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WHO WILL BE THE WORKERS MOST AFFECTED BY AI?

A CLOSER LOOK AT THE IMPACT OF AI ON WOMEN, LOW-SKILLED WORKERS AND OTHER GROUPS

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Who will be the workers most affected by AI?: A closer look at the impact of AI on women, low-skilled workers and other groups

Marguerita Lane

This paper examines how different socio-demographic groups experience AI at work. As AI can automate non-routine, cognitive tasks, tertiary-educated workers in "white-collar" occupations will likely face disruption, even if empirical analysis does not suggest that overall employment levels have fallen due to AI, even in "white-collar" occupations. The main risk for those without tertiary education, female and older workers is that they lose out due to lower access to AI-related employment opportunities and to productivity-enhancing AI tools in the workplace. By identifying the main risks and opportunities associated with different socio-demographic groups, the ultimate aim is to allow policy makers to target supports and to capture the benefits of AI (increased productivity and economic growth) without increasing inequalities and societal resistance to technological progress.

Keywords: Artificial Intelligence, Inequality, Employment, Gender, Education.

JEL Codes: J16, J21, J23, J24, O33.

Résumé

Cette étude explore la façon dont l'AI a pu impacter différents groupes socio-démographiques. L'IA permettant d'automatiser des tâches cognitives, non routinières, il est probable que cette technologie affecte en premier lieu les travailleurs les plus qualifiés, notamment ceux dotés d'un diplôme de l'enseignement supérieur et occupant des fonctions de cadre, les « cols blancs ». Néanmoins, l'étude suggère que l'IA n'a globalement pas réduit l'emploi, y compris celui des « cols blancs ». L'IA pourrait en revanche avoir un effet négatif sur certaines catégories de travailleurs ; les personnes non diplômées de l'enseignement supérieur, les femmes, et les travailleurs plus âgés. Pour ces groupes, l'accès aux opportunités d'emploi liées à l'IA est plus limité. Ils sont également moins susceptibles d'utiliser les applications développées à partir d'IA, permettant d'accroitre la productivité du travail. En identifiant les principaux risques et les principales opportunités que l'IA peut engendrer pour différents groupes socio-démographiques, cette étude a pour objectif d'aider à mieux cibler les politiques à mettre en place, afin de tirer le meilleur parti de l'IA (augmentation de la productivité et de la croissance économique) sans accroître les inégalités, ni la résistance de la société au progrès technologique.

Abstract

In dieser Studie geht es um die Frage, wie verschiedene soziodemografische Gruppen künstliche Intelligenz (KI) am Arbeitsplatz erleben. KI erlaubt die Automatisierung nichtroutinemäßiger kognitiver Tätigkeiten, sodass Arbeitskräfte mit Tertiärabschluss in nichtmanuellen Berufen wahrscheinlich mit tiefgreifenden Umwälzungen rechnen müssen. Die empirischen Befunde deuten bisher aber nicht darauf hin, dass es zu einem KI-bedingten Rückgang der Gesamtbeschäftigung gekommen ist, auch nicht in diesen Berufen. Für Arbeitskräfte ohne tertiären Bildungsabschluss sowie für Frauen und ältere Arbeitskräfte besteht das Hauptrisiko darin, dass ihnen durch geringere Chancen auf Jobs mit KI-Bezug und durch begrenzten Zugang zu produktivitätssteigernden KI-Tools am Arbeitsplatz Nachteile entstehen. Die Studie beschreibt die wichtigsten Chancen und Risiken der KI für verschiedene soziodemografische Gruppen. Damit soll sie Politikverantwortlichen helfen, Fördermaßnahmen zielgenau auszurichten, sodass die positiven Effekte von KI (Produktivitätssteigerung und Wirtschaftswachstum) zum Tragen kommen und weder Ungleichheiten noch gesellschaftliche Widerstände gegen technische Fortschritte verstärkt werden.

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Executive summary

AI has made most progress in automating non-routine, cognitive tasks. Many of the occupations most exposed to AI (including the latest developments in generative AI) are therefore “white-collar” occupations typically requiring several years of formal training and/or tertiary education, e.g. IT professionals, managers, and science and engineering professionals. Occupations which rely on manual skills and strength, such as cleaners, labourers and food preparation assistants, tend to have low AI exposure.

As a result, education is an important determinant of AI exposure. Occupations highly exposed to AI not only have a large proportion of highly educated workers, but education also mediates the relation between AI exposure and other socio-demographic characteristics. Native-born and prime-age workers can be considered among the groups most exposed to AI, partly because they tend to be in occupations with higher educational attainment. Female and male workers face roughly the same occupational exposure to AI overall.

Occupations with the highest exposure to AI will be most impacted by AI and could face the most disruption. While AI advances are emerging in fast succession, analysis of historical data does not suggest that AI exposure has led to negative employment or wage outcomes on aggregate so far. Some studies even suggest that AI exposure has been linked to positive outcomes and that these links have been stronger among more educated and higher-income workers, potentially deepening existing inequalities.

New analysis reinforces the idea that there was a positive relationship between AI exposure and employment in the period from 2012 to 2022. It shows that:

- Both female and male employment are positively related with AI exposure, when controlling for other technological advances, offshorability and international trade as well as for trends at occupation and country levels. Women’s employment growth was even higher than men’s in occupations highly exposed to AI, which can be interpreted as a continuation of the trend of declining occupational gender segregation, i.e. women’s entry into traditionally male-dominated occupations and vice versa. Examples of occupations highly exposed to AI in which female employment has grown include chief executives (32% to 39% female between 2012 and 2022) and science and engineering professionals (31% to 35%).
- The relation between AI exposure and employment growth for prime-age workers and for native-born workers is also positive, suggesting that employment of these groups has either grown more or reduced less in occupations more exposed to AI (countering trends observed in the working population on the whole).
- There is little to suggest that, so far, exposure to AI has led to different outcomes for different demographic groups in terms of usual working hours or wage growth.

Some groups have greater access to opportunities associated with AI, which could prevent the benefits of AI from being broadly and fairly shared. Male workers with a university degree are overrepresented in both the *AI workforce* (the narrow set of workers with the skills to develop and maintain AI systems) and among *AI users* (workers who interact with AI at work). Consequently, women and lower-educated workers could have less access to AI-related employment opportunities and to productivity-enhancing AI tools in the workplace. At the same time, if used correctly, some features of AI could open up new opportunities for traditionally underrepresented groups.

Interviews with workers on the topic of AI reveal the hopes, expectations and worries of different groups. Male, university-educated and foreign-born workers tend to have more positive perceptions of AI, according to an international survey of workers undertaken in early 2022 in the manufacturing and finance sectors. These groups were more likely to say that AI had improved their productivity and working conditions, that AI would increase their wages in the future, and that they were enthusiastic to learn more about AI. The same groups (along with younger workers) were also more likely to agree that technology had an overall positive impact on society. Despite this, university-educated workers were more likely to say that they were worried about job loss due to AI in the following 10 years (primarily because this group were more likely to be AI users). Foreign-born workers and younger workers were also more worried about job loss due to AI in the following 10 years and more worried that data collection would lead to decisions biased against them.

Case study interviews conducted in parallel suggest that young and older workers are facing different risks. Older workers face preconceived and potentially even prejudicial notions regarding their ability and willingness to engage with new technologies. On the other hand, their tenure and seniority may afford them greater protection from job loss than younger workers.

Table: Synthesis of the main risks and opportunities pertaining to each socio-demographic group

Worker group	Main risks	Main opportunities
Tertiary-educated	High AI exposure means this group will be most impacted by AI, which could mean disruption. Fears of job instability.	If AI exposure continues to be linked to positive employment outcomes, this group could benefit the most.
Without tertiary education	Less access to AI-related employment opportunities and to productivity-enhancing AI tools in the workplace.	Potential for AI to open up new opportunities for traditionally underrepresented groups.
Male	Higher risk of automation generally, i.e. not AI-specific.	Optimism, confidence and positive perceptions about AI.
Female	Less access to AI-related employment opportunities and productivity-enhancing AI tools at work.	Stronger positive link between AI exposure and employment growth. Entry into male-dominated professions highly exposed to AI.
Young	Fear of job instability and biased decision-making.	Positive perceptions regarding impact of technology on society.
Prime age	High AI exposure means this group will be most impacted by AI, which could mean massive disruption.	Positive link between AI exposure and employment growth.
Older	Less access to AI-related employment opportunities and productivity-enhancing AI tools at work. Preconceived notions regarding ability and willingness to engage.	Tenure and seniority may afford protection.
Native born	High AI exposure means this group will be most impacted by AI, which could mean massive disruption.	Positive link between AI exposure and employment growth.
Foreign born	Fear of job instability and biased decision-making.	Optimism, confidence and positive perceptions about AI.

The synthesis of main risks and opportunities may allow policy makers to think about how to target different supports as to capture the benefits of AI (increased productivity and economic growth) without increasing inequalities and societal resistance to technological progress. For instance, programmes aimed at upskilling and empowering workers to use AI may be best targeted to those without tertiary education, to women and to older workers. Even if AI exposure has traditionally been associated with positive employment outcomes, some tertiary-educated workers will require support to overcome disruption and allow them to transition to new jobs. Policy makers will want to ensure that AI is used in a trustworthy manner, that it is not being used to perpetuate historical patterns of disadvantage, and that the benefits from AI are broadly and fairly shared.

Synthèse

Les avancées les plus notables de l'IA ont été réalisées dans le domaine de l'automatisation de tâches cognitives, non routinières. Nombre des professions les plus exposées à l'IA (y compris à l'IA générative dont le développement est très récent) sont celles occupées par les « cols blanc », cadres ou cadres supérieurs ayant effectué des études longues, tels que les informaticiens, les ingénieurs, ou les managers. Les professions comportant pour l'essentiel des tâches manuelles ou physiques, telles que les employés dans les services de nettoyage, de la restauration, ou les ouvriers agricoles, sont en général peu exposées à l'IA.

Le niveau d'étude est par conséquent un déterminant important du degré d'exposition à l'IA. Non seulement les professions les plus exposées regroupent une proportion importante de travailleurs très qualifiés, mais l'éducation a également une influence marquée sur le lien entre exposition à l'IA et d'autres caractéristiques socio-démographiques. Les personnes d'âge très actif, et celles travaillant dans leurs pays d'origine, sont en général plus exposées à l'IA, notamment parce qu'elles exercent des professions requérant un niveau d'étude élevé. Les travailleurs féminins et masculins sont à peu près exposés de la même manière à l'IA en général.

Les professions les plus exposées à l'IA seront plus impactées, et pourraient être sujettes à de profondes transformations. Toutefois, bien que les avancées dans le domaine de l'IA se succèdent à un rythme élevé, l'analyse des données historiques suggèrent que, globalement, l'exposition à l'IA n'a pas eu jusqu'à présent d'impact négatif sur l'emploi ni les salaires. Certaines études avancent même que l'exposition à l'IA aurait eu des effets positifs, notamment pour les personnes les plus qualifiées et/ou se situant en haut de l'échelle des revenus, ce qui aurait potentiellement renforcé les inégalités existantes.

Une nouvelle étude tend à confirmer qu'au cours de la période 2012-22, il a eu une relation positive entre exposition à l'IA et emploi. Cette étude montre que :

- À la fois l'emploi des femmes et des hommes est positivement relié à l'exposition à l'IA, y compris lorsque l'on tient compte des autres avancées technologiques, des délocalisations et des échanges internationaux, ainsi que d'autres tendances au niveau des professions et des pays. La croissance de l'emploi des femmes a même été plus forte que celle observée pour les hommes au sein des professions les plus exposées à l'IA. Ce résultat peut être interprété comme s'inscrivant dans la continuité d'une tendance à la baisse de la segmentation entre homme et femmes en termes de professions exercées, les femmes accédant de plus en plus à des métiers où les hommes étaient traditionnellement surreprésentés, et vice versa. Parmi les professions les plus exposées à l'IA et pour lesquelles la proportion de femmes a augmenté, on peut par exemple citer les postes de directrices générales (32% à 39% entre 2012 et 2022) ou d'ingénieures (31% à 35%).
- Il existe également un lien positif entre l'exposition à l'IA et la croissance de l'emploi des personnes d'âge très actif et des travailleurs natifs, suggérant que l'emploi de ces deux groupes a augmenté, ou moins baissé, au sein des professions les plus exposées à l'IA (à l'inverse des tendances observées pour l'ensemble de la population active).
- Aucun résultat concluant ne permet à ce jour de savoir si l'IA a eu un effet différent selon les groupes socio-démographiques en termes heures habituelles de travail ou de croissance des salaires.

Certains groupes ont plus facilement accès aux opportunités que l'IA peut offrir, ce qui pourrait faire obstacle à une distribution large et équitable des bénéfices associés à l'IA. Les hommes diplômés de l'enseignement supérieur sont surreprésentés à la fois au sein des *métiers de l'IA* (l'ensemble restreint de métiers requérant des compétences pour développer et assurer la maintenance des systèmes d'IA) et au sein des *utilisateurs de l'IA* (les travailleurs qui interagissent avec l'IA dans le cadre de leur travail). De ce fait, les femmes et les travailleurs moins diplômés ont un accès plus limité aux opportunités d'emplois offertes par l'IA, ainsi qu'aux applications de l'IA qui permettent des gains de productivité. Néanmoins, à conditions d'être utilisée correctement, l'IA peut dans certains cas offrir de nouvelles opportunités à des groupes traditionnellement sous-représentés.

Des entretiens conduits auprès de différents travailleurs au sujet de l'IA révèlent les espoirs, les attentes, et les inquiétudes des différents groupes. Selon une enquête internationale menée en 2022 dans le secteur manufacturier et celui de la finance, les hommes, les diplômés de l'enseignement supérieur, et les personnes nées à l'étranger, tendent à avoir une perception plus positive de l'IA. Ces groupes répondaient plus souvent que l'IA avait augmenté leur productivité et amélioré leurs conditions de travail, que l'IA pourrait à l'avenir conduire à une hausse de leur salaire et qu'ils étaient enthousiastes à l'idée d'en apprendre davantage sur l'IA. Ces groupes (mais aussi les jeunes) étaient également plus enclins à répondre que la technologie avait un impact globalement positif sur la société. Néanmoins, les diplômés de l'enseignement supérieurs se montraient plus inquiets quant au risque de perdre leur emploi au cours des 10 ans à venir (essentiellement parce qu'ils étaient le plus souvent utilisateurs de l'IA). Cette inquiétude étaient partagées par les travailleurs nés à l'étranger et les jeunes, qui parallèlement étaient plus nombreux à exprimer une inquiétude quant au fait que les données collectées pourraient conduire à des décisions biaisées prizes à leur encontre.

Des études de cas conduites en parallèle suggèrent que les jeunes et les seniors faisaient face à des risques différents. Les travailleurs plus âgés ont une vision préconçue, voire potentiellement préjudiciable, de leur aptitude et de leur désir de se confronter à une nouvelle technologie. Mais par rapport aux jeunes, leur expérience et leur ancienneté pouvaient, potentiellement, mieux les protéger contre le risque de perdre leur emploi.

Tableau : Synthèse des principaux risques et bénéfices, selon le groupe socio-démographique

Groupe	Principaux risques	Principales opportunités
Diplômés de l'enseignent supérieur (ES)	Niveau élevé d'exposition à l'IA : impact le plus important, qui pourrait conduire à de profondes transformations. Craintes en termes de sécurité de l'emploi.	Si l'IA continue à être associée à des effets positifs sur l'emploi, ce groupe en bénéficiera le plus.
Non diplômés de l'ES	Moindre accès aux emplois liés à l'IA, et aux applications de l'IA permettant d'augmenter la productivité du travail.	Possibilité que l'IA crée de nouvelles opportunités pour les groupes traditionnellement sous-représentés.
Hommes	Risque d'automatisation plus élevé, non spécifique à l'IA.	Optimisme, confiance, et perception positive de l'IA.
Femmes	Moindre accès aux emplois liés à l'IA, et aux applications de l'IA permettant d'augmenter la productivité du travail.	Lien positif plus fort entre exposition à l'IA et croissance de l'emploi. Entrée au sein de professions fortement exposées à l'IA et où les hommes sont surreprésentés.
Jeunes	Craintes en termes de sécurité de l'emploi et de biais dans le processus de décision.	Perception positive de l'impact de la technologie sur la société.
Age très actif	Niveau élevé d'exposition à l'IA : impact le plus important, qui pourrait conduire à de profondes transformations.	Lien positif entre exposition à l'IA et croissance de l'emploi.
Plus âgés	Moindre accès aux emplois liés à l'IA, et aux applications de l'IA permettant d'augmenter la productivité du travail. Visions préconçues de leur capacité et désir de s'investir.	Expérience et ancienneté pourrait offrir une protection.
Natifs	Niveau élevé d'exposition à l'IA : impact le plus important, qui pourrait conduire à de profondes transformations.	Lien positif entre exposition à l'IA et croissance de l'emploi.
Nés à l'étranger	Craintes en termes de sécurité de l'emploi et de biais dans le processus de décision.	Optimisme, confiance, et perception positive de l'IA.

Cette synthèse des principaux risques et des principales opportunités peut aider à mieux cibler les politiques à mettre en place, afin de tirer le meilleur parti de l'IA (augmentation de la productivité et de la croissance économique) sans accroître les inégalités, ni la résistance de la société au progrès technologique. Par exemple, les programmes destinés à former et à permettre aux travailleurs de se saisir de l'IA, devraient en premier lieu cibler les personnes n'ayant pas suivi d'études supérieures, les femmes, et les travailleurs plus âgés. Même si l'exposition à l'IA a plutôt été associée à des effets positif sur l'emploi, certains travailleurs diplômés de l'enseignement supérieur devront être accompagnés pour faire face aux transformations majeures auxquelles ils seront confrontés et pour effectuer une transition vers un nouvel emploi. Les autorités devront s'assurer que l'IA est utilisée convenablement, de manière responsable, et non d'une façon qui perpétue les clivages historiques, afin de veiller à ce que les bénéfices apportés par l'IA soient équitablement partagés, le plus largement possible.

Zusammenfassung

KI hat vor allem bei der Automatisierung nichtroutinemäßiger kognitiver Aufgaben große Fortschritte gemacht. Nicht zuletzt aufgrund der neuesten Entwicklungen im Bereich generative KI weisen deshalb vor allem viele nichtmanuelle Berufe, die in der Regel eine mehrjährige formale Ausbildung und/oder einen Tertiärabschluss erfordern, ein besonders hohes KI-Potenzial auf. Zu diesen Berufen zählen z. B. IT-Fachkraft, Führungskraft, Naturwissenschaftler*in oder Ingenieur*in. Dass KI in Berufen wie Reinigungskraft, Hilfsarbeiter*in oder Hilfskraft in der Nahrungsmittelzubereitung zum Einsatz kommt, ist demgegenüber deutlich weniger wahrscheinlich, da es bei diesen Tätigkeiten vor allem auf manuelle Kompetenzen und Körperkraft ankommt.

Daraus ergibt sich ein deutlicher Zusammenhang zwischen KI-Potenzial und Bildungsniveau: In Berufen, die sich gut für den KI-Einsatz eignen, arbeiten vergleichsweise viele Hochqualifizierte. Über die Bildung lassen sich zudem Zusammenhänge zwischen dem KI-Potenzial und weiteren soziodemografischen Merkmalen ableiten. Im Inland Geborene und Personen im Haupterwerbsalter gehören zu den Gruppen, die am Arbeitsplatz mit besonders hoher Wahrscheinlichkeit mit KI in Berührung kommen, was z. T. daran liegt, dass sie häufig in Berufen tätig sind, die ein höheres Bildungsniveau voraussetzen. Frauen haben ungefähr in gleichem Maße beruflich mit KI zu tun wie Männer.

In den Berufen mit dem höchsten KI-Potenzial werden die Auswirkungen der KI am stärksten sein. Hier könnte mit tiefgreifenden Umwälzungen zu rechnen sein. Zwar kommt es im KI-Bereich ständig zu neuen Entwicklungen, Analysen historischer Daten lassen jedoch nicht darauf schließen, dass ein hohes KI-Potenzial zu negativen Beschäftigungs- oder Lohnergebnissen führt. Vielmehr enthalten einige Studien sogar Hinweise auf positive Zusammenhänge, die zudem unter Arbeitskräften mit höherem Bildungsniveau und Einkommen deutlicher ausgeprägt sind und die bestehende Ungleichheiten verstärken könnten.

Neue Analysen liefern weitere Indizien für einen positiven Zusammenhang zwischen KI-Potenzial und Beschäftigung im Zeitraum 2012-22. Sie zeigen Folgendes:

- Werden andere technologische Fortschritte, Offshoring, der internationale Handel sowie Trends auf Branchen- und nationaler Ebene herausgerechnet, besteht für Männer wie Frauen ein positiver Zusammenhang zwischen KI-Potenzial und Beschäftigung. In Berufen mit hohem KI-Potenzial war das Beschäftigungswachstum unter den Frauen sogar höher, was möglicherweise ein Indiz dafür ist, dass die berufliche Geschlechtersegregation weiter abnimmt: Frauen wie Männer drängen weiter in klassische Domänen des jeweils anderen Geschlechts vor. Zu den Berufen mit hohem KI-Potenzial und steigendem Frauenanteil zählen beispielsweise Geschäftsführer*in (Anstieg des Frauenanteils zwischen 2012 und 2022 von 32% auf 39%) sowie Naturwissenschaftler*in und Ingenieur*in (Anstieg von 31% auf 35%).
- Der Zusammenhang zwischen KI-Potenzial und Beschäftigungswachstum ist bei Personen im Haupterwerbsalter und bei im Inland Geborenen ebenfalls positiv: Die Beschäftigung dieser Gruppen in Berufen mit höherem KI-Potenzial ist (entgegen den Gesamttrends in der Erwerbsbevölkerung) vergleichsweise stark gestiegen bzw. wenig gesunken.
- Was die Regelarbeitszeiten und das Lohnwachstum betrifft, deutet bislang wenig darauf hin, dass sich das KI-Potenzial auf verschiedene soziodemografische Gruppen unterschiedlich ausgewirkt hat.

Manche Gruppen haben besseren Zugang als andere zu den mit KI verbundenen Möglichkeiten, was einer breiten und gerechten Verteilung der Vorteile von KI entgegenstehen könnte. Männliche Arbeitskräfte mit Hochschulabschluss sind in der kleinen Gruppe der *KI-Fachkräfte*, die KI-Systeme entwickeln und pflegen können, ebenso überrepräsentiert wie unter den *KI-Nutzer*innen*, die am Arbeitsplatz mit KI interagieren. Dementsprechend könnten Frauen und Arbeitskräfte mit niedrigerem Bildungsniveau geringere Chancen auf Jobs mit KI-Bezug und weniger Zugang zu produktivitätssteigernden KI-Tools am Arbeitsplatz haben. Gleichzeitig bietet KI technische Möglichkeiten, die bislang unterrepräsentierten Gruppen neue Chancen eröffnen könnten, wenn sie richtig eingesetzt werden.

Interviews mit Beschäftigten zum Thema KI geben Aufschluss über die Hoffnungen, Erwartungen und Sorgen verschiedener Gruppen. Im Allgemeinen haben Männer, Personen mit Hochschulabschluss und im Ausland Geborene eine positivere Sichtweise auf KI, wie aus einer Anfang 2022 im Verarbeitenden Gewerbe und im Finanzsektor durchgeführten internationalen Befragung hervorgeht. Angehörige dieser Gruppen äußerten häufiger, dass KI ihre Produktivität und ihre Arbeitsbedingungen verbessert habe und sich positiv auf ihr Lohnniveau auswirken werde, außerdem zeigten sie mehr Lernbegeisterung in Bezug auf KI. Ebenso wie die Gruppe der jüngeren Beschäftigten waren sie zudem vergleichsweise häufig der Meinung, dass sich Technologien insgesamt positiv auf die Gesellschaft auswirken. Allerdings gingen Arbeitskräfte mit Hochschulabschluss auch häufiger davon aus, dass sie sich in den kommenden zehn Jahren wegen KI Sorgen um ihren Arbeitsplatz machen müssen (wobei dies vor allem damit zu tun hat, dass es sich bei dieser Gruppe mit höherer Wahrscheinlichkeit um KI-Nutzer*innen handelt). Auch bei im Ausland geborenen Beschäftigten und jüngeren Arbeitskräften waren diese Bedenken vergleichsweise stark ausgeprägt, ebenso wie die Befürchtung, dass Datenerfassung zu verzerrten und für sie nachteiligen Entscheidungen führen könnte.

Gleichzeitig lieferten im Rahmen von Fallstudien durchgeführte Interviews Hinweise darauf, dass sich jüngere und ältere Beschäftigte nicht denselben Risiken gegenübersehen. Ältere Arbeitskräfte sind in Bezug auf ihre Fähigkeit und Bereitschaft, sich mit neuen Technologien auseinanderzusetzen, Vorurteilen ausgesetzt, die negative Konsequenzen haben könnten. Andererseits sind sie aufgrund langer Betriebszugehörigkeiten u. U. besser vor einem Arbeitsplatzverlust geschützt als jüngere Arbeitskräfte.

Tabelle: Überblick über die Hauptrisiken und -chancen für die verschiedenen soziodemografischen Gruppen

Gruppe	Hauptrisiken	Hauptchancen
Mit Tertiärabschluss	Besonders starke Auswirkungen der KI und möglicherweise tiefgreifende Umwälzungen wegen hohen KI-Potenzials. Angst vor beruflicher Instabilität.	Bleibt der Zusammenhang zwischen KI-Potenzial und Beschäftigung positiv, könnte diese Gruppe am stärksten profitieren.
Ohne Tertiärabschluss	Geringere Chancen auf Jobs mit KI-Bezug, eingeschränkter Zugang zu produktivitätssteigernden KI-Tools am Arbeitsplatz.	Möglicherweise neue Chancen für unterrepräsentierte Gruppen durch KI.
Männer	Generell höheres Automatisierungsrisiko, nicht nur durch KI.	Optimistische, vertrauensvolle und positive Wahrnehmung von KI.
Frauen	Geringere Chancen auf Jobs mit KI-Bezug, eingeschränkter Zugang zu produktivitätssteigernden KI-Tools am Arbeitsplatz.	Stärkerer positiver Zusammenhang zwischen KI-Potenzial und Beschäftigungswachstum. Zugang zu Männerdomänen mit hohem KI-Potenzial.
Junge Menschen	Angst vor beruflicher Instabilität und verzerrten Entscheidungsprozessen.	Positive Wahrnehmung der gesellschaftlichen Auswirkungen von Technologien.
Menschen im Haupterwerbsalter	Besonders starke Auswirkungen der KI und möglicherweise besonders tiefgreifende Umwälzungen wegen hohen KI-Potenzials.	Positiver Zusammenhang zwischen KI-Potenzial und Beschäftigungswachstum.
Ältere Menschen	Geringere Chancen auf Jobs mit KI-Bezug, eingeschränkter Zugang zu produktivitätssteigernden KI-Tools am Arbeitsplatz. Vorurteile hinsichtlich der Fähigkeiten und Offenheit dieser Gruppe im Umgang mit KI.	Möglicherweise durch lange Betriebszugehörigkeit geschützt.

Gruppe	Hauptrisiken	Hauptchancen
Im Inland Geborene	Besonders starke Auswirkungen der KI und möglicherweise besonders tiefgreifende Umwälzungen wegen hohen KI-Potenzials.	Positiver Zusammenhang zwischen KI-Potenzial und Beschäftigungswachstum.
Im Ausland Geborene	Angst vor beruflicher Instabilität und verzerrten Entscheidungsprozessen.	Optimistische, vertrauensvolle und positive Wahrnehmung von KI.

Dieser Überblick über die wichtigsten Chancen und Risiken kann Politikverantwortlichen helfen abzuwägen, wie verschiedene Förderinstrumente ausgerichtet werden müssen, damit die positiven Effekte von KI (Produktivität und Wirtschaftswachstum) zum Tragen kommen und weder Ungleichheiten noch gesellschaftliche Widerstände gegen technische Fortschritte verstärkt werden. Qualifizierungsprogramme und andere Bildungsmaßnahmen zur Erleichterung der Nutzung von KI könnten sich beispielweise besonders für Personen ohne Tertiärabschluss, Frauen und ältere Arbeitskräfte eignen. Auch Arbeitskräfte mit Tertiärabschluss werden teilweise Unterstützung benötigen, denn obwohl bisher von einem positiven Zusammenhang zwischen KI-Potenzial und Beschäftigung ausgegangen wurde, stehen einige von ihnen möglicherweise vor tiefgreifenden Umwälzungen oder müssen in neue Berufe wechseln. Aufgabe der Politikverantwortlichen ist es zudem, sicherzustellen, dass KI vertrauenswürdig ist, dass ihr Einsatz nicht überkommene Muster der Benachteiligung verfestigt und dass ihre Vorteile breit und gerecht verteilt sind.

1 Introduction

Technological change does not affect all workers equally and there is no reason to believe that AI will differ. Some groups of workers will be at greater risk and will therefore need more support from governments in managing the transition. Additionally, different groups will face different risks and some groups will be more capable or better positioned to benefit from AI.

Chapter 2 identifies the socio-demographic groups (primarily by educational attainment, gender, age and country of birth) currently facing the greatest exposure to AI, based on the occupations they work in. Chapter 3 explores what exposure AI has traditionally meant for employment outcomes for different groups, based on trends observed over the last decade. Chapter 4 examines whether some groups have greater access to opportunities associated with AI while others face barriers. Chapter 5 discusses the hopes, expectations and worries of different socio-demographic groups in relation to AI.

By identifying the main risks and opportunities associated with different socio-demographic groups, the aim is to allow policy makers to target supports and to capture the benefits of AI (increased productivity and economic growth) without increasing inequalities and societal resistance to technological progress.

2 Which groups are most exposed to AI?

Main findings

- AI exposure refers to the overlap between the abilities required in an occupation and the technical abilities of AI. Since AI has recently experienced the most progress in non-routine, cognitive tasks, many of the occupations most exposed to AI, including the latest developments in generative AI, are white-collar occupations typically requiring several years of formal training and/or tertiary education, e.g. IT professionals, managers, and science and engineering professionals. Occupations which rely on manual skills and strength, such as cleaners, labourers and food preparation assistants tend to have low AI exposure.
- A natural consequence of this is that, of the socio-demographic characteristics considered in this paper, education is the most important determinant of AI exposure. Occupations highly exposed to AI not only have a large proportion of highly educated workers, but education also mediates the relation between AI exposure and other socio-demographic characteristics. Native-born and prime-age workers are among the groups most exposed to AI, partly because they tend to be in occupations with higher educational attainment. Female and male workers face roughly the same occupational exposure to AI overall.

This chapter starts by establishing the concept of AI exposure. Next, labour force survey data is used to identify the socio-demographic groups facing the greatest exposure to AI, based on the occupations and industries they work in.

What is meant by exposure to AI?

Measures of occupational AI exposure, such as the one used in this chapter (Felten, Raj and Seamans, 2021[1]) (described further in Box 2.1), typically try to assess the overlap between the abilities required in an occupation and the technical abilities of AI. In recent years, AI has experienced the most progress in non-routine, cognitive tasks, such as information ordering, memorisation and perceptual speed, often demanded in occupations that require several years of formal training and/or tertiary education (OECD, 2023[2]). Examples of occupations highly exposed to AI include IT professionals, managers, and science and engineering professionals. Occupations which rely on manual skills and strength, such as cleaners, labourers and food preparation assistants tend to have low AI exposure. This contrasts with previous technologies, that have traditionally automated routine tasks and displaced low- and medium-skilled workers (Autor, Levy and Murnane, 2003[3]).

There is nothing in the construction of these measures that allows researchers to predict whether an occupation with high AI exposure will be affected positively or negatively by AI. The AI exposure indicator reflects the potential for automation of tasks within an occupation by AI. However, automation of tasks within an occupation does not necessarily mean that jobs will disappear and wages will decline. Automation of tasks could result in productivity increases, of changes in the nature of work performed, and/or of greater interaction between workers and technology. In other words, occupations with the highest exposure to AI will be most impacted by AI but is unclear what form this impact will take. This is a question that can only be answered through empirical research such as that in Chapter 3.

The following analysis exploits differences in socio-demographic composition between occupations to comment on different groups' exposure to AI. Because the AI exposure measure is calculated at the occupational level, the analysis cannot capture differences in AI exposure within occupations or between sectors. For instance, it cannot distinguish between a young scientist in an entry-level role in a manufacturing plant and an older experienced research scientist in that same plant or occupation, even if the nature of their jobs (and their interaction with AI) could be quite different.

Box 2.1. About the AI exposure measure used in this analysis

The measure of AI exposure used in this chapter (Felten, Raj and Seamans, 2021[1]) was originally constructed to assess the extent to which different occupations rely on abilities in which AI has made progress between 2010 and 2015 (e.g. abstract strategy games, translation and image recognition). Computer-science PhD students mapped these abilities to the skill content of occupations in the O*NET database, which were then aggregated to produce an estimate of AI exposure at occupation level.

The measure was updated in 2023 to reflect more recent developments in image generation (Felten, Raj and Seamans, 2023[4]), but the analysis in Chapter 3 uses the original measure for closer alignment of the time periods. The original measure is also used in this chapter for consistency. Notwithstanding the significant advances made in language modelling (for instance, with the release of ChatGPT in November 2022), it makes little practical difference to occupational exposure to update the measure for recent developments in language modelling, as the correlation between the updated measure and the original measure is 0.979.

This paper uses a similar approach as Georgieff and Hyee (2021[5]) in extending Felten et al.'s AI exposure measure to 22 OECD countries by linking it to the Survey of Adult Skills, PIAAC. This step allows the indicator to vary at country-occupation level (i.e. every ISCO 2-digit-level occupation in all 22 countries has a different AI exposure level). Matching the indicator to Labour Force Survey data permits analysis of the relationship with the socio-demographic profile of different occupations (and in Chapter 3, with historical employment outcomes).

Which groups are most exposed to AI?

The socio-demographic composition of the occupations most and least exposed to AI differs significantly (Table 2.1). The five most exposed occupations are dominated by tertiary-educated workers. Prime-age (aged 30 to 54) and native-born workers are also overrepresented in these occupations. While the five most exposed occupations tend to be male dominated (with the exception of business professionals), the five least exposed occupations are also considerably segregated by gender but display a more mixed pattern: women are overrepresented among cleaners and helpers, and men among labourers.

Table 2.1. Tertiary-educated, prime-age and native-born workers are overrepresented in the five occupations most exposed to AI (2022 data)

	Average AI exposure	% tertiary educated	% male	% prime age	% native-born
5 most exposed occupations					
Science, engineering professionals	0.84	87%	69%	67%	86%
Chief executives	0.85	72%	68%	62%	89%
Managers	0.86	76%	59%	73%	91%
Business professionals	0.87	82%	45%	69%	89%
IT technology professionals	0.88	79%	81%	70%	84%
5 least exposed occupations					
Cleaners, helpers	0.25	9%	18%	56%	66%
Agricultural forestry, fishery labourers	0.34	8%	65%	46%	82%
Food preparation assistants	0.39	7%	31%	47%	71%
Labourers	0.42	8%	72%	54%	79%
Refuse workers, other elementary workers	0.43	10%	72%	49%	83%
Average across all country-occupations	**0.65**	**37%**	**57%**	**60%**	**86%**

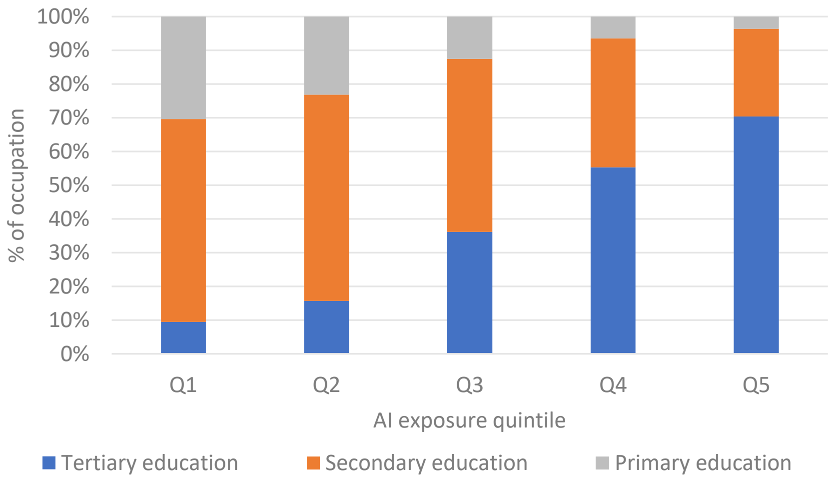
Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czech Republic (henceforth Czechia), Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, the Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States. Occupations are classified using two-digit ISCO-08.
Source: Author's calculations using 2022 data from the European Union Labour Force Survey (EU-LFS), the US Current Population Survey (US-CPS), and the United Kingdom Labour Force Survey (UK-LFS), and the AI exposure measure described in Box 2.1.

The analysis that follows examines these relations in more detail, covering the full set of occupations at ISCO 2-digit level and allowing for variation across countries in both exposure to AI and socio-demographic breakdown, i.e. the data is analysed at country-occupation level. All graphs in this section organise these country-occupations into quintiles according to AI exposure to aid interpretation.

Looking across the full set of country-occupation combinations, there is a strong positive relationship between AI exposure and workers' education level, as has been reported in (Felten, Raj and Seamans, 2023[6]) and Georgieff and Hyee (2021[5]). In other words, the greater an occupation's exposure to AI, the greater the proportion of tertiary-educated workers in the occupation. Figure 2.1 distributes country-occupations into quintiles according to AI exposure. It shows that tertiary-educated workers are a majority in the fourth and fifth quintiles of AI exposure. Tertiary-educated workers make up on average 70% of the workforce of the fifth quintile (typified by occupations such as business and IT technology professionals) compared to just 9% in the first quintile (typified by occupations such as food preparation assistants and cleaners and helpers).[1]

[1] Using regression analysis to control for other factors, such as age, gender, country of origin and country, suggests a positive but smaller relation between AI exposure and the proportion of a country-occupation's workforce with second-level education (relative to primary-level education).

Figure 2.1. There is a strong positive relation between AI exposure and workers' education level

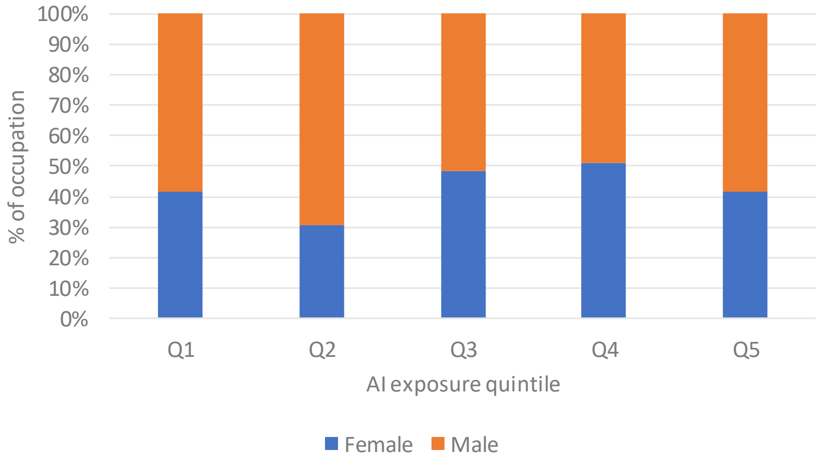


Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, the Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States.
Source: Author's calculations using 2022 data from EU-LFS, US-CPS and UK-LFS, and the AI exposure measure described in Box 2.1.

By comparison, the relation between AI exposure and gender is much weaker, with female and male workers facing roughly the same occupational exposure to AI overall (Figure 2.2). Looking at the underlying occupations provides some additional insight. Women account for just 40% of employment in the fifth quintile, containing the occupations most exposed to AI, which typically require tertiary education, e.g. IT technology professionals, chief executives and science and engineering professionals. The only quintile in which women constitute a majority (51%) is the fourth quintile, containing a range of occupations related to clerking, which do not typically require tertiary education, e.g. general, keyboard clerks, customer service clerks, and numerical recording clerks. The relevance of tertiary education is that some studies have shown that AI exposure is linked to more positive outcomes among more educated workers, as discussed in the next chapter.

Women constitute a minority in the two quintiles associated with the occupations least exposed to AI (and not typically requiring tertiary education), with the second quartile including occupations typically associated with trades (e.g. metal, machinery workers; drivers, mobile plant operators; building workers) and the first quintile comprised of occupations which rely heavily on manual skills and strength (such as labourers and refuse workers, other elementary workers). Many of the same occupations are at high risk of automation (if not highly exposed to AI), as explained at the end of this chapter.

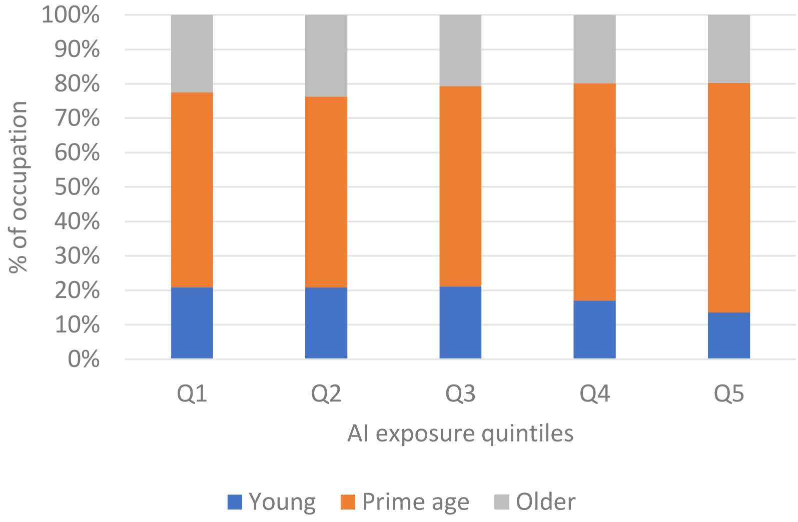
Figure 2.2. The relationship between AI exposure and gender is confounded by education level



Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, the Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States.
Source: Author's calculations using 2022 data from EU-LFS, US-CPS and UK-LFS, and the AI exposure measure described in Box 2.1.

The relationship between AI exposure and age depends heavily on education level (Figure 2.3). There is a positive association between AI exposure and the proportion of a workforce that is of prime age (i.e. aged 30 to 54). Regression analysis suggests that this association is mediated through education, since prime-age workers are more likely to have a tertiary education than younger or older workers. Controlling for education closes most of this gap. For instance, prime-age workers with tertiary education are strongly represented among "professionals" (e.g. science and engineering professionals, ICT professionals, and legal, social and cultural professionals) and "managers" (e.g. chief executives, senior officials and legislators), all highly exposed occupations.

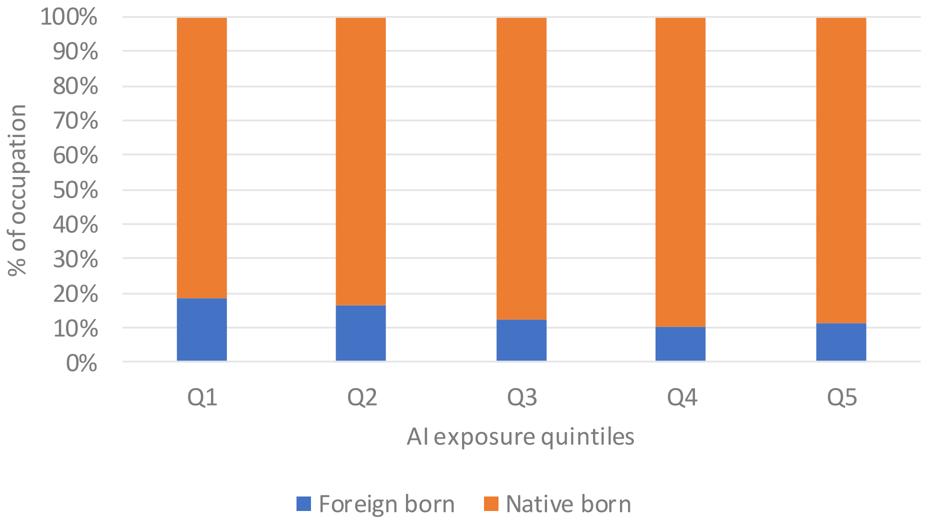
Figure 2.3. The relation between AI exposure and age depends heavily on education level



Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, the Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States.
Note: "Young" workers are those aged 15 to 29, "Prime-age" workers are those aged 30 to 54, while "Older" workers are those aged 55 to 69.
Source: Author's calculations using 2022 data from EU-LFS, US-CPS and UK-LFS, and the AI exposure measure described in Box 2.1.

AI exposure is negatively related to the proportion of an occupation's workforce that was born abroad (Figure 2.4). In other words, the greater a country-occupation's exposure to AI, the greater the proportion of native-born workers on average. Foreign-born workers constitute 19% on average of the workforce of country-occupations in the first quintile (i.e. the 20% of country-occupations with the lowest AI exposure) compared to approximately 10% of the fourth and fifth quintiles. For instance, the job of food preparation assistant, associated with low AI exposure, is characterised by a significant proportion of foreign-born workers in most countries. Regression analysis suggests that accounting for tertiary education halves the gap in AI exposure between foreign- and native-born workers. In other words, the negative relation is partly explained by the fact that occupations with more foreign-born workers tend to be those with fewer tertiary-educated workers.

Figure 2.4. AI exposure is negatively related to the proportion of an occupation's workforce that was born abroad



Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, the Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States.
Source: Author's calculations using 2022 data from EU-LFS, US-CPS and UK-LFS, and the AI exposure measure described in Box 2.1.

Which groups are most exposed to automation?

As noted previously, the set of occupations most exposed to AI are not the same occupations facing a high risk of automation (from all technologies).[2] Using the approach of Lassébie and Quintini (2022[7]), the three occupations[3] at highest risk of automation include: Fishing and Hunting Workers; Food Processing Workers; and Textile, Apparel, and Furnishings Workers. These occupations and other occupations considered at high risk of automation (i.e. in which over 25% of important skills and abilities are highly automatable) have on average a higher presence of male, non-university-educated, and foreign-born workers. More detail is provided in Annex A. Considering the distribution of different groups across different occupations, the picture across the workforce averaged across countries is as follows:

- 12% of male workers are in occupations at high risk of automation vs. 6% of female workers.
- 2% of university-educated workers are in occupations at high risk of automation vs. 12% of those with upper secondary level education and 22% of those with lower levels.
- 9% of young workers are in occupations at high risk of automation vs. 9% of prime-age workers and 10% of older workers.
- 12% of foreign-born workers are in occupations at high risk of automation vs. 8% of native-born workers.

[2] This is because AI exposure measures tend not to consider how improvements in AI can be applied to existing automation technologies, thereby accelerating automation. As Felten et al. (2021[1]) explain, their AI exposure measure "aim[s] to isolate the exposure to advances in AI (as opposed to, say, robotics, machine vision, autonomous guided vehicles, or other types of advanced technologies)". As such, this measure considers AI technologies as largely software-based and relying on iterative learning and perception.

[3] Occupations here are categorised at 3-digit level under the Standard Occupational Classification (SOC).

As might be expected. occupations at high risk of automation experienced much lower employment growth than occupations at low risk of automation over the period 2012 to 2019, as shown by Georgieff and Milanez (2021[8]). At the same time, *countries* with higher risk of automation did not experience lower employment growth over the period. In other words, automation may destroy jobs and reduce employment in certain occupations but may also contribute to employment growth at the overall economy level through increases in productivity. The next chapter takes a similar approach to examine how employment growth of different socio-demographic groups has changed in the occupations most exposed to AI.

3 What are the implications of high exposure to AI?

Main findings

- While AI advances are emerging in fast succession, the empirical literature to date provides little evidence of negative employment outcomes due to AI. Some studies even suggest that AI exposure has been linked to positive employment and wage outcomes, and that these links have been stronger among more educated and higher-income workers, potentially deepening existing inequalities. One study shows that the positive links between AI exposure and employment stability have been stronger for women than for men.
- New analysis reinforces the idea that there was a positive relationship between AI exposure and employment in the period from 2012 to 2022. It shows that:
    - Both female and male employment growth are positively related with AI exposure, but the relationship with female employment is stronger than the relationship with male employment. This difference may reflect declining gender segregation within traditionally male-dominated occupations that are highly exposed to AI, rather than proving definitively that AI has created opportunities more suited to women.
    - The relationship between AI exposure and employment growth for prime-age workers and for native-born workers is also positive, suggesting that employment of these groups has either grown more or reduced less in occupations more exposed to AI. While the working population in most occupations has become older and more likely to have been born abroad, these trends have been less pronounced in the occupations most exposed to AI.
    - There is little evidence to suggest that exposure to AI has led to different outcomes for different demographic groups in terms of hours worked (Georgieff and Hyee, 2021[5]) or wage growth (Georgieff, 2024[9]).

This chapter begins with a brief summary of the literature on how AI exposure has affected employment outcomes, with a particular focus on studies that explore the idea that there could be different outcomes for different demographic groups. Then, regression analysis is used to test this idea using data at country-occupation level on employment, wages and hours over the last decade or so. The aim is to understand what AI exposure means in terms of job prospects, based on trends observed over the last decade.

What does the literature say are the implications of AI exposure and do they differ by group?

The empirical literature to date provides little evidence of negative employment outcomes due to AI (OECD, 2023[2]), while some studies even find positive effects. A number of studies find no effect of AI exposure on aggregate employment (Georgieff and Hyee, 2021[5]; Acemoglu et al., 2022[10]; Felten, Raj and Seamans, 2019[11]). Fossen and Sorgner (2022[12]) find that exposure to AI is positively related to employment stability. Exposure to AI is found to be positively associated with wage growth by Felten, Raj and Seamans (2019[11]) and Fossen and Sorgner (2022[12]), but not by Acemoglu et al. (2022[10]).Another idea explored in the empirical literature is that certain socio-demographic groups would be better positioned to adapt to the changes that AI brings. If workers in highly exposed occupations, such as science and engineering professionals and chief executives, can successfully adapt to the reorganisation of tasks and the emergence of new tasks, weather potential job loss and navigate transitions to new jobs, they may ultimately benefit. Exposure to AI could provide these workers with the means to increase their productivity and gain access to new employment opportunities, as discussed in the next chapter. Fossen and Sorgner (2022[12]) argue that highly educated workers have a greater ability to learn new information and adapt to new technologies, and are more likely to possess skills which cannot be easily automated, such as creative and social intelligence, reasoning skills, and critical thinking. An additional factor could be that highly educated workers have greater bargaining power. For instance, even if some of their tasks can be automated by AI, their employer may choose to retain the individual and restructure the job, due to the scarcity of their skills and the expense of replacing them. If the process of adapting to AI overwhelmingly favours more educated workers and higher-income workers, then AI will deepen existing inequalities.

There is some evidence to support the idea that more educated and higher-income workers have better employment prospects when exposed to AI than other workers. Fossen and Sorgner (2022[12]) show that the positive links between AI exposure and employment stability (lower odds of transition into non-employment or occupational switching) and wage growth are strongest for more educated workers. Felten, Raj and Seamans (2019[11]) find a positive relationship between employment growth and AI exposure for higher-wage occupations only, occupations in which positive wage effects of AI adoption are larger also. Georgieff and Hyee (2021[5]) find that AI exposure increases employment growth only in occupations with the highest degree of computer use (which tend to be associated with higher education and income levels) and decreases working hours in occupations with the lowest degree of computer use.

Very few studies so far have looked at differences by other demographic factors, such as gender, age and country of birth. Fossen and Sorgner (2022[12]) show that positive employment stability effects of AI exposure are stronger for women than for men, but there is no difference in wage growth between the two genders. They find a positive effect of AI exposure on wage growth among workers aged under 50 only, suggesting that this benefit does not reach the oldest workers.

How have different groups' employment outcomes changed in occupations highly exposed to AI?

This section explores whether employment outcomes in occupations highly exposed to AI have evolved differently for different demographic groups over the last decade. This begins with commentary on general trends in the countries and occupations under consideration. Then regression analysis is used to establish the link between AI exposure and employment for different groups. The employment outcomes considered are employment level, usual working hours and wages, all intended as indicators of underlying labour demand. Positive links between AI exposure and these outcomes would suggest that the complementary and productivity-enhancing aspect of AI has outweighed its propensity to substitute and displace labour within occupations exposed to AI.

Empirical strategy

This analysis builds on the work of Georgieff and Hyee (2021[5]), which examines the links between AI exposure and employment growth over the period of 2012-19. It extends the analysis to the period 2012-22 and focuses on impact by socio-demographic group rather than aggregate impact. The model specification is the same with two modifications to the dependent variable.

$$Y_{ij} = \alpha_j + \beta\, AI_{ij} + \gamma\, X_{ij} + u_{ij}.$$

First, the dependent variable Yij is no longer the percentage change in the *overall* number of workers[4] in occupation i[5] in country j, but is instead split by socio-demographic group so that it represents the percentage change in the number of male workers in the country and occupation. In other words, what is being tested is whether there is the same link (as represented by coefficient β) between AI exposure and male employment as there is between AI exposure and female employment, to take the gender categories as an example. Second, the dependent variable is transformed into the log change in employment (and later, in average usual working hours) in order to normalise its distribution.[6] AI_{ij} is the Felten et al. AI exposure measure for occupation i in country j; X_{ij} is a vector of controls including exposure to other technological advances (software and industrial robots), offshorability, exposure to international trade, and 1-digit occupational ISCO dummies (occupation fixed effects); αj are country fixed effects; and u_{ij} is the error term.

General trends in employment between 2012 and 2022

Between 2012 and 2022,[7] employment grew in most of the occupations included in the analysis (as shown in Figure 3.1). Furthermore, this growth was stronger in occupations with higher exposure to AI. On average, a one standard deviation increase in AI exposure was associated with 11.3 percentage points higher employment growth.[8,9] The positive relationship between AI exposure and employment growth is consistent with the literature discussed in the previous section. The regression table is relegated to Annex B, since the primary focus of this paper is socio-demographic differences rather than aggregate trends.

4 Employment includes all people engaged in productive activities, whether as employees or self-employed. Employment data is taken from the European Union Labour Force Survey (EU-LFS) and the US Current Population Survey (US-CPS) and the United Kingdom Labour Force Survey (UK-LFS). For more detail about how the sample is built, see Georgieff and Hyee (2021[5]).

5 At the 2-digit level of the International Standard Classification of Occupations 2008 (ISCO-08).

6 For instance, the employment growth rates can reach extremely high values where a demographic group had a minimal presence in a country-occupation cell in 2012.

7 A break appears in the EU-LFS data in the first quarter of 2021 due to methodological changes in the way Eurostat collects and manages data as well as changes to the definition of employee, e.g. aligning age cut-offs at 89 for all countries and making the questionnaire more precise so that it accurately identifies people temporarily away from work, people in casual jobs, etc. (Eurostat, 2022[40]). Outcomes like employment level or change in employment would naturally be sensitive to such changes but Eurostat explains that it is not possible to make clear statements on the cumulative effect, i.e. that employment in a particular country would swing one way or another. Changes in composition could also affect outcomes like usual working hours. No adjustment is made in this analysis to correct for this break. Using different end years (2019, 2020, 2021) for the analysis involving change in aggregate employment suggests a steady increase in the magnitude of the estimated link with AI exposure over time, which could reflect a maturing and diffusing over time of the technology and its employment effect.

8 The standard deviation of exposure to AI is.176. Multiplying this by the coefficient in Annex B in Column 2 gives 0.176* 64.09= 11.299.

9 As in Georgieff and Hyee (2021[5]), two occupations (IT technology professionals and IT technicians) are removed from the analysis on the basis that employment growth in these occupations may stem from a surge in AI development, rather than the propensity for AI to complement or substitute labour when used in the workplace. As these two occupations are associated with high exposure to AI and high employment growth, including them in the analysis naturally suggests a stronger positive link between AI exposure and employment growth.

Figure 3.1. Employment growth between 2012 and 2022 was stronger in occupations with higher AI exposure

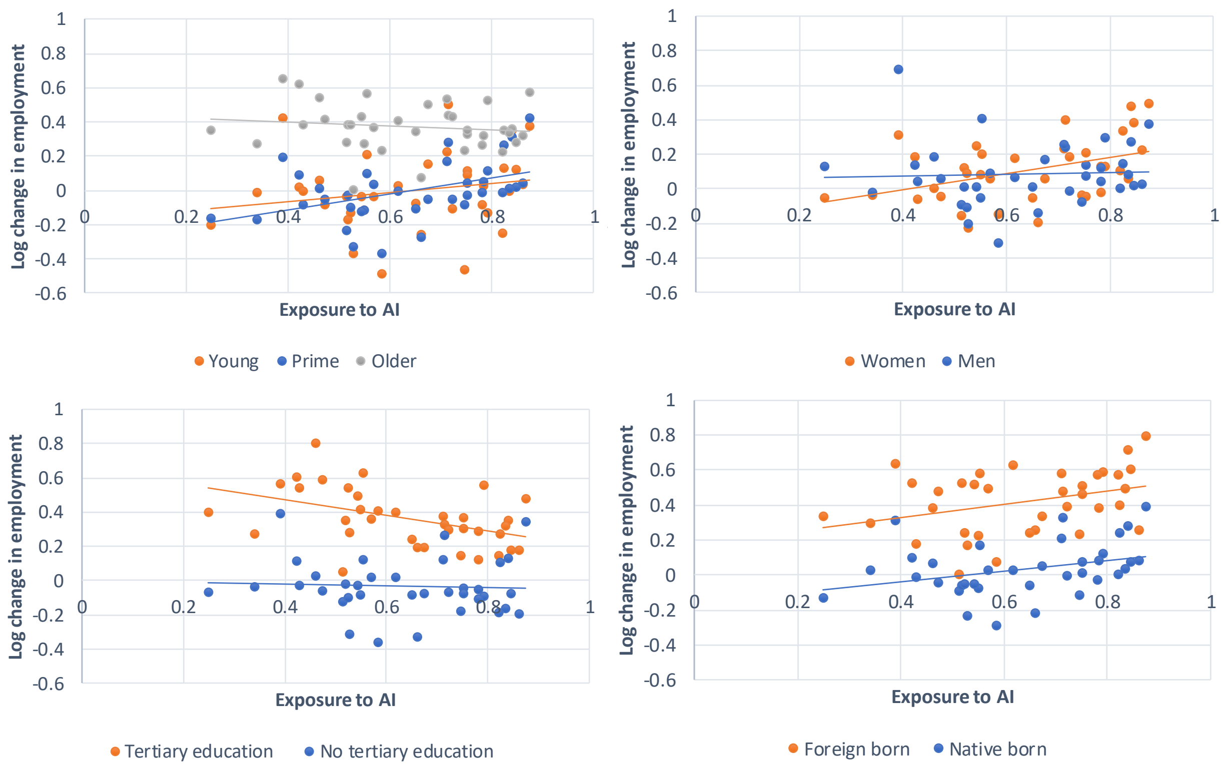
Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, The Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States. Occupations are classified using two-digit ISCO-08. As noted in footnote 9, IT technology professionals and IT technicians are excluded from the analysis that follows.
Source: Author's calculations using data from EU-LFS, US-CPS and UK-LFS.

How have different groups' employment levels changed in occupations highly exposed to AI?

In the period from 2012 to 2022, the working population in most occupations became older, more likely to have been born abroad, and more likely to have tertiary education. This can be observed in the distribution of the points in Figure 3.2 along the y-axis which represents the log change in employment of different socio-economic groups in this time period. Not only did these groups experience a greater increase in employment than their younger, native-born and lower educated counterparts, but in no occupation (averaged across countries) did these groups experience a decrease in employment. Gender trends were more mixed, with almost as many occupations experiencing a growth in female employment (among them, chief executives and electrical workers) as experiencing a growth in male employment (among them, food preparation workers and numerical clerks).

Employment growth among female workers, prime-age and young workers, and foreign-born and native-born workers alike, appears to have been higher in occupations more exposed to AI. This positive link is indicated by an upward sloping line in Figure 3.2. While these examples mirror the positive link between AI exposure and overall employment growth, there are some counterexamples: there appears to be no link between AI exposure and male employment growth, while lines even slope downward for older employment growth, and for employment growth for both workers with and without tertiary education. However, the regression analysis that follows will demonstrate that many of these counterexamples are driven by increases in employment in an occupation in which a group previously had low representation (e.g. increased representation of tertiary educated workers among food preparation assistants or refuse workers).[10] The graphs should therefore only be interpreted in association with the full set of regression results.

Figure 3.2. Since 2012, workers in most occupations have become older, more highly educated and more likely to have been born abroad



Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, The Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States. Occupations are classified using two-digit ISCO-08.
Source: Author's calculations using data from EU-LFS, US-CPS and UK-LFS.

Regression results

The first result to note is that for none of the groups listed in Table 3.1 is there a negative relation between AI exposure and log change in employment, once controls are added. For all groups, the relation is positive, as it is when the analysis is run over the full working population.

The controls are crucial to isolate the relationship between artificial intelligence and employment at country-occupation level from the effects of other technological advances, offshorability and international trade as well as from trends at broader ISCO 1-digit occupation levels. Without these controls, the coefficient on AI exposure for tertiary educated workers is negative and statistically significant, which aligns with the downward sloping line seen in previous graph and suggests that employment has decreased for the most educated workers in the occupations most exposed to AI. However, this is being driven primarily by strong employment growth in the "Plant and Machine Operators, and Assemblers" and "Elementary Occupations"

[10] Neither can the graphs take into account fixed effects according to country or occupation, nor the effects of technological advances, offshorability and exposure to international trade.

ISCO 1-digit categories among all workers regardless of education level. Once these broader occupational trends are accounted for, the signs become positive, if still not statistically significant at the 5% level.

With controls, both female and male log employment growth are positively related with AI exposure, but the relationship with female employment is much stronger than the relationship with male employment.[11] Examples of occupations highly exposed to AI in which female employment has grown include chief executives (in which female representation has increased from 25% to 32%) and science and engineering professionals (in which female representation has increased from 27% to 31%).

The relationship between AI exposure and log employment growth for prime-age workers and for native-born workers is also positive and significant when controls are included, suggesting that employment of these groups has either grown more or reduced less in occupations more exposed to AI. Even if the working population in most occupations has become older and more likely to have been born abroad, these trends appear to be less pronounced in the occupations most exposed to AI.

It is nevertheless very difficult to distinguish what is the gendered employment impact of AI and what is a continuation in the trend of declining occupational gender segregation, i.e. women's entry into traditionally male-dominated occupations and vice versa. In other words, do women constitute a higher proportion of chief executives in 2022 because AI has created more opportunities for women and/or been more complementary to women's skills, or is it a correction of previous decades' gender imbalances concentrated in the (generally highly paid, knowledge-intensive) occupations exposed to AI? Adding a further control for the proportion of women in country-occupations in 2012 causes the female and male results to converge, suggesting that the link between female employment growth and AI exposure favours the latter explanation. In other words, female employment growth has been high where female representation was initially low (and these occupations are typically highly exposed to AI) and male employment growth has been high where male representation was initially low (and these occupations are typically not highly exposed to AI).[12] Once the gender composition of each country-occupation in 2012 is taken into account, women's employment and men's employment is positively related with AI exposure to a similar extent.

Accounting for the proportion of younger and tertiary-educated workers in country-occupations in 2012 produces positive and statistically significant coefficients for AI exposure, where they were previously positive but not statistically significant. Similar to before, employment growth for these groups has been higher in occupations where they were previously underrepresented and, similarly to the male results previously, many of these occupations are not highly exposed to AI.

[11] Furthermore, regressing AI exposure on the log change in the female/male employment ratio also produces a positive and statistically significant result. None of the age ratios nor the foreign- /native-born ratio produced results that were robust to the addition of controls.

[12] Additionally, controlling for the interaction between "white-collar" occupations and women's representation in a country-occupation in 2012 does not suggest a faster decline in occupational sex segregation in "white-collar work" (ISCO categories 1 to 4) than in "blue-collar" work (ISCO categories 5 to 9). With the data at hand, it is challenging to test whether AI has sped up the decline in occupational sex segregation, specifically to set up a counterfactual for how occupational sex segregation would have evolved in the absence of AI.

Table 3.1. Estimated link between AI exposure and employment growth for different groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable is the 2012-22 log change in employment for:								
	Female	Male	Young	Prime age	Older	Tertiary education	No tertiary education	Native-born	Foreign-born
Coefficient on AI exposure *without controls*	.47322***	.08444	.27226**	.45570***	-.08513	-.40431***	-.00618	.32877***	.30423**
	(.0956)	(.0895)	(.1086)	(.0778)	(.0960)	(.1226)	(.0942)	(.0717)	(.1358)
R-squared	0.082	0.037	0.085	0.095	0.175	0.199	0.052	0.094	0.219
Coefficient on AI exposure *with controls*	.83132***	.38498**	.38080	.53206***	.32117	.33939	.34674*	.53334***	.44148
	(.2212)	(.1868)	(.2604)	(.1705)	(.2157)	(.2961)	(.1946)	(.1597)	(.2971)
R-squared	0.159	0.163	0.169	0.191	0.217	0.239	0.131	0.200	0.238
Coefficient on AI exposure *with controls & control for 2012 level*[13]	.50698**	.54085**	.54590**	.48722***	.22155	.60165**	.25923	.59180***	.09603
	(.2376)	(.2045)	(.2594)	(.1710)	(.1938)	(.2913)	(.1970)	(.1648)	(.3039)
R-squared	0.180	0.170	0.195	0.197	0.304	0.273	0.137	0.206	0.297
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	782	786	779	786	785	777	784	786	763

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell.
Source: Author's calculations using data from EU-LFS, US-CPS and UK-LFS, and and the AI exposure measure described in Box 2.1.

General trends in usual working hours between 2012 and 2022

Between 2012 and 2022, average usual working hours declined in most of the occupations included in the analysis, as shown in Figure 3.3, where the majority of points sit below the x axis. As noted in the 2023 OECD Employment Outlook (2023[2]), while employment levels in 2023 had grown to exceed pre-pandemic levels, average usual working hours were still below pre-pandemic levels. The authors suggest that workers' preferences for work-life balance may be a cause, in which case it may be more difficult to interpret usual working hours as an indicator of labour demand, compared to employment levels.[14,15]

Defining Yij (from the previous model specification) as the percentage change in the usual working hours averaged across the full working population, a one standard deviation increase in exposure to AI is associated with a 0.84 percentage point larger decline in usual weekly working hours (the results table is shown in Annex B).[16] While statistically significant only at the 10% level, a negative relationship between AI exposure and the change in usual working hours is consistent with Georgieff and Hyee (2021[5]).[17] In

[13] Specifications (1) and (2) include a control for the proportion of women in the occupation in 2012. Specifications (4) includes a control for the proportion of young workers in the occupation in 2012. A control corresponding to the group specified in the dependent variable are also included in each specification (5) to (9).

[14] Across country-occupations, change in usual hours is not statistically significantly related with change in employment, nor were the changes between 2012 and 2019 related.

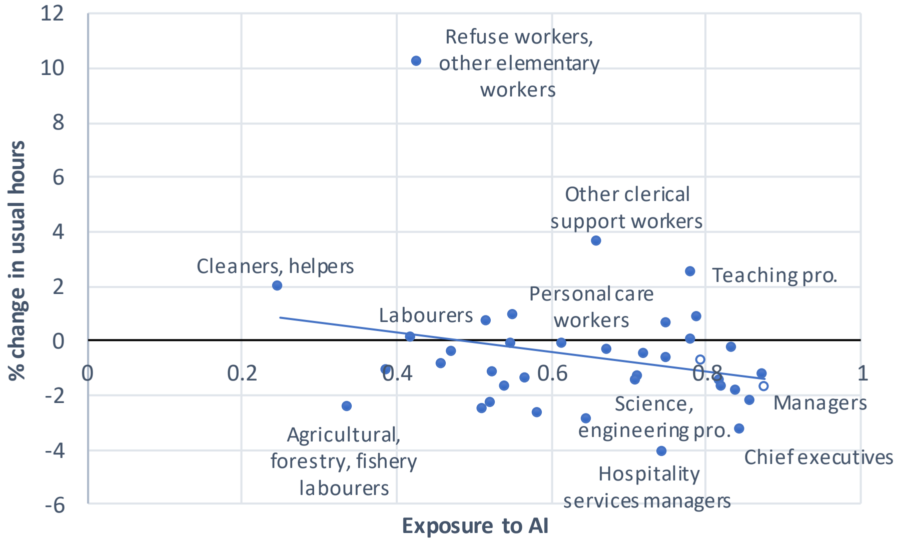
[15] In general, this paper does not attempt to disentangle residual effects of the pandemic from other factors.

[16] The standard deviation of exposure to AI is .176. Multiplying this by the coefficient in Annex B in Column 4 gives 0.176* -4.764= -.840.

[17] Splitting the data by the degree of computer use in each occupation, they found that this negative relation was present among occupations requiring low computer use only. A similar pattern is found in the period from 2012 to 2022, where there is a negative relation among occupations requiring low computer use and a positive relation among occupations requiring high computer use. Among occupations requiring medium computer use, the relation is not statistically significant.

other words, while the occupations most exposed to AI have experienced increases in employment, they have experienced a decrease in usual working hours.

Figure 3.3. Usual working hours decreased between 2012 and 2022 in occupations with higher AI exposure



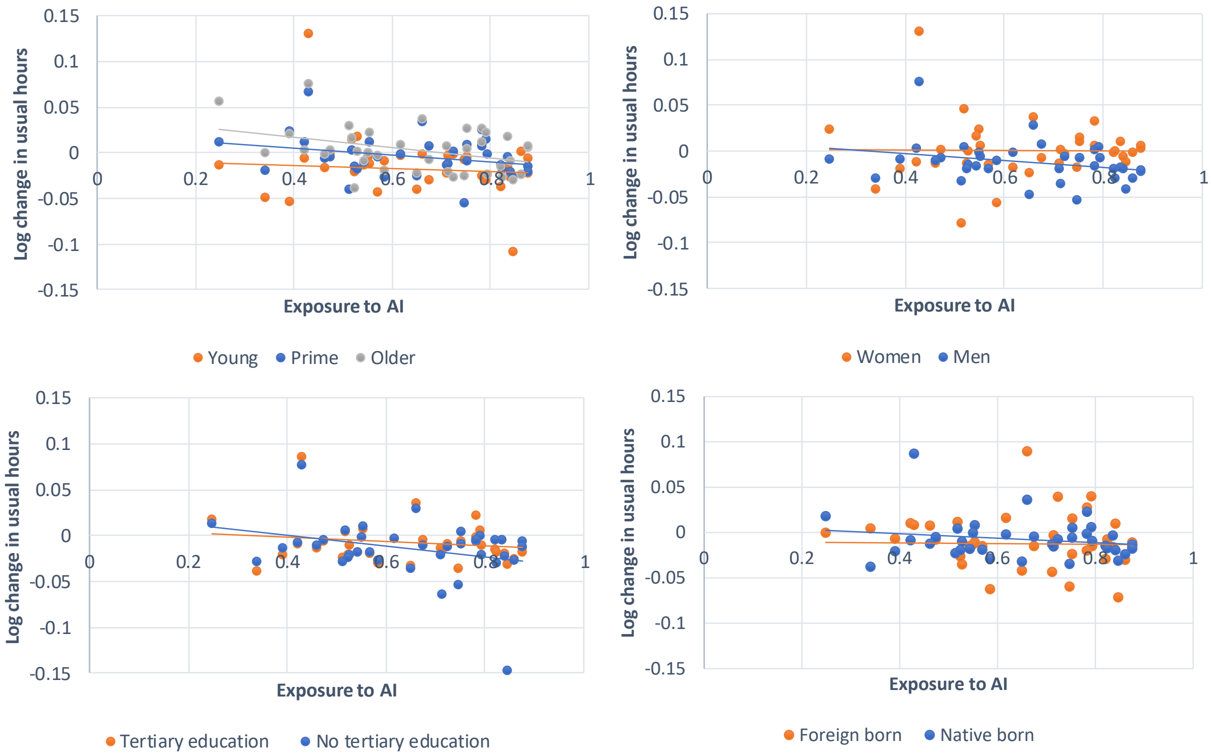
Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, The Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States. Occupations are classified using two-digit ISCO-08.
Source: Author's calculations using data from EU-LFS, US-CPS and UK-LFS.

How have different groups' usual hours changed in occupations highly exposed to AI?

In the period from 2012 to 2022, average working hours reduced more for young and male workers than for older and female workers, as can be observed in the distribution of the points in Figure 3.4 along the y-axis, which represents the log change in average usual working hours. Usual hours also reduced more for native-born and non-tertiary-educated workers than for foreign-born workers and those with tertiary education, but the differences are smaller. In both 2012 and 2022, prime-age, male, tertiary educated workers, foreign-born workers had the longest average usual working hours. So, the differences in trends over this period would have narrowed the gender gap but widened the gap by age, country of birth and education level.

There is a negative relation between average usual working hours and AI exposure for native-born workers, workers without tertiary education, male workers, and prime-age and older workers, as indicated by a downward sloping line in Figure 3.4. As before, the graphs should only be interpreted in association with the full set of regression results to account for fixed effects according to country or occupation, and the effects of technological advances, offshorability and exposure to international trade.

Figure 3.4. Since 2012, average working hours have reduced most for young and male workers



Note: Non-weighted averages over 22 countries for which data are available: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, The Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom and the United States. Occupations are classified using two-digit ISCO-08.
Source: Author's calculations using data from EU-LFS, US-CPS and UK-LFS.

Regression results

For all of the groups listed in Table 3.2, the relationship between AI exposure and log change in usual hours is either negative or not statistically significant. In other words, no group diverges from the overall trend.

Without controls, there is a negative relationship between AI exposure and log change in usual hours for male, prime-age, non-tertiary educated and native-born workers. However, when controls for software and industrial robots, offshorability, exposure to international trade, and country and occupation fixed effects are added, none of these results remain statistically significant at the 5% level.[18] Therefore, there is very little to suggest that exposure to AI has led to different outcomes in terms of usual hours worked by different groups.

[18] Running the same regression with the percentage of part-time workers as the dependent variable produces similar results, i.e. the relation with AI exposure is positive for most groups (and statistically significant for male workers), but results are not robust to the addition of controls.

Table 3.2. Estimated link between AI exposure and usual working hours for different groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable is the 2012-22 log change in usual hours for:								
	Female	Male	Young	Prime age	Older	Tertiary education	No tertiary education	Native-born	Foreign-born
Coefficient on exposure to AI in regressions *without controls*	-.01717	-.04349***	-.03655	-.04338***	-.04460***	-.00811	-.06476***	-.02920**	-.02324
	(.0196)	(.0163)	(.0241)	(.0137)	(.0163)	(.0390)	(.0209)	(.0133)	(.0211)
R-squared	0.090	0.120	0.064	0.156	0.097	0.116	0.102	0.158	0.043
Coefficient on exposure to AI in regressions *with controls*	-.06083	-.01803	-.07012	-.04521*	.00943	-.05063	-.02521	-.05356*	-.08483
	(.0503)	(.0346)	(.0787)	(.0261)	(.0370)	(.0937)	(.0311)	(.0301)	(.0593)
R-squared	0.119	0.157	0.092	0.216	0.137	0.133	0.134	0.206	0.094
Country Fes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	782	786	779	786	785	777	784	786	763

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell.
Source: Author's calculations using data from EU-LFS, US-CPS and UK-LFS, and the AI exposure measure described in Box 2.1.

How have different groups' wages changed in occupations highly exposed to AI?

Occupations' AI exposure does not appear to be associated with changes in wage inequality between demographic groups in those occupations. After finding that AI exposure is linked with less growth in wage inequality within occupations, Georgieff (2024[9]) tests whether it is also associated with less growth in wage differentials between lower-paid socio-demographic groups (e.g. women and young workers) and higher-paid ones within occupations. Regressions are run using the same model specification as above, except that the dependent variable is the 2014-18 log change in the wage ratio of male workers to female workers and of prime-age workers to young workers. Within occupations, the author finds that AI exposure is not associated with changes in wage inequality between demographic groups in either case.

4 AI and access to opportunities

Main findings

- Women and lower-educated workers could have less access to AI-related employment opportunities and to productivity-enhancing AI tools in the workplace, which could prevent the benefits of AI from being broadly and fairly shared.
- The *AI workforce*, defined as those with the skills to develop and maintain AI systems, is confined to a narrow socio-demographic segment of the population, primarily male and university educated.
- Similar patterns are found among *AI users*, a broader category capturing workers who say that they interact with AI at work in one way or another, AI users in the manufacturing and financial sectors are more likely to be younger, male and university educated compared to non-users.
- Some features of AI could open up new opportunities for traditionally underrepresented groups, if used correctly. AI has the potential to complement skills and to compensate where skills are lacking. Its data-driven methods for decision-making and matching offer an opportunity to break away from traditional methods and traditional patterns of underrepresentation.
- However, AI can also amplify and systematise biases, perpetuate the exclusion of underrepresented groups and reinforce historical patterns of disadvantage. When used to hire, fire or evaluate workers, the consequences for individuals can be severe.

This chapter examines whether some groups have greater access to opportunities associated with AI while others face barriers. It starts by assessing the representation of different socio-demographic groups in the AI workforce (i.e. workers with AI skills) and among AI users (i.e. workers who say that they interact with AI in their jobs in one way or another). A consistent picture emerges: male workers with a university degree are overrepresented in both the AI workforce and among AI users. The chapter concludes with a discussion of the sources of unequal access to AI-related opportunities and the potential of AI itself to bridge or widen labour market divisions.

The AI workforce is primarily male and university educated

Green and Lamby (2023[13]) examine the "AI workforce", defined as those with the skills to develop and maintain AI systems. The authors find that the AI workforce is small, accounting for just above 0.3% of employment across OECD countries, ranging from 0.5% in the United Kingdom to 0.2% in Greece. They conclude that the AI workforce is confined to a narrow socio-demographic segment of the population, primarily male and university educated. Table 4.1 shows the socio-demographic composition of the

10 occupations at 3-digit ISCO level with the highest share of AI-related job postings.[19] All top 10 occupations are characterised by a higher-than-average presence of men[20] (the only exceptions are Mathematicians, Actuaries and Statisticians and Life Science Professionals), university educated (the only exception is Chemical and Photographic Products Plant and Machine Operators) and prime-age workers (no exceptions).

Table 4.1. Male, university-educated and prime-age workers are overrepresented in the 10 occupations with the highest share of AI-related job postings

Occupations	% of AI-related job postings	% university educated	% male	% prime age	% native-born
Mathematicians, Actuaries and Statisticians	5.2%	93%	50%	62%	84%
Software & Applications Developers & Analysts	4.6%	82%	81%	69%	81%
Information and Communications Technology Services Managers	4.0%	80%	80%	78%	82%
Database and Network Professionals	3.2%	75%	78%	71%	84%
Electrotechnology Engineers	3.1%	88%	90%	67%	81%
Physical and Earth Science Professionals	2.1%	94%	55%	62%	82%
Life Science Professionals	1.7%	95%	45%	68%	83%
Sales, Marketing and Development Managers	1.7%	75%	66%	77%	87%
Engineering Professionals (excluding Electrotechnology)	1.5%	90%	78%	67%	84%
Chemical and Photographic Products Plant and Machine Operators	1.1%	15%	73%	67%	87%
Average across all occupations	**0.4%**	**41%**	**57%**	**62%**	**85%**

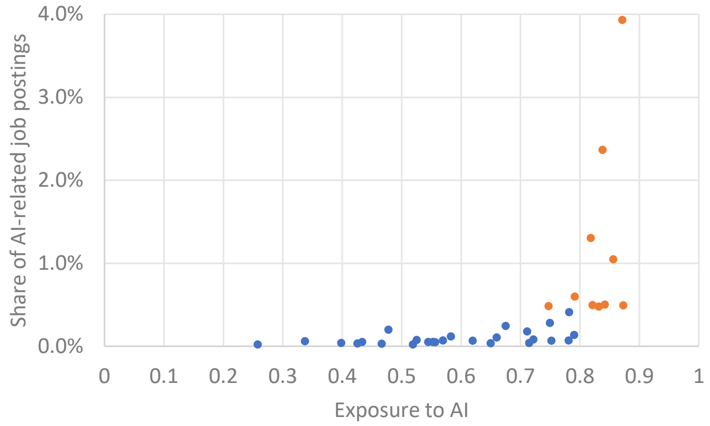
Note: Animal producers are removed from this table, on the basis that the estimates are unreliable due to undersampling of this group in the original data source, as noted by Green and Lamby (2023[13]). This allows Chemical and Photographic Products Plant and Machine Operators to enter. Figures are non-weighted averages over 29 countries for which data are available: Austria, Belgium, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Romania, the Slovak Republic, Spain, Sweden, Switzerland, the United Kingdom and the United States.
Source: Author's calculations based on by Green and Lamby (2023[13]) and updated with 2022 data from the European Union Labour Force Survey (EU-LFS), the US Current Population Survey (US-CPS), and the United Kingdom Labour Force Survey (UK-LFS).

There is considerable overlap between the occupations identified as highly exposed to AI and the occupations where AI skills are most in demand. Figure 4.1 shows that there is an almost perfect overlap (with just one exception) between the 10 occupations with the highest share of job postings demanding AI-related skills (aggregated to 2-digit ISCO level) and the 10 occupations with the highest AI exposure. The implication is that to the extent that certain groups (like university-educated male workers) are overrepresented in occupations highly exposed to AI, they are equally overrepresented in occupations with the highest potential for AI-related employment opportunities. Today, many ICT- and AI-related jobs are relatively lucrative (OECD, 2018[14]; Manca, 2023[15]) and inequalities in pay and employment may increase further as AI becomes more prevalent. Additionally, underrepresentation of any vulnerable group in decision-making roles developing and implementing AI increases the risk that the experiences and voices of these groups are omitted from the process.

[19] To measure the AI workforce, Green and Lamby (2023[13]) calculate the share of online job postings within each occupation that mention AI-related skills, as identified in Alekseeva et al. (2021[39]). This demand for AI skills within the job posting is assumed to reflect the potential (or upper-bound of) prevalence of AI skills within the actual job.

[20] Exploring interactions between gender and education, Green and Lamby found that the AI workforce was disproportionately male, even compared to the employed population with a university education. However, the AI workforce was not noticeably younger or older or more likely to be born abroad than the employed population with a university education.

Figure 4.1. There is considerable overlap between the occupations identified as highly exposed to AI and the occupations where AI skills are most in demand



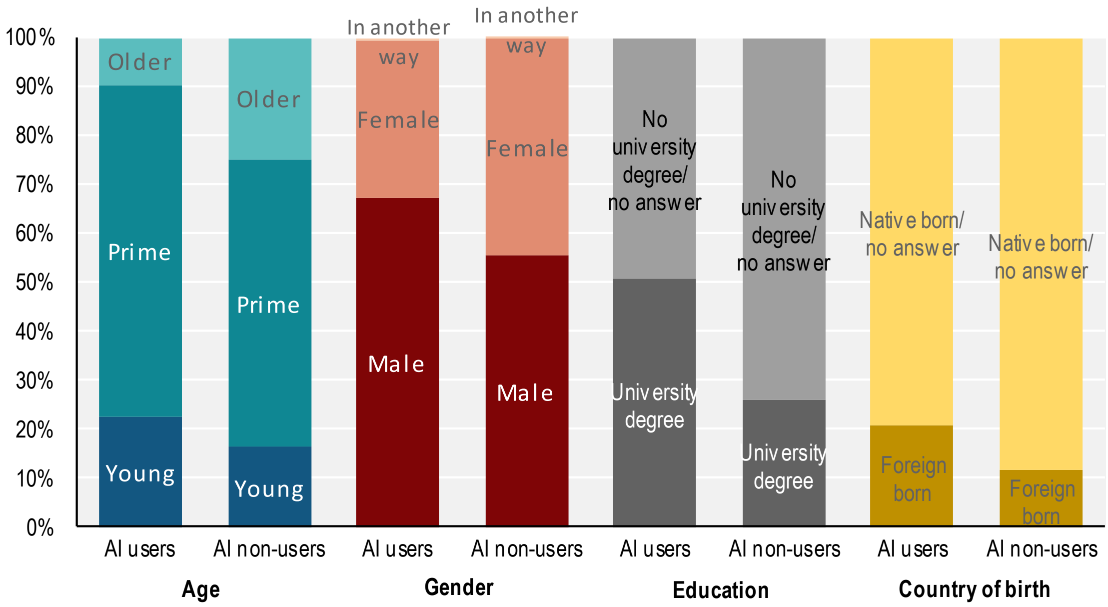
Note: Occupations are aggregated to 2-digit level by taking an unweighted average across countries. The 10 occupations with the highest share of AI-related job postings are shown in orange.
Source: Combination of the AI exposure measure described in Box 2.1 and the AI workforce measure used in Green and Lamby (2023[13]).

AI users are also primarily male and university educated

A survey of workers in the financial and manufacturing sectors (Lane, Williams and Broecke, 2023[16]), undertaken in early 2022, revealed similar socio-demographic patterns among AI users, defined as those who say that they interact with AI at work in one way or another. In both sectors, AI users were more likely to be younger, male and university educated compared to non-users (Figure 4.2). Some 41% of male workers surveyed were AI users compared to 29% of women. Workers born in another country were also more likely to be AI users. In the United States, where respondents could provide information on race, non-white workers were more likely to be AI users. The next chapter discusses these survey results in more detail, but it is worth noting that most AI users had positive views on AI's impact on their performance and working conditions, with the implication that groups less likely to use AI are at a perceived disadvantage.

Figure 4.2. AI users are more likely to be younger, male, foreign-born and have a university education than non-users

Percentage of workers in companies that use AI, by age, gender and education



Note: Graph shows simple average across workers in the manufacturing sector and workers in the financial sector. Workers in companies that use AI were asked: “Which of these statements best describes your interaction with AI at work? I work with AI; I manage workers who work with AI; I develop/maintain AI; I am managed by AI; I interact with AI in another way; I have no interaction with AI at work; Don’t know”. Workers who selected “no interaction” or “Don’t know” or who said that their companies did not use AI are described as “non-users”, while the rest are described as “AI users”.
Source: OECD worker survey on the impact of AI on the workplace (2022).

Sources of uneven access to opportunities associated with AI

Uneven access to opportunities associated with AI may reflect digital skill divides. The OECD Survey of Adult Skills – conducted as part of the Programme for the International Assessment of Adult Competencies (PIAAC) – has shown that male, younger and more educated respondents have on average greater proficiency in problem solving in technology-rich environments and greater likelihood to report some experience with computers (OECD, 2015[17]). Women are underrepresented among ICT specialists (OECD, 2018[18]). Gender gaps in digital skills emerge even earlier than this. Girls and women are less than half as likely to be able to programme as men at age 16 to 24 (OECD[19]), and are underrepresented in upper secondary level and tertiary level ICT studies (OECD, 2018[18]). These digital skill divides not only risk excluding women and lower educated individuals from the opportunities associated with AI throughout their working lives, but they could also hinder their ability to adapt to changes that AI brings to the workforce.

Another factor that could contribute to uneven access to the opportunities associated with AI is the lower participation rates among low-skilled workers in formal or non-formal job-related training. Adults with low skills (according to PIAAC tests) are 23 percentage points less likely to train than those with medium/higher skills (OECD, 2019[20]).[21] Furthermore, research shows a negative relationship between an occupation’s

[21] Other groups that participate less in adult learning include: older people, low-wage workers, workers in SMEs and temporary workers.

exposure to automation and the share of workers undertaking training (Lassébie and Quintini, 2022[7]) workers in high-risk occupations are 8 percentage points less likely to respond that they have participated in education and training activities in the four weeks preceding the survey than workers in other occupations. As such, the workers in most need of upskilling and reskilling are the ones engaging least in these activities.

Bridging these digital divides and gaps in access to training is crucial to guarantee that all groups can benefit from opportunities associated with AI, participate fully in an increasingly digital economy, and adapt to changes in the workplace. The next section discusses how AI itself could bridge or widen the gaps that already exist.

New opportunities for traditionally underrepresented groups

This section begins with a brief discussion of how AI can perpetuate and magnify bias and discrimination before exploring how AI, if used correctly, could open up opportunities for traditionally underrepresented groups.

AI can perpetuate and magnify bias and discrimination

While AI did not originate societal biases, it can amplify and systematise them, perpetuate the exclusion of underrepresented groups and reinforce historical patterns of disadvantage (Salvi del Pero, Wyckoff and Vourc'h, 2022[21]). When used to hire, fire or evaluate workers, the consequences for individuals can be severe, but because AI is often a black box, it may not even be clear what is driving decisions (Broecke, 2023[22]).

Bias and discrimination can occur in the recruitment process where AI is used to match workers to jobs. Kim (2018[23]) describes a lawsuit in which it was alleged that companies had targeted job postings using Facebook algorithms that excluded older workers from seeing them. Bias can even result unintentionally, because of how algorithms learn from existing data (Salvi del Pero, Wyckoff and Vourc'h, 2022[21]). For instance, if a training dataset of ICT specialists comprises mostly men, an algorithm used for recruitment may become very good at predicting the top performing men and just average at predicting the top performing women. Even if the company makes the effort to interview an equal number of men and women, in which case the hiring practice could appear unbiased, the system will still favour the male candidates whose profiles will more closely match the top performers'.

Once hired, underrepresented groups may face further risk of bias and discrimination (Salvi del Pero, Wyckoff and Vourc'h, 2022[21]), in the form of facial recognition systems which perform worse for people of colour (Harwell, 2021[24]), or performance evaluation systems once again affected by bias in the data on which they are trained.

If used correctly, AI could open up opportunities for traditionally underrepresented groups

Some features of AI could open up new opportunities for traditionally underrepresented groups. AI has the potential to complement skills and to compensate where skills are lacking. Its data-driven methods for decision-making and matching offers an opportunity to break away from traditional methods. Inspired by David Autor's suggestion (2022[25]) to "*ask* not what *AI will do* to *us*, but what *we want it to do for us*", the following section considers a few ways that AI could potentially bridge the gaps that exist by providing new opportunities for traditionally underrepresented groups, as long as systems are specifically designed not to perpetuate the biases that already exist.

David Autor's (2024[26]) ambition for AI is that it will expand expertise to a wider set of workers, thereby reversing the trend of polarisation which has hollowed out the middle-skill and middle-class and relegated workers without bachelor's degrees to low-paid service jobs.[22] In his view, AI can supplement foundational training and experience to enable a much wider set of non-elite workers to engage in high-stakes decision-making tasks, such as those currently trusted to doctors, lawyers, software engineers and college professors. This would allow workers without bachelor's degrees to access employment opportunities with better pay and job quality than they currently experience.

Early research on generative AI in the workplace suggests that these tools can improve the performance of the least experienced or lowest performing workers the most. Noy and Zhang (2023[27]) study the use of ChatGPT by business professionals in writing tasks and find that the poorest performers in an earlier tasks see quality improvements, while the top performers do not. Brynjolfsson, Li and Raymond (2023[28]) test customer support agents' use of a generative AI-based conversational assistant and find that the productivity gains mostly accrue to the least experienced workers. Peng et al. (2023[29]) find that Copilot, an AI tool to help programmers write basic code, produced the largest productivity increases among the least experienced programmers. In addition to improving performance overall, these tools appear to bridge performance gaps.

By compensating where specific skills are lacking, AI can open up opportunities to workers who might not otherwise be considered suitable for a role. For example, AI's capacity to translate written and spoken word in real time can increase the chances of non-native speakers being hired.

AI-powered assistive devices to aid workers with visual, speech or hearing impairments, or prosthetic limbs, are becoming more widespread, improving the access to, and the quality of work for people with disabilities, as discussed further in Box 4.1 and in Touzet (2023[30]). For example, speech recognition solutions for people with dysarthric voices, or live captioning systems for deaf and hard of hearing people can facilitate communication with colleagues and access to jobs where inter-personal communication is necessary.

While there are concerns about AI perpetuating and amplifying biases in labour market matching, there is also the potential to use AI to improve the efficiency and quality of matching job seekers to vacancies, with advantages for underrepresented groups (Broecke, 2023[22]). One consequence of improved matching is that vacancies are filled more quickly, reducing unemployment across the board. Another is that firms are more likely to hire the right jobseeker for the right job, overcoming the challenge of imperfect information as well as bias and discrimination, which may be factors in the exclusion or underrepresentation of certain groups. Some recent studies have shown reason for optimism. One study suggests AI-enabled hiring algorithms can simultaneously increase the diversity of the talent pool and find the best workers if they strike a balance between selecting from groups with proven track records and selecting from under-represented groups to learn about quality (Li, Raymond and Bergman, 2020[31]). Another study (Pisanelli, 2022[32]) showed that the use of assessment software increased the share of female managers hired by companies, possibly because they offered a more data-driven and objective approach.

AI may improve access to training for those who would otherwise face barriers, as long as they have the skills necessary to use these tools. Verhagen (2021[33]) describes how using AI for training has the potential to increase participation, including among currently underrepresented groups, by lowering some existing barriers and by increasing motivation to train. For instance, tailored content and assessment may shorten the required time commitment and reduce costs. The use of practice-oriented augmented reality and virtual reality may be more engaging for adults who struggle with classroom-based education and written

[22] Computerisation of the type seen in the 1980s and 1990s contributed to this trend, by enabling the automation of routine and therefore codifiable tasks, primarily impacting medium-skilled workers. For instance, it was high school graduates and those with some college experience but without a bachelor's degree whose tasks appeared to be most impacted by computerisation (Autor, Levy and Murnane, 2003[3]).

materials and instructions (e.g. non-native speakers or people with low literacy skills). Finally, just as AI can match job seekers to jobs, certain AI solutions for training may improve the alignment of training to labour market needs and also to learner's entry level, increasing the relevance of training.

Box 4.1. Can AI improve access to the labour market for people with disabilities?

People with disabilities continue to struggle in the labour market. In 2019, across 32 OECD countries, they were over twice as likely to be unemployed as people without disabilities. The employment rate of people with disabilities was 27 percentage points lower than for people without. This gap has not declined over the last decade (OECD, 2020[34]). It is a challenge for equity as well as for the efficiency of the labour market, as skills and talent of many people remain undervalued and underused.

There are concerns that artificial intelligence could further exacerbate these disparities, by perpetuating and amplifying biases, as discussed earlier in the chapter. Additionally, risks to privacy are heightened for people with disability, who may be more easily identifiable because of their uniqueness, and AI tools might exclude people with disability by design if user interfaces are inaccessible to them.

However, AI could also support people with disability in the labour market, by creating more inclusive and accommodating environments and removing some existing barriers.

Disability-centred solutions, directly aimed at addressing individual impairments, can facilitate the daily and professional lives of people with disabilities. Examples include: speech recognition solutions for people with dysarthric voices; live captioning systems for deaf and hard-of-hearing people; and image recognition devices for people with vision impairments. Generalist natural language processing applications can also help support workers in their jobs (e.g. neurodiverse workers struggling with reading and/or writing long texts).

Environment-adaptation solutions make content and workplaces more accessible to persons with disabilities. For example, conversational chatbots that can read aloud and summarise the content of job offers allow blind and/or neurodivergent users to access traditionally inaccessible job boards. AI-powered accessibility checkers help refine documents and websites to ensure they can be accessed by people with disabilities.

AI can also unlock work opportunities that were previously inaccessible to people with disability. For instance, a US-based company Phantom.auto is developing a solution for the remote operation of forklifts, opening this industry up to people with physical disabilities. A Korean company CO: ACTUS has developed a live captioning solution aimed at opening up new job opportunities for deaf drivers in the taxi trade.

Governments have a role to play in tackling the risks and seizing the opportunities of AI to support people with disability in the labour market. Stakeholders call on governments to explicitly outlaw uses of AI that result in discrimination against people with disability. There are suggestions to use liability laws, accessibility standards and quality control systems to incentivise the development of safe, accessible and interoperable AI products. To seize the opportunities, stakeholders call for government-backed venture capital streams for R&D in this arena. Another idea is to focus on enabling and empowering users to make the best choices regarding AI-powered solutions, for instance through certification mechanisms or by developing metrics that capture the representation of people with disability in the innovation process.

Source: Touzet (2023[30]), "Using AI to support people with disability in the labour market: Opportunities and challenges", *OECD Artificial Intelligence Papers, No. 7*, OECD Publishing, Paris, https://doi.org/10.1787/008b32b7-en.

5 How do perceptions differ between groups?

Main findings

- Interviews with workers on the topic of AI reveal the hopes, expectations and worries of different groups. Male, university-educated and foreign-born workers are generally more positive about AI, in that they were more likely than female, non-university-educated and native-born workers to respond in a 2022 survey that AI had improved their productivity and working conditions, that AI would increase their wages in future, that they had specialised AI skills, and that they were enthusiastic to learn more about AI.
- The same groups (along with younger workers) were more likely to agree with the sentiment that technology had an overall positive impact on society, although regression analysis did not suggest that it was this sentiment driving the main findings.
- Despite the positive sentiments regarding AI, workers with a university degree were more likely to say they worried about job loss due to AI in the following 10 years. This finding is driven primarily by the fact that workers with a university degree are more likely to be AI users and this group were more worried about job stability. Foreign-born workers too were more worried than native-born workers about job loss due to AI in the following 10 years. They were also more worried that the collection of data would lead to decisions biased against them.
- Although results by age were generally mixed, younger workers were more worried about job loss and biased decision-making. Case study interviews conducted in parallel suggest that young and older workers are facing different risks. Older workers face preconceived and potentially even prejudicial notions regarding their ability and willingness to engage with new technologies. On the other hand, their tenure and seniority may afford them greater protection than younger workers.

In an effort to capture workers' and employers' own perceptions of the impact of AI on their workplaces, the OECD conducted two data collection exercises in 2022: the OECD AI surveys of employers and workers[23] and the OECD case studies of AI implementation.[24] This chapter revisits the data to examine how perceptions about AI differ between socio-demographic groups.

[23] 5 334 workers and 2 053 firms in the manufacturing and financial sectors were surveyed in Austria, Canada, France, Germany, Ireland, the United Kingdom and the United States.

[24] 325 interviews were conducted within 90 firms in the same sectors and the same countries, with the addition of Japan.

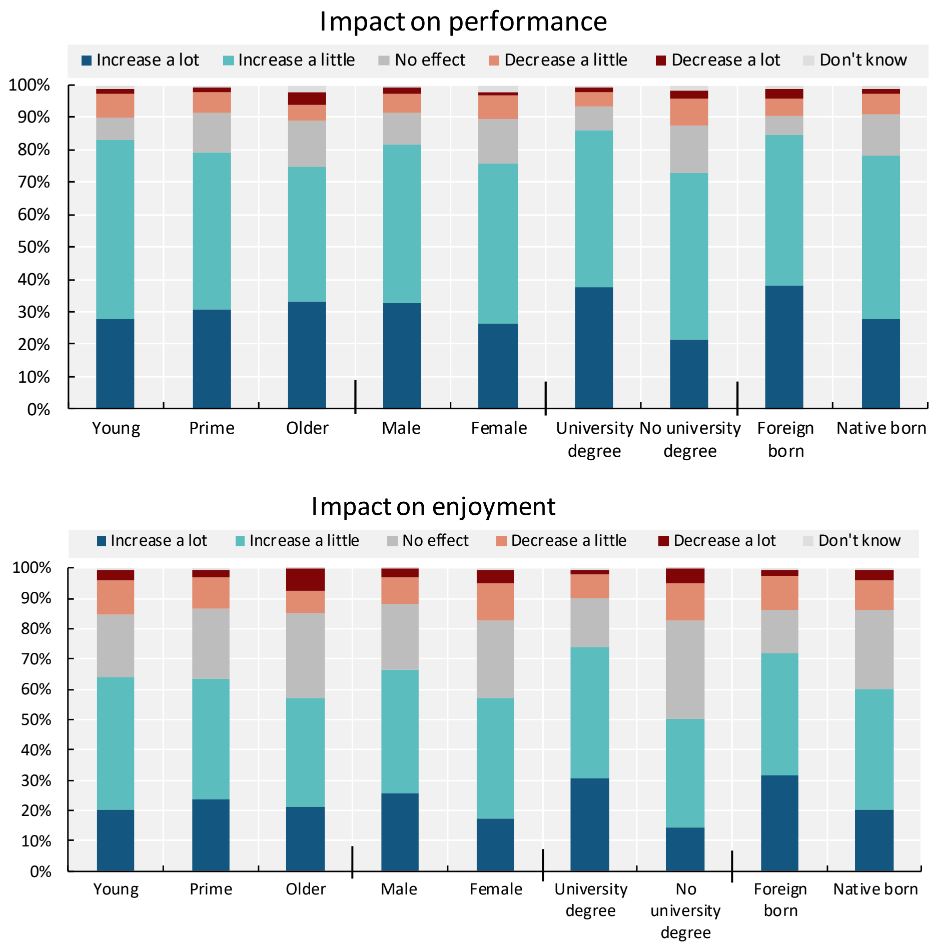
Findings from the OECD AI surveys of employers and workers

Male, university-educated and foreign-born workers were more positive about the impact of AI on their jobs. The same groups (along with younger workers) were more likely to agree with the sentiment that technology had an overall positive impact on society. These findings are not unexpected. Another global survey (Ipsos, 2022[35]) suggested that self-reported understanding of AI was higher among male, younger and more educated respondents, and that the same groups were generally more optimistic about the benefits of AI-based products and services.

Productivity and working conditions

Male, university-educated and foreign-born workers were most positive about how AI had impacted their productivity and enjoyment, as shown in Figure 5.1. The same groups were also most likely to report positive impacts on mental and physical health, and how fairly their management treats them (not shown). Results by age group suggested mixed opinions: older AI users were the most likely to say that AI had decreased their performance and enjoyment a lot (although these opinions were still limited to a small minority), but also the most likely to say that it had increased their performance a lot.

Figure 5.1. Male, university-educated and foreign-born workers were most positive about how AI had impacted their productivity and enjoyment



Notes: Graph shows simple average across workers in the manufacturing sector and workers in the financial sector. AI users were asked: “How do you think AI has changed your own job performance/how much you enjoy your job?”
Source: OECD worker survey on the impact of AI on the workplace (2022).

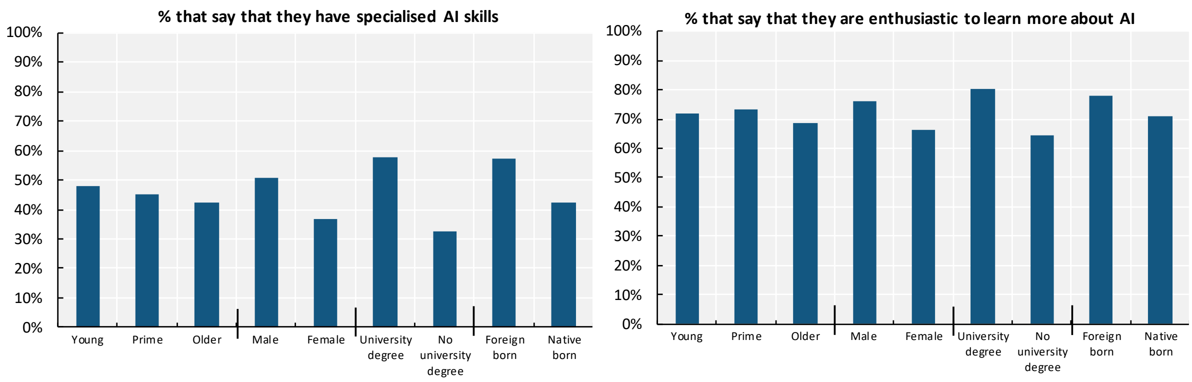
The differences in impact on worker productivity and working conditions[25] by gender, education and country of origin were statistically significant even when controlling for these characteristics plus age, sector, occupation and overall sentiment about technology. For instance, male AI users were more likely to be managers and professionals (whose views about AI are typically more positive), while female AI users were more likely to be clerical support or service and sales workers (whose views are typically less positive). Regression analysis suggests that occupation explains roughly a quarter of the gender gap. In other words, male managers and professionals were still more positive than female managers and professionals about the impact of AI on performance and working conditions.

In the United States, where workers who participated in the survey could provide information on race and ethnicity, there was no statistically significant difference between the responses of white and non-white workers nor between the responses of workers of Hispanic, Latino or Spanish origin and workers not of these origins.

Skills

Male, university-educated and foreign-born workers were more likely to say that they had specialised AI skills, as shown in graph. The education differences were present in both sectors, while the differences by gender and country of birth were only present in finance.[26] These differences persist even when controlling for the same characteristics plus age, sector, occupation and overall sentiment about technology. Broadly, the same types of AI users who were more likely to already have specialised AI skills were also more enthusiastic than average to learn more (as shown in Figure 5.2) – this enthusiasm may have led them to learn the skills in the first place.

Figure 5.2. Male, university-educated and foreign-born workers were more likely to say that they had specialised AI skills and that they were enthusiastic to learn more



Note: Graph shows simple average across workers in the manufacturing sector and workers in the financial sector. AI users were asked: "Please think about the skills you need in your job. Do you agree or disagree with the following statements? I have specialised AI skills, such as those needed to maintain or develop AI/I am enthusiastic to learn more about AI. Strongly agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Strongly disagree; Don't know"
Source: OECD worker survey on the impact of AI on the workplace (2022).

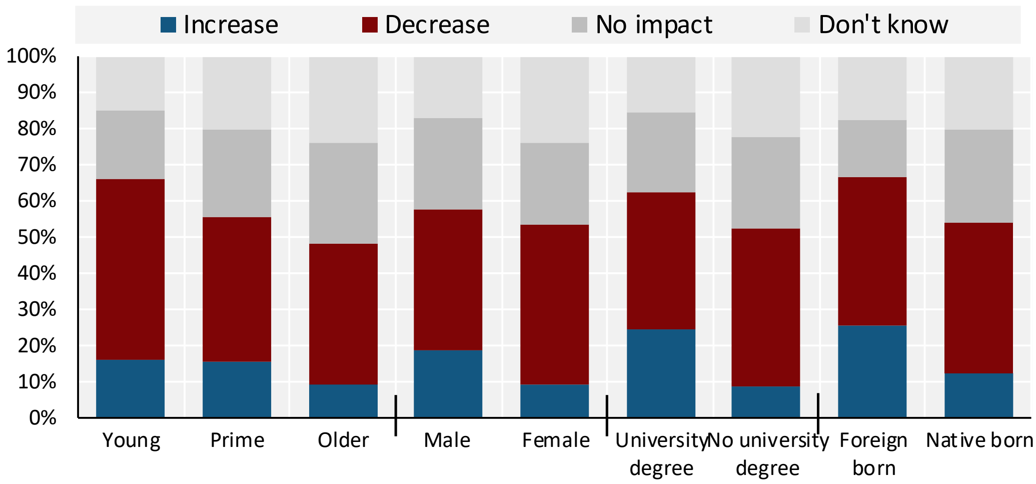
[25] Based on an indicator of working conditions, comprising impact on enjoyment, mental and physical health, and fairness in management, constructed using principal component analysis.

[26] In the United States, differences between white and non-white workers and differences between those with Hispanic, Latino or Spanish origins and those without such origins were not statistically significant.

Since the survey relied on self-reporting of skills, it should be noted that other studies comparing self-reported ICT skills with objective assessments have found evidence of over-reporting, and that the demographic groups most likely to possess ICT skills (younger individuals and men) are also most likely to over-report (Ipsos, 2022[35]) The authors attribute this to social desirability bias, which is likely also a factor in the OECD survey of workers. Indeed, male, university-educated and foreign-born workers rated their familiarity with the concept of AI more highly. Prime-age workers rated their familiarity more highly but differences by age group were much smaller. Similar to the overall sentiment regarding technology, results in this chapter were not attributable to differences in self-reported familiarity with AI.

Figure 5.3. Male, university-educated and foreign-born workers were more likely to expect wages to increase due to AI

Percentage of all workers, by age, gender, education and country of birth



Note: Graph shows simple average across workers in the manufacturing sector and workers in the financial sector. Workers were asked: "Do you think that AI will have an impact on wages in your sector in the next 10 years? Yes, AI will increase wages; Yes, AI will decrease wages; No, AI will not impact wages; Don't know". Workers who described their gender in another way and workers who did not say whether they had a university degree are not included in the figure.
Source: OECD worker survey on the impact of AI on the workplace (2022).

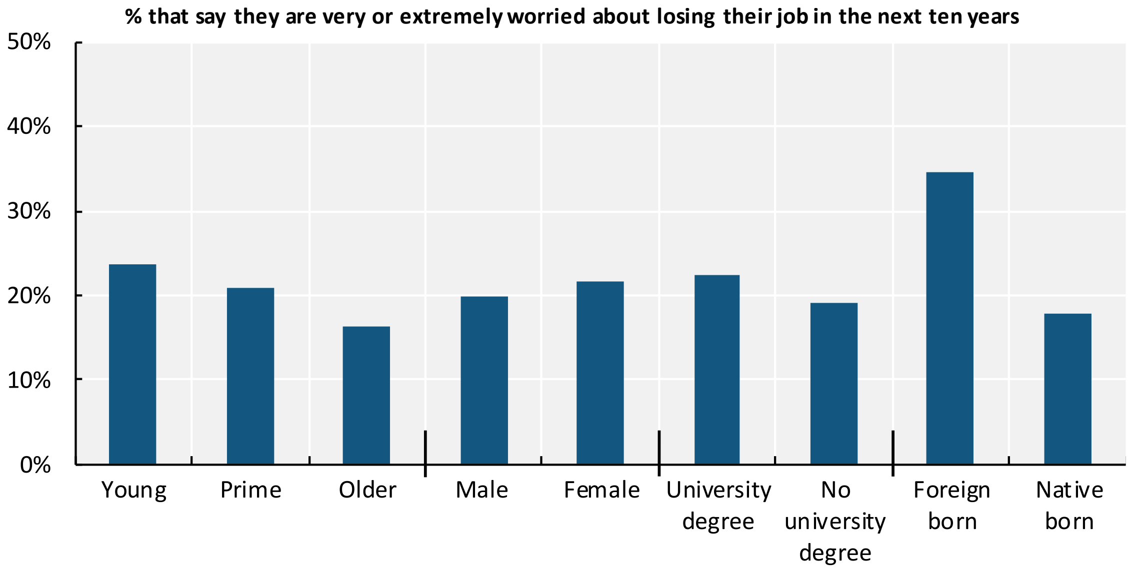
Men, workers with a university degree and foreign-born workers were more likely to say that they expected that AI would increase wages in their sector in the following ten years Figure 5.3. These differences persist even when controlling for these characteristics plus age, sector, occupation and overall sentiment about technology. The same groups were less likely to expect AI to decrease wages, although the differences were smaller. Opinion was split among young workers even if they expected a change in wages. They were more likely than older workers to expect an increase but also more likely to expect a decrease.

For workers in the United States, it was also possible to analyse responses by race and ethnicity. Workers who described themselves as Asian were less likely than the average to say that wages would increase and more likely to say that wages would be unchanged. Workers of Hispanic, Latino or Spanish origin were more likely to expect wages to change as a result of AI, although views were divided on whether wages would increase or decrease. Other groups answered either similarly to the average or were too small to support robust analysis.

Job loss worries

Of all groups, foreign-born workers were most likely to say that they were very or extremely worried about losing their jobs due to AI in the following 10 years (Figure 5.4). Younger workers and those with a university degree were also more worried. There was little difference according to gender. The difference between foreign-born and native-born workers persisted even when controlling for occupation, education, gender, age, sector, overall sentiment about technology and whether or not the individual actually uses AI.

Figure 5.4. Foreign-born workers were most likely to say that they were very or extremely worried about losing their jobs in the following 10 years



Note: Graph shows simple average across workers in the manufacturing sector and workers in the financial sector. Workers were asked: “How worried are you about losing your job as a result of AI in the next 10 years? Extremely worried; Very worried; Moderately worried; Slightly worried; Not worried at all; Don’t know”
Source: OECD worker survey on the impact of AI on the workplace (2022).

Regression analysis suggests that one of the reasons why older workers were less worried about job loss is that they tend to be in more secure working arrangements; specifically, they are less likely to hold temporary or fixed-term contracts.

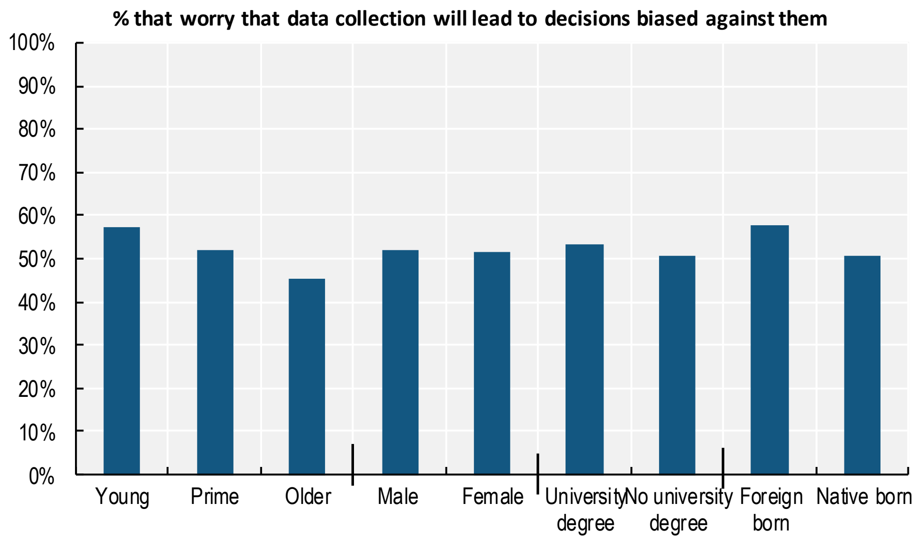
That workers with a university degree were more likely to worry about job loss seems surprising, given that education is thought to enable workers to use AI to complement their own labour, boost their productivity and to share in the benefits of AI (Lane and Saint-Martin, 2021[36]). This finding is driven primarily by the fact that workers with a university degree were more likely to be AI users and this group were more worried about job stability. One possible explanation for this is that AI users are more aware of the capabilities of AI and the current and likely future potential for automation, which could differ from trends observed to date. Another is that AI users simply anticipate that they will be more exposed to the effects of AI and any resulting labour market disruption. Disruption and job loss are not necessarily inconsistent with an increase in aggregate employment either.

Other groups that were more likely to say that they were very or extremely worried about losing their jobs in the following 10 years included workers who did not describe themselves as White,[27] including in particular Black or African American workers.

Data collection and bias

Across all workers (including both those that do and do not experience AI-related data collection),[28] approximately half said that they were extremely or very worried that the collection of their data would lead to decisions biased against them. These worries were greater among younger workers and among foreign workers and these differences remained when controlling for occupation, education, gender, age, whether or not the individual actually uses AI, and sector (Figure 5.5). The differences according to gender and education were small.

Figure 5.5. Younger and foreign-born workers were more concerned that data collected could lead to decisions biased against them



Note: Graph shows simple average across workers in the manufacturing sector and workers in the financial sector. Workers who asked: "To what extent do you agree or disagree with the following statements? I worry that the collection of my data will/would lead to decisions biased against me".
Source: OECD worker survey on the impact of AI on the workplace (2022).

In the United States, there were some notable differences by race and ethnicity in the manufacturing sector. Workers of Hispanic, Latino or Spanish origin appeared to be more worried – in particular, workers of Puerto Rican or Mexican, Mexican American or Chicano origin, as well as Asian workers.

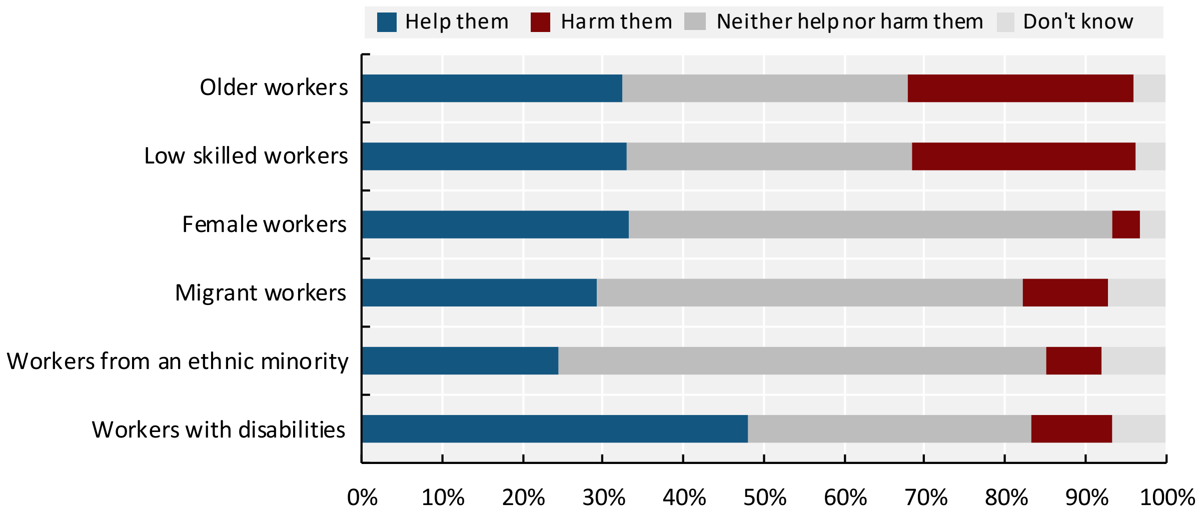
[27] This question on race was only asked of workers in the United States. No differences by ethnicity were statistically significant.

[28] The analysis here aggregates the responses of those that do and do not experience AI-related data collection in order to break down worries about biased decision-making with more precision. Workers who did not report AI-related data collection in their company were asked to imagine that their company started using AI-based software that collected data on them and their work.

The potential for AI to help or harm different groups

Employers saw workers with disabilities as the group that could benefit most from AI in the workplace, when asked which potentially vulnerable groups they thought AI would help or harm. Employers were more than four times as likely to say that AI would help workers with disabilities as to say that it would harm them (Figure 5.6). This could be because employers think that AI can enable more such workers to enter the workforce, overcome employability barriers, and supplement and complement their skills.

Figure 5.6. Employers saw older and low-skilled workers as the groups facing most harm from AI



Note: Graph shows simple average across employers in the manufacturing sector and workers in the financial sector. Employers were asked "I'm going to name a few different groups of workers. For each of them, please tell me whether you think artificial intelligence is more likely to help them or harm them or neither help nor harm them in their work".
Source: OECD employer survey on the impact of AI on the workplace (2022).

In the eyes of employers, older and low-skilled workers were the groups facing most harm from AI. Over a quarter thought that AI was likely to harm low-skilled workers and the same for older workers.[29] This perception was echoed in the OECD case studies of AI implementation, which were based on in-depth interviews with those tasked with implementing or managing AI within firms.

Findings from the OECD case studies of AI implementation

Individuals interviewed in 2022 for the OECD case studies of AI implementation (Milanez, 2023[37]) reported some instances of AI having disproportionate impacts on certain groups, including greater risks for older workers and low-skilled workers. In a small number of cases, interviewees saw AI as offering some benefits to male workers in manufacturing and non-native language speakers.

Older workers may face greater risks from AI

The case studies suggested that older workers may face preconceived and even prejudicial notions regarding their ability and willingness to engage with new technologies. On the other hand, it appears plausible that their tenure and seniority could afford them greater protection than younger workers.

[29] The question did not ask about younger workers specifically.

Interviewees often reported that younger workers, seen as more tech-savvy and open to new opportunities, tended to be enthusiastic about the use of AI in the workplace. Older workers were sometimes described as sceptical towards AI and less willing and able to adapt, particularly in the manufacturing sector (as in the example in Box 5.1).

It is important to note that the case studies did not contain any first-hand accounts of older workers voicing their scepticism regarding AI or lack of willingness to work with it. As such, it is possible that the AI developers and managers interviewed project biases against older workers that do not reflect the workers' actual abilities and attitudes. Ageism in the workforce has been documented in other studies (OECD, 2020[34]), as has the idea of age-biased technological change, whereby the adoption of technology disadvantages older workers (Behaghel, Caroli and Roger, 2011[38]). Some interviewees were optimistic that training could override negative attitudes towards AI as well as addressing skills gaps.

There were also suggestions that workers' tenure and seniority may afford them certain protections. Some interviewees described a strong cultural impetus to retain and redeploy workers with long tenures (including until retirement or voluntary separation), even when the AI had reduced the need for labour – a practice that some stated was more tenable in favourable business conditions. In one instance, an AI developer reported that older workers had low ICT skills and that the firm had reallocated them from the task performed previously (now largely automated) to other areas of the firm where ICT skills were not required, while new, typically younger, workers were hired into their roles.

Box 5.1. Case study example showing negative perceptions about older workers using AI

One of the case studies in which interviewees spoke about negative attitudes among older workers related to a German manufacturer of home appliances that uses AI to evaluate assembly line data, detect anomalies and predict their causes. Prior to implementation of the AI, maintenance workers evaluated data in Excel or inspected the production line manually. AI allowed a more data-driven approach to production line surveillance and maintenance, with the AI system delivering predictions and insights beyond workers' capabilities. In this company, the workers most affected by the introduction of AI were production-planning experts who take care of the production process. Working with AI consists of providing the necessary data and adapting the production systems, which requires basic knowledge of AI, data engineering, data science, and a deep understanding of the software used.

Facing these new job skill requirements was a particular hurdle for older workers due to negative attitudes towards AI, according to one interviewee: "[Older] employees or those biased against [AI] seem to be negatively influenced. This is because age partly seems to affect the motivation to acquire new knowledge. In the same way, a defensive attitude towards the AI application makes it more difficult to feel comfortable at work."

Another interviewee, a younger worker, attributed greater barriers for older workers to a genuine lack of fluency with data and technology in general: "I often felt resistance from older colleagues. Sometimes they could not follow me at all [when explaining the data]. I often had the feeling that you explained it to them, and they didn't know what was meant by it." However, this interviewee did not see these barriers as insurmountable, suggesting that older workers could benefit from more guided training for workers less capable of self-study. The view that training could override negative attitudes towards AI was echoed by interviewees in some other companies.

Source: Milanez (2023[37]), "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.

Low-skilled workers may be less able to adapt to changing skill requirements

Some interviewees reported that AI had a disproportionately detrimental impact on low-skilled workers due to their lack of readiness to transition to new tasks and/or jobs. In many case studies, AI led to a change in skill requirements, demanding higher skills (e.g. sharpened analytical skills, improved interpersonal skills) and/or a broader skillset (e.g. specialised AI skills, new subject-specific knowledge, such as data science). In some companies, all workers interacting with AI were expected to have an understanding of data mechanisms and even limited AI knowledge. Some interviewees perceived the learning gap for some workers to be too large, preferring to hire new workers over training existing ones.

AI may offer benefits for male workers in manufacturing and non-native language speakers

The case studies suggested that male workers in manufacturing could benefit disproportionately from safety improvements arising from the automation of potentially dangerous, manual tasks predominantly performed by male workers. However, the case studies showed no clear patterns of impacts by gender beyond this.

Some interviewees in Canada and the United States mentioned that AI allowed firms to hire non-native English speakers. One example was an AI-based video training system used by a manufacturing firm where the video captions could be transcribed into multiple languages. This capability was created for the sake of easy dissemination and standardisation of training materials worldwide. An HR manager mentioned that it also benefitted Spanish-speaking workers in the US plant, who have been hired in greater numbers since the technology was introduced.

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. [10]

Alekseeva, L. et al. (2021), "The demand for AI skills in the labor market", *Labour Economics*, Vol. 71, https://doi.org/10.1016/j.labeco.2021.102002. [39]

Autor, D. (2024), "AI Could Actually Help Rebuild The Middle Class", *Noema Magazine* 12 February 2024, https://www.noemamag.com/how-ai-could-help-rebuild-the-middle-class/ (accessed on 15 March 2024). [26]

Autor, D., F. Levy and R. Murnane (2003), "The Skill Content of Recent Technological Change: An Empirical Exploration", *The Quarterly journal of economics*, Vol. 118/(4), pp. 1279-1333. [3]

Behaghel, L., E. Caroli and M. Roger (2011), "Age Biased Technical and Organisational Change, Training and Employment Prospects of Older Workers", *IZA Discussion Papers*, https://www.iza.org/publications/dp/5544/age-biased-technical-and-organisational-change-training-and-employment-prospects-of-older-workers (accessed on 10 August 2020). [38]

Broecke, S. (2023), "Artificial intelligence and labour market matching"*, OECD Social, Employment and Migration Working Papers, No. 284*, OECD Publishing, Paris, https://doi.org/10.1787/2b440821-en (accessed on 11 May 2023). [22]

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. [28]

Eurostat (2022), *EU labour force survey - correction for breaks in time series*, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey_-_correction_for_breaks_in_time_series#Comparability_over_time_-_correction_of_br. [40]

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. [4]

Felten, E., M. Raj and R. Seamans (2023), "Occupational Heterogeneity in Exposure to Generative AI", *SSRN Electronic Journal*, https://doi.org/10.2139/SSRN.4414065. [6]

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. [1]

Felten, E., M. Raj and R. Seamans (2019), "The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization", *NYU Stern School of Business*, https://doi.org/10.2139/ssrn.3368605. [11]

Fossen, F. and A. Sorgner (2022), “New digital technologies and heterogeneous wage and employment dynamics in the United States: Evidence from individual-level data”, *Technological Forecasting and Social Change*, Vol. 175, p. 121381, https://doi.org/10.1016/J.TECHFORE.2021.121381. [12]

Georgieff, A. (2024), “Artificial intelligence and wage inequality”*, OECD Artificial Intelligence Papers*, No. 13, OECD Publishing, Paris, https://doi.org/10.1787/bf98a45c-en. [9]

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. [5]

Georgieff, A. and A. Milanez (2021), “What happened to jobs at high risk of automation?”*, OECD Social, Employment and Migration Working Papers*, No. 255, OECD Publishing, Paris, https://doi.org/10.1787/10bc97f4-en. [8]

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. [13]

Harwell, D. (2021), *Contract lawyers face a growing invasion of surveillance programs that monitor their work*, The Washington Post, https://www.washingtonpost.com/technology/2021/11/11/lawyer-facial-recognition-monitoring/ (accessed on 14 March 2024). [24]

Ipsos (2022), *Global opinions and expectations about Artificial Intelligence: A global advisor survey*, https://www.ipsos.com/sites/default/files/ct/news/documents/2022-01/Global-opinions-and-expectations-about-AI-2022.pdf. [35]

Kim, P. (2018), *Big Data and Artificial Intelligence: New Challenges for Workplace Equality*, https://papers.ssrn.com/abstract=3296521 (accessed on 14 March 2024). [23]

Lane, M. and A. Saint-Martin (2021), “The impact of Artificial Intelligence on the labour market: What do we know so far?”*, OECD Social, Employment and Migration Working Papers*, No. 256, OECD Publishing, Paris, https://doi.org/10.1787/7c895724-en. [36]

Lane, M., M. Williams and S. Broecke (2023), “The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers”*, OECD Social, Employment and Migration Working Papers*, No. 288, OECD Publishing, Paris, https://doi.org/10.1787/ea0a0fe1-en. [16]

Lassébie, J. and G. Quintini (2022), “What skills and abilities can automation technologies replicate and what does it mean for workers?: New evidence”*, OECD Social, Employment and Migration Working Papers*, No. 282, OECD Publishing, Paris, https://doi.org/10.1787/646aad77-en. [7]

Li, D., L. Raymond and P. Bergman (2020), *Hiring as Exploration*. [31]

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]

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. [37]

Noy, S. and W. Zhang (2023), "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4375283. [27]

OECD (2023), *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris, https://doi.org/10.1787/08785bba-en. [2]

OECD (2020), *Promoting an Age-Inclusive Workforce: Living, Learning and Earning Longer*, OECD Publishing, Paris, https://doi.org/10.1787/59752153-en. [34]

OECD (2019), *Getting Skills Right: Future-Ready Adult Learning Systems, Getting Skills Right*, OECD Publishing, https://doi.org/10.1787/9789264311756-en. [20]

OECD (2018), *Bridging the digital gender divide: include, upskill, innovate*, https://www.oecd.org/digital/bridging-the-digital-gender-divide.pdf (accessed on 11 May 2023). [18]

OECD (2018), "Bridging the digital gender divide: Include, upskill, innovate", https://www.oecd.org/digital/bridging-the-digital-gender-divide.pdf. [14]

OECD (2015), *Adults, Computers and Problem Solving: What's the Problem?*, OECD Skills Studies, OECD Publishing, Paris, https://doi.org/10.1787/9789264236844-en. [17]

OECD (n.d.), *The OECD Going Digital Toolkit, based on the OECD ICT Access and Usage by Households and Individuals Database,*, https://goingdigital.oecd.org/indicator/54. [19]

Peng, S. et al. (2023), "The Impact of AI on Developer Productivity: Evidence from GitHub Copilot". [29]

Pisanelli, E. (2022), *A New Turning Point for Women: Artificial Intelligence as a Tool for Reducing Gender Discrimination in Hiring*, https://doi.org/10.2139/ssrn.4254965. [32]

Qureshi, Z. (ed.) (2022), *The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty*, Brookings Institution, https://www.brookings.edu/wp-content/uploads/2022/05/Inclusive-future_Technology-newdynamics-policy-challenges.pdf. [25]

Salvi del Pero, A., P. Wyckoff and A. Vourc'h (2022), "Using Artificial Intelligence in the workplace: What are the main ethical risks?", *OECD Social, Employment and Migration Working Papers*, No. 273, OECD Publishing, Paris, https://doi.org/10.1787/840a2d9f-en. [21]

Touzet, C. (2023), "Using AI to support people with disability in the labour market: Opportunities and challenges", *OECD Artificial Intelligence Papers, No. 7*, https://doi.org/10.1787/008b32b7-en. [30]

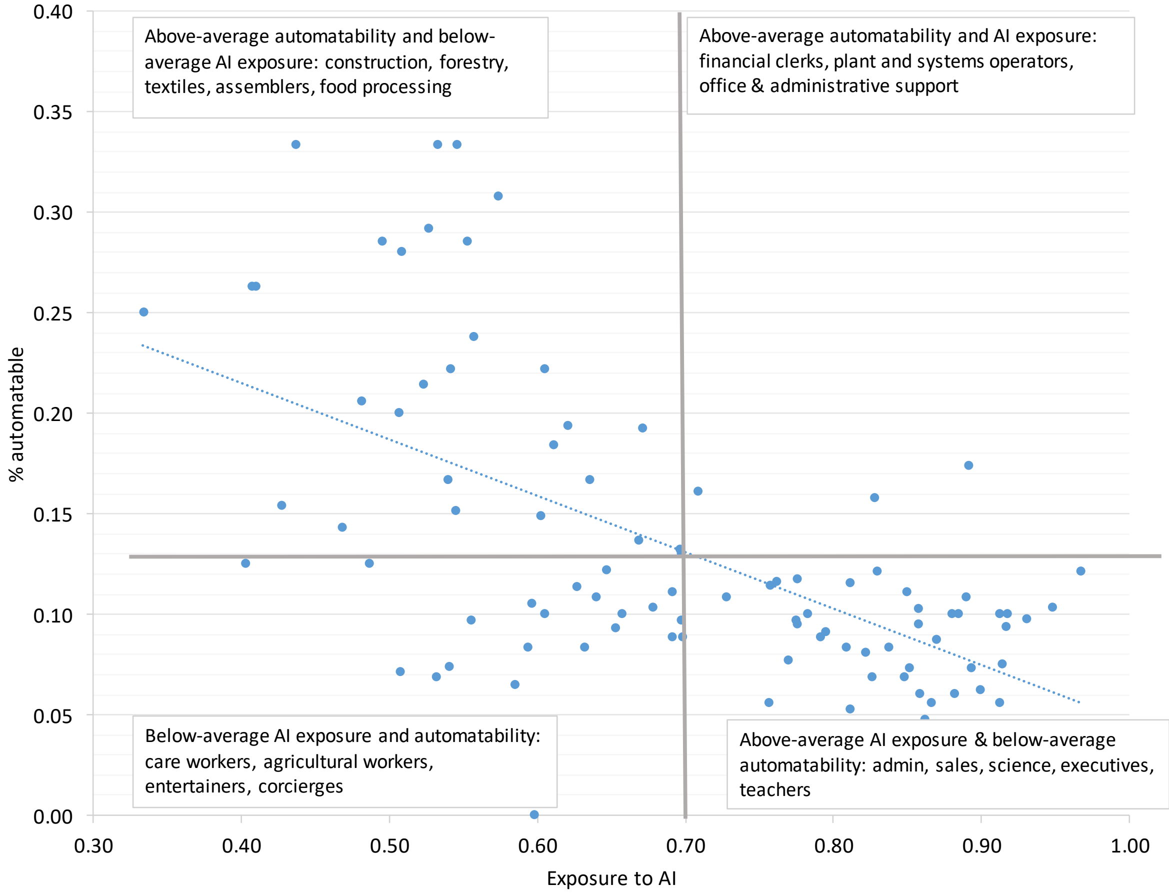
Verhagen, A. (2021), "Opportunities and drawbacks of using artificial intelligence for training", *OECD Social, Employment and Migration Working Papers*, No. 266, OECD Publishing, Paris, https://doi.org/10.1787/22729bd6-en. [33]

Annex A. Risk of automation

Risk of automation and AI exposure affect different occupations

Figure A A.1 demonstrates that risk of automation and AI exposure are different concepts, affecting different groups of workers. In Lassébie and Quintini (2022[7]) an occupation is considered at high risk of automation if over 25% of important skills and abilities associated with that occupation are highly automatable. The risk of automation measure has a broader focus than the AI exposure measure in that it considers all automation technologies including robotics and machinery in addition to AI. One stark difference with AI exposure measures is that abilities related to strength tend to be considered highly automatable. This leads occupations such as woodworkers, construction trades workers and material moving workers to be associated with high risk of automation, while associated with low AI exposure. Occupations related to administration, science and executive leadership have high exposure to AI but have low automatability. Occupations in agriculture and entertainment have low exposure to AI and low automatability, while there are very few occupations with both high exposure to AI and high automatability.

Figure A A.1. Occupations highly exposed to AI are not necessarily at high risk of automation (from all technologies)



Note: Occupations are at SOC 3-digit level. Horizontal lines are added to represent average AI exposure of 0.70 and average automatability of 0.13.
Source: Author's analysis of measures from Lassébie and Quintini (2022[7]) and Felten, Raj and Seamans (2021[1]).

Male, lower-educated and foreign-born workers are in occupations at high risk of automation

Across the countries included in the analysis, occupations at high risk of automation have on average a higher presence of male, non-university-educated, and foreign-born workers than other occupations (Table A A.1). There are fewer prime-aged workers in these occupations, but the differences are relatively small.

Table A A.1. Occupations at high risk of automation have on average a higher presence of male, non-university-educated, and foreign-born workers

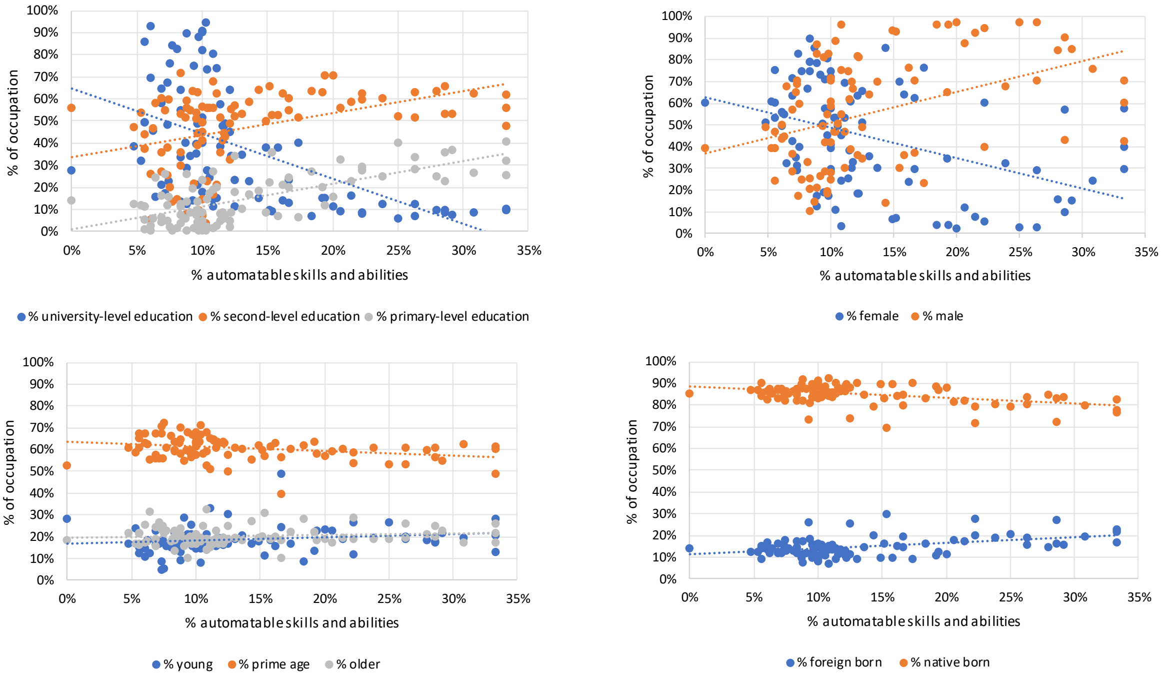
Occupations at high risk of automation	% of highly automatable skills & abilities	% university educated	% male	% prime age	% native-born
Fishing and Hunting Workers	33%	9.9%	70.4%	49.4%	83.0%
Food Processing Workers	33%	10.6%	60.3%	61.5%	78.1%
Textile, Apparel, and Furnishings Workers	33%	10.1%	42.4%	60.4%	76.7%
Assemblers and Fabricators	31%	8.8%	75.9%	62.7%	80.4%
Forest, Conservation, and Logging Workers	29%	7.9%	84.9%	55.4%	84.2%
Metal Workers and Plastic Workers	29%	9.8%	90.4%	61.4%	83.4%
Material Moving Workers	29%	8.7%	43.0%	56.9%	72.5%
Woodworkers	28%	9.8%	84.5%	60.0%	85.1%
Grounds Maintenance Workers	26%	12.5%	70.6%	53.4%	83.8%
Construction Trades Workers	26%	7.2%	97.2%	61.2%	80.6%
Helpers, Construction Trades	25%	5.9%	97.4%	53.5%	79.4%
Average across all occupations	**13%**	**37.6%**	**55.8%**	**60.9%**	**85.2%**

Source: Author's analysis of measures from Lassébie and Quintini (2022[7]), "What skills and abilities can automation technologies replicate and what does it mean for workers?: New evidence", *OECD Social, Employment and Migration Working Papers*, No. 282, https://doi.org/10.1787/646aad77-en.

That male, lower-educated and foreign-born workers are at higher risk of automation is confirmed by the graphs below, which plot the distribution of socio-demographic groups within each occupation against the proportion of important skills and abilities in that occupation,[30] and by regression analysis, which controls for gender, age, education, country of birth and country. With these controls, younger workers appear also to be at higher risk of automation. As with the analysis of AI exposure, university education plays an important mediating role for socio-demographic characteristics. Regression on individual-level data suggests that the risk of automation for male and foreign-born workers is even larger among those without a university education and that the risk of automation for younger workers is larger among those with a university education.

[30] Lassébie and Quintini also assessed the extent to which each occupation relies on skills and abilities that are bottlenecks (i.e. cannot be automated). The occupations that have a high share of highly automatable skills and abilities tend to also have a low share of bottlenecks (the correlation coefficient is -0.8). The result is that when the same analysis is conducted using the proportion of bottlenecks in each occupation, an inverse trend is generally observed, i.e. occupations with more bottlenecks tend to have more women, university-educated and foreign-born workers on average. However, there is one exception. Occupations with a higher proportion of young workers have both slightly greater proportion of highly automatable skills and abilities and slightly greater proportion of bottlenecks (e.g. Food and Beverage Serving Workers (where 49% of workers are young) and Other Transportation Workers (which includes parking Attendants and passenger attendants) (where 25% of workers are young), which are both associated with >15% important skills and abilities that are automatable and >15% that are bottlenecks.

Figure A A.2. Male, lower-educated and foreign-born workers are at higher risk of automation



Source: Author’s analysis of measures from Lassébie and Quintini (2022[7])

Annex B. Overall link between AI exposure and employment outcomes

There is a positive link between AI exposure and employment growth between 2012 and 2022

Employment growth between 2012 and 2022, was stronger in occupations with higher exposure to AI, even when controlling for the prevalence of software and industrial robots, offshorability, exposure to international trade, and country and occupation fixed effects. This finding is established by extending the work of Georgieff and Hyee (2021[5]), which focused on the period of 2012-19, to the period 2012-22. Results are shown in Table A B.1. While Georgieff and Hyee found that the effects on employment across all occupations were positive but not robust to the addition of controls (they were robust if the analysis was limited to occupations with high computer use only), this may be because 2019 was just too early to observe the impact across all occupations. It may have taken the period between 2019 and 2022 for AI to be sufficiently diffused or sufficiently mature in its application for its impact to be felt more broadly. On average, a one standard deviation increase in AI exposure is associated with 11.3 percentage points higher employment growth.

Table A B.1. There is a positive link between AI exposure and employment growth between 2012 and 2022

Estimated link between AI exposure and employment growth at aggregate level

	(1)	(2)	(3)	(4)
	Dependent variable is the 2012-22			
	Log change in employment	Change in employment	Log change in average usual working hours	Change in average usual working hours
Coefficient on AI exposure *without controls*	.29378***	33.57594***	-.03527***	-3.99823***
	(.0704)	(8.6404)	(.0126)	(1.3873)
R-squared	0.072	0.079	0.166	0.156
Coefficient on AI exposure *with controls*	.49688***	64.09928***	-.04543*	-4.76429*
	(.1523)	(19.2406)	(.0262)	(2.7791)
R-squared	0.186	0.188	0.225	0.215
Country FEs	Yes	Yes	Yes	Yes
Observations	786	786	786	786

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell.
Source: Author's calculations using data from EU-LFS, US-CPS and UK-LFS, and the AI exposure measure described in Box 2.1.

There is a weak negative link between AI exposure and usual working hours between 2012 and 2022

A one standard deviation increase in exposure to AI is associated with a 0.84 percentage point larger decline in usual weekly working hours (Table A B.1).[31] While statistically significant only at the 10% level, a negative relation between AI exposure and the change in average working hours is consistent with Georgieff and Hyee.[32] In other words, while the occupations most exposed to AI have experienced increases in employment, they have experienced a decrease in usual working hours. As noted in the 2023 OECD Employment Outlook (2023[2]), while employment levels in 2023 had grown to exceed pre-pandemic levels, average usual hours worked were still below pre-pandemic levels. The authors suggest that workers' preferences for work-life balance may be a cause, in which case it may be more difficult to interpret usual working hours as an indicator of labour demand, compared to employment levels.

[31] The standard deviation of exposure to AI is.176. Multiplying this by the coefficient in Annex B in Column 4 gives 0.176* -4.764= -.840.

[32] Splitting the data by the degree of computer use in each occupation, they found that this negative relation was present among occupations requiring low computer use only. A similar pattern is found in the period from 2012 to 2022, where there is a negative relation among occupations requiring low computer use and a positive relation among occupations requiring high computer use. Among occupations requiring medium computer use, the relation is not statistically significant.