0%	-1.6%
Languages	22.8%	29.7%	6.9%	29.1%	36.6%	7.5%	12.7%	17.5%	4.8%
Law and Public Safety	3.8%	5.4%	1.5%	4.8%	7.0%	2.2%	2.7%	3.3%	0.6%
Medicine	9.1%	11.8%	2.7%	8.1%	11.0%	2.9%	4.7%	6.5%	1.8%
Physical Skills	10.0%	12.7%	2.7%	6.9%	8.4%	1.5%	15.1%	19.1%	4.1%
Production and Technology	28.9%	35.5%	6.5%	28.9%	34.5%	5.6%	35.1%	41.0%	5.9%
Resource Management	45.5%	50.1%	4.6%	63.1%	68.0%	4.9%	17.2%	22.6%	5.4%
Science	5.6%	8.0%	2.4%	5.7%	8.4%	2.7%	3.9%	5.8%	1.9%
Social Skills	43.1%	48.9%	5.8%	49.6%	56.9%	7.3%	30.3%	35.7%	5.4%
Training and Education	4.1%	4.4%	0.3%	4.2%	4.7%	0.4%	1.6%	1.6%	0.0%

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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. All shares reflect unweighted averages across countries. 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[3]). 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[26]) for the United States, Canada and the United Kingdom. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

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

Skill	AUT	BEL	CAN	CZE	DEU	FRA	GBR	NLD	SWE	USA
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

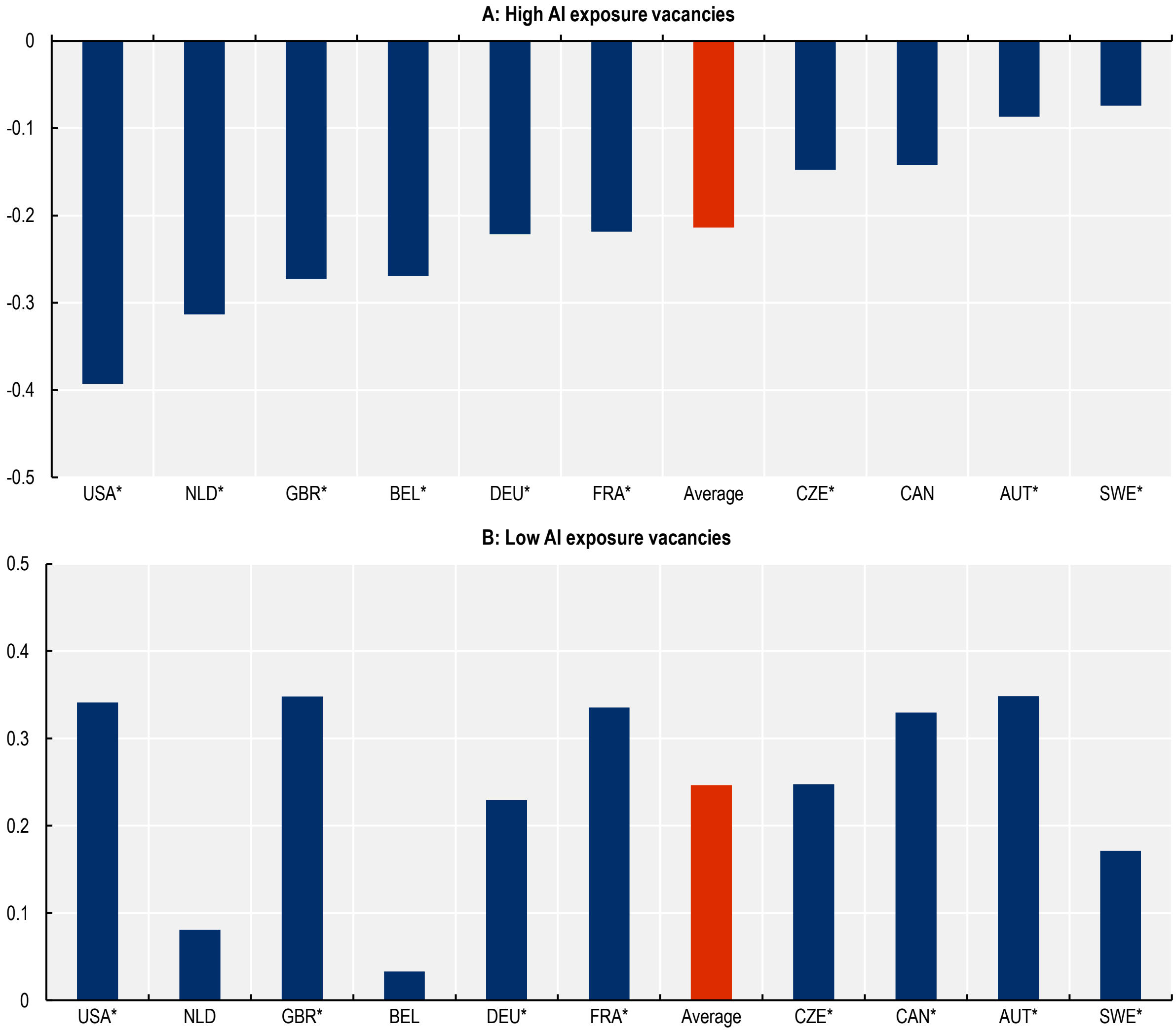
Note: Numbers in the table are regression coefficients on establishment-level AI exposure and they are interpreted as the percentage point change in the share of vacancies demanding at least one skill from the grouping between the base and end years for a one standard deviation increase in establishment-level 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 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure in an establishment from Felten, Raj and Seamans (2021[3]) 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[26]) for the United States, Canada and the United Kingdom. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

Table A A.4. Average of country regression coefficients for the percentage point change in demand for skill groupings and establishment-level AI exposure, by skill grouping and occupational exposure

Skill	Overall		High-exposure		Low-exposure	
	Coef.	Country count	Coef.	Country count	Coef.	Country count
Arts and Humanities	-0.001	5	-0.001	3	0.00	0
Attitudes	-0.015	7	-0.032	7	0.02	5
Business Processes	-0.035	9	-0.035	10	0.01	4
Cognitive Skills	-0.032	7	-0.030	9	-0.01	3
Communication	-0.008	7	-0.015	8	0.01	3
Digital	-0.032	9	-0.028	8	0.00	3
Industry Specific Knowledge	0.001	3	-0.001	1	0.00	4
Languages	-0.005	6	-0.013	6	0.01	5
Law and Public Safety	0.002	4	0.000	2	0.00	4
Medicine	0.002	4	-0.001	5	0.01	6
Physical Skills	0.003	2	-0.005	5	0.01	6
Production and Technology	0.006	3	-0.011	5	0.02	8
Resource Management	-0.035	10	-0.040	10	0.01	4
Science	0.003	4	0.001	4	0.00	1
Social Skills	-0.008	4	-0.026	6	0.02	6
Training and Education	0.000	2	-0.001	5	0.00	4

Note: Coef. denotes the cross-country unweighted average of 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. Overall corresponds to the share of all vacancies in an establishment while high-exposure and low-exposure correspond to the change in shares among high-exposure and low-exposure occupations only. Country count gives the number of countries whose i) regression coefficients are the same sign as cross-country average and ii) whose regression coefficicents are significant at the 95% confidence level. All regressions run separately for each skill grouping, country and dependent variable (overall, high-exposure, low-exposure), and include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Base years are 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure in an establishment from Felten, Raj and Seamans (2021[3]) weighted by the establishment's base year occupation shares. High-exposure occupations have an exposure measure at least one standard deviation greater than the mean, and low-exposure occupations have an exposure at most one standard deviation less than the mean. Skill groups are defined by mapping Lightcast skills to the ONET+ taxonomy of Lassébie et al. (2021[26]) for the United States, Canada and the United Kingdom. European countries mapped using crosswalk from ESCO to ONET+.
Source: OECD analysis of Lightcast data, Felten, Raj and Seamans (2021[3]) and Lassébie et al. (2021[26]).

Figure A A.1. Regression coefficients of the effect of AI exposure on the percentage change in vacancy demand for high and low-exposure occupations, respectively



Note: Bars denote the regression coefficients on establishment-level AI exposure and they are interpreted as the percentage change in the number of high-exposure (low-exposure, respectively) vacancies between the base and end years for a one standard deviation increase in establishment-level AI exposure. High-exposure (low-exposure) vacancies are defined as vacancies whose corresponding occupation's AI exposure measure is one standard deviation greater (lower) than the mean. All regressions run separately for high- and low-exposure and country. All specifications include TL2 region, industry and establishment size fixed effects. Standard errors are clustered at the employer level. Base years are 2012-2013 for Canada, the United Kingdom and the United States, and 2018-2019 for Austria, Belgium, Czechia, France, Germany the Netherlands and Sweden. The end years are 2021-2022. Establishment-level AI exposure is the average occupational AI-exposure in an establishment from Felten, Raj and Seamans (2021[3]) weighted by the establishment's base year occupation shares.
Source: OECD analysis of Lightcast data and Felten, Raj and Seamans (2021[3]).

Annex B. Details of Naive Bayes classifier for classifying vacancies

This report classifies vacancies demanding AI skills using a Naive Bayes (NB) classifier trained separately on each country in the sample. The standard approach to classifying AI vacancies in Lightcast data is to use a pre-defined list of skills or keywords that signal a vacancy demanding AI skills, for example: "machine learning" or "natural language" processing. If a vacancy contains any skills on the list, it is classified as demanding AI skills. This approach has its advantages, but it assumes that lists of skills will be applicable across countries, and it requires constant review and judgement to update the list to the fast-evolving world of AI development. The NB classifier, which is a generalisation of the list-based approach, departs in two important ways. First, rather than using a set list of skills, the NB classifier used in this report produces a parsimonious list of skills for each country using a data-driven approach. Second, rather than classifying vacancies by whether they contain any skill on the list, the NB classifier used in this analysis uses all skills on the list and their associated probabilities to classify a vacancy. In practice, this means that the lists contain more general skills, but vacancies, in general, require three or four skills from the list to be classified as demanding AI skills. See Annex B in Green and Lamby (2023[2]) for a detailed discussion of the connection between the NB classifier and list-based approaches to classification.

The results of the NB classifier used in this report accord well with list-based approaches to classifying vacancies with AI skills. Figure A B.1 gives the overall share of vacancies classified as requiring AI skills pooling years 2021 and 2022 by country. Borgonovi et al. (2023[21]) produce the most similar analysis of the share of vacancies demanding AI skills by OECD country. The authors use a list-based approach for classifying AI vacancies. Although the sets of countries do not completely overlap, the two approaches accord well. That analysis, like the one presented here, have the United States, Canada and the United Kingdom as the three countries with the highest share of vacancies demanding AI skills. The level of the shares is quite similar as well. Both reports also find that Belgium, France and Austria have some of the lowest shares among the countries that overlap in the two analyses. The rest of this section details the procedure for how the NB classifier was applied in this report.

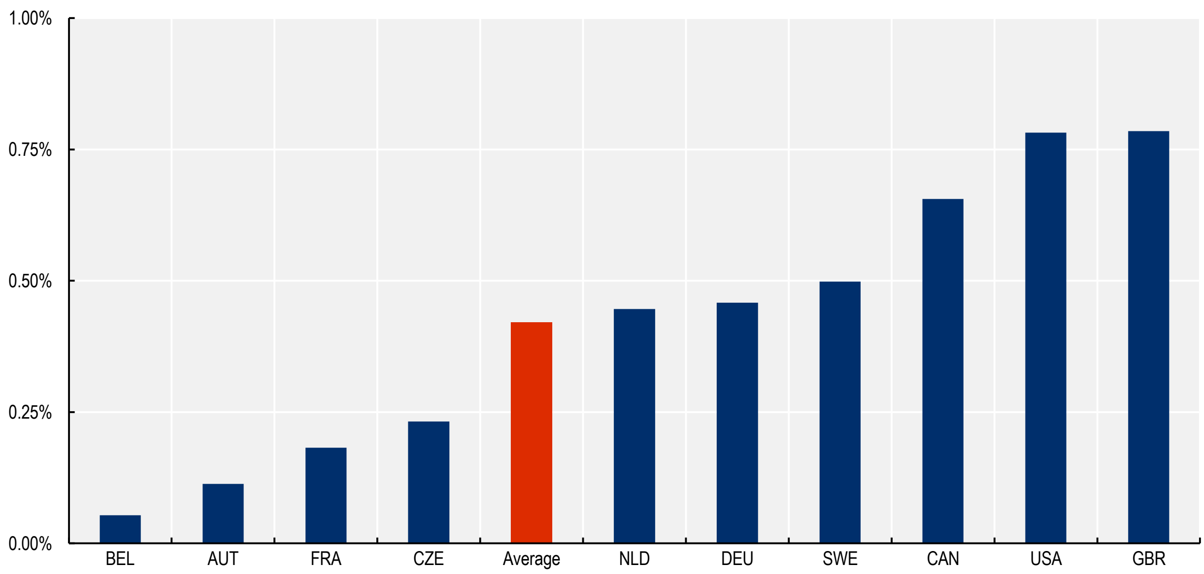
Procedure for classifying vacancies demanding AI skills using a Naive Bayes classifier

1. **Training samples and designating the truth set**. The first step entails generating two random samples (A and B) of vacancies for each country. One sample is used to train the model, and the second sample is used to assess the results. The same is then done after flipping the samples; the sample that was first used to test or assess is now the training sample, and the sample used to train is now used to assess. This produces a primitive "2-fold" cross validation set-up. In each of the two samples, the vacancies are further partitioned into those vacancies that demand the skill "machine learning" and those that do not. The vacancies that demand the skill machine learning are by assumption vacancies that demand AI skills. These two groups form the basis for fitting the probabilities for skills that enter the classifier.
2. **Model fit**. In both samples, one computes the probability that each skill appears in the set of vacancies demanding AI skills (those demanding the skill "machine learning"), and those vacancies

that do not, respectively. These are the probabilities that enter the NB classifier and it is akin to modelling demanded skills using a Bernoulli model. There are over 10,000 skills in the database for the United States alone, and modelling the presence or absence of each one would be both unwieldly and inefficient. To reduce the dimensionality, the model additionally uses average mutual information to rank skills based on their importance for classifying vacancies as demanding AI skills. See Green and Lamby (2023[2]) for model details.

3. **Model assessment**. The final model is chosen by using the probabilities calculated on one sample to classify vacancies in the other sample. This is done for hundreds of models where the models differ on the number of skills included. The skills are successively added according to their average mutual information until a maximum is found. Model performance is assessed by calculating the F1 score. The F1 score is the harmonic mean of precision, which is the share of correctly classified vacancies divided by vacancies classified as demanding AI skills (those demanding "machine learning"), and recall, which is the share of correctly classified vacancies divided by all vacancies that should have been classified as demanding AI skills. There is an inherent tension between precision and recall, and the F1 score finds the set of skills that maximises the combination of the two. For all countries in the sample, the F1 score is maximised with less than eight skills in each country.
4. **Final classification**. The model parameters where the F1 score is maximised (estimated probabilities and skills to be used) from the two samples do not always accord, and some analyst discretion is necessary to reconcile the right mix of skills to use in the classifier. Once that is determined, the probabilities estimated in the two samples are averaged to get the final probabilities. The last step is to run the NB classifier with the chosen number of skills and the averaged probabilities on the entire data. Vacancies which are determined to have a higher probability of demanding AI skills than not are classified as demanding AI skills. In addition, any vacancy that demands "machine learning" regardless of how it was classified is considered to demand AI skills.

Figure A B.1. The share of vacancies demanding AI skills by country, 2021-2022



Note: Share is defined as the share of vacancies demanding AI skills. Average is an unweighted cross-country average. 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.

Annex C. 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 C.1). This is slightly more skills than reported in the working paper (17,331) from Lassébie et al. (2021[26]), 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, on average, 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 C.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
Languages	Foreign Languages
Law and Public Safety	Law and government
Law and Public Safety	Public Safety and Security
Medicine	Medicine and Dentistry

Broad Category	Category label
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 B.1) in Lassébie et al. (2021[26]). 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[26]).