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What skills and abilities can automation technologies replicate and what does it mean for workers?

New evidence

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Abstract

What skills and abilities can be replicated through automation technologies and what does it mean for jobs and workers? This paper addresses this question with the specific aim of accounting for the latest progress in AI technologies and robotics. It exploits novel data collected through an original survey on the degree of automatability of approximately 100 skills and abilities. The survey was developed with the help of, and completed by, experts from different AI research fields. In a second step, the degree of automatability of skills and abilities obtained through the survey was applied to occupations using information on skill and ability requirements extracted from the Occupational Information Network database. Similar to previous studies, this allows gauging the number of jobs potentially affected by automation and the workers who are most at risk of automation. The focus on the automatability of skills and abilities as opposed to the automatability of entire occupations also allows for a direct assessment of the share of highly automatable and bottleneck tasks in each occupation. The study finds that thanks to advances in AI and robotics, several high-level cognitive skills can now be automated. However, high-skilled occupations continue to be less at risk of automation because they also require skills and abilities that remain important bottlenecks to automation. Furthermore, this work shows that jobs at highest risk of automation will not disappear completely, as only 18 to 27% of skills and abilities required in these occupations are highly automatable. Rather, the organisation of work will have to be radically adapted and workers in these jobs will need to retrain, as technologies replace workers for several tasks.

Résumé

Quelles compétences peuvent être répliquées par les technologies d'automatisation ? Qu'est-ce que cela signifie pour les emplois et les travailleurs ? Cet article répond à cette question en prenant en compte les dernières avancées en Intelligence Artificielle et en robotique. L'étude exploite des données inédites recueillies grâce à une nouvelle enquête sur le degré d'automatisation d'une centaine de compétences et d'aptitudes, élaborée avec l'aide de, et remplie par, plusieurs experts spécialisés dans différents domaines de recherche en Intelligence Artificielle et robotique. Dans un deuxième temps, le degré d'automatisation des aptitudes et compétences obtenu grâce à l'enquête a été traduit en degré d'automatisation des différentes professions en utilisant les informations sur les exigences en matière d'aptitudes et de compétences contenues dans la base de données O*NET. Cela permet d'évaluer le nombre et le type d'emplois et de travailleurs potentiellement touchés par l'automatisation. L'accent mis sur l'automatisation des aptitudes et compétences plutôt que sur l'automatisation des professions dans leur ensemble permet d'évaluer la part des tâches hautement automatisables et des tâches peu automatisables dans chaque profession et donc de réaliser une analyse précise des risques. L'étude révèle que, grâce aux progrès en Intelligence Artificielle et en robotique, plusieurs compétences cognitives de haut niveau peuvent désormais être automatisées. Toutefois, les professions hautement qualifiées continuent d'être moins exposées au risque d'automatisation, car elles requièrent également des compétences et des aptitudes qui sont peu automatisables. En outre, l'étude montre que les emplois les plus exposés au risque d'automatisation ne disparaîtront pas complètement, car seulement 18 à 27 % des compétences et aptitudes requises dans ces professions sont hautement automatisables. En revanche, lorsque les technologies remplaceront les travailleurs dans ces tâches, ceux-ci devront se former afin de faire face à la nouvelle organisation du travail.

Kurzfassung

Welche Fähigkeiten und Fertigkeiten können von Automatisierungstechnologien übernommen werden und was bedeutet dies für Arbeitsplätze und Arbeitnehmer? Der vorliegende Bericht befasst sich mit dieser Frage und zielt darauf ab, den jüngsten Fortschritten in der KI-Technologie und Robotik Rechnung zu tragen. Er nutzt Daten, die im Rahmen einer neuen Umfrage zum Automatisierungsgrad von etwa 100 Fertigkeiten und Fähigkeiten erhoben wurden. Die Umfrage wurde mithilfe von Experten aus verschiedenen Bereichen der KI-Forschung entwickelt und von diesen beantwortet. In einem zweiten Schritt wird der durch die Umfrage ermittelte Automatisierungsgrad von Fähigkeiten und Fertigkeiten auf Berufe angewandt, wobei Informationen aus der Datenbank des Occupational Information Network verwendet werden. Ähnlich wie in früheren Studien lässt sich auf diese Weise die Zahl der potenziell von Automatisierung betroffenen Arbeitsplätze und der am stärksten von Automatisierung bedrohten Arbeitnehmer ermitteln. Der Fokus auf Automatisierbarkeit von Fähigkeiten und Fertigkeiten - im Gegensatz zur Automatisierbarkeit ganzer Berufe - ermöglicht eine direkte Bewertung des Anteils hochgradig automatisierbarer Aufgaben und Engpassaufgaben (d.h. weniger einfach zu automatisierende Aufgaben) in jedem Beruf. Die Studie kommt zu dem Ergebnis, dass mehrere hoch-kognitive Fähigkeiten heute auf Grund von Fortschritten in der KI und Robotik automatisiert werden können. Hochqualifizierte Berufe sind jedoch nach wie vor weniger stark von Automatisierung bedroht, da sie auch Fähigkeiten und Fertigkeiten erfordern, die weiterhin wichtige Nadelöhre für Automatisierung darstellen. Außerdem zeigt dieser Bericht, dass die am stärksten von Automatisierung bedrohten Berufe nicht vollständig verschwinden werden, da nur 18 bis 27 % der in diesen Berufen erforderlichen Fähigkeiten und Fertigkeiten in hohem Maße automatisierbar sind. Vielmehr wird die Arbeitsorganisation radikal angepasst und Arbeitnehmer in diesen Berufen umgeschult werden müssen, wenn Technologien mehr Aufgaben übernehmen.

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Executive summary

Recent advances in Artificial Intelligence have broadened the set of skills and abilities that can be replicated by automation technologies. In the past, computers and robots could only follow rules specified by programmers. However, machine learning algorithms, the branch of AI that has experienced the most important advances recently, can now make decisions without following pre-specified rules. Furthermore, AI technologies are able to work with unstructured environments and data. As a result, AI can help automate non-routine activities, contrary to computers that needed codified environments and hence could replace workers only in routine tasks.

To explore the implications of these developments on jobs and workers, this study re-assesses the degree of automatability of skills and abilities, adopting a forward-looking approach. It exploits new data on the potential automatability of approximately 100 skills and abilities collected through an original survey of AI experts. This information is richer than previous studies that relied on few bottlenecks or a small set of highly automatable skills and abilities. It then uses information on skill and ability requirements in occupations from the Occupational Information Network (O*NET) to evaluate how automatability of skills and abilities may translate into a risk of automation at the occupation level, and to understand which groups of workers are likely to be most affected based on their education level, age, and gender. Looking directly and granularly at skills and abilities, rather than considering that occupations are either automatable entirely or not at all, allows drawing a more precise picture of the impact of AI and automation technologies on jobs. The much broader range of skills and abilities also allows shedding light on the issues of displacement and complementarity that have received much attention recently but for which the evidence base is not yet sufficiently robust. This is crucial, as most occupations require a combination of bottleneck skills and abilities (i.e. skills and abilities that cannot be automated given the current state of technologies) and automatable ones. Studies that focus only on a very small number of bottlenecks or only on highly automatable skills and abilities likely provide a distorted picture of job automatability.

Following discussions with the AI experts consulted for this study, this paper focuses on the automatability of skills and abilities, without distinguishing between the specific technologies that might be driving it. Such classification of AI systems is outside the scope of the study. Furthermore, even when it is possible to distinguish between the different types of automation technologies, their impact on labour markets are much harder, if not impossible, to disentangle from one another since production processes are likely to use a mix of different technologies and because their effects tend to reinforce each other. In addition, it is the view of the consulted experts that the vast majority of recent technological developments concerning automation technologies are now in the field of AI and a number of less novel technologies, in particular in robotics, are being improved thanks to AI. This is the case for instance of AI-powered robots that can now pick up objects of variable shapes and sizes in unpredictable orientations and with remarkable accuracy, while previous generations of robots could only move objects of fixed size and could not deviate from their programmed trajectory. It is also important to note that the present study focuses on the *potential* of automation technologies to replicate human skills and abilities as opposed to *actual* automation which depends on economic, operational, and cultural feasibility. While important for technology adoption, these factors and the interaction between them would be too complex and too country-specific to analyse in a single unified framework, particularly using a forward looking approach.

This study finds that, thanks to important advances in automation technologies driven by AI, some skills and abilities previously identified as bottlenecks to automation are now more susceptible to automation. This is the case of the knowledge of fine arts and several psychomotor abilities (the ability to work in cramped workspace and awkward positions, finger dexterity, and manual dexterity). Recent advances in AI also make several skills required in high-skilled jobs susceptible to automation. This is the case for instance of reading comprehension, deductive and inductive reasoning skills, fluency of ideas and scheduling skills. However, there remains significant bottlenecks to automation. In particular, skills related to complex problem-solving, high-level management and social interaction can hardly be automated given the current state of technological developments.

Construction and extraction, farming, fishing, and forestry, and to a lower extent production and transportation occupations, rely importantly on skills and abilities that are highly susceptible to automation and hence are among the occupations most at risk of automation. Least at risk jobs include management and community and social service occupations. However, the crucial takeaway is that most occupations rely importantly on both bottleneck and highly automatable skills and abilities.

This is a clear gain in precision over previous studies focusing on a limited number of bottlenecks to automation. Thanks to the more granular assessment conducted for this paper, it emerges quite clearly that most jobs that are at highest risk of automation are not at risk of being entirely automated as they involve bottleneck tasks and even jobs that are shielded from the risk of disappearing involve a small set of automatable tasks. For example, only about 18 to 27% of skills and abilities required by the most at risk occupations listed above are highly automatable and these occupations still require around 5% of bottleneck skills. In other words, even the occupations at highest risk of automation are not likely to be entirely substituted by automated solutions. Rather, the organisation of work will have to be adapted and workers in these jobs may need to retrain, as technologies replace workers for several tasks.

Another important takeaway of this work is that, even if AI increasingly allows automating skills and abilities required in high-skilled occupations, the occupations at highest risk of automation remain essentially low-skilled. This is because high-skilled jobs also involve many bottleneck skills and abilities. For example, the occupations least at risk of automation mentioned above involve about 5-10% of skills and abilities that are highly automatable but this is countered by approximately 25% of important skills and abilities that are bottlenecks.

On average across OECD countries, occupations at highest risk of automation account for about 28% of employment. This is higher than previous figures published by OECD which put the share of workers at high risk of automation to about 14%. This may be due to progress in AI technologies but also to the different methodology adopted. What is clear is that while more jobs may be exposed to AI, very few are at the risk of disappearing entirely. Based on the granular analysis of the degree of automatability of skills and abilities conducted in this study, only 9% of workers are employed in occupations with a significant share of highly automatable skills and abilities. This figure varies substantially across countries – ranging from less than 6% in the United Kingdom, Luxembourg, Sweden, Netherlands, Norway, and Switzerland to over 12% in Hungary, Latvia, Slovak Republic, and Czechia – but remains contained. Workers in occupations with the highest shares of automatable skills and abilities continue to be low-skilled, young, and male. Finally, and despite important efforts made by governments over the past years to retrain workers in occupations most at risk of job automation, the relationship between an occupation's risk of automation and the share of workers in this occupation participating in training remains significantly negative.

Principaux résultats

Les récents progrès en Intelligence Artificielle (IA) ont élargi l'ensemble des aptitudes et compétences qui peuvent être répliquées par les technologies d'automatisation. Dans le passé, les ordinateurs et les robots étaient contraints à suivre des règles spécifiées par les programmeurs. Cependant, les algorithmes d'apprentissage automatique (Machine Learning), la branche de l'IA qui a connu les progrès les plus importants récemment, peuvent désormais fonctionner sans suivre de règles préétablies. De plus, les technologies d'IA sont capables de travailler avec des environnements et des données non structurés. Par conséquent, l'IA peut contribuer à l'automatisation d'activités non routinières, contrairement aux ordinateurs qui avaient besoin d'environnements codifiés et ne pouvaient donc remplacer les travailleurs que pour les tâches routinières.

Afin d'explorer les implications de ces évolutions sur les emplois et les travailleurs, la présente étude réévalue le degré d'automatisation des aptitudes et compétences, en adoptant une approche prospective. Elle exploite des données originales sur l'automatisation potentielle d'une centaine d'aptitudes et compétences recueillies dans le cadre d'une nouvelle enquête menée auprès d'experts en IA. Ces informations sont plus riches que les études précédentes qui se focalisaient sur un nombre restreint d'aptitudes et compétences. L'étude utilise ensuite les informations sur les exigences en matière de d'aptitudes et compétences dans les professions contenues dans la base de données O*NET pour évaluer comment leur automatisation peut se traduire par un risque d'automatisation des différentes professions, et pour comprendre quels groupes de travailleurs sont susceptibles d'être les plus touchés, en fonction de leur niveau d'éducation, de leur âge et de leur sexe. Examiner directement et de manière détaillée les aptitudes et compétences plutôt que de considérer les professions dans leur ensemble permet de dresser un tableau plus précis de l'impact de l'IA et des technologies d'automatisation sur les emplois. L'éventail beaucoup plus large des aptitudes et compétences étudiées permet également de faire la lumière sur les questions de substitution et de complémentarité entre travailleurs et technologies qui ont fait l'objet d'une grande attention récemment, mais pour lesquelles les preuves empiriques ne sont pas encore suffisamment solides. Cet aspect est crucial, car la plupart des professions requièrent à la fois des aptitudes et compétences peu automatisables et d'autres qui le sont. Les études qui se concentrent uniquement sur un nombre restreint d'aptitudes et compétences donnent probablement une image déformée de l'automatisation des emplois.

À la suite des discussions avec les experts en IA consultés pour l'élaboration de l'enquête, la présente étude se concentre sur l'automatisation des compétences et des aptitudes, sans faire de distinction entre les technologies spécifiques (IA, robotique, ou autre) qui pourraient la permettre. Une telle classification des technologies d'automatisation sort du cadre de l'étude. En outre, même s'il est possible d'effectuer une distinction entre les différentes technologies, leur impact sur le marché du travail est beaucoup plus difficile, voire impossible, à distinguer, car les processus de production sont susceptibles d'utiliser un mélange de différentes technologies et parce que leurs effets ont tendance à se renforcer mutuellement. En outre, les experts consultés estiment que la grande majorité des développements technologiques récents concernant les technologies d'automatisation relèvent désormais de l'IA et qu'un certain nombre de technologies moins nouvelles, en particulier dans le domaine de la robotique, sont améliorées grâce à l'IA. C'est le cas par exemple des robots qui peuvent être opérés ou complémentés par une Intelligence

Artificielle. Par exemple, certains robots peuvent désormais ramasser des objets de formes et de tailles variables dans des orientations imprévisibles et avec une précision remarquable, alors que ceux des générations précédentes ne pouvaient déplacer que des objets de taille fixe et ne pouvaient pas dévier de leur trajectoire programmée. Il est également important de noter que la présente étude se concentre sur l'automatisation *potentielle* des aptitudes et compétences, par opposition à leur automatisation *réelle* qui dépend de la facteurs économiques, opérationnels et culturels. Bien qu'importants pour l'adoption des technologies d'automatisation, ces facteurs et leur interaction seraient trop complexes et trop spécifiques à chaque pays pour être analysés dans un cadre unifié, en particulier en adoptant une approche prospective.

Cette étude révèle que, grâce à d'importants progrès dans les technologies d'automatisation permis par l'IA, certaines compétences et aptitudes précédemment identifiées comme peu automatisables sont désormais plus à risque. C'est le cas de la connaissance des arts et belles lettres, et de plusieurs capacités psychomotrices (capacité à travailler dans un espace de travail exigu et dans des positions inconfortables, dextérité des doigts et dextérité manuelle). Les progrès récents de l'IA rendent également susceptibles à l'automatisation plusieurs compétences requises dans les emplois hautement qualifiés. C'est le cas par exemple de la compréhension écrite, des capacités de raisonnement déductif et inductif, de la fluidité des idées et des capacités de planification. Toutefois, plusieurs aptitudes et compétences restent peu automatisable. En particulier, les compétences liées à la résolution de problèmes complexes, à la gestion et à l'interaction sociale peuvent difficilement être automatisées dans l'état actuel des connaissances.

Les métiers de la construction et de l'extraction, de l'agriculture, de la pêche et de la sylviculture et, dans une moindre mesure, les métiers de la production et du transport, reposent en grande partie sur des aptitudes et compétences très susceptibles à l'automatisation et font donc partie des professions les plus à risque. Les emplois les moins menacés sont ceux du management et des services sociaux et communautaires. Toutefois, l'élément essentiel à retenir est que la plupart des professions reposent à la fois sur des compétences et des capacités peu automatisables et sur d'autres qui le sont grandement.

Il s'agit d'un net gain de précision par rapport aux études antérieures qui se concentraient sur un nombre limité d'aptitudes et compétences. Grâce à l'évaluation plus fine réalisée dans cette étude, il apparaît très clairement que la plupart des emplois les plus exposés au risque d'automatisation ne risquent pas d'être entièrement automatisés car ils requièrent des aptitudes et compétences peu automatisables et que même les emplois qui sont moins à risque comportent tout de même un petit nombre de tâches automatisables. Par exemple, seuls 18 à 27 % des compétences et aptitudes requises par les professions les plus menacées énumérées ci-dessus sont hautement automatisables et ces professions requièrent encore environ 5 % de compétences peu automatisables. En d'autres termes, même les professions les plus exposées à l'automatisation ne sont pas susceptibles d'être entièrement automatisées. Lorsque les technologies remplaceront les travailleurs dans ces tâches, ceux-ci devront se former afin de faire face à la nouvelle organisation du travail.

Un autre enseignement important de cette étude est que, même si l'IA permet d'automatiser de plus en plus d'aptitudes et compétences requises dans les professions hautement qualifiées, les professions les plus exposées au risque d'automatisation restent essentiellement les professions peu qualifiées. Cela s'explique par le fait que les emplois hautement qualifiés impliquent également de nombreuses compétences et aptitudes peu automatisables. Par exemple, les professions les moins exposées au risque d'automatisation mentionnées ci-dessus comportent environ 5 à 10 % de compétences et d'aptitudes hautement automatisables, mais cela est contrebalancé par environ 25 % de compétences et d'aptitudes peu automatisables.

En moyenne, dans les pays de l'OCDE, les professions les plus exposées à l'automatisation représentent environ 28 % de l'emploi. Ce chiffre est plus élevé que les chiffres précédents publiés par l'OCDE, qui situaient la part des travailleurs à haut risque d'automatisation à environ 14 %. Cela peut être dû aux progrès des technologies d'IA, mais aussi à l'adoption d'une méthodologie très différente. Ce qui est clair, c'est que si davantage d'emplois peuvent être exposés à l'IA, très peu risquent de disparaître entièrement. Sur la base de l'analyse du potentiel d'automatisation des compétences menée dans cette étude, seuls 9 % des travailleurs sont employés dans des professions comportant une part importante de compétences hautement automatisables. Ce chiffre varie considérablement d'un pays à l'autre - allant de moins de 6 % au Royaume-Uni, au Luxembourg, en Suède, aux Pays-Bas, en Norvège et en Suisse à plus de 12 % en Hongrie, en Lettonie, en République slovaque et en République tchèque - mais reste modéré. Les travailleurs exerçant les professions où la part des compétences et aptitudes automatisables est la plus élevée sont peu qualifiés, jeunes et de genre masculin. Enfin, et malgré les efforts importants déployés par les gouvernements au cours des dernières années pour former les travailleurs dans les professions les plus à risque d'automatisation, la relation entre potentiel d'automatisation et part des travailleurs qui entreprennent une formation reste significativement négative.

Zusammenfassung

Jüngste Fortschritte auf dem Gebiet der künstlichen Intelligenz (KI) haben die Palette der Fähigkeiten und Fertigkeiten, die durch Automatisierungstechnologien repliziert werden können, erweitert. In der Vergangenheit konnten Computer und Roboter nur von Programmierern vorgegebene Regeln befolgen. Die Algorithmen des maschinellen Lernens, der Zweig der KI, der aktuell die größten Fortschritte macht, können jetzt jedoch Entscheidungen treffen, ohne vorher festgelegten Regeln zu folgen. Außerdem sind KI-Technologien in der Lage, mit unstrukturierten Umgebungen und Daten zu arbeiten. Im Gegensatz zu Computern, die kodifizierte Umgebungen benötigen und daher Arbeitnehmer nur bei Routineaufgaben ersetzen können, kann KI daher zur Automatisierung von nicht routinemäßigen Tätigkeiten beitragen.

Um die Auswirkung dieser Entwicklungen auf Arbeitsplätze und Arbeitnehmer zu untersuchen, wird in dieser Studie der Automatisierungsgrad von Fähigkeiten und Fertigkeiten neu bewertet. Sie nutzt neue Daten über die potenzielle Automatisierbarkeit von etwa 100 Fähigkeiten und Fertigkeiten, die durch eine neue Umfrage unter KI-Experten erhoben wurden. Diese Informationen sind detaillierter als in früheren Studien, die sich auf wenige Engpässe oder eine kleine Gruppe von hochgradig automatisierbaren Fähigkeiten und Fertigkeiten stützten. Anschließend werden Informationen über die Fähigkeits- und Fertigkeitsanforderungen in Berufen aus dem Occupational Information Network (O*NET) verwendet, um das Automatisierungsrisiko auf Berufsebene zu bewerten. Sie ermöglichen es auch zu verstehen, welche Gruppen von Arbeitnehmern auf der Grundlage ihres Bildungsniveaus, Alters und Geschlechts wahrscheinlich am stärksten von Automatisierung betroffen sein werden. Die direkte und granulare Betrachtung von Fähigkeiten und Fertigkeiten, anstatt davon auszugehen, dass Berufe entweder ganz oder gar nicht automatisierbar sind, zeichnet ein genaueres Bild der Auswirkungen von KI und Automatisierungstechnologien auf Arbeitsplätze. Das breite Spektrum an Fähigkeiten und Fertigkeiten ermöglicht es auch, Fragen von Verdrängung und Komplementarität zu beleuchten, die in letzter Zeit viel Aufmerksamkeit erhalten haben, für die es aber noch keine ausreichende Evidenzbasis gibt. Dies ist von entscheidender Bedeutung, da die meisten Berufe eine Kombination aus Engpassfähigkeiten und -fertigkeiten (d. h. Fähigkeiten und Fertigkeiten, die nach derzeitigen Stand der Technik nicht automatisiert werden können) und automatisierbaren Fähigkeiten und Fertigkeiten erfordern. Studien, die sich nur auf eine sehr kleine Zahl von Engpässen oder nur auf hochgradig automatisierbare Fähigkeiten und Fertigkeiten konzentrieren, geben wahrscheinlich ein verzerrtes Bild der Automatisierbarkeit von Arbeitsplätzen.

Nach Diskussion mit denen in dieser Studie konsultierten KI-Experten, konzentriert sich dieses Papier auf die Automatisierbarkeit von Fähigkeiten und Fertigkeiten, ohne zwischen spezifischen Automatisierungstechnologien zu unterscheiden. Eine solche Klassifizierung von KI-Systemen liegt außerhalb des Rahmens der Studie. Selbst wenn es möglich wäre, zwischen verschiedenen Automatisierungstechnologien zu unterscheiden, ist es schwierig – wenn nicht gar unmöglich – ihren Einfluss auf Arbeitsmärkte getrennt voneinander zu betrachten, da in Produktionsprozessen zumeist eine Mischung aus verschiedenen Technologien zum Einsatz kommt. Darüber hinaus sind die befragten Experten der Ansicht, dass die meisten technologischen Entwicklungen im Bereich der Automatisierungstechnologien inzwischen auf dem Gebiet der KI stattfinden und dass andere weniger neue Technologien, insbesondere in der Robotik, dank der KI verbessert werden. Dies ist beispielsweise bei KI-gesteuerten Robotern der Fall, die nun Objekte unterschiedlicher Form und Größe in unvorhersehbaren Ausrichtungen und mit bemerkenswerter Genauigkeit aufnehmen können. Frühere Robotergenerationen konnten nur Objekte fester Größe bewegen und nicht von ihrer programmierten Bahn abweichen. Wichtig ist auch, dass sich die vorliegende Studie auf das Potenzial von Automatisierungstechnologien konzentriert und nicht auf die tatsächliche Automatisierung menschlicher Fähigkeiten und Fertigkeiten, die auch von wirtschaftlichen, betrieblichen und kulturellen Faktoren abhängt. Diese Faktoren und ihre Wechselwirkungen sind zwar wichtig für die Einführung von Technologien, wären aber zu komplex und zu länderspezifisch, um sie in einem einheitlichen Rahmen zu analysieren.

Die Studie kommt zu dem Schluss, dass einige Fähigkeiten und Fertigkeiten, die früher als Nadelöhre für Automatisierung galten, auf Grund der Fortschritte in den KI-getriebenen Automatisierungstechnologien nun anfälliger für Automatisierung sind. Dies betrifft die Kenntnisse der bildenden Künste und mehrere psychomotorische Fähigkeiten (die Fähigkeit, auf engem Raum und in ungünstigen Positionen zu arbeiten, Fingerfertigkeit und manuelle Geschicklichkeit). Jüngste Fortschritte in der KI machen auch mehrere Fähigkeiten, die in hochqualifizierten Berufen erforderlich sind, anfällig für Automatisierung. Dies gilt beispielsweise für das Leseverständnis, die Fähigkeit zum deduktiven und induktiven Schlussfolgern, die Fluidität der Ideen, und die Fähigkeit zur Zeitplanung. Dennoch gibt es nach wie vor erhebliche Nadelöhre für Automatisierung. Insbesondere Fähigkeiten, die mit komplexer Problemlösung, Management auf hohem Niveau und sozialer Interaktion zusammenhängen, können beim derzeitigen Stand der technologischen Entwicklung kaum automatisiert werden.

Das Baugewerbe und die Gewinnung von Bodenschätzen, die Land-, Fischerei- und Forstwirtschaft und in geringerem Umfang auch Produktions- und Transportberufe sind in hohem Maße von Fertigkeiten und Fähigkeiten abhängig, die sehr anfällig für Automatisierung sind. Sie gehören daher zu den am stärksten von Automatisierung bedrohten Berufen. Zu den am wenigsten gefährdeten Berufen gehören Managementberufe und Berufe im Bereich der gesellschaftlichen und sozialen Dienstleistungen. Die entscheidende Erkenntnis ist jedoch, dass die meisten Berufe sowohl auf Engpass- als auch auf hochgradig automatisierbare Fähigkeiten und Fertigkeiten angewiesen sind.

Dies ist ein deutlicher Präzisionsgewinn gegenüber früheren Studien, die sich auf eine begrenzte Anzahl von Engpässen bei der Automatisierung konzentrierten. Dank der detaillierteren Bewertung, die für diese Studie durchgeführt wurde, wird deutlich, dass selbst die am stärksten von der Automatisierung bedrohten Berufe nicht Gefahr laufen, vollständig automatisiert zu werden, da sie Engpassaufgaben beinhalten. Auf der anderen Seite involvieren selbst Berufe, die vor dem Risiko des Verschwindens geschützt sind, einen kleinen Teil automatisierbarer Aufgaben. So sind beispielsweise nur etwa 18 bis 27 % der Fähigkeiten und Fertigkeiten, die in den oben aufgeführten am stärksten gefährdeten Berufen erforderlich sind, in hohem Maße automatisierbar, und diese Berufe erfordern immer noch etwa 5 % der Engpassfähigkeiten. Mit anderen Worten: Selbst die am stärksten von der Automatisierung bedrohten Berufe werden wahrscheinlich nicht vollständig durch automatisierte Lösungen ersetzt werden. Vielmehr wird die Arbeitsorganisation angepasst und die Arbeitnehmer in diesen Berufen umgeschult werden müssen, da Technologien sie in mehreren Aufgaben ersetzen.

Eine weitere wichtige Erkenntnis aus dieser Arbeit ist, dass die Berufe mit dem höchsten Automatisierungsrisiko weiterhin im Wesentlichen niedrigqualifiziert sind. Dies ist der Fall, obwohl die KI zunehmend auch die Automatisierung von Fähigkeiten und Fertigkeiten ermöglicht, die in hochqualifizierten Berufen erforderlich sind. Dies liegt daran, dass hochqualifizierte Tätigkeiten auch viele Engpassfähigkeiten und -fertigkeiten erfordern. Die oben erwähnten Berufe, die am wenigsten von der Automatisierung bedroht sind, weisen beispielsweise etwa 5-10 % hochautomatisierbare Fähigkeiten und Fertigkeiten auf, denen jedoch etwa 25 % wichtige Fähigkeiten und Fertigkeiten gegenüberstehen, die Engpässe darstellen.

Im Durchschnitt der OECD-Länder machen die Berufe mit dem höchsten Automatisierungsrisiko etwa 28 % der Beschäftigung aus. Dies ist höher als frühere von der OECD veröffentlichte Zahlen, die den Anteil der Arbeitnehmer mit hohem Automatisierungsrisiko auf etwa 14 % bezifferten. Dies könnte auf Fortschritte bei den KI-Technologien zurückzuführen sein, aber auch auf methodologische Unterschiede bei der Schätzung. Klar ist, dass zwar mehr Arbeitsplätze mit KI in Berührung kommen, aber nur sehr wenige vom völligen Verschwinden bedroht sind. Ausgehend von der detaillierten Analyse der Automatisierbarkeit von Fähigkeiten und Fertigkeiten, die in dieser Studie durchgeführt wurde, sind nur 9 % der Arbeitnehmer in Berufen beschäftigt, die einen erheblichen Anteil an hochgradig automatisierbaren Fähigkeiten und Fertigkeiten aufweisen. Diese Zahl variiert zwischen Ländern - von weniger als 6 % im Vereinigten Königreich, Luxemburg, Schweden, den Niederlanden, Norwegen und der Schweiz bis zu über 12 % in Ungarn, Lettland, der Slowakischen Republik und der Tschechischen Republik -, bleibt aber begrenzt. Die Arbeitnehmer in Berufen mit dem höchsten Anteil an automatisierbaren Fähigkeiten und Fertigkeiten sind nach wie vor gering qualifiziert, jung und männlich. Trotz der Anstrengungen der letzten Jahre, Arbeitnehmer in stark von Automatisierung bedrohten Berufen umzuschulen, bleibt die Beziehung zwischen Automatisierungsrisiko eines Berufs und dem Anteil der Arbeitnehmer, die an Weiterbildungen teilnehmen, deutlich negativ.

1 Insights from the existing literature

1. Automation has been a recurrent topic in the public debate for many years. Already in the 19th century, English textile workers protested against the introduction of textile machines. The concern that technological progress may lead to mass unemployment gained importance during the 20th century and remains a hot issue today, both in the policy debate and in academic research (Autor, 2015[1]). Several authors have estimated empirically the impact of automation technologies on jobs and workers by taking a backward-looking approach, i.e. looking at technology adoption at the firm or industry level in past years and linking this to labour market outcomes, but their findings have been mixed. Some studies find positive employment impacts of automation technologies (Aghion et al., 2021[2]; Dixon, Hong and Wu, 2021[3]; Koch, Manuylov and Smolka, 2021[4]) while others document negative effects (Acemoglu and Restrepo, 2020[5]; Bessen et al., forthcoming[6]). In a recent comprehensive study, Georgieff and Milanez (2021[7]) look at what happened to jobs at risk of automation over the past decade and across 21 countries. Even though they find no evidence of net overall job destruction at the country level, they show that employment growth has been much lower in jobs at high risk of automation than in jobs at low risk.

2. Overall, while these backward-looking approaches help to understand the labour market impact of previous waves of technological development, they are less helpful for anticipating future developments. To do so, a forward-looking approach is necessary, as adopted in this study and in several other papers that are discussed in more details below.

3. One of the first papers to use this approach was by Frey and Osborne (2017[8]) who studied jobs' susceptibility to computerisation. To do so, the authors presented a group of experts with a subset of 70 occupations (SOC 6 digits) drawn from a longer list of 702 selected occupations from the O*NET database[1] (for more details on this database, see Box 1) and asked them to indicate which occupations could be fully automated. From this, they identified nine skills and abilities present in O*NET and related to perception, manipulation, creativity, and social intelligence, that could not be mastered by computers or robots, referred to as bottlenecks to computerisation, and then extrapolated the risk of automation from the 70 to the 702 occupations. They found that about 47 percent of total employment in the United States is at risk of computerisation, and in particular workers in transportation and logistics occupations, office and administrative support workers, as well as those in production occupations.

4. Subsequent studies that built on the expert assessment by Frey and Osborne (2017[8]) but used different methodologies to estimate the impact on employment found smaller estimates. For instance, Nedelkoska and Quintini (2018[9]) estimated the risk of automation for individual jobs in 32 OECD countries using the Survey of Adult Skills (PIAAC), that allows accounting for variation in tasks across workers holding the same occupation. They found that only about 14% of jobs in OECD countries participating in PIAAC are at a high risk of automation (i.e., a probability of automation of over 70%) and that 32% of jobs present a significant risk (a probability of automation comprised between 50 and 70%), with important differences across countries due to differences in industry and occupational structure and in the organisation of job tasks within economic sectors and within occupations. Arntz, Gregory and Zierahn (2017[10]) also built on the Frey and Osborne (2017[8]) study using PIAAC data but included more variables

[1] The authors selected only occupations in the O*NET database that matched with the six-digit 2010 SOC system to be able to retrieve information on employment and wages.

to predict automation risk: not only bottleneck variables as in previous studies, but also additional job tasks, as well as individual and company characteristics to take into account the fact that the actual content of an occupation may vary across individuals and firms. They find that 9% of jobs in the United States are at risk, an estimate again much smaller than the one published by Frey and Osborne (2017[8]).

5. These two studies underscore how adopting a task-level rather than an occupation-level approach is crucial to accurately take into account the task content of jobs and how it varies across jobs belonging to the same occupation, between and within countries. This observation that occupations are best understood as a bundle of tasks, some of which might be automated while others may not, is not new as it dates back to Autor, Levy and Murnane (2003[11]). It motivated the approach undertaken in a new strand of the literature that directly assesses automatability of job tasks, skills, and abilities. More specifically, researchers have adopted two different methodologies. Some studies measure advances in AI and automation technologies using data from the Electronic Frontier Foundation (EFF) AI Progress Measurement project (Felten, Raj and Seamans, 2021[12]) or patent activity data (Webb, 2020[13]) and link those with skills and abilities. Other works use expert surveys to directly estimate the degree of automatability of skills and abilities (Brynjolfsson, Mitchell and Rock, 2018[14]; Duckworth, Graham and Osborne, 2019[15]; Grace et al., 2018[16]). Brynjolfsson, Mitchell and Rock (2018[14]) focus on Machine Learning and Grace et al. (2018[16]) on AI, contrary to Duckworth, Graham and Osborne (2019[15]) that consider all automation technologies.

6. What is striking in these studies, irrespective of the methodology employed (starting from advances in technologies or from job tasks, skills, and abilities) is that they find that several high-skilled occupations are particularly exposed to AI, contrary to previous waves of automation that affected low- and middle-skilled jobs. However, these studies do not detail how high-skilled occupations will be impacted. In particular, because they focus on skills and abilities that can be replicated by machines and overlook bottleneck items, they are agnostic about whether AI technologies will substitute for or, on the contrary, complement human labour (Lane and Saint-Martin, 2021[17]).

7. Yet, the idea that automation technologies could displace or augment labour is not new. It was introduced and popularised by Acemoglu (2003[18]). Later, Acemoglu and Restrepo (2018[19]; 2019[20]) developed the idea further by taking into account the fact that new technologies may automate certain tasks but may also create new tasks (or new versions of existing tasks) for which labour maintains a comparative advantage. In a more recent paper, they argue that recent technological change, and in particular AI, has been biased towards the former type of technologies (aiming at task automation) rather than the latter (for new task creation) (Acemoglu and Restrepo, 2019[21]).

8. While several theoretical studies mention this substitution *vs.* complementarity concept, its empirical relevance is hard to assess. Holm and Lorenz (2021[22]), using a dataset on the use of AI among employees in Denmark, show that the effects of AI are varied and depend on whether AI is used for providing orders to humans or providing information for further human handling. Agrawal, Gans and Goldfarb (2019[23]) develop the idea further but focus on Machine-Learning, arguing that the majority of recent achievements in AI are the result of advances in this field. Since Machine-Learning algorithms are designed to perform prediction tasks and usually excel in those, they may replace human labour. However, as prediction is an important input into decision-making that still needs to be performed by humans, improvements in prediction will lead to an increase in the returns to human labour for decision-making. Furthermore, they argue that improvements in Machine Learning may also lead to the creation of new tasks, although they can cite only few examples.

9. However, for AI to complement human labour, several technical challenges remain. First, effective human-AI collaboration is needed, which is not the case yet. Indeed, despite a growing body of work on this topic, human-AI teams often do not outperform AI-only or humans-only teams (Littman et al., 2021[24]). Furthermore, it is not always clear how to divide up tasks and assign them to workers or to machines, nor whether this is possible at all. Indeed, even though occupations can be seen as a bundle of tasks and rely

on skills and abilities to perform those tasks, some of which might be automated and some of which may not, the different tasks may not always be performed independently.

10. As will become evident in the next section, the present work belongs to the second group of studies that assesses automatability of skills and abilities using expert surveys and links them to occupations in a second step. It uses original data on the degree of automatability of skills and abilities collected thanks to a newly developed expert survey and O*NET information on skills and ability requirements in occupations to understand how automatability of skills and abilities will translate into occupations' exposure to automation, and which groups of workers are likely to be most affected according to education level, age, and gender.

11. Collecting updated information on the automatability of almost 100 skills and abilities represented an important, albeit necessary, effort and allowed the production of a rich and granular dataset. These new data permit taking account the latest technological developments concerning automation technologies, including in the field of AI and in robotics that has also experienced significant progress recently. Asking experts to rate the degree of automatability of skills and abilities instead of occupations as a whole allows drawing a more precise picture of the impact of AI and automation technologies on jobs. Using experts' assessments instead of relying on data on technological progress permits the identification of skills and abilities that are not automatable, referred to as bottlenecks, in addition to highly automatable items. This is crucial to distinguish between occupations that are likely to be substituted by technologies (those that rely mostly on highly automatable items) from those that will be complemented by automated solutions (those that also require bottleneck skills and abilities).

12. Following discussions with the AI experts consulted for this study, this paper focuses on the automatability of skills and abilities, without distinguishing between the specific technologies that might be driving it. Such classification of AI systems is outside the scope of the study. Furthermore, even when it is possible to distinguish between the different types of automation technologies, their impact on labour markets are much harder, if not impossible, to disentangle from one another since production processes are likely to use a mix of different technologies and because their effects tend to reinforce each other.

13. This work finds that, thanks to important advances in automation technologies driven by AI, some skills and abilities previously identified as bottlenecks are now more susceptible to automation. This is the case of the knowledge of fine arts and several psychomotor abilities (the ability to work in cramped workspace and awkward positions, finger dexterity, and manual dexterity). Recent advances in AI also make several skills required in high-skilled jobs susceptible to automation, as evidenced in previous studies. This is the case for instance of reading comprehension, deductive and inductive reasoning skills, fluency of ideas and scheduling skills. However, there remains significant bottlenecks to automation. In particular, skills related to complex problem-solving, high-level management and social interaction can hardly be automated given the current state of technological developments. As a result, construction and extraction, farming, fishing, and forestry, and to a lower extent production and transportation occupations are among the ones most at risk of automation since they rely importantly on skills and abilities that are highly susceptible to automation. Least exposed jobs include management and community and social service occupations, because they require importantly bottleneck skills and abilities. However, the crucial takeaway is that most occupations rely importantly on both bottleneck and highly automatable skills and abilities.

14. On average across OECD countries, occupations at highest risk of automation account for about 28% of employment. This is higher than previous figures published by OECD which put the share of workers at high risk of automation to about 14% (Nedelkoska and Quintini, 2018[9]). This may be due to progress in AI technologies but also to the different methodology adopted. What is clear is that while more jobs may be exposed to AI, very few are exposed to the extent of disappearing entirely. Based on the granular analysis of the automatability of skills and abilities conducted in this study, only 9% of workers are employed in occupations with at least 25% of highly automatable skills and abilities.

2 A new methodology to assess automatability of skills and abilities and occupational exposure to automation

Automatability of skills and abilities

15. An important part of the work underlying this report consisted in the identification of skills and abilities that can be automated and the ones that cannot. This was done by setting up an expert group of eight leading researchers in AI and robotics (members listed in Table A E.1). The experts were selected to ensure diversity in terms of research topics and interests, and to cover as far as possible the wide range of AI and robotics fields. Experts were tasked with deciding on the best method to assess automatability of occupations, helping with the actual assessment, and reviewing results. The main advantage of relying on an expert survey instead of relying on data on technological progress (as in Felten, Raj and Seamans, 2021, or Webb, 2020) is that it allows identifying skills and abilities that are not automatable, as opposed to focusing only on highly automatable items. This is crucial to understand how different occupations will be affected, and in particular to distinguish between those in which workers might be substituted by automation technologies and those in which workers will rather be complemented.

16. Two expert meetings were organised. During the first meeting, experts were given an introduction to the project, its objectives and timeline and they discussed the best approach to assess automatability of occupations. They expressed their preference for an assessment of automatability of skills and abilities required in occupations rather than working at the occupation level directly. This choice is motivated by the observation that occupations are best understood as a bundle of tasks, some of which might be automated while others may not (Autor, Levy and Murnane, 2003[11]) and by the fact that adopting a task-level rather than an occupation-level approach has proved crucial in previous works to accurately take into account how the task content of jobs varies across jobs belonging to the same occupation, between and within countries (Nedelkoska and Quintini, 2018[9]). Experts agreed on a survey to be sent to a broader group of AI and robotics researchers asking one question to rate the degree of automatability of a list of skills and abilities:

Given current capabilities, would you say that the following skills or abilities can be automated?

0a - No, and it will not be possible in the near future (in the next 5 to 20 years)

0b - No, but it will most likely be possible in the near future (at least in certain contexts)

1 - Yes, in few contexts

2 - Yes, in some contexts

3 - Yes, in many contexts

4 - Yes, in most contexts

5 - Yes, in all contexts

17. It is important to note that while the expert group comprised mostly experts in AI, they were asked to rate the degree of automatability of skills and abilities in general, and did not distinguish between the specific technologies that might be driving it. Even if most recent advances have been in the field of AI, their ratings thus reflect the capabilities of older and newer automation technologies. Furthermore, experts recognised that it would be best to focus on the capabilities of current technologies, since predictions regarding the distant future made in the past proved far from reality. Nevertheless, the two possible answers *0a* and *0b* were introduced to distinguish between skills and abilities that are not automatable today but could become automatable in the near future. In the present study, these two possible answers are attributed a value of zero. Experts also mentioned that context matters to assess automatability (for instance, the degree of precision needed to perform a task, and the tolerance for mistakes, are important factors to take into account); this explains the use of an answering scale ranging from one to five.

18. The list of skills and abilities for which the degree of automatability is assessed is an augmented version of O*NET (see Box 1). More precisely, it includes all O*NET skills and abilities, additional items from O*NET that had been shown to be important bottlenecks to automation in previous studies (some work context and work activities), and five additional digital skills inspired by ESCO,[2] on top of Programming already included in the O*NET database. The entire list of skills and abilities included in the survey contains 98 items and is shown in Table A F.1 in Annex E.

Box 1. The O*NET database

The O*NET database was created in 1998 by the U.S. Department of Labor, building on its predecessor the Dictionary of Occupational Titles (DOT), and is updated on a regular basis. O*NET contains a wealth of information on occupations, including skills and abilities needed to work in each of the almost 1 000 occupations.[3] Most of this information is collected from job incumbents and occupations experts through surveys (Tsacoumis and Willison, 2010[25]). Skill and ability requirements of occupations are measured in terms of importance and level. The former indicates whether the particular skill or ability is important to perform the job. The latter indicates the level of mastery or proficiency in that skill or ability needed for the job. Both O*NET Skills and Abilities ratings on Importance and Level are developed by Occupational Analysts based on the responses of incumbent workers (or occupational experts) to other items on the O*NET survey questionnaire. The version of the database used for this study (O*NET 26.2) contains 35 skills and 52 abilities. O*NET defines skills as “developed capacities that facilitate learning or the more rapid acquisition of knowledge”, and abilities as “enduring attributes of the

[2] ESCO stands for European Skills, Competences, Qualifications and Occupations. It is a multilingual classification that identifies and categorises skills, competences, qualifications and occupations relevant for the EU labour market and education. It has been developed by The European Commission since 2010. It is considered as the European equivalent of O*NET, although the two databases differ along several dimension. Importantly, ESCO do not specify importance values of the different skills for the various occupations, but contains more precise digital categories.

[3] See O*NET Taxonomy at: https://www.onetcenter.org/taxonomy.html#latest

individual that influence performance". More information on the O*NET database, and current and archive versions of the dataset can be found online.[4]

As O*NET is developed by the Employment and Training Administration in the United States, it is geared towards the occupational content of jobs in the labour market in the United States. Despite this, O*NET has been regularly used for the analysis of countries other than the United States. The assumption that skill measures from one country can be generalised to other countries has been tested and largely holds (Cedefop, 2013[26]; Handel, 2012[27]; Koucký, Kovařovic and Lepič, 2012[28]). For example, Handel (2012[27]) finds that occupational titles refer to very similar activities and skill demands across different countries. Specifically, high correlations between O*NET scores and parallel measures from the European Social Survey, EU Labour Force Survey, Canadian skill scores, the International Social Survey Program, and the UK Skill Survey are found, with average correlations of 0.80. Most skill scores can thus be generalised to other countries with a reasonable degree of confidence. As a result, the O*NET information on skill and ability requirements has been used extensively in labour market research, including to study issues of automation. For example, Deming (2017[29]) uses the database to measure the extent to which occupations use non-routine analytical tasks, service tasks, and social skills. Webb (2020[13]) analyses the text of job task descriptions contained in O*NET and measures the overlap with patents' descriptions to construct a measure of tasks' exposure to automation. A caveat should, however, be raised about the use of O*NET to describe skills and tasks of occupations in low-income countries, as these could differ significantly in terms of technology and regulatory context compared to the United States.

19. Once finalised, the survey was sent to 40 experts in AI and robotics, including members of the expert group. In total, 20 experts (the eight members of the expert group as well as 12 additional researchers) answered the survey. They had the possibility to answer only questions for which they felt they had enough expertise. For each question, there are thus between 13 and 20 answers. Descriptive statistics are provided in the next section.

20. To construct automatability variables for each item *i=1,…,I* of the survey, answers provided by experts *n=1,…,N* are aggregated using the following formula:

$$automatability_i = \frac{1}{N}\sum_{n=1}^{N} automatability_{in} \quad (1)$$

where $automatability_{in}$ is the answer provided by expert *n* for variable *i.* This is thus a simple average of answers across experts.

21. For each item, highest values were not considered as outliers and thus were not excluded from the analysis. This is common in analyses of expert survey data that do not rely on the Law of Large Numbers and where the most extreme values may actually come from the most knowledgeable expert and hence may be the most accurate (Maestas, 2016[30]). In order to take into account uncertainty and variability around experts' answers, 95% confidence intervals are also reported. In addition, several robustness checks are performed: taking the mode instead of the mean,[5] dropping from the analysis the four experts that provided the most extreme answers on average, and, for each response, demeaning

[4] https://www.onetcenter.org/database.html#overview

[5] Corresponding to the result of a hypothetical majority vote between experts.

each answer by the corresponding expert average across all variables before computing the mean across experts.[6]

22. Some analyses in this paper rely on dummy variables for bottleneck and highly automatable items. Bottleneck items are those for which the mean across experts is lower or equal to one. Highly automatable items correspond to variables for which the mean is higher or equal to 3.5. These cut-off values were chosen to bring together variables at the two extreme of the distribution, and after extensive discussions with members of the expert group. Indeed, during the second meeting, experts had the opportunity to review in details and discuss results from the survey. More specifically, they were presented with variables' mean, mode and standard deviation and were invited to comment on these results, particularly to indicate whether they agreed with the average values, discuss whether major advances on the item had been made over the past 10 years, and to provide examples of contexts in which the item could be automated. A summary of the discussions is reported in the next section.

Empirical strategy to link skills and abilities to jobs

23. In order to transform automatability of skills and abilities into job automatability, one needs information on the importance of each skill and ability needed to perform a job. A particular skill used in a job may be highly automatable but if it only plays only a very minor role in performing the job it is unlikely to have much of an impact on the overall automatability of that job. This information can be found in the O*NET database. The degree of automatability of each occupation *o=1,…,O* is then computed as:

$$degree\ of\ automatability_o = \sum_{i=1}^{I} automatability_i * importance_{io} \qquad (2)$$

where *i* indicates a specific skill or ability, $automatability_i$ is computed as in Equation (1) (i.e. a simple average of experts' answers for skills or ability *i*), and $importance_{io}$ is the O*NET importance value of skill or ability *i* in occupation *o.*

24. Importance values in O*NET range from "Not Important" (1) to "Extremely Important" (5). One issue with these values is that they do not sum to the same value for different occupations. In other words, higher degree of automatability for different occupations could be the result of higher importance values in general for this occupation, and not to higher importance of highly automatable items. To control for this, in this study, O*NET importance values have been standardised across occupations to always sum to 100.

25. Because this formula relies on the availability of importance values in O*NET, the five digital skills inspired by ESCO, i.e. digital content creation, digital communication and collaboration, ICT safety, networks and servers, and digital data processing, are excluded. Only the digital skill appearing in O*NET, programming, can be taken into account. However, it is worth noting that the degrees of automatability of digital content creation, digital communication and collaboration, and ICT safety, networks and servers are not statistically different from that of programming (see descriptive statistics provided in the next section). Including these variables would not significantly modify the results. The work context variable (working in cramped work space and awkward positions) is also excluded when analysing exposure to automation technologies by occupation because it does not have an importance value in O*NET.

26. One caveat of this formula is that a similar degree of automatability will be attributed to occupations for which all important skills show a moderate degree of automatability, and to occupations for which some

[6] Similar to getting rid of experts "fixed effects". Formula (1) hence becomes:

$$automatability_i = \frac{1}{N}\sum_{n=1}^{N}(automatability_{in} - \frac{1}{I}\sum_{j=1}^{I} automatability_{jn})$$

important skills are highly automatable while some others are bottlenecks. In other words, the formula above is useful to provide an aggregated score for the general exposure to automation for different occupations, but it does not allow distinguishing distinguish between occupations where workers might be displaced (intuitively, occupations with a significant number of skills and abilities with high degree of automatability and very few bottleneck variables) from occupations where workers might be complemented by technologies (occupations with only a small number of skills and abilities with high automatability and a significant share of bottleneck items).

27. However, because automatability has been assessed in a first stage at the skills and abilities level, it becomes possible to identify which occupations rely strongly on highly automatable skills and abilities. In this study, occupations with a significant share of important skills and abilities (more than 25%) that are highly automatable (value of 3.5 and above) are defined as at high risk of automation (where important items are those with an importance value higher than 3, on a scale between 1 and 5).

28. In order to understand how many jobs might be impacted, and which demographic groups will suffer the most, information on employment shares by country, occupation and demographic groups is necessary. This information is extracted from the EU Labour Force Survey (EU-LFS) for EU OECD countries and the United Kingdom, Iceland, Norway, and Switzerland. The EU-LFS is a large household survey providing quarterly and yearly results on labour participation and labour outcomes of people aged 15 and over and containing detailed information on several socio-demographic characteristics. Similar information is extracted from the Current Population Survey for the United States. It is important to note that the measure indicating occupations at highest risk of automation varies only across occupations, but not across countries. Differences in demographics or employment shares at risk of automation between countries will thus be purely driven by differences in the size and composition of occupations across countries.

3 The degree of automatability of skills and abilities

29. Figure 1 and Figure 2 show descriptive statistics (mean, mode, and 95% confidence interval) of the answers provided by experts regarding automatability of each skill and ability included in the survey (unweighted by importance). Figure 1 focuses on the 42 least automatable variables, i.e. skills and abilities for which the mean is lower than two (answers “No”, and “Yes, in few contexts”, and “Yes, in some contexts”). Figure 2 concentrates on the 56 most automatable items for which the mean is higher than 2 (answers ”Yes, in some contexts”, ”Yes, in many contexts”, ”Yes, in most contexts”, “Yes, in all contexts”). For each variable, the average value is used to compute the degree of automatability of the skill and ability. Average values range from 0.41 to 4.84, and modal values range between zero and five. In both figures, confidence intervals are narrow to moderate, indicating no important variability among experts.[7] As defined in Section 2, the first 13 variables in Figure 1, with a mean lower than one, are referred to as bottlenecks to automation. The last 15 variables in Figure 2 have a mean higher than 3.5 and are referred to as highly automatable.

30. Results shown in Figure 1 and Figure 2 can be compared to findings from the previous literature. The work closer to the present study is the one by Frey and Osborne (2017[8]) that identified perception and manipulation abilities, and creative and social intelligence as bottlenecks to computerisation and linked them to nine O*NET variables: negotiation, social perceptiveness, assisting and caring for others, originality, persuasion, fine arts, cramped workspace and awkward positions, finger dexterity, manual dexterity. Most bottlenecks identified by Frey and Osborne (2017[8]) present a low degree of automatability according to the present study. Indeed, five of them (negotiation, social perceptiveness, assisting and caring for others, originality, persuasion) have a mean lower than one and are also referred to as bottlenecks to automation in this work. However, several items, namely fine arts, cramped workspace and awkward positions, finger dexterity, and manual dexterity have a higher degree of automatability, ranging from one to three, and are not considered as bottlenecks in the present study. A detailed discussion of these variables is provided below. Furthermore, the present study has identified additional bottlenecks to automation: management of personnel resources, technology design, management of material resources, active learning, service orientation, repairing, and active listening. These variables have been overlooked in the study by Frey and Osborne (2017[8]) because of a less precise methodology.

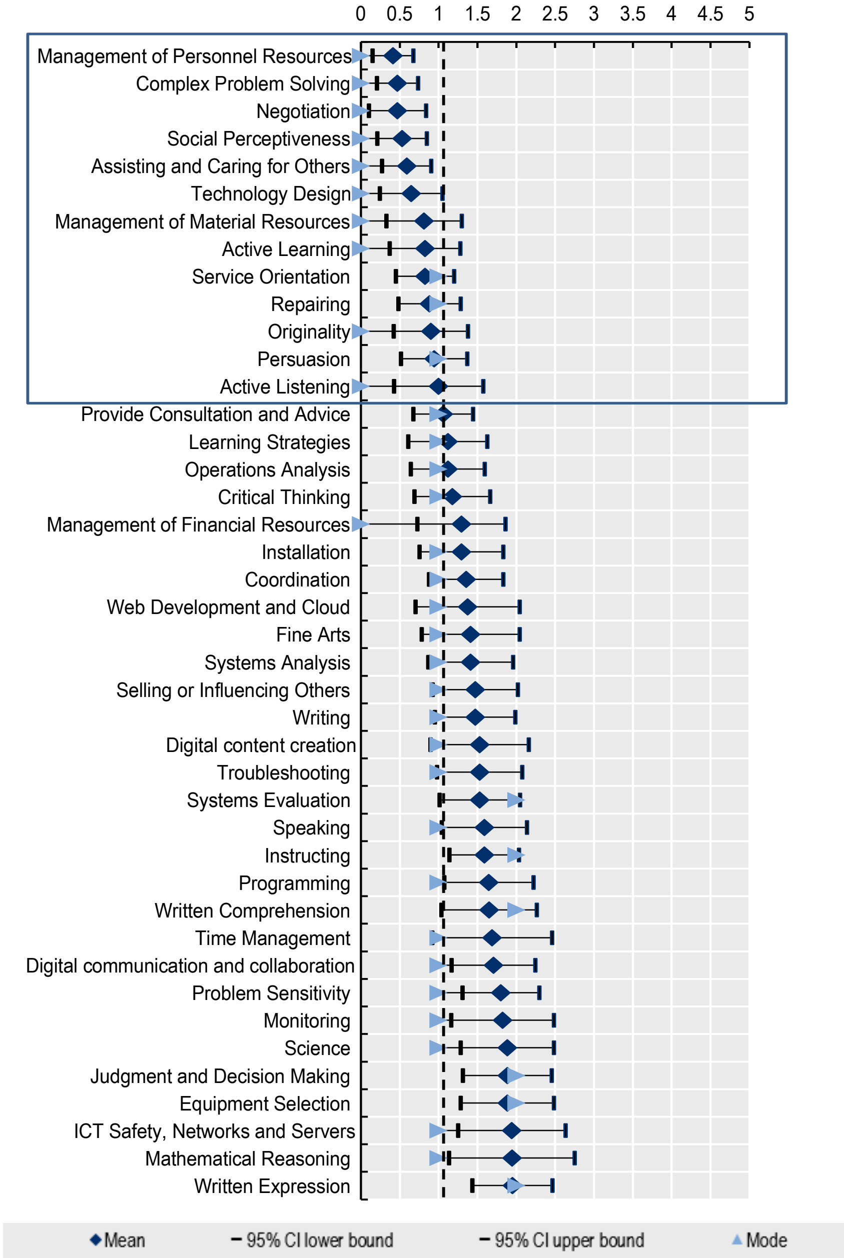
31. Another work that considers O*NET variables is the study by Duckworth, Graham and Osborne (2019[15]). They surveyed academic and industry experts on whether specific job tasks of 70 occupations are automatable given the state of current technologies and then aggregated these figures by work activity and by occupation. They show that skills and abilities such as number facility, depth perception, and control precision tend to increase an activity’s automatability. These variables also show higher than average

[7] Experts may differ in the way they understood the questionnaire and answered the survey. For instance, they may interpret the scale of potential responses differently, or be biased towards some answers. It is thus important to analyse how respondents answered the survey. One straightforward way to shed a light on these issues is to look at confidence intervals around the mean, as reported in the figure. A more detailed analysis of experts’ responses is reported in Annex B.

degree of automatability in the present study, and two of them, number facility and control precision, are classified as highly automatable. On the contrary, the three strongest features driving decreased automatability are installation, programming and technology design that show lower than average degree of automatability in the present work, even though only one of these items, technology design, is identified as a bottleneck to automation. The results of the present study are thus consistent with those of Duckworth, Graham and Osborne (2019[15]) but they are also more complete, in the sense that the present work considers all O*NET skills and abilities.

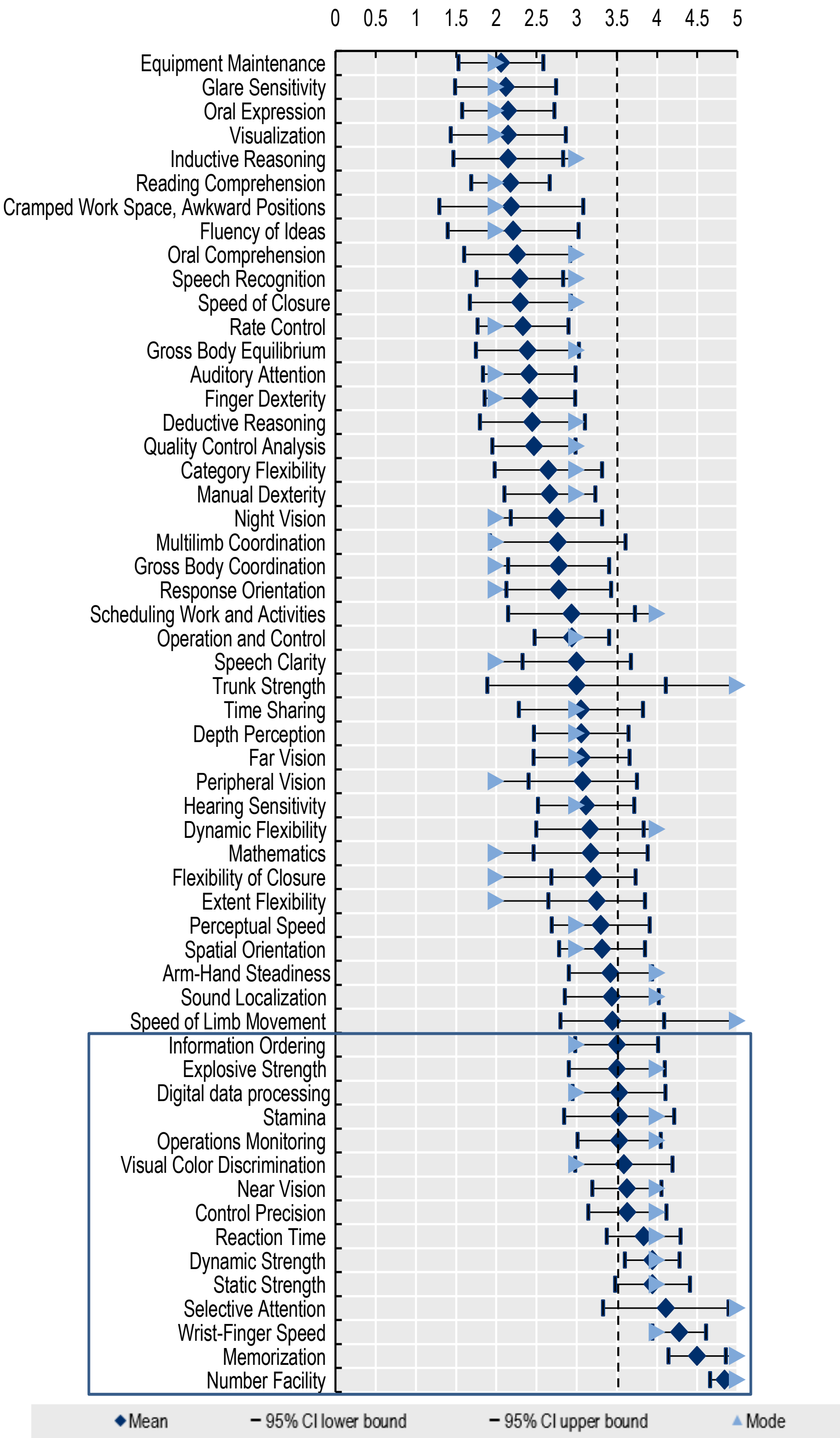
32. There are several reasons for which the results presented above may differ from findings by Frey and Osborne (2017[8]) and Duckworth, Graham and Osborne (2019[15]). First, the expert assessment conducted for this study was done at the skills and abilities level, contrary to the exercise by Frey and Osborne (2017[8]) who start by studying computerisation at the occupation level and the one by Duckworth, Graham and Osborne (2019[15]) that first considers O*NET work activities. The present exercise is thus more direct. It is also more precise and more complete as it considers all skills and abilities from O*NET. Second, more than ten years have passed since Frey and Osborne (2017[8]) collected their data. In the meantime, significant advances in automation possibilities have been made, mostly thanks to advances in AI. Indeed, in the last five years, major progress has been made in many AI fields, including vision, speech recognition and generation, natural language processing (understanding and generation), image and video generation, multi-agent systems, planning, decision-making, and integration of vision and motor control for robotics. Breakthrough applications emerged in a variety of domains including games, medical diagnosis, logistics systems, autonomous driving, language translation, and interactive personal assistance. These advances have been made possible by considerable progress in machine learning algorithms, especially deep learning and reinforcement learning, and the increased availability of large-scale data and computing resources (Littman et al., 2021[24]). This can explain why some skills and abilities previously identified as bottlenecks can potentially now be automated, at least in certain contexts.

Figure 1. Automatability of skills and abilities in the lower half of the automatability scale



Note: Skills and abilities highlighted in the blue box have an average degree of automatability lower or equal to one and are identified as bottlenecks for the purpose of this study.
Source: OECD Expert Survey on Skills and Abilities Automatability.

Figure 2. Automatability of skills and abilities in the upper half of the automatability scale



Note: Skills and abilities highlighted in the blue box have an average degree of automatability greater or equal to 3.5 and are identified as highly automatable for the purpose of this study.
Source: OECD Expert Survey on Skills and Abilities Automatability.

33. Experts were invited to comment on the results in Figure 1 and Figure 2 during the second expert meeting. Due to time constraints, the discussions focused on a sample of variables. Priority was given to bottlenecks to automation previously identified in the literature and to variables newly identified as bottlenecks in this study. A summary of the discussions is provided below, backed when possible by additional evidence from the AI literature.

34. Among the skills and abilities identified as bottlenecks in this study and in the previous literature, the following were discussed:

- **Negotiation**, defined as "bringing others together and trying to reconcile differences" cannot be performed entirely by machines. AI systems can automatically develop arguments, and hence support mediation processes, but bringing people together, facilitating the right mindset, and reconciling different views need the intervention of humans, according to experts interviewed in the context of this study.
- **Social perceptiveness** is defined as "being aware of others' reactions and understanding why they react as they do". Experts explained that the first component, "being aware of others' reactions" can be performed by machines to a certain extent. There has been enormous progress over the past years in modelling people's reactions. However, the second component, understanding reactions, is still complicated for machines.
- **Assisting and caring for others**, i.e. "providing personal assistance, medical attention, emotional support, or other personal care to others such as co-workers, customers, or patients", has seen some progress recently, and there are now examples of AI systems capable of providing personal assistance, medical attention, or emotional support. However, these systems are still imperfect and far from performing as well as humans.
- **Technology design**, defined as "generating or adapting equipment and technology to serve user needs" remains a bottleneck to automation according to the experts, and very few examples of automation solutions to perform technology design could be identified (one exception being the automatic adaptation of a website).
- **Persuading** others to change their minds or behaviour is also judged as complicated for AI systems and there exist only very few applications. There are AI systems that can influence individuals, but persuasion is intentional and necessitates a thorough understanding of one's opinions and reactions, and especially of why they think or act as they do, which automated solutions are not capable of. As a result, persuasion remains an important bottleneck to automation, according to experts consulted for this study.

35. Among the skills and abilities identified as bottlenecks in this study but not in the previous literature, the following were discussed:

- According to the expert group, **complex-problem solving** corresponds to General Artificial Intelligence, a field in which important progress still needs to be made. While machines are better than humans at solving computational-intensive and narrowly defined problems, they lag behind when it comes to identifying and formulating problems, and implementing solutions. A similar view is shared by the AI experts participating in the AI 100 study (Littman et al., 2021[24]). They argue that most advances in AI so far concern narrow AI, where algorithms learn how to perform a specific task but are usually not able to generalise the knowledge they acquired to other tasks. Indeed, most mature AI systems rely on supervised learning in which the system is trained on examples that have been labelled by humans. Important progress towards more general AI has been made though, especially thanks to the development of two types of techniques: reinforcement learning, where algorithms rely not on labelled examples but on signals rewarding desired behaviours and/or punishing undesired ones for actions taken in an often simulated environment; and probabilistic program induction, where programs are developed to learn a large class of concepts (represented as probabilistic generative models) from just a single example and generalise to other cases.

- **Active listening** is described as “giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times”. There is important research in this area but to date active listening remains very complicated for machines, as they cannot understand the points being made.

36. In addition, the following skills and abilities that went from being bottlenecks in the literature to being automatable in the current study were also discussed. The aim was to understand which new technologies might have brought about the change:

- The knowledge of **fine arts**, and more precisely of the theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture, seems possible in some cases. Some machines can compose music and written texts but it is not clear to what extent they are using knowledge to do so. On the other hand, there has been less progress in sculpture, drama, or dance for instance. One issue with the field of arts is that there is no common understanding on what can be labelled true or wrong, good or bad. Hence, it is difficult to find or construct reliable training sets with which algorithms can be trained. Zhang et al. (2022[31]) make a similar point in the AI Index 2022 report, as they claim that for some constrained applications, text, audio, and images generated by AI systems are as good as if they had been composed by humans.
- **Working in cramped workspace** that requires getting into awkward positions is a difficult, albeit not impossible task for robots. Specialised robots can be built for specific applications: for instance, there are robots that can manoeuvre inside airplane wings to verify their condition, and there exist drones to inspect industrial buildings. In these environments, one difficulty for robots lies in the darkness and absence of vision. While humans can rely on other senses to form a mental image of the space, robots cannot, as it would be computationally too demanding. Hence, many of the solutions that now exist are remotely controlled and still rely on human intervention. Experts also mentioned that it is complicated to develop robots working in tiny spaces where humans themselves cannot work. Further progress on automatability may be difficult to achieve in the short run.
- **Finger dexterity**, described in O*NET as the “ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects”, is still challenging for robots but significant progress has been made. Thanks to deep learning based vision systems, robots can manipulate objects, pick them up and place them at speeds that are practical for real-world applications[8] (Littman et al., 2021[24]). However, the gesture of pushing and all gestures that rely on feeling the texture of an object are much more challenging. Dealing with very small objects is also complex. One important difficulty is that tolerance for error must be very low because any mistake might lead the robot to harm persons, damage objects or disrupt systems (Nolan, 2021[32]).
- Robots that have **manual dexterity**, i.e. able to “quickly move the hand, the hand together with the arm, or the two hands to grasp, manipulate, or assemble objects” have existed for 60 years and are present in many manufacturing plants. This is a mature technology that cannot be considered as a bottleneck to automation, according to the expert group.

37. Several other variables deserve a more detailed analysis, because they were the subject of an in-depth discussion either during the second expert meeting or in the AI literature.

- **Consulting and advising others**, i.e. “providing guidance and expert advice to management or other groups on technical, systems- or process-related topics”, can be performed by AI systems in some contexts only (average value of 1.06 in Figure 1). For instance, there exist AI for career guidance, and for predictive or preventive maintenance. These AI solutions take the form of

[8] For instance, robots were used in a group of restaurants in China during the COVID-19 pandemic to help cook and serve food (Littman et al., 2021[24]).

consultation systems that can assist humans. In the case of predictive maintenance, AI systems can provide advice on what to replace or check on a machine.

- Technologies to **sell or influence others**, convincing them to buy merchandise, goods or to change their minds or actions (average degree of automatability in Figure 1 equal to 1.47) have seen some progress over the past few years. For instance, online marketing and advertising are areas where AI systems can perform very well. These systems, called “recommender systems”, that automatically prioritise what is seen online by users, have become essential and have an important influence on individuals’ consumption of products, services, and content (news, music, videos...).
- **Instructing**, or teaching others how to do something (average of 1.59 in Figure 1) is an interesting area for AI. Pure instruction remains difficult: an AI model needs to know what the student knows and this is hard to assess. Some promising technologies existed but, to date, they remain limited and necessitate a very structured environment. However, other complementary tasks can be performed by AI systems: targeting learning activities to students, determining which modules they should follow, or what instruction method to use. There has been important progress on these fronts over the past five years.
- The **management of one's own time and the time of others** – also referred to as « dynamic scheduling » (average value of 1.69 in the present study) can be assisted with the help of AI systems. Such tools have become particularly attractive during the COVID-19 crisis and since then research in this area has grown substantially. However, it is not clear whether these tools are effective. For these tools to perform well it is necessary to list and embed all existing time constraints in a system and this requires substantial effort. Furthermore, in many cases, the ultimate decision maker does not agree with the recommendation. While important investments have been made in these automatic schedulers, they still necessitate manual input to check, accept or reject the solution recommended.
- **Oral expression**, or “the ability to communicate information and ideas in speaking so others will understand” (average value of 2.15) and **written expression**, i.e. “the ability to communicate information and ideas in writing” (average value equal to 1.95), can be automated in some contexts but are not usually considered as an AI capability. There has been some progress, for example, in speech to text technologies. However, these technologies are not able to process information to turn it into words or text. In 2017, an OECD report investigating computer capabilities with respect to certain human skills found that computers were not performing as well as humans on answering literacy questions, even for those that were the easiest for adults, although the difference between computers and humans for these questions was small (Elliott, 2017[33]). It seems important advances have been made in the past years. In the 2022 AI Index report, Zhang et al. (2022[31]) explain that AI systems show significantly improved language capabilities, thanks to rapid progress in Natural Language Processing techniques. While AI does not master complex language tasks yet, it already exceeds human performance levels on basic reading comprehension benchmarks. Furthermore, the difference between human and AI performance on more complex linguistic tasks is narrowing, thanks to the development of network architectures with enhanced capability to learn from complex and context-sensitive data and relying on increasing data resources and computing power (Littman et al., 2021[24]).
- **Scheduling work and activities** seems a perfect AI problem. Its average degree of automatability is equal to 2.94 in Figure 2. This area of research is also referred to as « task planning ». Experts consulted for this study consider that in many cases computers can do it better than humans.
- Finally, several abilities in O*NET correspond to **visual abilities**: depth perception (the ability to judge which of several objects is closer or farther away from oneself, or to judge the distance between oneself and an object), far vision (the ability to see details at a distance), glare sensitivity (the ability to see objects in the presence of a glare or bright lighting), near vision (the ability to see

details at close range, i.e. within a few feet of the observer), night vision, (the ability to see under low-light conditions), peripheral vision (the ability to see objects or movement of objects to one's side when the eyes are looking ahead), and visual colour discrimination (the ability to match or detect differences between colours, including shades of colour and brightness). These abilities show degree of automatability higher than average (Figure 2), and this is consistent with the evidence reported in the AI literature. Indeed, according to the AI Index 2022 report (Zhang et al., 2022[31]), computer vision has experienced significant progress in the past decade, primarily due to the use of machine learning techniques (specifically deep learning). Furthermore, the COVID-19 crisis has renewed interest within the research community in specific computer vision tasks, such as medical image segmentation, masked-face identification, and inclusion of videoconference backgrounds.

4 Impact on jobs and workers

Which jobs are most at risk of automation?

38. As occupations can be seen as a bundle of tasks and rely on skills and abilities to perform those tasks, automatability of skills and abilities can be mapped into job automatability. Intuitively, jobs that require skills and abilities that are susceptible to automation will be at higher risk of automation. Using information from O*NET to link skills and abilities to occupations as described in section 2, Figure 3 ranks occupations (SOC 2 digits) by their degree of automatability (computed as in Equation 1).

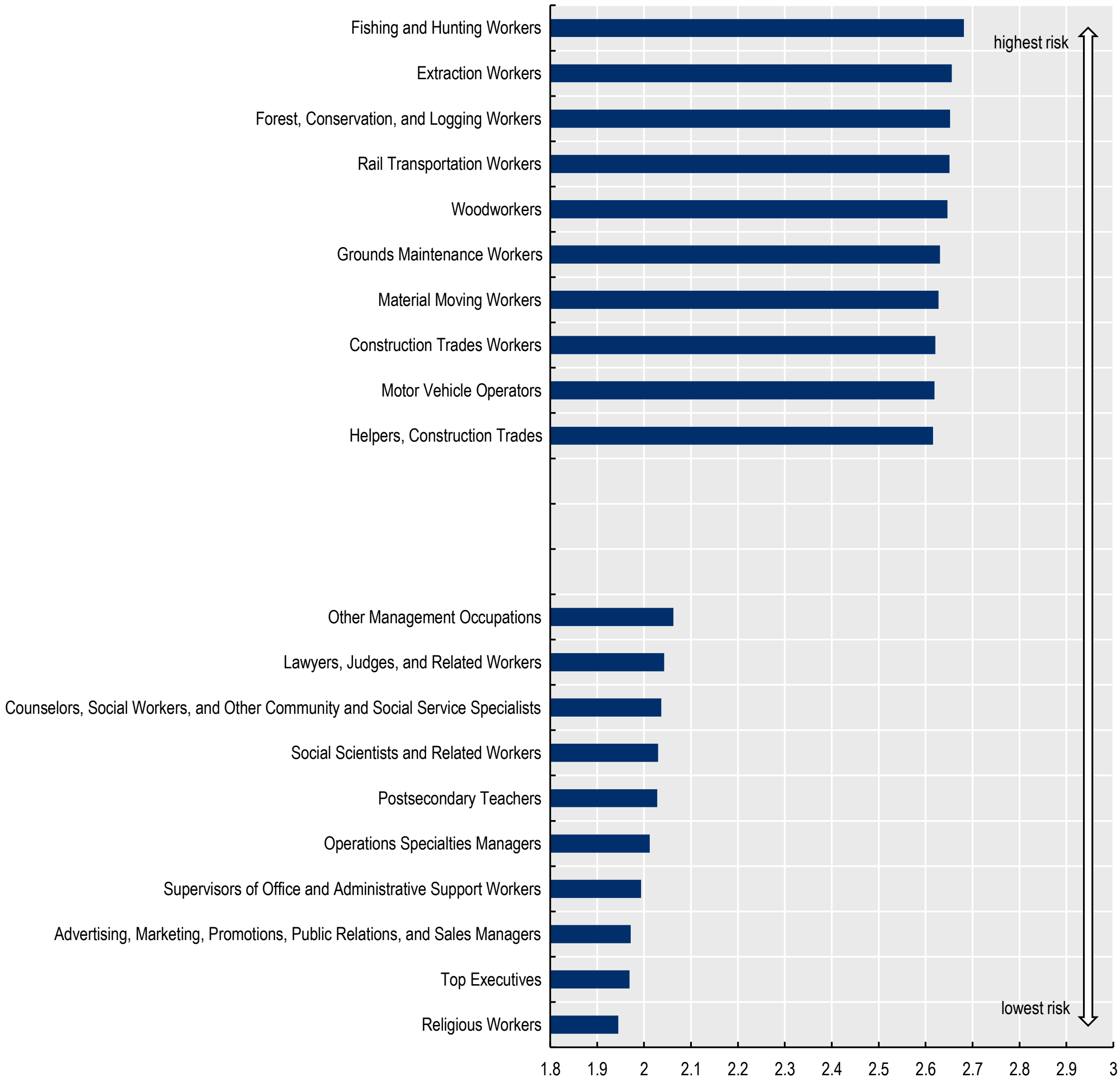
Figure 3. Ranking of occupations by degree of automatability

Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

39. Occupations at highest risk are construction and extraction, farming, fishing, and forestry, production, and transportation occupations. On average across OECD countries, these occupations account for about 28% of employment. Least at risk jobs include legal, education, management and community and social service jobs. Annex B shows a similar ranking of detailed occupations (SOC 3 digits), and Annex C shows ranking of broad occupations (SOC 2 digits) using alternative measures of automatability of skills and abilities. Figure 4 focuses on the ten most and ten least at risk detailed occupations (SOC 3 digits) and largely confirms results shown in Figure 3: most at risk occupations at the

three digit level indeed belong to the most at risk broad occupations. In general, there is no significant differences within broad occupations in terms of risk of automation.

Figure 4. Most and least affected detailed occupations



Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

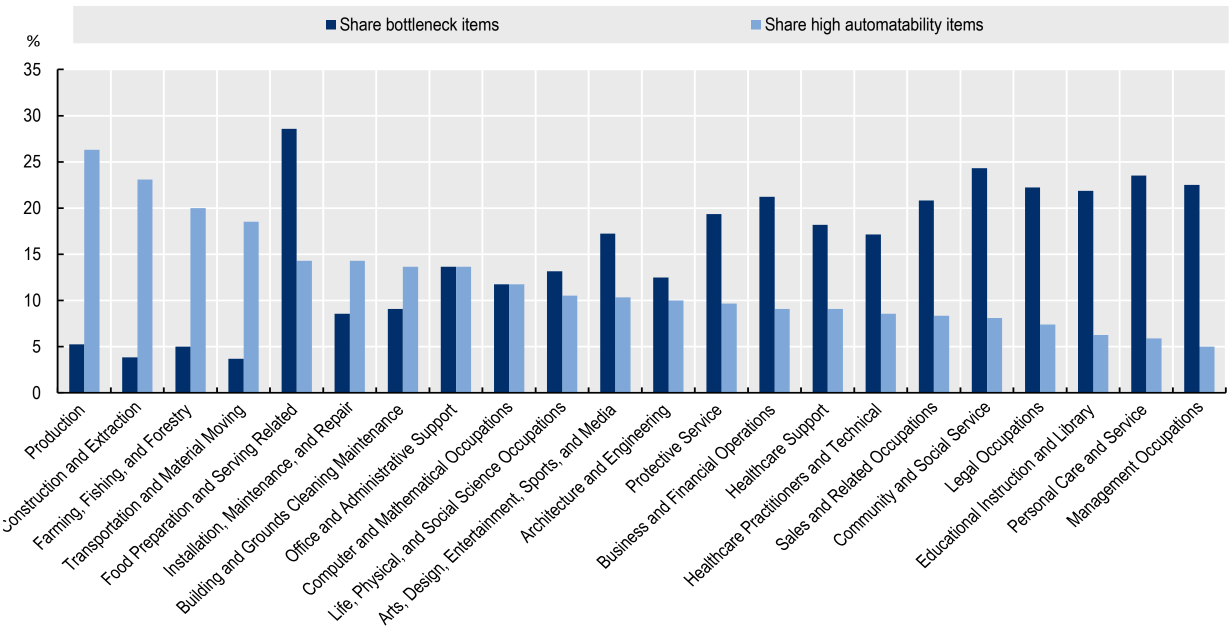
40. These results can be compared to results in the previous literature, and more particularly the seminal articles that predicted the risk of automation by occupation (Frey and Osborne, 2017[8]; Nedelkoska and Quintini, 2018[9]) as well as to more recent papers mainly focusing on AI technologies (Felten, Raj and Seamans, 2021[12]; Webb, 2020[13]). The seminal papers exhibited a negative relationship between risk of automation and an occupation's skill level, with occupations at highest risk of automation being mainly low-skilled and those at lowest risk being high-skilled jobs. The more recent papers focusing on AI found, on the contrary, that some high-skilled occupations are among the most exposed (even if other high-skilled occupations are among the least exposed, particularly when they require high-level reasoning skills).

41. The present study is more up-to-date than the seminal papers (Frey and Osborne, 2017[8]; Nedelkoska and Quintini, 2018[9]), considers all skills and all automation technologies together, contrary to most recent papers (Felten, Raj and Seamans, 2021[12]; Webb, 2020[13]), and adopts a more precise methodology. This explains the discrepancies that may exist between the different studies. In particular, the present study helps clarifying the fact that even though AI does not directly automate physical skills, it does not mean occupations relying mostly on these skills are less at risk. Actually, most studies predicted that routine manual occupations are highly exposed to the introduction of robots, and this risk might even be exacerbated when AI-powered robots will be deployed in companies. In addition, the fact that AI can automate skills and abilities mostly required in high-skilled occupations does not mean that these occupations are at high risk of automation, because those occupations also rely extensively on skills and abilities that remain bottlenecks to automation, as demonstrated below. Furthermore, it is important to note that while the present study estimates that 28% of workers are employed in occupations at highest risk of automation, it does not mean that the risk of automation has doubled. The increase in the share of workers employed in most at risk occupations might be due to advances in AI and other automation technologies, to the adoption of a different definition of exposure to automation, or to the more precise methodology, but it is not possible to disentangle between the different factors.

42. Occupations at highest risk of automation will not necessarily be fully automated and disappear. In these jobs, human work will not always be replaced by robots or software; instead, in several instances, human work will be complemented by automated solutions. Figure 5 attempts to shed a light on this question, by showing the shares of bottleneck and high automatability items in the most important skills for each occupation. The higher the share of highly automatable items, the more likely and the more radically the occupation will have to adapt. The higher the share of bottleneck variables, the lower the chance that automated solutions will replace human work.

Figure 5. Shares of bottleneck and highly automatable skills and abilities, by occupation

Percentage of the most important skills and abilities, by occupation



Note: Share of bottleneck and highly automatable items among important items by occupation (SOC 2 digits), where important items are skills and abilities with importance values strictly higher than three.
Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

43. In general, most at risk occupations identified in Figure 3 have the highest shares of high automatability skills and abilities, and usually low shares of bottleneck tasks. However, the share of high automatability skills and abilities remains moderate at between 15 or 25% of important skills and abilities. The contrary holds true for least affected occupations. According to the figure above, production occupations are particularly at risk of being displaced, as they have both significant shares of important items that are highly automatable, and negligible shares of important items identified as bottlenecks.

44. Food preparation and serving related occupations are particularly interesting as they show a high share of high automatability items among important ones (information ordering and near vision), but also a substantial share of bottleneck items (active listening, assisting and caring for others, service orientation, and social perceptiveness). This indicates that workers in this occupation are not likely to be substituted by automated solutions. On the contrary, in this occupation, technologies may complement humans. As a result, the organisation of work will have to be adapted. A similar observation can be made, to a lesser extent, for building and grounds cleaning and maintenance, office and administrative support, and computer and mathematical occupations. For building and grounds cleaning and maintenance occupations, bottleneck items are active listening, information ordering, and assisting and caring for others,

and high automatability items are near vision, and static strength. For office and administrative support occupations, bottleneck items are social perceptiveness, service orientation, and active listening and high automatability items are near vision, and selective attention, and information ordering. For computer and mathematical occupations, bottleneck items are complex problem-solving, active learning, originality, and active listening, and high automatability items are number facility, near vision, information ordering and selective attention.

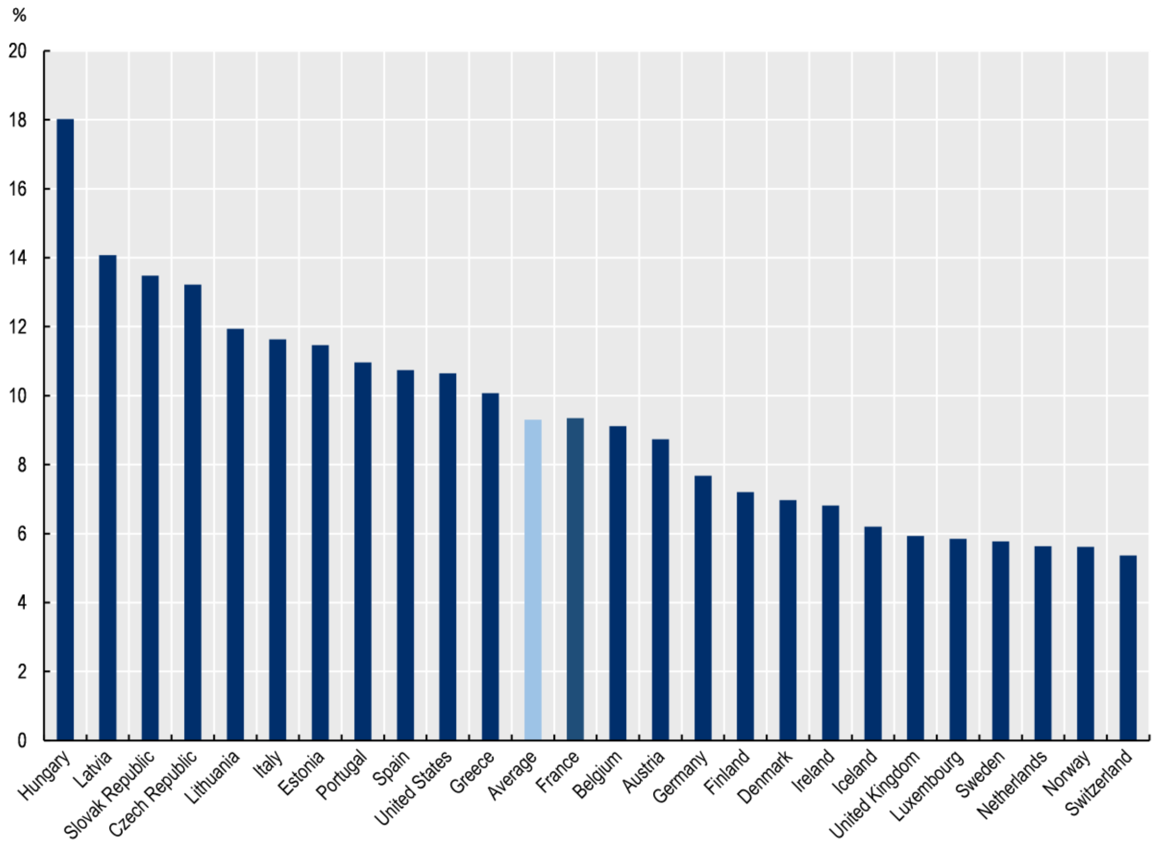
45. In the rest of the analysis, occupations are said to be at high risk of automation if they have a significant share of important skills and abilities (more than 25%) that are highly automatable. In Figure 5, it corresponds to Production occupations only, but this masks some heterogeneity within broadly defined occupations. Indeed, at a more disaggregated level (SOC 3 digits), jobs that are at high risk belong to different broad occupations: not only to production occupations but also to farming, fishing and forestry, construction, transportation, and building and grounds cleaning and maintenance occupations.

Which workers are most exposed?

46. For the sample of 27 OECD countries for which labour force survey data is available at a sufficiently disaggregated level, occupations at high risk of automation (i.e. those for which more than 25% of important skills and abilities can be replicated by technologies) represent slightly less than 10% of the total workforce (Figure 6). It is however important to reiterate that these shares are not easily comparable with those provided in previous papers such as Frey and Osborne (2017[8]) or Nedelkoska and Quintini (2018[9]) since the methodologies and definitions employed in the different papers are different.

47. There are however substantial differences between countries: Figure 6 shows that in Hungary, Latvia, Romania, Slovak Republic, and Czechia, more than 12% - and up to 18% - of total employment is at high risk. The United Kingdom, Luxembourg, Sweden, Netherlands, Norway, and Switzerland lie at the other end of the spectrum, with less than 6% of total employment at risk. On average for the countries included in the analysis, 9% of workers are employed in occupations for which a significant share of important skills and abilities are highly automatable.

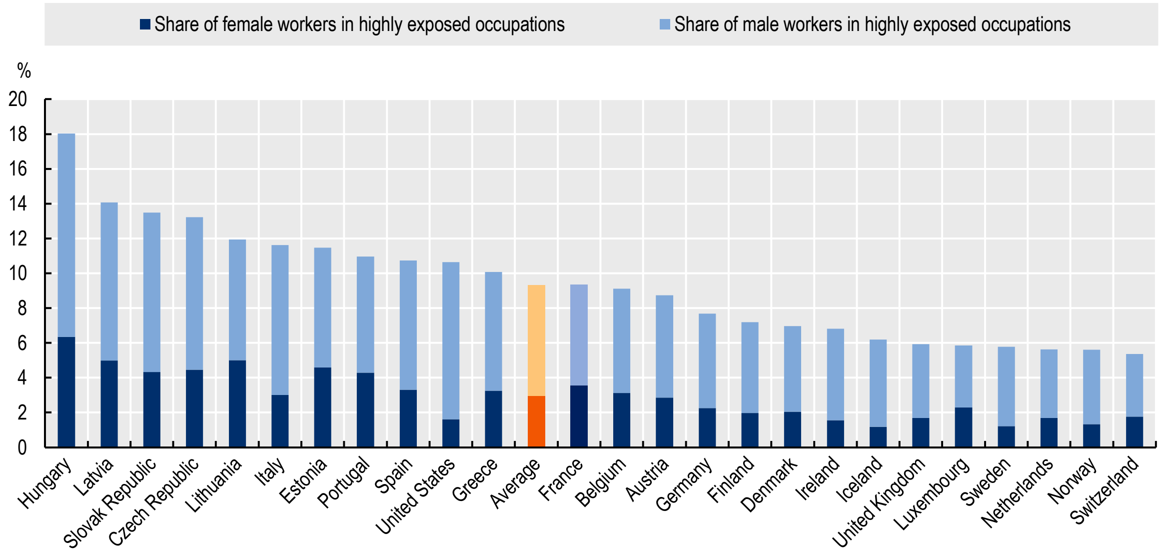
Figure 6. Share of employment in occupations at high risk of automation, by country



Note: Occupations at high risk of automation are those with more than 25% of highly automatable important skills and abilities. Relative weights were used to construct a crosswalk between ISCO-08 (three-digit) and SOC 2010 (three-digit). Average indicates the unweighted average of country shares.
Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability, O*NET, the European Union Labour Force Survey (EU-LFS) [2019], and Current Population Survey of United States 2019 (CPS).

48. Figure 7, Figure 8, and Figure 9 present a breakdown of employment shares by country and several socio-demographic characteristics.

Figure 7. Employment shares by country and gender

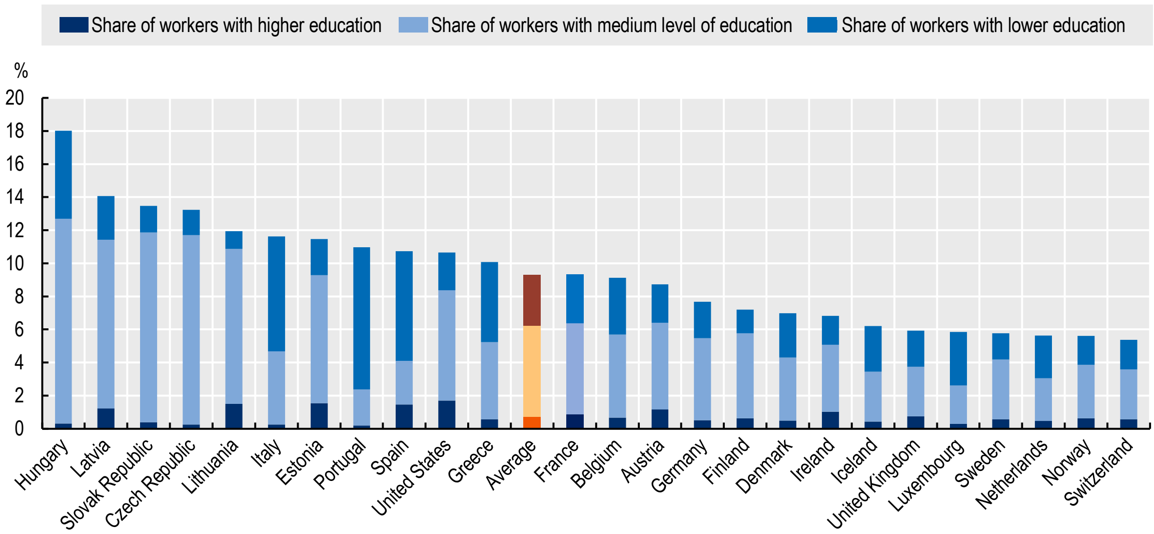


Note: Occupations at high risk of automation are those with more than 25% of highly automatable important skills and abilities. Relative weights were used to construct a crosswalk between ISCO-08 (three-digit) and SOC 2010 (three-digit). Average indicates the unweighted average of country shares.
Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability, O*NET, the European Union Labour Force Survey (EU-LFS) [2019], and Current Population Survey of United States 2019 (CPS).

49. Figure 7 reveals that in all countries analysed, occupations at high risk of automation are typically male-dominated. Women are 32 percentage points less likely to be employed in a high risk occupation than men. This figure decreases to 14 percentage points when controlling for age group, location, and education, but remains significant. This reflects the fact that women are present in occupations requiring interpersonal interaction abilities that cannot be performed by automation technologies. These results are consistent with other findings in the literature, reporting that women have been less exposed than men to the previous and current waves of automation (Webb, 2020[13]).

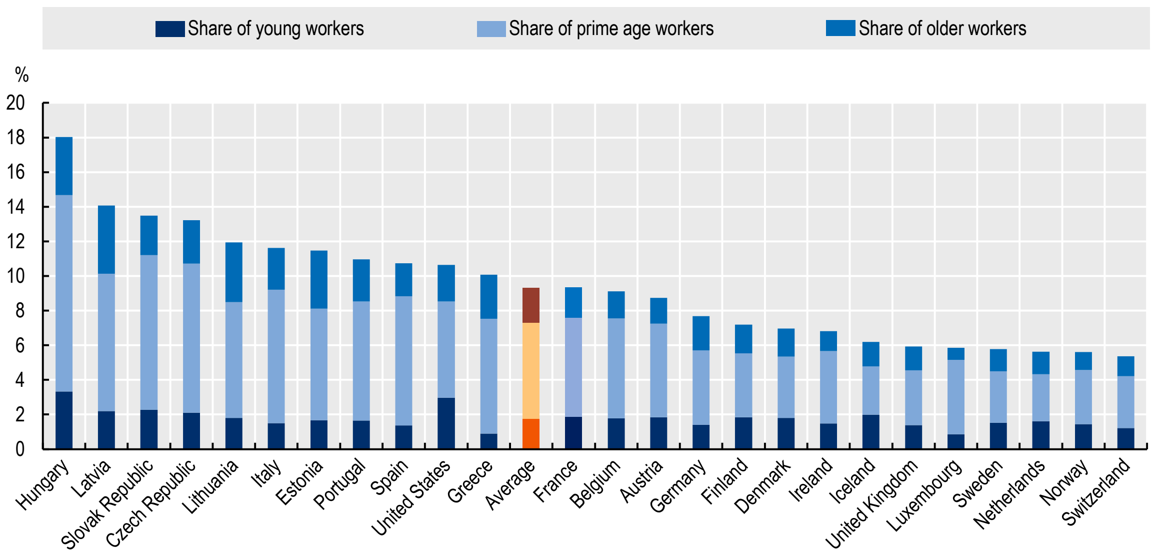
50. Low-educated workers are more likely than workers with middle or high levels of education to be employed in high risk occupations. Figure 8 shows that in several countries (Italy, Portugal, Spain, and Greece), low-educated workers represent the majority of employed in high risk occupations. Younger and older workers are also more likely to be employed in high risk occupations, even though the coefficient on older workers loses significance once controlling for other socio-demographic characteristics (Figure 9).

Figure 8. Employment shares by country and education level



Note: Occupations at high risk of automation are those with more than 25% of highly automatable important skills and abilities. Relative weights were used to construct a crosswalk between ISCO-08 (three-digit) and SOC 2010 (three-digit). Average indicates the unweighted average of country shares.
Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability, O*NET, the European Union Labour Force Survey (EU-LFS) [2019], and Current Population Survey of United States 2019 (CPS).

Figure 9. Employment shares by country and age group

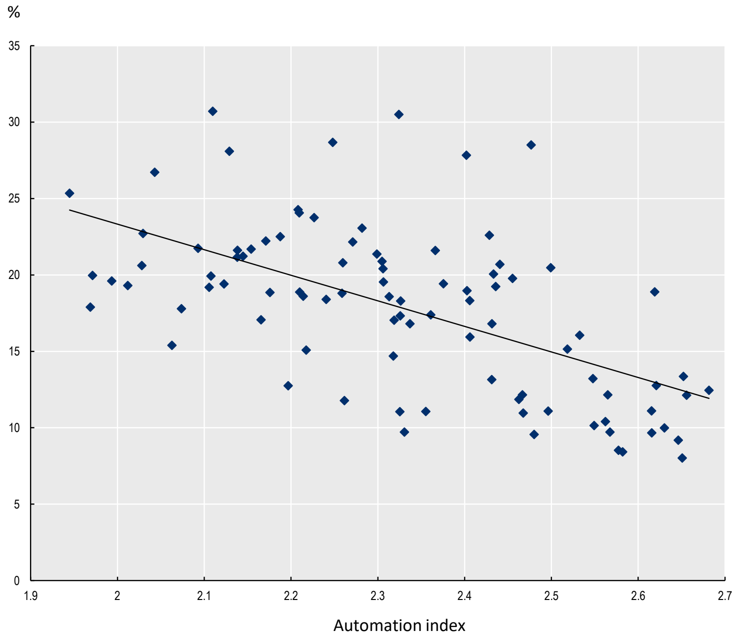


Note: Occupations at high risk of automation are those with more than 25% of highly automatable important skills and abilities. Relative weights were used to construct a crosswalk between ISCO-08 (three-digit) and SOC 2010 (three-digit). Average indicates the unweighted average of country shares.
Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability, O*NET, the European Union Labour Force Survey (EU-LFS) [2019], and Current Population Survey of United States 2019 (CPS).

51. Finally, Figure 10 shows the relationship between occupational exposure to automation (automation index as reported in Figure 3) and workers' propensity to train. Previous OECD work

(Nedelkoska and Quintini, 2018[9]) showed a negative correlation between an individual's risk of automation and propensity to train. Since this study, governments made important efforts to retrain most at risk workers. Given recent advances in training participation and changes in occupations at highest risk of automation, it is interesting to re-evaluate the relationship between automation exposure and training participation. This is what Figure 10 does. It highlights that despite important efforts made by governments over the past years to retrain workers in occupations most at risk of job automation, the relationship between an occupation's exposure to automation and the share of workers undertaking training remains significantly negative: 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.

Figure 10. Relationship between automation index and propensity to train



Note: The x-axis represents the automation index computed for detailed occupations (SOC 3 digits) as in Formula (2). The y-axis represents the share of workers that took part in training in the last four weeks preceding the interview. The sample is restricted to employed individuals in Austria, Belgium, Switzerland, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Greece, Hungary, Ireland, Italy, Iceland, Lithuania, Latvia, Luxembourg, Netherlands, Norway, Portugal, Sweden, Slovak Republic, and United Kingdom. Relative weights were used to construct a crosswalk between ISCO-08 (three-digit) and SOC 2010 (three-digit).
Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability, O*NET, the European Union Labour Force Survey (EU-LFS) [2019].

5 Concluding remarks

52. Have recent technological developments led to changes in the degree of automatability of skills and abilities? What occupations and workers are the most at risk of automation? This paper answers these questions using new data on the degree of automatability of skills and abilities collected through an original expert survey and linking it to labour force surveys to derive information on the share of employment potentially affected.

53. Thanks to important advances in automation technologies, some skills and abilities previously identified as bottlenecks to automation are now automatable to a larger extent. This is the case of the knowledge of fine arts and several psychomotor abilities (the ability to work in cramped workspace and awkward positions, finger dexterity, and manual dexterity). However, despite important research progress, there remains significant bottlenecks to automation. In particular, skills related to complex problem-solving, high-level management and social interaction are still hard to automate given the current state of technological developments. Recent advances in AI also make several skills required in high-skilled jobs susceptible to automation. This is the case for instance of reading comprehension, deductive and inductive reasoning skills, fluency of ideas and scheduling skills.

54. Construction and extraction, farming, fishing, and forestry, and to a lower extent production and transportation occupations, rely importantly on skills and abilities that are highly susceptible to automation and hence are among the occupations at highest risk of automation. Least at risk jobs include management and community and social service occupations. On average across OECD countries, occupations at highest risk of automation account for about 28% of employment. This is higher than previous figures published by OECD which put the share of workers at high risk of automation to about 14%. This may be due to progress in AI technologies but also to the different methodology adopted.

55. What is clear is that while more jobs may be exposed to AI, very few are exposed to the extent of disappearing entirely. Indeed, another important takeaway of this work is that most occupations involve a mix of bottleneck and automatable skills and abilities. Even jobs that are at high risk of automation involve bottleneck tasks and even jobs that are shielded from the risk of disappearing involve a small set of automatable tasks. In other words, even high risk occupations are not likely to be entirely substituted by automated solutions. Rather, the organisation of work will have to be adapted and workers in these jobs may need to retrain, as technologies replace workers for several tasks.

56. Based on the granular analysis of the automatability of skills and abilities conducted in this study, only 9% of workers are employed in occupations with at least 25% of highly automatable skills and abilities. This share varies substantially across countries – ranging from less than 6% in the United Kingdom, Luxembourg, Sweden, Netherlands, Norway, and Switzerland to over 12% in Hungary, Latvia, Slovak Republic, and Czech Republic – but remains contained. Workers in high risk occupations are typically young, male, and with low levels of education. Finally, and despite important investments in adult learning to support workers affected by technology change, the relationship between exposure to automation and the share of workers undertaking training remains significantly negative.

57. Since the present study relies on the O*NET database to translate automatability of skills and abilities into occupational exposure to automation, limitations of this dataset also apply here. In particular, as it is developed by the Employment and Training Administration in the United States, the dataset is geared towards the occupational content of jobs in the labour market in the United States. Despite this,

O*NET has been regularly used for the analysis of countries other than the United States. The assumption that skill measures from one country can be generalised to other countries has been tested and largely holds (Cedefop, 2013[26]; Handel, 2012[27]; Koucký, Kovařovic and Lepič, 2012[28]) and the information on skills, knowledge and ability requirements it contains has been used extensively in labour market research (see for instance Deming, 2017).

58. Another potential drawback of O*NET is that it essentially provides a static representation of skill and ability requirements in occupations and assumes that all workers in the same occupation carry out the same tasks. Indeed, even though the database is updated regularly, only approximately 100 occupations are amended at each new release and hence the data cannot be used to study changes in the skill content of occupations over time. This is not a critical issue for the present analysis as it uses an expert assessment of occupational exposure but it may still mean that the skill requirements used in each occupation are slightly outdated. O*NET also provides a picture by occupations while jobs with the same occupational titles may require different skills and abilities; in other words, job descriptions in the real world vary a lot more than in O*NET. Some evidence on how skill requirements may have changed over time, based on individual workers data, is provided in Box 2 below, but further research on this question, using data on skill requirements appearing in online vacancies as was done for the latest update of the Skills for Jobs database (Lassébie, Marcolin and Quintini, 2022[34]; Quintini and Verhagen, 2022[35]) (Quintini and Verhagen, 2022; Lassébie and Marcolin, 2022) or using new data from the Survey of Adult Skills (PIAAC), is warranted.

Box 2. Changes in skills and abilities required in occupations over time

The present study focuses on changes in the automatability of skills and abilities due to recent technological advances and links these to occupational exposure to automation. However, job content may have already adapted to automation and other megatrends. This box tries to shed light on this second issue.

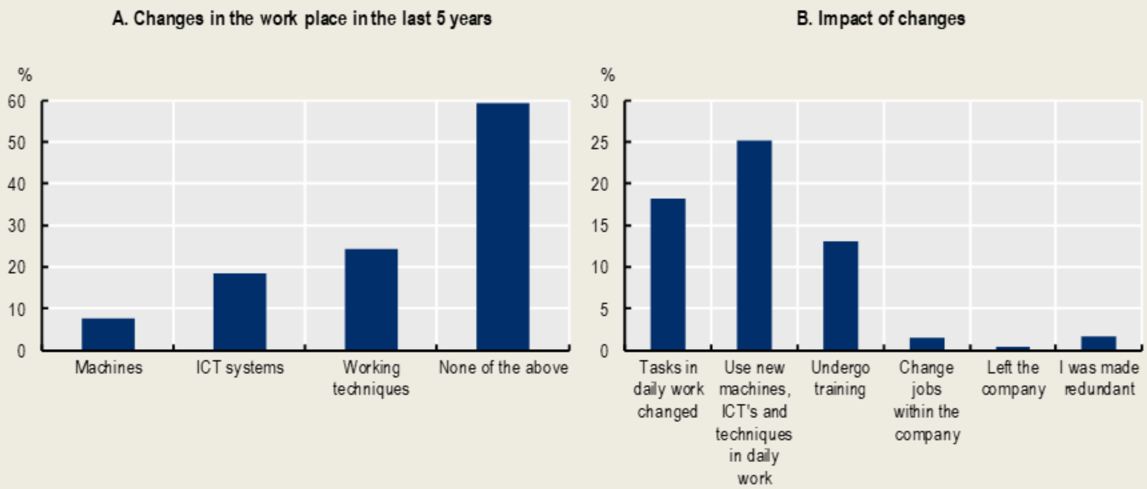
To this aim, the analyses discussed in this box use data on skills and abilities required in occupations collected via the OECD Future of Jobs webpage. Launched in December 2018, this free interactive tool allows individuals to assess the chance that their job changes due to automation. The online survey contains questions on 1) respondents, 2) skills and abilities required in their jobs, and 3) changes experienced in the workplace. The dataset used for this study, hereafter referred to as FoJ, contains information on 13,967 individuals from 27 countries. The sample is restricted to countries for which data from the OECD Survey of Adult Skills (PIAAC) is also available, and to employed individuals with tertiary education as they are over-represented in the FoJ data.

As highlighted in Panel A of

Figure 11, 41% of individuals in the FoJ sample declare having experienced important changes in their workplace in the last five years, including the introduction of machines, ICT, or new working techniques specifically dedicated to automate tasks. This figure seems significant given that the sample used in this study is restricted to employed individuals with tertiary education. As a result of such changes, 18% report that their daily tasks have changed. However, changes in task content are not the only consequence of automation. Indeed, 25% of workers report that they had to use these new machines, ICT systems and working techniques in their daily job, and 13% had to undergo training. In total, less than 5% had to change jobs within the company, left the company, or were made redundant (

Figure 11, Panel B).

Figure 11. Changes in the workplace

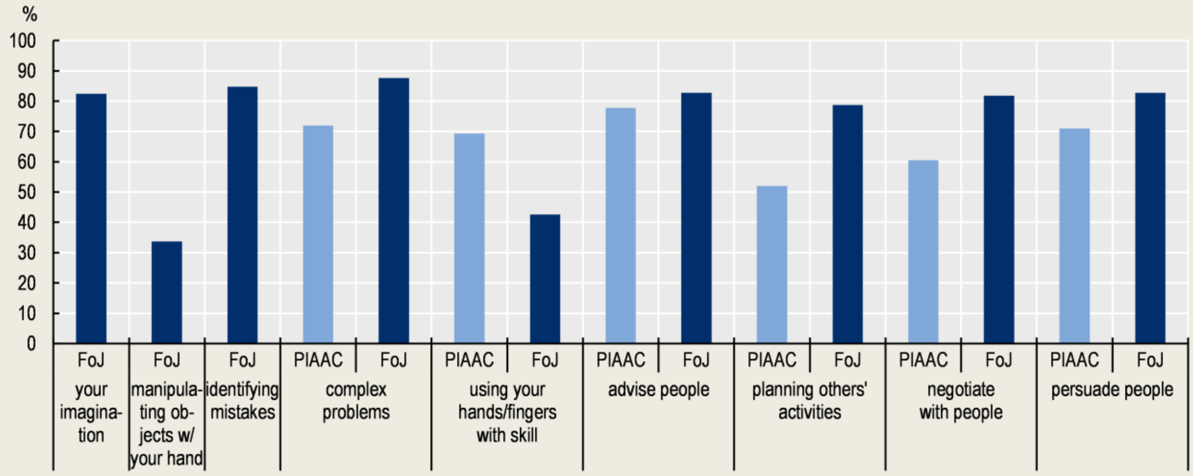


Note: Weighted average from Australia, Austria, Belgium, Canada, Chile, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Kazakhstan, Mexico, Netherlands, New Zealand, Norway, Poland, Russian Federation, Singapore, Spain, Sweden, Türkiye, United Kingdom and the United States. Weights adjusted to PIAAC data. The total sample includes only employed individuals with tertiary education.
Source: Elaborations on the Survey of Adult Skills (PIAAC) and data from the OECD Future of Jobs website.

Questions on skills and abilities required in people's jobs in the Future of Jobs webpage are similar to some questions in the OECD Survey of Adult Skills (PIAAC). Given that the data for the two surveys have been collected at different points in time (between 2014 and 2016 for PIAAC and between 2018 and 2020 for data collected via the Future of Jobs webpage), it is possible to study changes in the frequency of several tasks performed in the workplace. To do so, it is necessary to ensure that the two samples are comparable. This is done by restricting the analysis to employed individuals with tertiary education that are over-represented in the FoJ dataset. Weights for gender, age, and occupation have also been applied to FoJ data to make it comparable to PIAAC.

Figure 12 shows the share of respondents performing selected tasks at least once a week. It highlights several differences between the two surveys in the frequency of tasks performed in occupations: tasks involving the use of hands and fingers are less frequent in the FoJ data, i.e. in more recent years, while tasks such as solving complex problems, planning others' activities, negotiating, and persuading appear to be more frequent in more recent years. However, despite efforts to harmonise the two samples as mentioned above, it is important to recognise that the differences in skills and abilities required in jobs documented here could come from unobserved differences between respondents to the two surveys rather than indicating changes over time.

Figure 12. Frequency of tasks performed at work in PIAAC and FoJ datasets



Note: Weighted average from: Australia, Austria, Belgium, Canada, Chile, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Kazakhstan, Mexico, Netherlands, New Zealand, Norway, Poland, Russian Federation, Singapore, Spain, Sweden, Türkiye, United Kingdom and United States. Weights adjusted to PIAAC data. The total sample includes only employed individuals with tertiary education.
Source: Elaborations on the Survey of Adult Skills (PIAAC) and data from the OECD Future of Jobs website.

[1] The sample is restricted to countries for which data from the Survey of Adult Skills (PIAAC) is also available, and to employed individuals with tertiary education.

59. It is also necessary to note that the present study is focused on the degree of automatability of skills and abilities from a technical point of view, abstracting from economic, operational, and cultural feasibility and regulatory issues. This is why the report does not try to make predictions about the likelihood of automating entire occupations: in order to be accurate, such predictions would necessitate taking into account in a single unified framework too many factors. All these different factors will influence technology adoption and its impact on jobs, and this has made past predictions largely unreliable. Rather, the paper aims to inform policy makers about the possibilities of automation technologies and appropriate policy responses. Nonetheless, the issue of adoption of automation technologies and its skill implications is of a paramount importance and some insights on this are provided in Box 3 below. Forthcoming OECD work surveyed firms and workers to investigate in more detail how and why AI is being implemented in the workplace and its impact on employment, working conditions and skill needs, among other topics (Broecke, Lane, Williams, forthcoming).

Box 3. Adoption of automation technologies by firms – Insights from semi-structured interviews with leading AI companies

In order to shed light on adoption of automation technologies and its skill implications, this box summarises qualitative information collected during semi-structured interviews with four leading companies that commercialise AI solutions: Hewlett-Packard, IBM, Microsoft, and UiPath.

Popular or trending technologies commercialised by these companies comprise virtual assistants (handling e-mails, checking job candidates' applications), voice recognition and speech-to-text solutions, computer vision technologies, technologies for data extraction, inventory systems, robots to inspect machines, goods, or settings or to identify issues in assembly lines, and even machines automating food preparation and service. Some of these solutions have been used extensively during the COVID-19 crisis: for instance, computer vision technologies were adopted to monitor social distancing and mask wearing. Virtual assistants and chatbots were also very useful as lockdowns prevented the proper functioning of many call centres. During the pandemic, the use of AI in healthcare also gained attention: for example, AI systems to identify target molecules to develop innovative treatments, or fully digital administrative support systems for health providers.

Experts unanimously insisted on the fact that the main reason behind adoption of these automation technologies is not the replacement of workers but rather to complement labour, allowing the work to be done faster and more efficiently. They mentioned that AI and other technologies do not automate jobs as a whole but only some skills and abilities within jobs. Humans will still need to write the programs, check the performance of new technologies, and carry out maintenance. They also listed other skills or abilities that AI systems do not possess: prioritisation, participation in long discussions, creativity, strategic thinking, complex problem solving, among others. This is why, according to them, the nature and organisation of work, rather than the quantity of jobs, will change. Yet, some also mentioned that these solutions are often implemented to decrease operational costs and redundancy or to mitigate the risk of human error, suggesting that there is some degree of substitution between human labour and automated solutions.

All the experts recognise the importance of employees' skills for the adoption of automation technologies. As AI utilises large amounts of data, employees in adopting firms need to know how to work with and use big data. In many cases, companies possess data but do not have the skills to process, analyse, and integrate them. When they have the necessary technical skills, communication between different departments remains an issue, as teams often do not speak the same language. According to one of the experts, bridging this gap is one of the most important challenge in the adoption of AI technologies. Managers' attitudes and skills also matter, as they usually are the ones initiating and driving change.

Other challenges listed by experts include the need for important computing resources, the difficulty to assess precisely where and how the innovation could be used in the company, the integration of AI systems in existing processes, issues related to AI systems uncertainties, and problems of cultural acceptance of the new technologies by existing employees.

Finally, one expert argued that the main challenge for governments will be keeping up with the pace of technological developments so that they can develop appropriate policies to respond, notably regarding training.

Source: Author's elaborations on data collected during semi-structured interviews with experts from four leading companies that commercialise AI solutions: Hewlett Packard Enterprise, IBM, Microsoft, and UiPath.

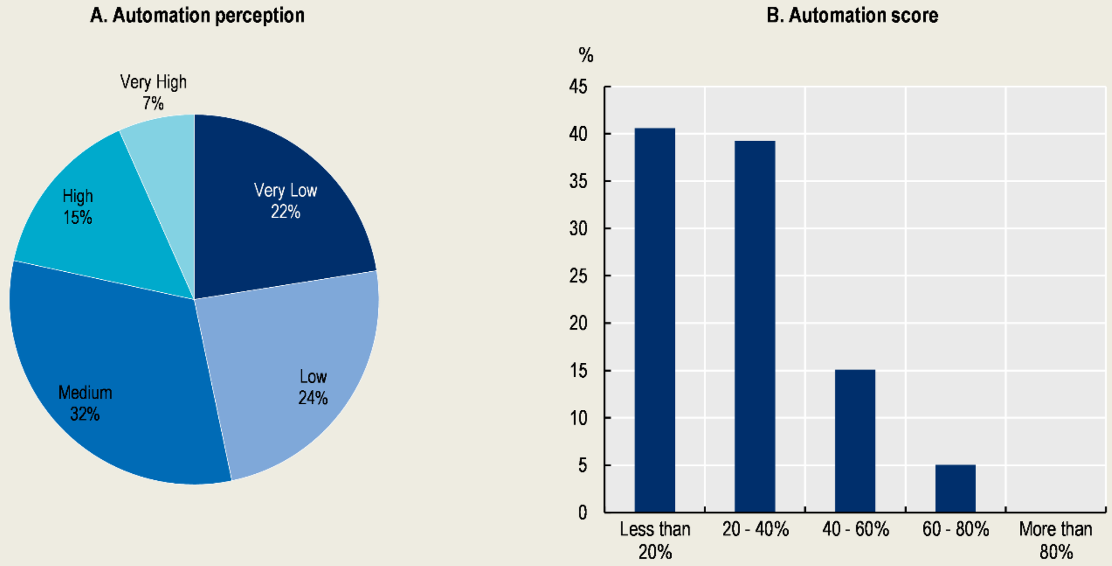
60. Another aspect overlooked in this study as in most papers in the literature is that the deployment of automation technologies in firms will presumably entail new job creation, both in existing occupations if technology adoption leads to important decreases in output price and hence increases in demand, and in new occupations as new technologies require new tasks to be performed by humans (PWC, 2018[36]; Wilson, Daugherty and Morini-Bianzino, 2017[37]). For these two reasons, the diagnosis painted in this paper is probably more alarming than what the future holds, particularly if training investments are focused on upskilling the groups that are most likely to be at risk of automation.

61. The results of the analysis should be used to draw attention to the needs for upskilling and reskilling of workers who are likely to be exposed to AI technologies as their jobs change. Public intervention is necessary to help workers gain the necessary skills to work with automation technologies that may be introduced in workplaces or to transition to less at risk occupations, as many seem to underestimate the risk of their jobs being affected (see Box 4). This may partly explain why workers in occupations at highest risk of automation are still less likely to participate in education and training activities than individuals in jobs less at risk. Furthermore, even if high-skilled individuals particularly concerned by advances in AI participate more in training activities than low-skilled workers, it is not clear that they follow the right type of training (i.e. training that will equip them with the skills to work with AI). In this context, awareness activities and career guidance for adults represent interesting options.

Box 4. Perceived vs. actual risk of automation

The Future of Jobs survey (see Box 2 for more details on this survey) also includes information on individuals' perceptions of their own automation risk. Figure 13, Panel A shows that more than 50% of respondents in the sample (restricted to employed individuals with tertiary education) think that they have medium, high, or very high chances that their jobs will change due to automation in the next five years. Moreover, after completing the survey, participants received information on their "actual" risk of automation, calculated using the parameters estimated by Nedelkoska and Quintini (2018[9]). Figure 13, Panel B highlights that the large majority of respondents in the sample (80%) have an actual risk of automation lower than 40%, and only 20% of individuals have a risk higher than 40%. However, the correlation between perceived automation and actual automation risk is very weak and most respondents with a high risk of automation tend to underestimate it. This is particularly worrisome, as those individuals are unlikely to take actions to prepare for the future of jobs.

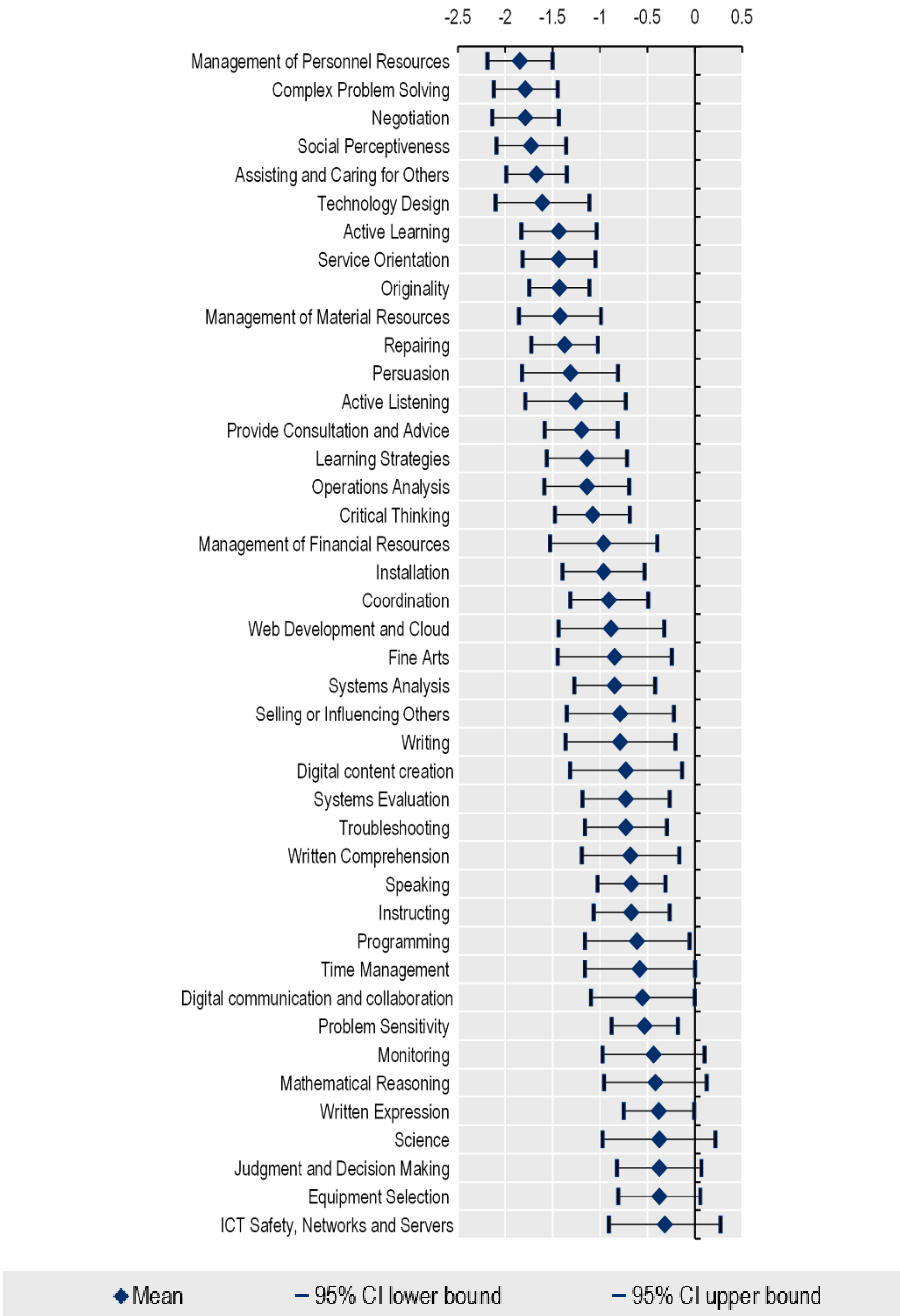
Figure 13. Perceived vs. actual automation risk



Note: Weighted average from: Australia, Austria, Belgium, Canada, Chile, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Kazakhstan, Mexico, Netherlands, New Zealand, Norway, Poland, Russian Federation, Singapore, Spain, Sweden, Türkiye, United Kingdom and United States. Weights adjusted to PIAAC data. Total sample includes ONLY employed individuals with tertiary education. Source: Elaborations on the Survey of Adult Skills (PIAAC) and data from the OECD Future of Jobs website.

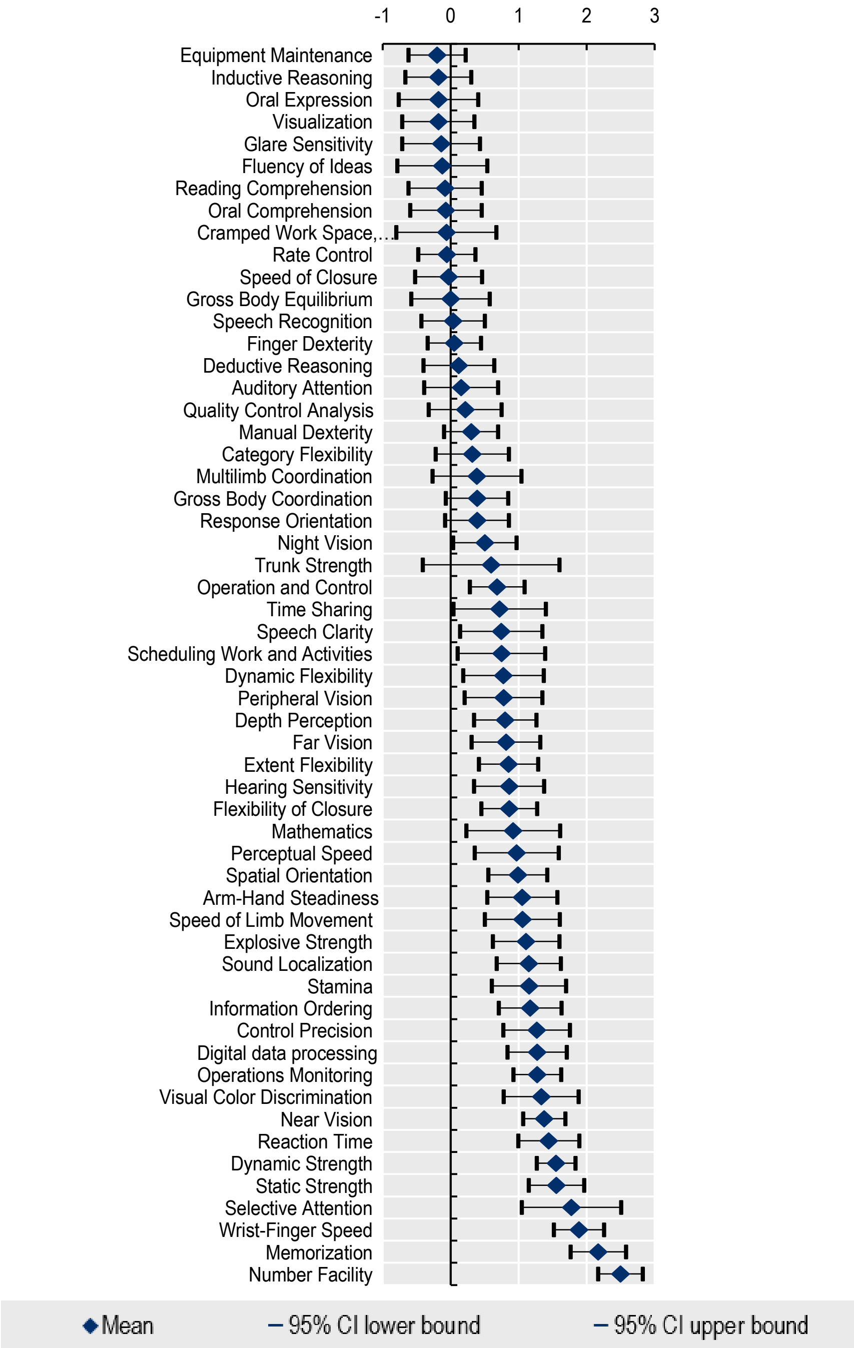
Annex A. Alternative automatability measures

Figure A A.1. Automatability of skills and abilities I – removing experts FE



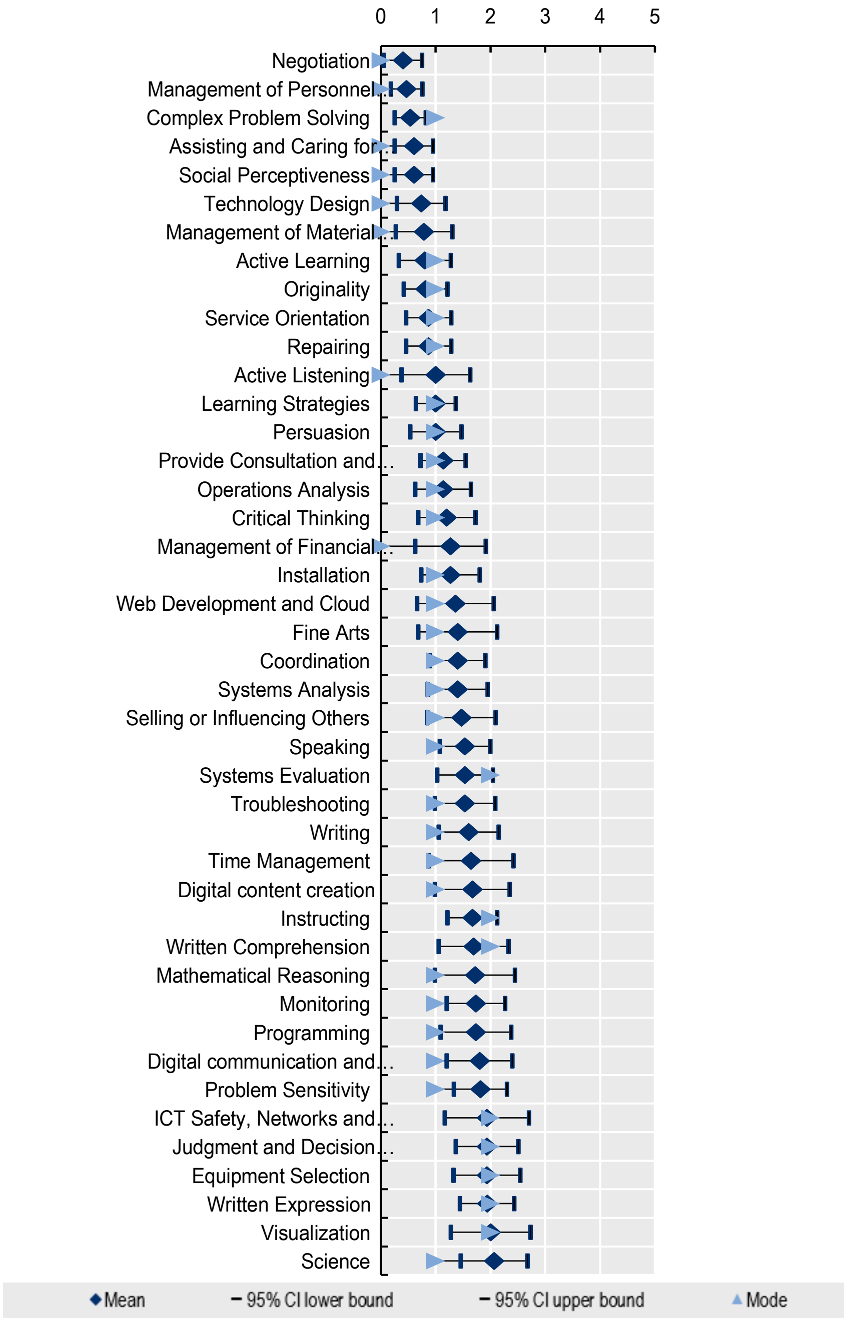
Source: OECD Expert Survey on Skills and Abilities Automatability

Figure A A.2. Automatability of skills and abilities II – removing experts FE



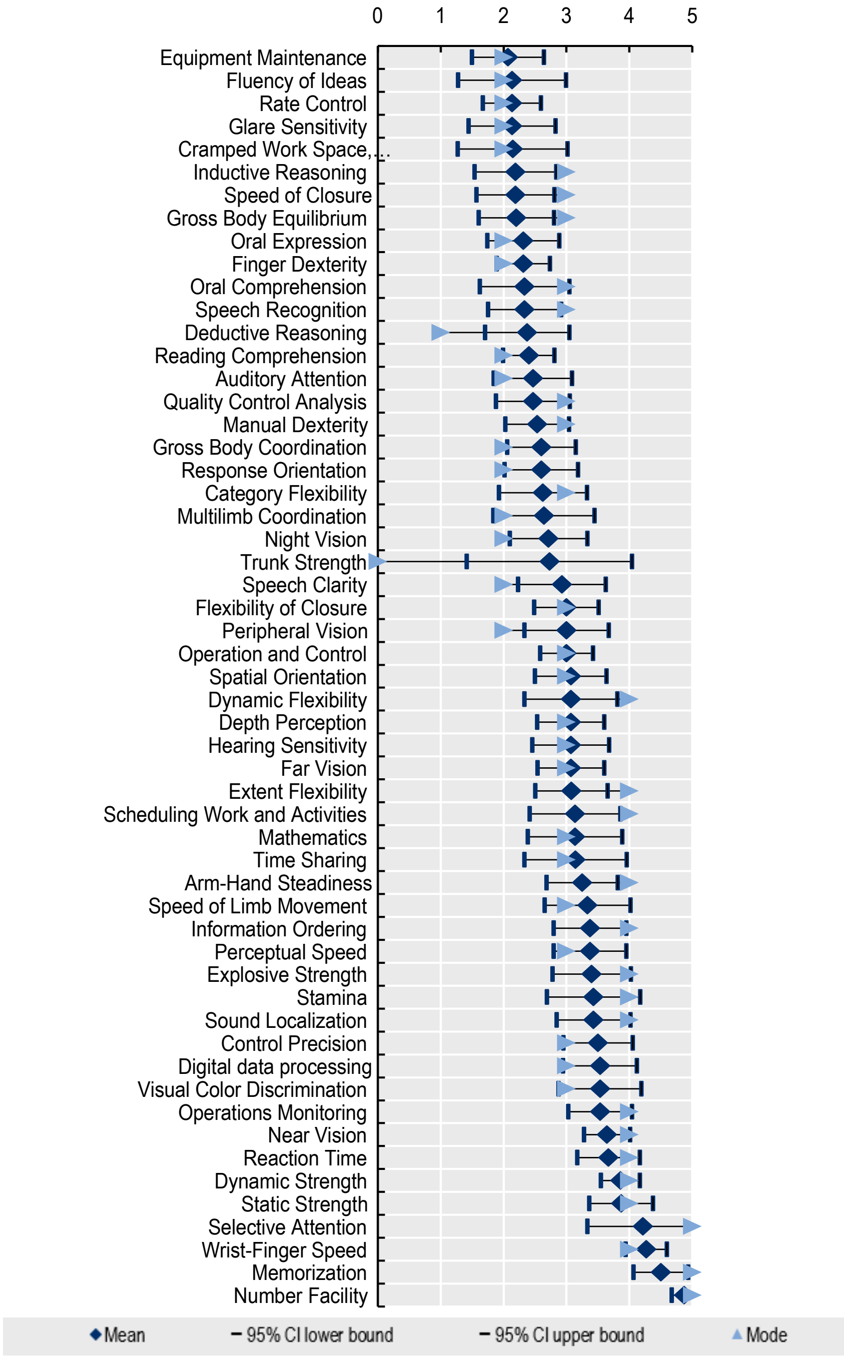
Source: OECD Expert Survey on Skills and Abilities Automatability

Figure A A.3. Automatability of skills and abilities I – excluding extreme raters



Source: OECD Expert Survey on Skills and Abilities Automatability

Figure A A.4. Automatability of skills and abilities II – excluding extreme raters

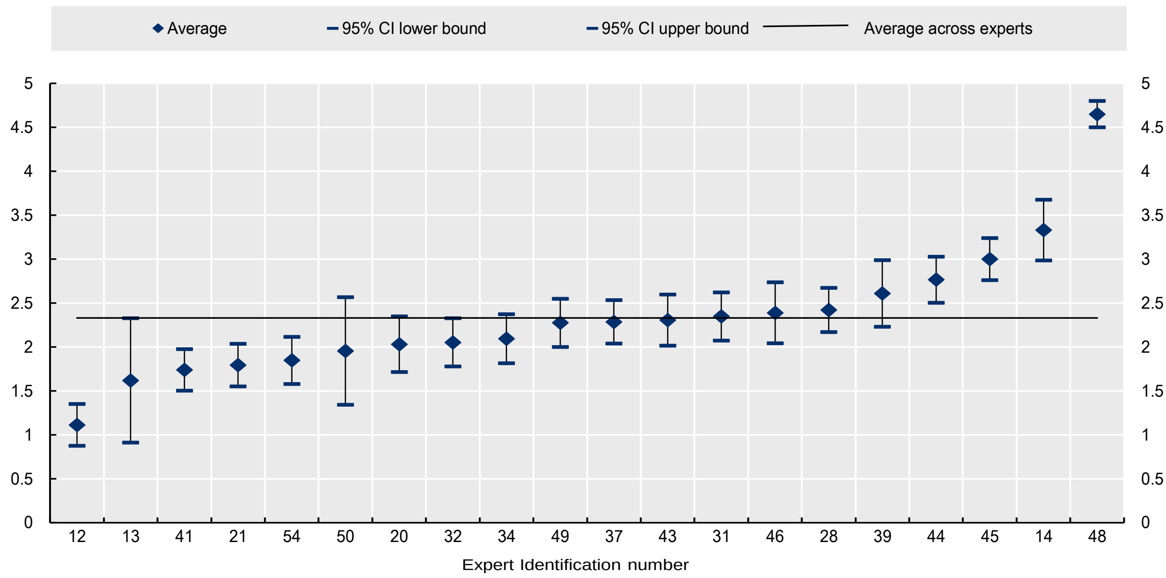


Source: OECD Expert Survey on Skills and Abilities Automatability

Annex B. Analysis of experts' answers

Experts may differ in the way they understood the questionnaire and answered the survey. For instance, they may interpret the scale of potential responses differently, or be biased towards some answers. It is thus important to analyse how respondents answered the survey. One straightforward way to shed a light on these issues is to study individuals' average answer and compare it to the general average. This is what Figure A B.1 does.

Figure A B.1. Comparison of experts' average answers

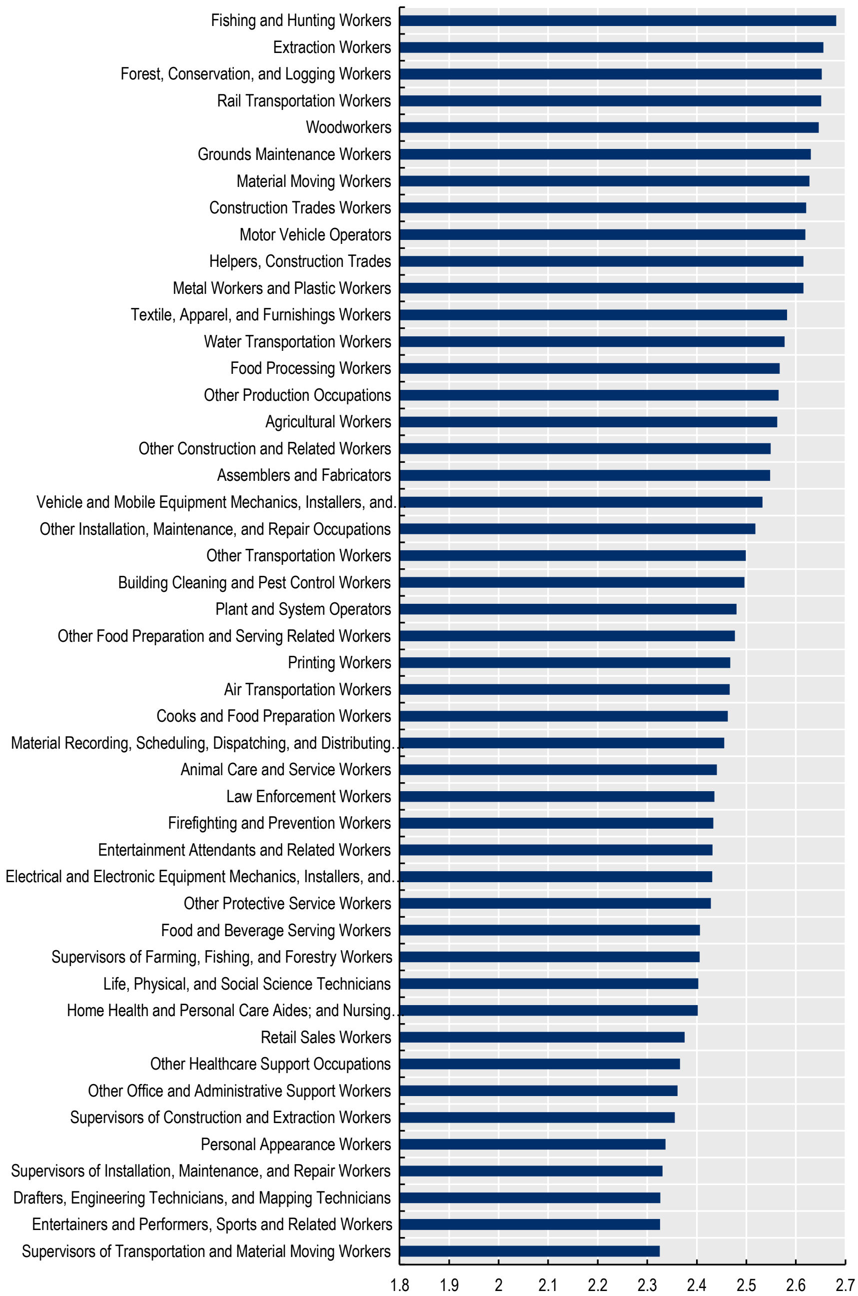


Note: The x-axis shows the identification number of each expert answering the survey. The y-axis represents the average answer of each expert computed for all skills and abilities for which the individual provided an answer, and the 95% confidence interval.
Source: OECD Expert Survey on Skills and Abilities Automatability

In general experts' average answers are close to the general average, with exceptions for expert 12 (and to a lesser extent expert 13) who tends to provide answers that are systematically lower than the average and expert 48 (and expert 14 to a lesser extent) who tends to answer with higher values than the average. Confidence intervals for each expert are quite narrow, meaning that each individual tend to provide answers close to their own average. This suggests that they may have a different understanding of the scale of the different possible answers or a different anchoring. A robustness analysis to mitigate this potential issue is provided in Annex A: for each response, expert answers are "demeaned" by their own average across all variables before computing the mean across experts (see Formula in footnote 6). This is similar to getting rid of experts' idiosyncrasies when answering the survey. Annex A also shows results when excluding the two most optimistic and pessimistic experts (experts 12, 13, 14, and 48). In both robustness analyses, the ranking of skills and abilities according to their average degree of automatability changes only marginally, and importantly the sets of bottleneck and highly automatable items remain the same.

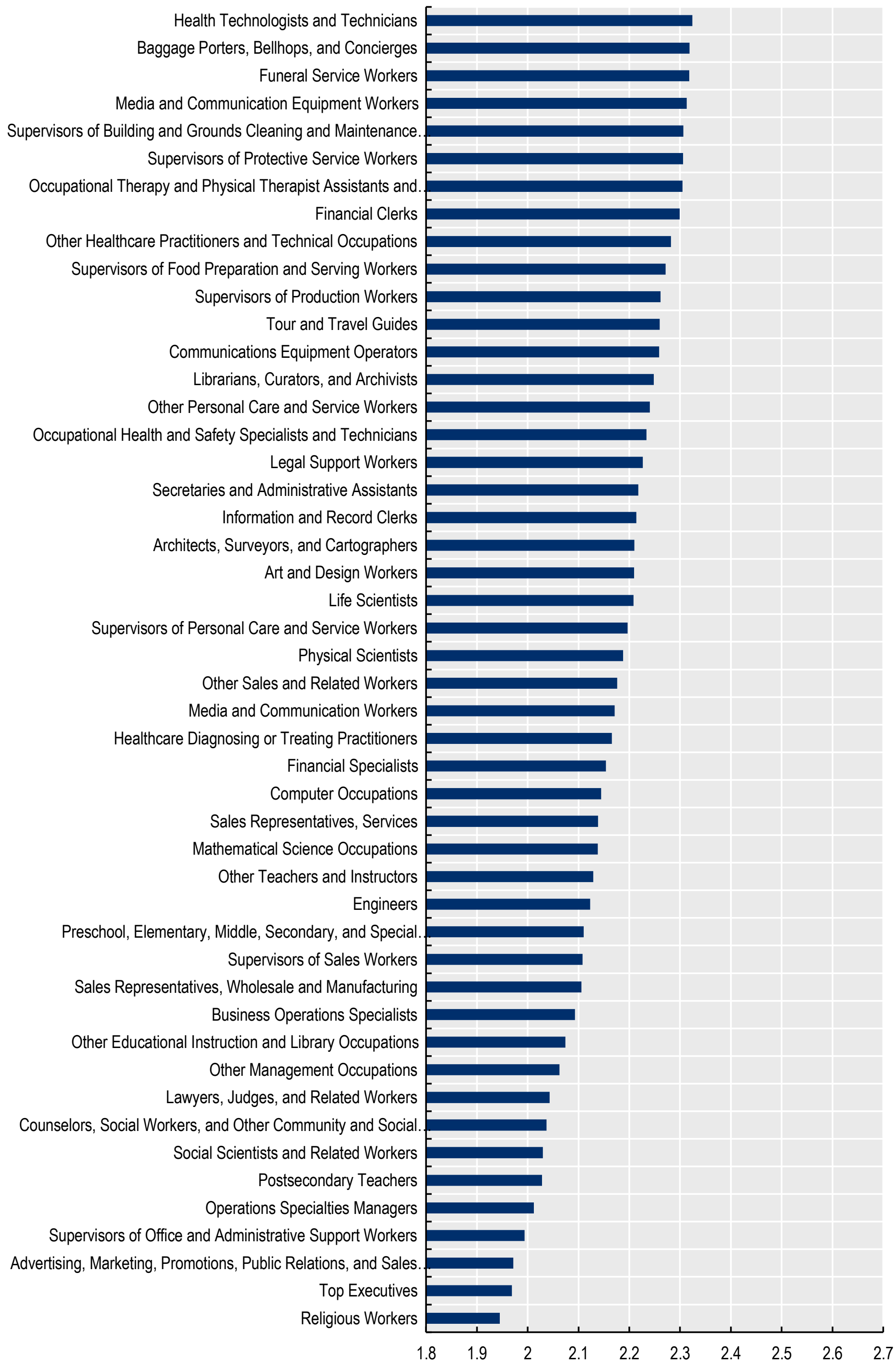
Annex C. Impact on detailed occupations

Figure A C.1. Ranking of detailed occupations by degree of automatability I



Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

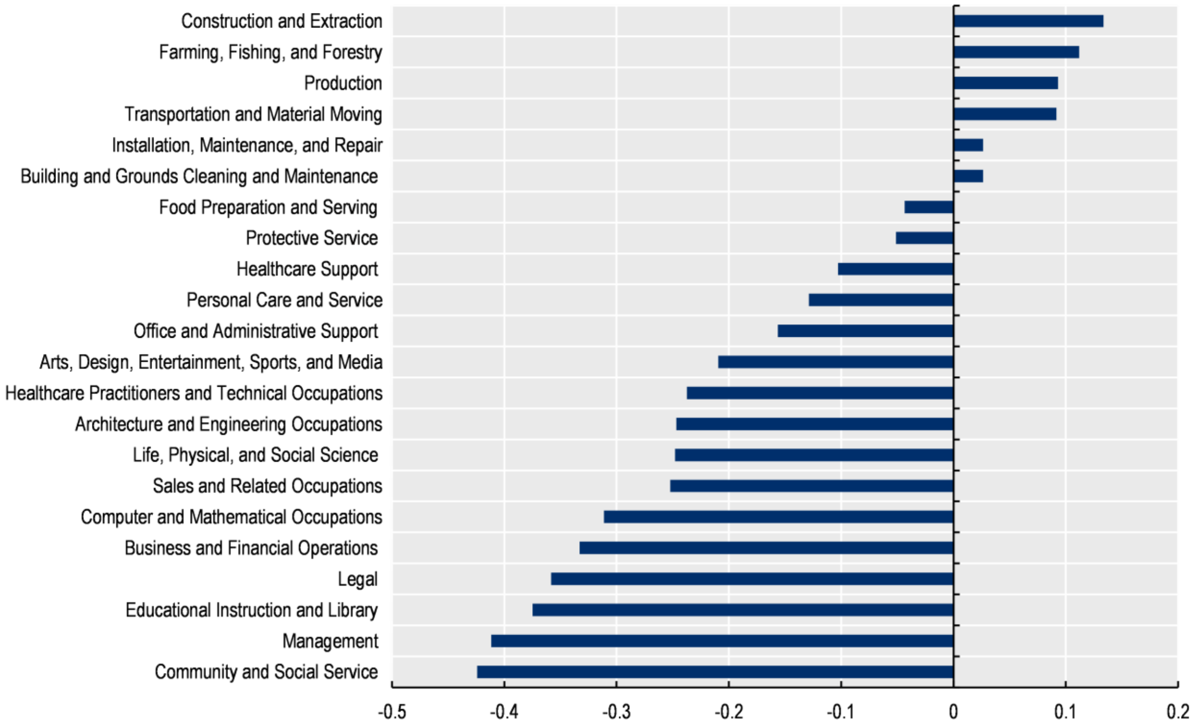
Figure A C.2. Ranking of detailed occupations by degree of automatability II



Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

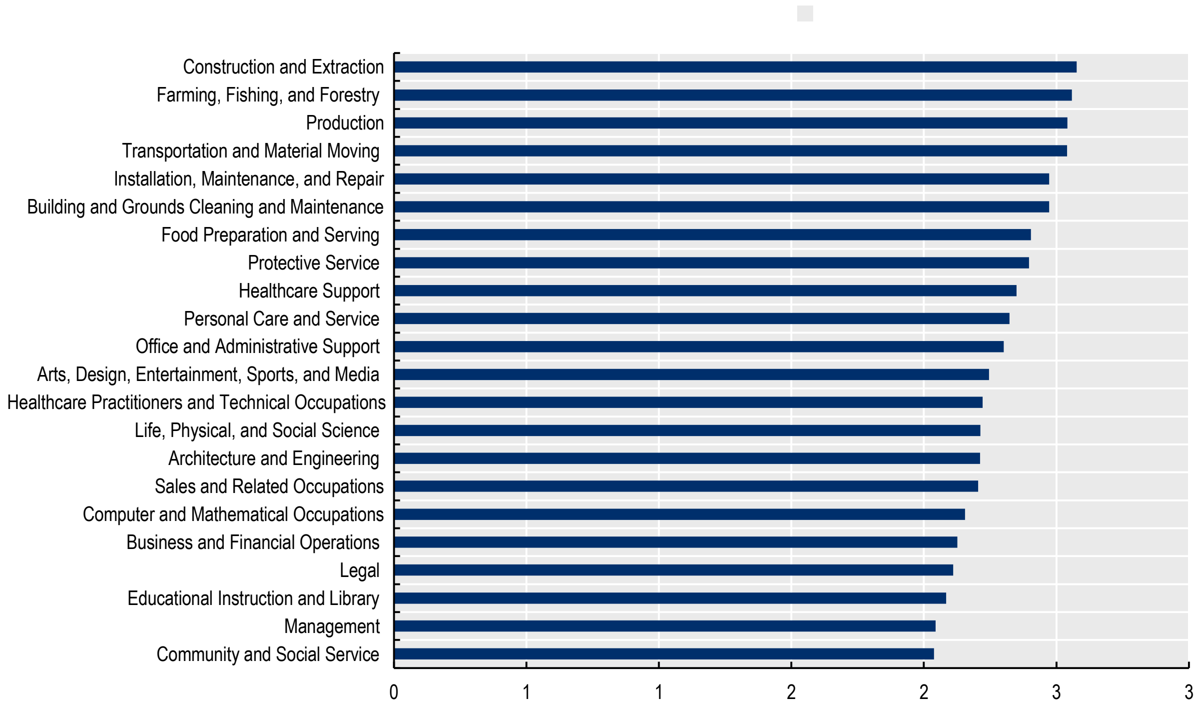
Annex D. Impact on jobs and workers using alternative automatability measures

Figure A D.1. Ranking of occupations by degree of automatability – removing experts FE



Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

Figure A D.2. Ranking of occupations by degree of automatability – excluding extreme raters



Source: OECD calculations based on OECD Expert Survey on Skills and Abilities Automatability and O*NET.

Annex E. List of experts

Table A E.1. Members of the expert group

Name	Position and affiliation
Guillaume Avrin	Evaluation in AI and Robotics – Manager, LNE (Laboratoire national de métrologie et d'essais)
Peter Corke	Director, Queensland University of Technology Centre for Robotics
Mary L. Gray	Senior Principal Researcher, Microsoft Research
Duncan McFarlane	Professor of Industrial Information Engineering, Institute for Manufacturing, Cambridge University
Tom Mitchell	Professor, Carnegie Mellon University
Anika Schumann	Leader AI Research Partnerships Europe, Senior Senior Research Scientist AI, IBM Research
Julie Shah	H.N. Slater Professor of Aeronautics and Astronautics, MIT
Keith Strier	Vice President, Worldwide AI Initiative, NVIDIA

Annex F. Skills and abilities included in the survey

Table A F.1. Skills and abilities included in the OECD Expert Survey on Skills and Abilities Automatability

Variable	Definition	Source	Category	Sub-category
Category Flexibility	The ability to generate or use different sets of rules for combining or grouping things in different ways.	O*NET	Abilities	Cognitive Abilities
Deductive Reasoning	The ability to apply general rules to specific problems to produce answers that make sense.	O*NET	Abilities	Cognitive Abilities
Flexibility of Closure	The ability to identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material.	O*NET	Abilities	Cognitive Abilities
Fluency of Ideas	The ability to come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).	O*NET	Abilities	Cognitive Abilities
Inductive Reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).	O*NET	Abilities	Cognitive Abilities
Information Ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).	O*NET	Abilities	Cognitive Abilities
Mathematical Reasoning	The ability to choose the right mathematical methods or formulas to solve a problem.	O*NET	Abilities	Cognitive Abilities
Memorisation	The ability to remember information such as words, numbers, pictures, and procedures.	O*NET	Abilities	Cognitive Abilities
Number Facility	The ability to add, subtract, multiply, or divide quickly and correctly.	O*NET	Abilities	Cognitive Abilities
Oral Comprehension	The ability to listen to and understand information and ideas presented through spoken words and sentences.	O*NET	Abilities	Cognitive Abilities
Oral Expression	The ability to communicate information and ideas in speaking so others will understand.	O*NET	Abilities	Cognitive Abilities
Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.	O*NET	Abilities	Cognitive Abilities
Perceptual Speed	The ability to quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns. The things to be compared may be presented at the same time or one after the other. This ability also includes comparing a presented object with a remembered object.	O*NET	Abilities	Cognitive Abilities
Problem Sensitivity	The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognising there is a problem.	O*NET	Abilities	Cognitive Abilities
Selective Attention	The ability to concentrate on a task over a period of time without being distracted.	O*NET	Abilities	Cognitive Abilities
Spatial Orientation	The ability to know your location in relation to the environment or to know where other objects are in relation to you.	O*NET	Abilities	Cognitive Abilities
Speed of Closure -	The ability to quickly make sense of, combine, and organise information into meaningful patterns.	O*NET	Abilities	Cognitive Abilities
Time Sharing	The ability to shift back and forth between two or more activities or sources of information (such as speech, sounds, touch, or other sources).	O*NET	Abilities	Cognitive Abilities

Visualisation	The ability to imagine how something will look after it is moved around or when its parts are moved or rearranged.	O*NET	Abilities	Cognitive Abilities
Written Comprehension	The ability to read and understand information and ideas presented in writing.	O*NET	Abilities	Cognitive Abilities
Written Expression	The ability to communicate information and ideas in writing so others will understand.	O*NET	Abilities	Cognitive Abilities
Arm-Hand Steadiness	The ability to keep steady while moving other parts.	O*NET	Abilities	Psychomotor Abilities
Control Precision	The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.	O*NET	Abilities	Psychomotor Abilities
Finger Dexterity	The ability to make precisely coordinated movements to grasp, manipulate, or assemble very small objects.	O*NET	Abilities	Psychomotor Abilities
Manual Dexterity	The ability to move quickly to grasp, manipulate, or assemble objects.	O*NET	Abilities	Psychomotor Abilities
Multilimb Coordination	The ability to coordinate two or more limbs while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.	O*NET	Abilities	Psychomotor Abilities
Rate Control	The ability to time your movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene.	O*NET	Abilities	Psychomotor Abilities
Reaction Time	The ability to quickly respond to a signal when it appears.	O*NET	Abilities	Psychomotor Abilities
Response Orientation	The ability to choose quickly between two or more movements in response to two or more different signals. It includes the speed with which the correct response is started.	O*NET	Abilities	Psychomotor Abilities
Speed of Limb Movement	The ability to move quickly.	O*NET	Abilities	Psychomotor Abilities
Wrist-Finger Speed	The ability to make fast, simple, repeated movements.	O*NET	Abilities	Psychomotor Abilities
Dynamic Flexibility	The ability to quickly and repeatedly bend, stretch, twist, or reach out.	O*NET	Abilities	Physical Abilities
Dynamic Strength	The ability to exert force repeatedly or continuously over time. This involves endurance and resistance to fatigue.	O*NET	Abilities	Physical Abilities
Explosive Strength	The ability to use force to propel oneself or to throw an object.	O*NET	Abilities	Physical Abilities
Extent Flexibility	The ability to bend, stretch, twist, or reach.	O*NET	Abilities	Physical Abilities
Gross Body Coordination	The ability to coordinate different movements when the whole body is in motion.	O*NET	Abilities	Physical Abilities
Gross Body Equilibrium	The ability to keep or regain balance or stay upright when in an unstable position.	O*NET	Abilities	Physical Abilities
Stamina	The ability to exert yourself physically over long periods of time.	O*NET	Abilities	Physical Abilities
Static Strength	The ability to exert maximum force to lift, push, pull, or carry objects.	O*NET	Abilities	Physical Abilities
Trunk Strength	The ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without 'giving out' or fatiguing.	O*NET	Abilities	Physical Abilities
Auditory Attention	The ability to focus on a single source of sound in the presence of other distracting sounds.	O*NET	Abilities	Sensory Abilities
Depth Perception	The ability to judge which of several objects is closer or farther away from you, or to judge the distance between you and an object.	O*NET	Abilities	Sensory Abilities
Far Vision	The ability to detect details at a distance.	O*NET	Abilities	Sensory Abilities
Glare Sensitivity	The ability to detect objects in the presence of glare or bright lighting.	O*NET	Abilities	Sensory Abilities
Hearing Sensitivity	The ability to detect or tell the differences between sounds that vary in pitch and loudness.	O*NET	Abilities	Sensory Abilities
Near Vision	The ability to detect details at close range (within a few feet of the observer).	O*NET	Abilities	Sensory Abilities
Night Vision	The ability to detect under low light conditions.	O*NET	Abilities	Sensory Abilities
Peripheral Vision	The ability to detect objects or movement of objects to one's side when the eyes are looking ahead.	O*NET	Abilities	Sensory Abilities
Sound Localisation	The ability to tell the direction from which a sound originated.	O*NET	Abilities	Sensory Abilities
Speech Clarity	The ability to speak clearly so others can understand you.	O*NET	Abilities	Sensory Abilities

Speech Recognition	The ability to identify and understand the speech of another person.	O*NET	Abilities	Sensory Abilities
Visual Color Discrimination	The ability to match or detect differences between colors, including shades of color and brightness.	O*NET	Abilities	Sensory Abilities
Active Learning	Understanding the implications of new information for both current and future problem-solving and decision-making.	O*NET	Skills	Basic Skills
Active Listening	Giving full attention to what people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.	O*NET	Skills	Basic Skills
Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.	O*NET	Skills	Basic Skills
Learning Strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.	O*NET	Skills	Basic Skills
Mathematics	Using mathematics to solve problems.	O*NET	Skills	Basic Skills
Monitoring	Monitoring/Assessing performance of yourself, other individuals, or organisations to make improvements or take corrective action.	O*NET	Skills	Basic Skills
Reading Comprehension	Understanding written sentences and paragraphs in work related documents.	O*NET	Skills	Basic Skills
Science	Using scientific rules and methods to solve problems.	O*NET	Skills	Basic Skills
Speaking	Talking to convey information effectively.	O*NET	Skills	Basic Skills
Writing	Communicating effectively in writing as appropriate for the needs of the audience.	O*NET	Skills	Basic Skills
Complex Problem Solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.	O*NET	Skills	Complex Problem Solving Skills
Coordination	Adjusting actions in relation to people's actions.	O*NET	Skills	Social Skills
Instructing	Teaching others how to do something.	O*NET	Skills	Social Skills
Negotiation	Bringing people together and trying to reconcile differences.	O*NET	Skills	Social Skills
Persuasion	Persuading people to change their minds or behavior.	O*NET	Skills	Social Skills
Service Orientation	Actively looking for ways to help people.	O*NET	Skills	Social Skills
Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.	O*NET	Skills	Social Skills
Equipment Maintenance	Performing routine maintenance on equipment and determining when and what kind of maintenance is needed.	O*NET	Skills	Technical Skills
Equipment Selection	Determining the kind of tools and equipment needed to do a job.	O*NET	Skills	Technical Skills
Installation	Installing equipment, machines, wiring, or programs to meet specifications.	O*NET	Skills	Technical Skills
Operation and Control	Controlling operations of equipment or systems.	O*NET	Skills	Technical Skills
Operations Analysis	Analysing needs and product requirements to create a design.	O*NET	Skills	Technical Skills
Operations Monitoring	Watching gauges, dials, or other indicators to make sure a machine is working properly.	O*NET	Skills	Technical Skills
Quality Control Analysis	Conducting tests and inspections of products, services, or processes to evaluate quality or performance.	O*NET	Skills	Technical Skills
Repairing	Repairing machines or systems using the needed tools.	O*NET	Skills	Technical Skills
Technology Design	Generating or adapting equipment and technology to serve user needs.	O*NET	Skills	Technical Skills
Troubleshooting	Determining causes of operating errors and deciding what to do about it.	O*NET	Skills	Technical Skills
Judgment and Decision Making	Considering the relative costs and benefits of potential actions to choose the most appropriate one.	O*NET	Skills	Systems Skills
Systems Analysis	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.	O*NET	Skills	Systems Skills
Systems Evaluation	Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system.	O*NET	Skills	Systems Skills
Management of Financial Resources	Determining how money will be spent to get the work done, and accounting for these expenditures.	O*NET	Skills	Resource Management Skills
Management of Material Resources	Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.	O*NET	Skills	Resource Management Skills
Management of	Motivating, developing, and directing people as they work, identifying	O*NET	Skills	Resource

Personnel Resources	the best people for the job.			Management Skills
Time Management	Managing one's own time and the time of others.	O*NET	Skills	Resource Management Skills
Scheduling Work and Activities	Scheduling events, programs, and activities, as well as the work of others.	O*NET	Work Activities	Mental Processes
Assisting and Caring for Others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.	O*NET	Work Activities	Interacting With Others
Provide Consultation and Advice to Others	Providing guidance and expert advice to management or other groups on technical, systems-, or process-related topics.	O*NET	Work Activities	Interacting With Others
Selling or Influencing Others	Convincing others to buy merchandise/goods or to otherwise change their minds or actions.	O*NET	Work Activities	Interacting With Others
Cramped Work Space, Awkward Positions	Working in cramped work spaces that requires getting into awkward positions	O*NET	Work Context	Physical Work Conditions
Fine Arts	Knowledge of the theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.	O*NET	Knowledge	Knowledge
Programming	Maintaining and developing websites for the Internet or an intranet, knowledge of cloud computing technologies	O*NET	Skills	Digital Skills
Digital content creation	Identifying, locating, retrieving, storing, organising and analysing digital information	ESCO	Skills	Digital Skills
Digital data processing	Creating and editing new content, from word processing to images and video, integrating and re-elaborating previous knowledge and content, producing creative expressions, media outputs and programming	ESCO	Skills	Digital Skills
ICT Safety, Networks and Servers	Communicating in digital environments, sharing resources through online tools, linking with others and collaborating through digital tools, interacting with and participating in communities and networks	ESCO	Skills	Digital Skills
Digital communication and collaboration	Writing computer programs for various purposes	ESCO	Skills	Digital Skills
Web Development and Cloud Technologies	Personal protection, data protection, digital identity protection, security measures, safe and sustainable use	ESCO	Skills	Digital Skills

Source: OECD Expert Survey on Skills and Abilities Automatability, building on O*NET and ESCO.

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