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The impact of Artificial Intelligence on the labour market: What do we know so far?

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Abstract

Recent developments in Artificial Intelligence (AI) have stoked new fears about large-scale job loss, stemming from its ability to automate a rapidly expanding set of tasks (including non-routine cognitive tasks), and its potential to affect every sector of the economy. Furthermore, there are concerns about employee well-being and the broader work environment, linked to the idea that AI may soon become pervasive in the workplace and threaten and undermine humans' place in it. However, AI also has the potential to complement and augment human capabilities, leading to higher productivity, greater demand for human labour and improved job quality.

From a theoretical perspective, the impact of AI on employment and wages is ambiguous, and it may depend strongly on the type of AI being developed and deployed, how it is developed and deployed, and on market conditions and policy. However, the empirical evidence based on AI adopted in the last 10 years does not support the idea of an overall decline in employment and wages in occupations exposed to AI. While AI is capable of performing some non-routine cognitive tasks, some bottlenecks to adoption still remain, and many tasks still require humans to carry them out. Thus, much of the impact of AI on jobs is likely to be experienced through the reorganisation of tasks within an occupation. Certain groups of workers may be more capable or better positioned to take advantage of the benefits that AI brings, use AI in a way that is complementary to their work, and avoid its negative impacts.

AI is likely to reshape the work environment of many people, by changing the content and design of their jobs, the way workers interact with each other and with machines, and how work effort and efficiency are monitored. AI can play an important role in facilitating human-machine collaboration, helping workers in the execution of tedious or physically demanding tasks while allowing them to leverage their own uniquely human abilities. However, the same AI applications could also entail significant risks for the work environment, especially if applied badly or with the singular motivation to cut costs.

Synthèse

Les récents progrès de l'intelligence artificielle (IA) ont ravivé les craintes de destructions massives d'emplois, craintes dont l'origine tient au fait que cette technologie permet l'automatisation d'un ensemble de tâches qui s'élargit rapidement, et qu'elle est susceptible de trouver des applications dans tous les secteurs de l'économie. En outre, le bien-être des salariés et l'environnement de travail dans son ensemble font aussi l'objet de préoccupations, liées à l'idée que l'IA pourrait devenir bientôt omniprésente dans l'entreprise et fragiliser la place de l'humain en son sein. Pourtant, l'IA est aussi à même de compléter et d'augmenter les capacités humaines et, partant, de susciter des gains de productivité, de soutenir la demande de main-d'œuvre et d'accroître la qualité des emplois.

Du point de vue théorique, les effets de l'IA sur l'emploi et les salaires sont ambivalents et dépendent probablement dans une large mesure de la nature des technologies en question, de la manière dont elles sont développées et déployées, des conditions de marché et des politiques en place. Quoi qu'il en soit, les observations empiriques portant sur l'adoption de telles technologies au cours de ces 10 dernières années n'accréditent pas la thèse d'un recul global de l'emploi et des salaires dans les professions exposées à l'IA. Les systèmes d'IA sont certes capables d'exécuter un certain nombre de tâches cognitives non répétitives, cependant il demeure quelques freins à leur adoption, et de nombreuses tâches exigent encore l'intervention d'opérateurs humains pour être menées à bien. Il s'ensuit que l'essentiel des répercussions de l'IA sur l'emploi se matérialisera sans doute à travers la réorganisation des tâches relevant d'une profession donnée. Certaines catégories de travailleurs pourraient être mieux préparées ou mieux positionnées pour tirer le meilleur parti de l'IA, en utilisant les nouveaux outils qu'elle apporte de façon complémentaire à leur activité professionnelle, évitant ainsi les effets négatifs de cette technologie.

L'IA va vraisemblablement remodeler l'environnement de travail de beaucoup en modifiant la teneur de leur emploi et la manière de le concevoir, leurs interactions avec leurs semblables et avec les machines, et la façon dont l'effort et l'efficacité au travail seront observés. L'IA peut jouer un rôle important en facilitant la collaboration entre humains et machines, en aidant les travailleurs dans l'exécution de tâches fastidieuses ou physiquement éprouvantes, tout en leur permettant d'exploiter au mieux leurs compétences uniques, spécifiques à l'humain. Cela étant, ces mêmes applications de l'IA peuvent aussi faire planer des risques non négligeables sur l'environnement de travail, surtout si elles sont mises en œuvre de manière inappropriée ou à seule fin de réduire les coûts.

Kurzfassung

Die jüngsten Entwicklungen im Bereich der künstlichen Intelligenz (KI) haben die Furcht vor weitreichenden Arbeitsplatzverlusten durch KI erneut angefacht. Grund dafür ist, dass immer mehr Tätigkeiten durch KI automatisiert werden können und jeder Wirtschaftssektor davon betroffen sein könnte. Darüber hinaus werden negative Auswirkungen auf das Wohlergehen der Arbeitskräfte und das allgemeine Arbeitsumfeld befürchtet. Dahinter steht der Gedanke, dass KI am Arbeitsplatz bald allgegenwärtig sein könnte und die menschliche Arbeitskraft dadurch an Bedeutung verlieren und verdrängt werden könnte. KI bietet aber auch das Potenzial, menschliche Fähigkeiten zu ergänzen und zu steigern. Die Folge sind höhere Produktivität, größere Nachfrage nach menschlicher Arbeitsleistung und bessere Arbeitsplatzqualität.

Aus theoretischer Sicht ist der Effekt der künstlichen Intelligenz auf die Beschäftigungs- und Lohnentwicklung uneindeutig. Er kann stark davon abhängen, um welche Art von KI es sich handelt, wie sie entwickelt und eingesetzt wird, und wie die Marktbedingungen und das Politikumfeld aussehen. Die empirischen Befunde auf Basis der KI-Nutzung der letzten zehn Jahre lassen in Berufen, in denen KI besonders gut eingesetzt werden kann, jedoch keinen generellen Beschäftigungs- und Lohnrückgang erkennen. Obwohl KI einige nichtroutinemäßige kognitive Aufgaben übernehmen kann, ist dies nach wie vor nicht in allen Bereichen möglich und für viele Tätigkeiten sind weiterhin Menschen erforderlich. Der Effekt der künstlichen Intelligenz auf die Arbeitswelt dürfte daher vor allem in einer Neuorganisation der Aufgaben bestehen, aus denen sich die jeweilige berufliche Tätigkeit zusammensetzt. Bestimmte Gruppen von Arbeitskräften sind möglicherweise besser in der Lage, künstliche Intelligenz zu ihrem Vorteil zu nutzen, sie zur Ergänzung ihrer eigenen Arbeitsleistung einzusetzen und ihre negativen Folgen zu vermeiden.

KI dürfte das Arbeitsumfeld vieler Menschen erheblich verändern. Dies betrifft u. a. die Arbeitsinhalte und die Arbeitsgestaltung, die Interaktion der Arbeitskräfte untereinander und mit Maschinen und die Methoden, mit denen Arbeitsleistung und Effizienz gemessen werden. KI kann einen wichtigen Beitrag zur Verbesserung der Mensch-Maschine-Interaktion leisten, indem die Arbeitskräfte von eintönigen oder körperlich anstrengenden Tätigkeiten entlastet werden und stattdessen ihre menschlichen Fähigkeiten stärker einbringen können. Von denselben KI-Anwendungen könnten jedoch auch erhebliche Risiken für das Arbeitsumfeld ausgehen, insbesondere wenn sie unsach-gemäß genutzt oder ausschließlich zur Kostensenkung eingesetzt werden.

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Recent developments in Artificial Intelligence (AI) have stoked new fears about large-scale job loss, stemming from its ability to automate a rapidly expanding set of tasks (including non-routine cognitive tasks), and its potential to affect every sector of the economy. Furthermore, there are concerns about employee well-being and the broader work environment, linked to the idea that AI may soon become pervasive in the workplace and threaten and undermine humans' place in it. However, AI also has the potential to complement and augment human capabilities, leading to higher productivity, greater demand for human labour and improved job quality.

From a theoretical perspective, the impact of AI on employment and wages is ambiguous, and it may depend strongly on the type of AI being developed and deployed, how it is developed and deployed, and on market conditions and policy. If AI facilitates the automation of tasks and delivers only modest increases in productivity, workers are unlikely to share in the benefits of this new technology. To produce positive outcomes for workers, AI must create new high-productivity tasks to replace those automated and boost productivity sufficiently to raise consumer demand, hence increasing demand for human labour.

The empirical evidence based on AI adopted in the last 10 years does not support the idea of an overall decline in employment and wages in occupations exposed to AI. Some studies suggest a positive impact of AI on wage growth.

The occupations judged to be most exposed to AI include high-skilled occupations involving non-routine cognitive tasks, such as lab technicians, engineers and actuaries. However, high exposure does not necessarily mean that jobs in these occupations will disappear. While AI's capabilities have expanded substantially, some bottlenecks to adoption still remain, and many tasks still require humans to carry them out. Thus, much of the impact of AI on jobs is likely to be experienced through the reorganisation of tasks within an occupation, with some workers ultimately complemented in their work by AI, rather than substituted by it.

Workers may need to re-skill or up-skill in order to adapt to the reorganisation of tasks and the emergence of new tasks, and to weather potential job loss and navigate transitions to new jobs. This will not only mean acquiring AI-related skills, but also acquiring skills in areas that AI cannot perform so well, such as creative and social intelligence, reasoning skills, and dealing with uncertainty. The smoothness of the AI transition and the extent of the impact on workers will also depend on firm-level incentives to retain and retrain staff and on institutional factors, such as the general infrastructure for training and job-search available in the country, direct government funding, tax incentives and social benefit systems.

Certain groups of workers may be more capable or better positioned to take advantage of the benefits that AI brings, use AI in a way that is complementary to their work, and avoid its negative impacts. While some high-skilled occupations are among those most exposed to AI, there is evidence that individuals in higher wage occupations and/or with higher educational attainment experience higher wage growth linked to AI, suggesting some degree of complementarity. This suggests that AI adoption could increase income inequality.

Similarly, some firms may be better placed than others to develop and/or deploy AI. Moreover, if the gains of AI accrue to a small number of superstar innovators or firms with excessive market power, this could produce a divide between innovators and workers and further reinforce the potentially negative impact of AI on inequality.

AI is likely to reshape the work environment of many people, by changing the content and design of their jobs, the way workers interact with each other and with machines, and how work effort and efficiency are monitored. AI can play an important role in facilitating human-machine collaboration, helping workers in the execution of tedious or physically demanding tasks while allowing them to leverage their own uniquely human abilities. AI can offer cheaper, faster and more scalable solutions in the field of human resource management, enabling workers to advance their own careers, helping managers to manage, and enhancing training.

However, the same AI applications could also entail significant risks for the work environment, especially if applied badly or with the singular motivation to cut costs. A lack of transparency and explainability around algorithmic predictions and decisions can make employees feel insecure, either psychologically or physically. By enabling extensive monitoring of workers' performance, AI can increase work pressure and generate stress about productivity and about how managers may interpret data.

Many questions remain for future research. Surveys and qualitative research may be useful for understanding how firms and workers view the AI transition, how decisions are made and under what management models and what national policy and institutions, and what measures lead to positive outcomes. Of particular interest is capturing evidence from different environments, including for instance the use of AI in facilitating close human-machine collaboration in manufacturing environments, the role of AI assisting the highly skilled in prediction tasks, and the use of AI-enabled career development tools.

Further empirical analysis will help establish to what extent the impact of AI resembles the impact of previous waves of automation, in terms of its potential to substitute and/or complement human labour and to create new tasks, and the implications for labour demand and income inequality. This will rely on data collection and the creation of indicators that capture AI and its inherent attributes (in addition to considering automation technologies more generally).

Résumé

Les récents progrès de l'intelligence artificielle (IA) ont ravivé les craintes de destructions massives d'emplois, craintes dont l'origine tient au fait que cette technologie permet l'automatisation d'un ensemble de tâches qui s'élargit rapidement (et s'étend notamment à des tâches cognitives non répétitives), et qu'elle est susceptible de trouver des applications dans tous les secteurs de l'économie. En outre, le bien-être des salariés et l'environnement de travail dans son ensemble sont aussi l'objet de préoccupations à l'idée qu'elle pourrait devenir bientôt omniprésente dans l'entreprise et y menacer et compromettre la place des intervenants humains. Pourtant, l'IA est aussi à même de compléter et d'augmenter les capacités humaines et, partant, de susciter des gains de productivité, de soutenir la demande de main-d'œuvre et d'accroître la qualité des emplois.

Du point de vue théorique, ses effets sur l'emploi et les salaires sont ambivalents et dépendent probablement dans une large mesure de la nature de ses applications, de la manière dont elles sont mises au point et déployées, de la situation du marché et du cadre réglementaire en place. Si cette nouvelle technologie facilite l'automatisation des tâches et n'apporte que des gains modestes sur le plan de la productivité, alors les travailleurs ont peu chances d'en recevoir eux aussi les bienfaits. Pour leur être bénéfique, l'IA doit faire émerger de nouvelles tâches fortement productives, en remplacement de celles qui auront été automatisées, et doper la productivité dans une mesure suffisante pour tirer la demande des consommateurs, et par là même la demande de main-d'œuvre.

Les données concrètes recueillies au sujet des systèmes adoptés au cours de ces 10 dernières années n'accréditent pas la thèse d'un recul global de l'emploi et des salaires dans les professions exposées à l'IA. Il semblerait, d'après certaines études, que celle-ci ait une influence positive sur la croissance des salaires.

On trouve, parmi les professions considérées comme les plus exposées à l'IA, des professions très qualifiées impliquant l'exécution de tâches cognitives non répétitives, ainsi celles de technicien de laboratoire, d'ingénieur et d'actuaire. Cela étant, forte exposition ne rime pas nécessairement avec destruction d'emplois. En dépit des progrès substantiels de l'IA, il demeure quelques freins à son adoption, et de nombreuses tâches exigent encore l'intervention d'opérateurs humains pour être menées à bien. Il s'ensuit que l'essentiel des répercussions de l'IA sur l'emploi se matérialisera sans doute à travers la réorganisation des tâches relevant d'une profession donnée, de sorte qu'*in fine*, cette technologie viendra compléter l'activité de certains travailleurs et non pas se substituer à eux.

Les travailleurs auront sans doute besoin de recycler ou de développer leurs compétences pour s'adapter à cette réorganisation et à l'apparition de tâches nouvelles, ainsi que pour surmonter une éventuelle perte d'emploi et se reconvertir dans l'exercice d'une activité nouvelle. Cela supposera d'acquérir des compétences non seulement dans le domaine de l'IA, mais aussi dans des domaines où celle-ci n'est pas en mesure de rivaliser avec l'humain, tels ceux de la créativité et de l'intelligence sociale, du raisonnement et de la gestion de l'incertitude. La souplesse de la transition vers l'IA et l'ampleur de ses conséquences pour les travailleurs dépendront aussi des incitations faites aux entreprises pour qu'elles conservent et reconvertissent leur personnel et de différents facteurs institutionnels, comme l'infrastructure générale de formation et de recherche d'emploi en place dans le pays, les financements publics directs, les incitations fiscales et les systèmes de prestations sociales.

Certaines catégories de travailleurs seront peut-être mieux à même, en raison de leurs capacités ou de leur situation, de tirer parti des avantages apportés par l'IA, de se servir des systèmes d'IA comme d'un auxiliaire dans leur activité professionnelle et de s'affranchir des effets négatifs de cette technologie. En dépit du fait que quelques professions très qualifiées comptent parmi les plus menacées, il apparaît que c'est à ceux qui occupent un emploi relativement bien rémunéré et/ou ont un niveau d'études élevé que l'IA procure la plus forte progression salariale, ce qui laisse supposer une certaine complémentarité. Il est dès lors permis de penser que la diffusion des applications de l'IA pourrait contribuer au creusement des inégalités de revenu.

De même, certaines entreprises seront probablement mieux à même que d'autres de mettre au point et/ou déployer des systèmes d'IA. En outre, si l'IA profite exclusivement à un petit nombre d'innovateurs « superstars » ou d'entreprises disposant d'une position de force excessive sur le marché, un fossé pourrait se creuser entre ceux qui innovent et ceux qui travaillent, et les possibles conséquences négatives sur les inégalités s'aggraver.

L'IA va vraisemblablement remodeler l'environnement de travail de beaucoup en modifiant la teneur de leur emploi et la manière de le concevoir, leurs interactions avec leurs semblables et avec les machines, et la mesure de l'effort de travail et de l'efficience professionnelle. L'IA peut faciliter grandement la collaboration entre l'homme et la machine, de même que l'exécution de tâches fastidieuses ou physiquement difficiles, et permettre dans le même temps aux travailleurs d'exploiter les aptitudes spécifiquement humaines dont ils sont dotés. Elle peut aussi apporter, dans le domaine des ressources humaines, des solutions moins onéreuses, plus rapides et plus facilement reproductibles à grande échelle, permettant aux travailleurs de gérer leur évolution professionnelle, aidant les responsables à remplir leur rôle et favorisant la formation.

Cela étant, ces mêmes applications de l'IA peuvent aussi faire planer des risques non négligeables sur l'environnement de travail, surtout si elles sont mises en œuvre de manière inappropriée ou à seule fin de réduire les coûts. Le manque de transparence et d'explicabilité des prédictions et décisions algorithmiques peut susciter chez les salariés un sentiment d'insécurité, aussi bien psychologique que physique. Du fait qu'elle permet un suivi complet de la performance des travailleurs, l'IA est susceptible d'accentuer les pressions professionnelles et d'être cause d'anxiété au sujet de la productivité et de l'interprétation que les dirigeants pourront faire des données à leur disposition.

De nombreuses questions demeurent, auxquelles la recherche devra apporter une réponse. Des enquêtes et des études qualitatives pourraient aider à comprendre comment les entreprises et les travailleurs envisagent la transition vers l'IA, comment les décisions sont prises, en vertu de quels modèles de gestion, dans quel cadre réglementaire et sous l'égide de quelles institutions nationales, et quelles mesures donnent des résultats positifs. Il serait particulièrement intéressant de réunir des éléments factuels issus de différents environnements, par exemple sur l'utilisation de l'IA au service d'une collaboration plus étroite entre l'homme et la machine dans les activités manufacturières, sur l'aide apportée aux travailleurs hautement qualifiés pour l'établissement de prévisions, et sur l'utilisation d'outils de développement professionnel fondés sur cette technologie.

De nouvelles analyses empiriques aideront à voir dans quelle mesure le déploiement de l'IA s'apparente, dans ses répercussions, à celui de vagues antérieures d'automatisation, du point de vue de sa capacité de se substituer au travail humain et/ou de le compléter et de susciter des tâches nouvelles et de ses conséquences sur la demande de main-d'œuvre et les inégalités de revenu. Ces analyses prendront appui sur la collecte de données et la construction d’indicateurs sur l’IA et ses caractéristiques propres (en plus de la prise en compte des technologies qui, de manière plus générale, rendent possible l’automatisation).

Zusammenfassung

Die jüngsten Entwicklungen im Bereich der künstlichen Intelligenz (KI) haben die Furcht vor weitreichenden Arbeitsplatzverlusten durch KI erneut angefacht. Grund dafür ist, dass immer mehr Tätigkeiten (auch nichtroutinemäßige kognitive Aufgaben) durch KI automatisiert werden können und jeder Wirtschaftssektor davon betroffen sein könnte. Darüber hinaus werden negative Auswirkungen auf das Wohlergehen der Arbeitskräfte und das allgemeine Arbeitsumfeld befürchtet. Dahinter steht der Gedanke, dass KI am Arbeitsplatz bald allgegenwärtig sein könnte und die menschliche Arbeitskraft dadurch an Bedeutung verlieren und verdrängt werden könnte. KI bietet aber auch das Potenzial, menschliche Fähigkeiten zu ergänzen und zu steigern. Die Folge sind höhere Produktivität, größere Nachfrage nach menschlicher Arbeitsleistung und bessere Arbeitsplatzqualität.

Aus theoretischer Sicht ist der Effekt der künstlichen Intelligenz auf die Beschäftigungs- und Lohnentwicklung uneindeutig. Er kann stark davon abhängen, um welche Art von KI es sich handelt, wie sie entwickelt und eingesetzt wird, und wie die Marktbedingungen und das Politikumfeld aussehen. Wenn KI die Automatisierung von Aufgaben erleichtert und nur geringfügige Produktivitätssteigerungen bewirkt, ist nicht davon auszugehen, dass auch die Arbeitskräfte von dieser neuen Technologie profitieren. Positive Effekte für die Arbeitskräfte ergeben sich dann, wenn durch KI neue hochproduktive Tätigkeiten als Ersatz für die automatisierten Aufgaben entstehen und die Produktivitätssteigerungen so hoch sind, dass die Verbrauchernachfrage wächst und dadurch die Nachfrage nach menschlicher Arbeitsleistung angekurbelt wird.

Die empirischen Befunde auf Basis der KI-Nutzung der letzten zehn Jahre lassen keinen generellen Beschäftigungs- und Lohnrückgang in Berufen erkennen, in denen KI besonders gut eingesetzt werden kann. Einige Studien zeigen einen positiven Effekt der KI-Nutzung auf das Lohnwachstum.

Zu den Berufen, in denen das KI-Potenzial als besonders groß eingeschätzt wird, zählen hochqualifizierte Tätigkeiten mit nichtroutinemäßigen kognitiven Aufgaben, wie z. B. Laborant*innen, Ingenieur*innen und Versicherungsmathematiker*innen. Ein hohes KI-Potenzial bedeutet jedoch nicht zwangsläufig, dass in diesen Berufszweigen Arbeitsplätze wegfallen. Obwohl die Fähigkeiten der künstlichen Intelligenz erheblich zugenommen haben, kann KI nach wie vor nicht in allen Bereichen genutzt werden und für viele Tätigkeiten sind weiterhin Menschen erforderlich. Der Effekt der künstlichen Intelligenz auf die Arbeitswelt dürfte daher vor allem in einer Neuorganisation der Aufgaben bestehen, aus denen sich die jeweilige berufliche Tätigkeit zusammensetzt. In einigen Berufen wird KI die Tätigkeit der Arbeitskräfte eher ergänzen, anstatt sie zu ersetzen.

Die Arbeitskräfte benötigen möglicherweise Umschulungen oder Höherqualifizierungen, damit sie auf die umstrukturierten bzw. neu entstehenden Aufgaben vorbereitet sind und einen potenziellen Arbeitsplatzverlust und Jobwechsel bewältigen können. Sie müssen dazu nicht nur KI-bezogene Kompetenzen erwerben, sondern auch Kompetenzen in Bereichen, die weniger KI-geeignet sind. Dazu zählen beispielsweise kreative und soziale Intelligenz, logisches Denken und der Umgang mit Unsicherheit. Wie reibungslos die KI-Einführung funktioniert und wie groß ihr Effekt auf die Arbeitskräfte ist, hängt auch davon ab, wie stark sich die einzelnen Unternehmen bemühen, ihre Beschäftigten zu halten und umzuschulen, und welche institutionellen Rahmenbedingungen in dem betreffenden

Land herrschen. Dies betrifft beispielsweise Aspekte wie die allgemeine Infrastruktur im Bereich der Weiterbildung und Arbeitsvermittlung, direkte staatliche Förderung, Steueranreize und die sozialen Sicherungssysteme.

Bestimmte Gruppen von Arbeitskräften sind möglicherweise besser in der Lage, künstliche Intelligenz zu ihrem Vorteil zu nutzen, sie zur Ergänzung ihrer eigenen Arbeitsleistung einzusetzen und ihre negativen Folgen zu vermeiden. So zählen zwar einige hochqualifizierte Tätigkeiten zu den Berufen mit dem höchsten KI-Potenzial, es gibt aber Anzeichen dafür, dass KI bei Arbeitskräften in besser bezahlten Berufen und/oder mit höherem Bildungsabschluss zu einem höheren Lohnwachstum führt. Dies lässt auf eine gewisse Komplementarität schließen. Es deutet jedoch auch darauf hin, dass KI-Nutzung die Einkommensungleichheit verstärken könnte.

Einige Unternehmen dürften ebenfalls besser als andere in der Lage sein, KI zu entwickeln und/oder einzuführen. Wenn die Vorteile von KI nur einigen führenden Innovatoren oder Unternehmen mit übermäßiger Marktmacht zugutekommen, könnte dies einen Keil zwischen Innovatoren und Arbeitskräfte treiben und den potenziell negativen Effekt von KI auf die Ungleichheit weiter verstärken.

KI dürfte das Arbeitsumfeld vieler Menschen erheblich verändern. Dies betrifft u. a. die Arbeitsinhalte und die Arbeitsgestaltung, die Interaktion der Arbeitskräfte untereinander und mit Maschinen und die Methoden, mit denen Arbeitsleistung und Effizienz gemessen werden. KI kann einen wichtigen Beitrag zur Verbesserung der Mensch-Maschine-Interaktion leisten, indem die Arbeitskräfte von eintönigen oder körperlich anstrengenden Tätigkeiten entlastet werden und stattdessen ihre menschlichen Fähigkeiten stärker einbringen können. KI kann auch für kostengünstigere, schnellere und besser skalierbare Lösungen im Personalmanagement eingesetzt werden. Dabei handelt es sich beispielsweise um Anwendungen, die den Beschäftigten in ihrer beruflichen Entwicklung helfen, Führungskräfte bei ihren Aufgaben unterstützen und die Schulungsmöglichkeiten verbessern.

Von denselben KI-Anwendungen könnten jedoch auch erhebliche Risiken für das Arbeitsumfeld ausgehen, insbesondere wenn sie unsachgemäß genutzt oder ausschließlich zur Kostensenkung eingesetzt werden. Mangelnde Transparenz und Nachvollziehbarkeit algorithmischer Vorhersagen und Entscheidungen kann bei den Beschäftigten zu einem Gefühl psychischer oder physischer Unsicherheit führen. Die umfassende Leistungskontrolle, die durch KI ermöglicht wird, kann den Arbeits- und Produktivitäts-druck erhöhen und bei den Beschäftigten verstärkten Stress auslösen, weil sie nicht wissen, wie ihre Vorgesetzten die Daten interpretieren.

Viele Fragen werden in künftigen Forschungsarbeiten noch zu klären sein. Erhebungen und qualitative Untersuchungen könnten Aufschluss darüber geben, wie Unternehmen und Arbeitskräfte die Einführung von KI beurteilen, wie und unter welchen Managementmodellen und nationalen politischen und institutionellen Rahmen-bedingungen Entscheidungen getroffen werden und welche Maßnahmen positive Effekte bewirken. Von besonderem Interesse ist es dabei, Erkenntnisse aus unter-schiedlichen Bereichen zu erlangen. Beispielsweise könnte untersucht werden, wie KI die Mensch-Maschine-Interaktion in Fertigungsumgebungen verbessert, wie KI hoch-qualifizierte Arbeitskräfte bei Prognoseaufgaben unterstützt oder wie KI in Tools für die Karriereentwicklung genutzt wird.

Weitere empirische Analysen werden sich damit auseinandersetzen, inwiefern der Effekt der künstlichen Intelligenz mit dem Effekt früherer Automatisierungswellen vergleichbar ist. Dabei geht es sowohl um ihr Potenzial, die menschliche Arbeitsleistung zu ersetzen und/oder zu ergänzen und neue Aufgaben zu schaffen, als auch um die Auswirkungen auf die Arbeitsnachfrage und die Einkommensungleichheit. Für diese Analysen müssen Daten erhoben und Indikatoren entwickelt werden, mit denen KI und ihre ganz spezifischen Eigenschaften erfasst werden (neben einer allgemeineren Betrachtung von Automatisierungstechnologien).

1. Introduction

1. Artificial intelligence (AI) is reshaping economies and societies, offering new products and services, and promising to generate productivity gains through greater efficiency and lower costs. At the same time, AI also raises questions and fuels anxieties about its impact on the labour market and society. Therefore, the purpose of this literature review is to take stock of what is already known about the impact of AI on the labour market, identify gaps in the evidence base and inform research under the OECD's three-year programme on AI in Work, Innovation, Productivity and Skills (AI-WIPS), financed by the German Federal Ministry of Labour and Social Affairs (BMAS).

2. AI-WIPS, which started in January 2020, will provide valuable resources and knowledge, including new in-depth analyses, measurement, international dialogue and concrete policy assessments on the impact of AI on labour markets and society. The AI-WIPS activity builds on previous OECD work on AI, including the OECD AI Principles, which promote an AI that is innovative and trustworthy and that respects human rights and democratic values. The OECD AI principles call on governments to build human capacity and prepare for labour market transformation by:

- Empowering people to effectively use and interact with AI systems, including equipping them with the necessary skills;
- Ensuring a fair transition for workers as AI is deployed, including via social dialogue, training programmes, support for those affected by displacement, and access to new opportunities in the labour market; and
- Promoting the responsible use of AI at work, to enhance the safety of workers and the quality of jobs, to foster entrepreneurship and productivity, and aim to ensure that the benefits from AI are broadly and fairly shared.

3. This literature review presents what is known about the impact of AI on the labour market, including the impact on employment and wages, how AI will transform jobs and skill needs, and the impact on the work environment. The important ethical issues raised around the use of AI at work are not dealt with in this literature review, and are instead examined in detail in the forthcoming issues note, "Ethical issues arising from AI implementation at the workplace and associated policy challenges" (OECD, 2021[1]).

4. Two challenges had to be faced in establishing the scope of this literature review. The first is that there is no widely accepted definition of AI. While this review tries to cast a broad net, it is centred on the definition of an AI system established by the OECD's AI Experts Group (AIGO) (OECD, 2019[2]):

> *An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. It uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models (in an automated manner e.g. with machine learning (ML) or manually); and use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy.*

5. The second challenge is that the development and deployment of AI has not happened in a vacuum, and as such, other technological advances (such as factory

automation and robotics) are frequently amalgamated with AI in the literature. Here, where possible, an attempt is made to focus on AI and its attributes, while treating automation as a potential consequence of AI and robotics as a potentially complementary technology.

6. In line with this, Chapter 2 begins by examining the capabilities of AI and what relevance they might have for the labour market. It questions what sets AI apart from previous technological changes, giving particular attention to the specific attributes of AI and the associated implications for the labour market.

7. Chapter 3 then summarises the literature on the impact of AI on productivity, employment and wages. These potential impacts are a source of concern for many, who fear that AI will drive down demand for human labour and wages or even make human labour obsolete.

8. Chapter 4 looks deeper into the mechanisms driving the AI transition and how they may transform the way we work, reorganise tasks within any given occupation, and lead to the emergence of new tasks and occupations. It also examines the abilities of different groups to adapt to AI adoption and other factors that could drive inequalities.

9. Chapter 5 discusses how AI can reshape the work environment, by changing the content and design of jobs, the way workers interact with each other and with machines, and how work effort and efficiency are monitored.

2. What can AI do?

10. This chapter focuses on the capabilities of AI and what relevance they might have for the labour market. It begins by laying out the characteristics of AI that are frequently cited by researchers, in particular, those characteristics that have convinced researchers that the impact of AI on the labour market (as distinct from the impact of technology or automation more generally) is worthy of special attention. These include: AI's potential to affect multiple sectors and occupations across the economy, its ability to self-improve and to expand the set of tasks that can be automated (including highly skilled ones) – characteristics that could magnify the labour market impact, whether positive or negative.

11. AI has surpassed some of the limitations of previous technologies. In particular, AI's problem solving, logical reasoning and perception capabilities mean that the automation of some non-routine cognitive tasks is now possible. This explains why some high-skilled occupations such as radiologists, lab technicians, engineers, lawyers and actuaries are judged to be highly exposed to AI, i.e. there is overlap between the tasks that these occupations comprise and the tasks that AI can perform. However, high exposure does not necessarily mean that jobs in these occupations will disappear.

12. Some bottlenecks in the development of AI remain: humans outperform AI in creative and social intelligence, reasoning skills and dealing with uncertainty. Even when AI facilitates automation of certain tasks, this still leaves other tasks that only humans can perform. Indeed, in these cases, AI can complement workers and enable them to increase their productivity. In this way, workers in occupations most exposed to AI could see parts of their work complemented or substituted by AI, and could experience substantial change in the tasks they perform.

2.1. AI can be considered a general purpose technology

13. The OECD (2019[3]) describes AI as a general purpose technology (or GPT), a concept developed by Bresnahan and Trajtenberg (1992[4]) to label technologies with potential application across a broad variety of sectors and occupations, and the ability to improve over time and to generate complementary innovation. Other examples are computing, electrification and the steam engine. Agrawal et al. (2019[5]) say that AI qualifies as a GPT due to its ability to produce predictions, which can be inputs into decision-making across occupations as diverse as teaching, radiology and translation. Brynjolfsson et al. (2017[6]) point out that machine learning systems are specifically designed to self-improve and give examples of how machine learning enables machines to perceive the outside world, spurring a multitude of innovations. Cockburn et al. (2018[7]) call machine learning an "invention of a method of invention", a concept introduced by Griliches (1957[8]). They describe how machine learning and neural networks not only offer productivity gains across a wide variety of sectors, but also offer transformation of the innovation processes within those sectors. They highlight the potential of AI to contribute to scientific discovery especially where research hinges on classification and prediction. Box 2.1 provides a brief summary of recent trends in AI and its adoption in the workplace.

14. The economic significance of the GPT label is that it adds depth and scale to the challenges and the opportunities presented by AI to the labour market. The potential for application across multiple sectors and occupations means that AI is associated with much larger potential for output and welfare gains (Brynjolfsson, Rock and Syverson, 2017[6]). It

also magnifies the labour market impact, whether positive or negative. One concern is that since automation has already led to job loss in certain industries, AI could lead to job loss in a much larger number of industries. On the other hand, the ability of AI to produce further innovations, by changing "the process by which we create new ideas and technologies, helping to solve complex problems and scaling creative effort" (Aghion et al., 2017[9]), could generate entirely new industries and create a myriad of new jobs (as discussed in section 4.2).

Box 2.1. Recent trends in AI and its adoption in the workplace

Coined as a term in 1956, AI has evolved from symbolic AI where humans built logic-based systems, through the AI "winter" of the 1970s to the chess-playing computer Deep Blue in the 1990s. Over the past few years, the availability of big data, cloud computing and the associated computational and storage capacity and breakthroughs in an AI technology called "machine learning" (ML), have dramatically increased the power, availability, growth and impact of AI. Continuing technological progress is also leading to better and cheaper sensors, which capture more-reliable data for use by AI systems. The OECD report "Artificial Intelligence in Society" describes these developments in more detail (OECD, 2019[3])

ML is a set of techniques to allow machines to learn in an automated manner through patterns and inferences from data rather than through explicit instructions from a human. ML approaches often teach machines to reach an outcome by showing them many examples of correct outcomes. However, they can also define a set of rules and let the machine learn by trial and error. The technology driving the current wave of ML applications is a sophisticated statistical modelling technique called "neural networks", which involve repeatedly interconnecting thousands or millions of simple transformations into a larger statistical machine that can learn sophisticated relationships between inputs and outputs.

Beyond large and established players in the technology sector, industry adoption of AI is at an early stage. A US-based nationally representative firm survey (Beede et al., 2020[10]) shows low adoption rates for AI-related technologies such as machine learning, machine vision, natural language processing and automated guided vehicles. Industries leading in AI adoption include high tech, automotive and assembly, telecoms, transport and logistics, financial services and consumer packaged goods, retail and healthcare (based on surveys by Bessen et al. (2018[11]) and McKinsey (2019[12])). The same studies show that AI tends to be embedded in technologies such as natural language understanding and text analysis, natural language classification and decision management, visual recognition (including image, face and video) and virtual agents or conversational interfaces ("chatbots") and robotic process automation.

2.2. AI can be considered an automation technology

15. Many economists also consider AI an automation technology, i.e. one designed to facilitate the automation of tasks that would otherwise be performed by humans, thereby reducing labour demand and wages for certain groups of workers (Acemoglu and Restrepo, 2018[13]; Aghion et al., 2017[9]). What may distinguish AI from other automation technologies, such as industrial robots and other automated machinery, is its greater potential to expand the range of tasks that can be automated. This may be particularly the

case with a technology such as machine learning, which is specifically designed to self-improve. Some believe this ability to self-improve could lead to the *singularity* (discussed in Box 2.2) and ultimately challenge humans' place in the labour market and society, though lagging productivity statistics throw doubt on this prediction.

16. There is already some evidence to suggest that AI can facilitate the automation of tasks where automation was previously impossible. Until recently, automation has affected mostly routine tasks (Autor, Levy and Murnane, 2003[14]) and low-skilled tasks (Nedelkoska and Quintini, 2018[15])[1]. Some identify AI as a force to enable the automation of non-routine and/or high-skilled tasks, because of the specific capabilities of AI (Aghion et al., 2017[9]). The next section shows that the occupations judged to be most exposed to AI include high-skilled occupations – including some traditionally 'white-collar professions' requiring non-routine cognitive tasks, such as lab technicians, engineers and actuaries.

17. As highlighted by the OECD 2019 *Employment Outlook* (2019[16]), the potential threat to people who have been historically more sheltered from economic changes, including white-collar workers with relatively high levels of education and secure jobs, may be another factor driving public concerns around AI. At the same time, if AI did displace higher paid workers, this could potentially mitigate the trends of increasing income inequality and polarisation associated with automation technologies up to now[2].

Box 2.2. AI and the singularity

In the eyes of some, AI's ability to self-improve could lead to a *singularity,* which describes a point in time at which machine intelligence exceeds human intelligence (Bostrom, 2006[17]; Good, 1966[18]) and economic growth accelerates "as an ever-accelerating pace of improvements cascade through the economy" (Nordhaus, 2015[19]), challenging humans' place in the labour market. Others are more sceptical. For instance, Luc Julia, one of the creators of voice assistant Siri argues that advancement in AI will always be dependent on human knowledge and decision-making (Julia, 2019[20]).

Nordhaus (2015[19]) notes that the proponents of the singularity theory are most often computer scientists although he identifies some economists (Brynjolfsson and McAfee, 2014[21]) who, in his view, propose a "soft version" of the theory. Nordhaus tests a variety of hypotheses that would indicate that technology-driven growth is accelerating but ultimately he does not find sufficient support for this theorised acceleration. For instance, the capital-output ratio is not rising rapidly, the decline in the cost of capital is not accelerating, and productivity growth is not rising (as discussed in section 3.1). He concludes that the singularity is at least 100 years away. This conclusion is roughly in line with the results of a survey of machine learning researchers, which assigns a 50% chance to the outcome in which AI outperforms humans in all tasks in 45 years and leads to the automation of all human jobs in 122 years (Grace et al., 2017[22]).

[1] These trends are referred to as routine-biased and skill-biased technological changes, respectively.

[2] However, the size of this impact could be limited if higher skilled individuals began competing for jobs typically performed by lower skilled individuals (Acemoglu and Restrepo, 2018[122]).

2.3. Certain occupations are more exposed to AI

18. One way to understand the capabilities of AI (and the likely labour market impact) is to ask which occupations comprise the tasks that AI can perform.[3] Researchers generally refer to these occupations as being "exposed" to AI. It should be noted that "most exposed" does not necessarily mean most likely to be replaced by AI, as the studies are based on assessments of the technical feasibility of AI, and are limited in their consideration of other factors. Additionally, "least exposed" to AI does not necessarily mean that that occupation escapes the risk of automation. Some of these occupations are exposed to other technologies, which have already led or could lead to their automation. Workers in occupations most exposed to AI could see substantial change in the tasks they perform, but could also see their work complemented (rather than substituted) by AI.

19. Whether AI has a positive or negative impact on jobs, one would expect the impact to be strongest in occupations or sectors that rely most on the tasks that AI can carry out. Researchers measure exposure using various methods:

- Webb (2020[23]) identifies AI patents (i.e. those with keywords such as "supervised learning" and "reinforcement learning" together with "neural network" and "deep learning" in their titles or abstracts) and then assesses the overlap (in verb-noun pairs[4]) between the text of the patents and the text of job task descriptions (from the O*NET database of occupations and tasks) in order to see which occupations are most exposed to AI.
- Felten et al. (2019[24]) map (with the help of some computer science PhD students) different AI categories (such as abstract strategy games, translation and image recognition) to skills (from the O*NET database), in order to assess which occupations rely on abilities where most AI progress has been seen.
- Brynjolfsson et al. (2018[25]) identify tasks (from the O*NET database) and occupations (using Burning Glass data) suitable for AI by applying a rubric which includes parameters such as: whether the task is describable with rules; whether it requires complex, abstract reasoning; and whether it is highly routine and repeated frequently.

2.3.1. High-skilled occupations are among those most exposed to AI

20. Table 2.1 provides a summary of the findings regarding which occupations are most and least exposed to AI (or, more specifically: machine learning, which all three papers interpret as representing AI's capabilities).

[3] Most researchers adopt a task-based approach (based on Autor et al.'s influential paper (2003[14])), such as this, to examine changes in the labour market. This is because the impact of AI is unlikely to act on an entire job all at once. As such, AI might automate a part of a job rather than a job in its entirety, and certain tasks will be more or less suitable for replacement by AI than others.

[4] Popular verb-noun pairs in AI patents include, for example: classify image, predict quality, generate rating.

Table 2.1. Occupations most and least exposed to AI

	(Webb, 2020[23])	(Felten, Raj and Seamans, 2019[24])	(Brynjolfsson, Mitchell and Rock, 2018[25])
Most exposed	– High-skilled occupations, including clinical lab technicians, optometrists and chemical engineers. – Production jobs involving inspection and quality control, which Webb describes as representing a small proportion of the low-skilled workforce	– White-collar occupations, such as chemical/civil/nuclear engineers, epidemiologists, actuaries, statisticians, credit analysts, accountants, computer programmers, operations research analysts.	– Concierges, mechanical drafters, credit authorisers, brokerage clerks, and morticians, undertakers, and funeral directors.
Least exposed	– High-skilled occupations requiring reasoning about novel situations (e.g. researchers). – Occupations requiring interpersonal skill (e.g. teachers and managers), including manual work such as baristas, food preparation workers or massage therapists.	– Physical occupations, including maids and cleaners, cafeteria attendants, dishwashers, hotel porters, slaughterers and meat packers, roofers and painters, massage therapists, fitness instructors.	– Massage therapists, animal scientists, archaeologists, public address system and other announcers, and plasterers and stucco masons.

Note: This is a selection of results. See papers for full lists of impacted occupations.

21. Looking across the results of these three studies, one of the most striking things is that some high-skilled occupations are found to be among the most exposed to AI. The results of Felten et al. show that almost all of the most exposed occupations are "white-collar" jobs requiring an advanced degree. Brynjolfsson et al. and Webb appear to find a greater skill mix among the most exposed occupations, but Webb notes that the highly exposed low-skilled occupations represent only a small proportion of the workforce.[5]

22. The finding that high-skilled occupations are exposed to AI can be contrasted with other research which finds that low-skilled occupations are highly exposed to automation technologies (in a broader sense) and therefore at highest risk of automation (while high-skilled jobs are at lowest risk) – as in Nedelkoska and Quintini (2018[15]) and Frey and Osborne (2017[26]). For instance, cleaners were considered at high risk of being automated within a 20-year period according to Nedelkoska and Quintini, but not particularly exposed to AI according to Felten et al. and Webb. One reason for this contrast may be the technological innovations that have emerged in the last decade, as the studies by Nedelkoska and Quintini and Frey and Osborne are based on an exercise performed in 2013.

23. Another reason may be differences in definition, as the analyses are likely to be quite sensitive in this regard.[6] The three more recent studies focus specifically on the technical capabilities of machine learning, while the studies by Nedelkoska and Quintini and Frey and Osborne consider a broader set of technological advances, including not only

[5] Examining wage differentials, Webb finds that higher wage occupations tend to be more exposed to AI while Brynjolfsson et al. find a low correlation between wages and exposure. Felten et al. do not report such findings.

[6] Indeed, Webb shows that by adapting his analysis to focus on technological changes other than machine learning (specifically software and robots), a different set of occupation is designated as highly exposed. Robots tend to automate repetitive manual tasks (e.g. materials movers in factories) while software performs non-manual tasks that can be hard-coded in advance (e.g. broadcast equipment operators).

AI but also mobile robotics (some of which use AI and some of which do not) (Frey and Osborne, 2018[27])[7]. It is possible that the narrow focus of the three more recent studies on the technical capabilities of machine learning could overlook less novel applications of AI. This could be the case if AI replaces or is embedded in older automation technologies, making them easier or cheaper to adopt. To the extent that AI could make older automation technologies more attractive, the impact of AI along skill lines could be more similar to previous waves of automation.

24. The researchers also attempt to identify the features that typify the occupations most exposed to AI. While other automation technologies have typically been capable of performing mostly routine tasks (Autor, Levy and Murnane, 2003[14]), Webb points to AI's capabilities to perform non-routine tasks, and particularly non-routine cognitive tasks. Felten et al. draw attention to AI's cognitive abilities, defined as abilities that "influence the acquisition and application of knowledge in problem solving". Improvements in AI in relation to problem solving, logical reasoning, and perception may explain why highly skilled technicians and engineers appear to be highly exposed to AI in the studies by Felten et al. and Webb.

25. Turning to demographic characteristics, Webb finds that occupations requiring higher skills, judgement and accumulated experience tend to be more exposed to AI, with the result that more educated workers and workers older than 30 are more exposed. Webb also finds that male workers are more likely to be exposed to AI (also to robotisation and software), which he attributes to female-dominated occupations tending to require more interpersonal skills and male-dominated occupations tending to require more technical skills.

26. These studies identify the occupations most exposed to AI based on technical feasibility, but are more limited in what they can say about whether workers in these occupations will see their work substituted or complemented and about the overall impact on demand for human labour.

2.3.2. Some bottlenecks to the development of AI remain

27. Despite advances in the technical capabilities of AI, some bottlenecks to development remain. Webb identifies social interaction as an important feature of occupations with low exposure to AI, regardless of skill level. He also finds that occupations which combine manual work with interpersonal skills are among those least exposed to AI, including for instance massage therapy, which is identified as having low exposure to AI by all three papers. Physical tasks are identified by Felten et al. as having low exposure to AI (although this does not exclude the possibility that they are exposed to non-AI technologies). High-skilled research occupations which require either reasoning about novel situations (Webb, 2020[23]) or some manual activities (e.g. animal scientists and archaeologists (Brynjolfsson, Mitchell and Rock, 2018[25])) are also judged to be only lightly exposed to AI.

[7] Both studies are based on an exercise in which a group of machine learning researchers assessed a list of occupations asking the question: "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?" The question does not reference AI specifically but it seems quite likely that machine learning researchers would have considered the capabilities of AI in addition to other automation technologies in their assessment.

28. It may not be obvious why lower skilled occupations might be only lightly exposed to AI. Gries and Naudé (2018[28]) refer to *Moravec's Paradox*, which observes that tasks that require high-level reasoning demand relatively light computational resources while tasks requiring sensor-motor skills (generally associated with lower skill occupations) demand enormous computational resources. They point to the challenge in using technology to replace humans in occupations such as security staff, cleaners, gardeners, receptionists and chefs. Related to *Moravec's Paradox* is *Polanyi's Paradox*, which refers to the challenge that computers face in performing tasks relying on tacit knowledge (i.e. tradition, intuition, inherited practices, implied values, and prejudgments), such as organising a closet. Michael Polanyi's observation is that "We can know more than we can tell" (Polanyi, 2009[29]). More precisely, there are many tasks which people understand intuitively how to perform, but cannot elicit the rules or procedures they follow.

29. As AI continues to advance, some existing bottlenecks may be overcome, potentially exposing certain occupations to AI that were previously unexposed. In particular, there is a debate among computer scientists about whether AI (and machine learning in particular) can in the future provide a solution to Polanyi's paradox, by applying statistics and inductive reasoning to supply best-guess answers in cases where formal procedural rules are unknown (Autor, 2014[30]). But even in this case, machine learning may only ever "get it right" on average while missing many of the most important and informative exceptions. The solution may require a multifaceted set of inputs: brains and brawn; technical mastery and intuitive judgment; adherence to rules and judicious application of discretion; creativity and rote repetition. Typically, these inputs each play essential roles: improvements in one do not obviate the need for the other. Perhaps, the most important limitation of AI systems is that they are devices for answering questions, not for posing them (Brynjolfsson and McAfee, 2017[31]). That means entrepreneurs, innovators, scientists, creators, and other kinds of people who figure out what problem or opportunity to tackle next, or what new territory to explore, will continue to be essential.

2.4. AI will not only lead to automation, but will also complement labour

30. The studies discussed in the previous section are based on the idea that certain tasks are more suited to being performed by AI. In fact, the study by Brynjolfsson et al. (2018[25]) finds that many occupations comprise both tasks with high and low suitability for machine learning. For instance, an economist may have to forecast economic trends using a dataset (high suitability for machine learning due to the use of digital data inputs) and also write reports and provide guidance based on their research (low suitability for machine learning due to the reliance on complex, abstract reasoning and the importance that these outputs are perceived to come from a human).[8]

31. As not all tasks within an occupation can be performed by AI, this suggests that the impact of AI will be to replace workers in certain tasks and lead to the transformation of occupations (discussed further in section 4.1) rather than their disappearance. Workers in the transformed occupations will thus be predominantly complemented by AI (Fossen and Sorgner, 2019[32]). Thus, AI has not only the potential to destroy jobs, but also to complement them.

[8] Overall, Brynjolfsson et al. assess the occupation of "economist" as close to average in terms of suitability for machine learning.

32. AI is expected to increase productivity not only by enabling firms to replace labour with cheaper capital, but also by complementing workers (Agrawal, Gans and Goldfarb, 2019[5]). AI is already enabling some workers to increase their productivity by leveraging their social interaction skills and ability to reason about novel situations (areas in which humans outperform AI, as shown in section 4.3.2). For instance, healthcare researchers expect AI to complement human clinicians as their jobs transform to draw more on uniquely human skills like empathy, persuasion and big-picture integration (Davenport and Kalakota, 2019[33]). Another example highlighted in the OECD's Artificial Intelligence in Society (OECD, 2019[3]) is Alibaba's chatbot, which handled more than 95% of customer inquiries during a 2017 sale, thereby allowing human customer representatives to handle more complicated or personal issues (Zeng, 2018[34]). Many other examples are provided throughout this literature review from AI assisting teachers to deliver individualised learning to AI enabling close human-machine collaboration in manufacturing environments.

33. Agrawal et al. (2019[5]) note from their interactions with AI start-ups that, while many talk about the impact of AI on labour in terms of potential substitution, complementarity, and demand expansion, very few companies say that they are building unambiguously labour-replacing technologies. In surveys, businesses also suggest that decisions to adopt AI are motivated more by the aim of complementing human capabilities than by the aim of substituting workers (Accenture, 2018[35]; Bessen et al., 2018[11]).

3. Impact of AI on productivity, employment and wages

34. Discussions about the predicted impact of AI on productivity, employment and wages are filled with uncertainty. AI is expected to increase productivity but there is debate about the size of the impact, particularly when predictions rely on advances that have yet to be seen.

35. Even if AI boosts productivity substantially, it is not clear that workers will necessarily share in the benefit in the form of higher employment and/or wages. This is because AI can facilitate automation, contributing to downward pressure on the demand for labour and a decoupling of productivity from labour market outcomes such as employment and wages. These forces may counteract the productivity effect, which might otherwise be expected to increase labour demand, employment and wages.

36. While the theory is ambiguous, the empirical evidence based on AI adopted in the last 10 years does not support the idea of an overall decline in employment and wages in occupations exposed to AI. Some studies suggest a positive impact of AI on wage growth, with larger increases experienced by individuals in higher wage occupations and/or with higher educational attainment. This suggests that these workers are more capable or better positioned to use AI to complement their own labour, boost their productivity and to share in the benefits.

3.1. AI will increase productivity but the size of the impact is debated

37. Much of the available economics literature on AI centres on its potential to increase productivity, by reducing costs (including by enabling firms to replace labour with cheaper capital), complementing labour and spurring complementary innovations (Agrawal, Gans and Goldfarb, 2019[5]; Brynjolfsson, Rock and Syverson, 2017[6]; Cockburn, Henderson and Stern, 2018[7]). However, the *productivity paradox*[9] is the term used to refer to the fact that productivity growth has been lagging over the past decade or so (Andrews, Criscuolo and Gal, 2016[36]), despite substantial progress in AI (in particular, breakthroughs in machine learning) and other technologies. Researchers attempt to understand the causes of this productivity paradox, in order to be able to predict how AI will affect future labour productivity growth.

38. One explanation is that the potential of AI (and more generally, other recent technological advances) has been overestimated and that the predicted productivity improvements will never come to pass. For instance, for Gordon (2018[37]), the modest contribution of AI and robotics to productivity is part of the reason why productivity growth was slower between 2006 and 2016 than in the preceding decade.[10] In his view, much of the impact of AI has been seen already (e.g. customer service bots, searching through legal texts, assisting radiology diagnostics) and any further innovations (e.g. in medical research, big data, and driverless vehicles) are more likely to be marginal improvements of past

[9] Similar to the Solow Paradox in which "you can see the computer age everywhere but in the productivity statistics" (Brynjolfsson, Rock and Syverson, 2017[6]).

[10] Gordon posits that the IT revolution which boosted productivity between 1996 and 2006 has reached "maturity", as evidenced by the declining productivity of researchers across many fields making true technological breakthroughs less likely in future.

technologies rather than true technological breakthroughs resulting in large productivity boosts. He expects AI to replace workers in some jobs, but that this will happen at a steady pace rather than as a sudden upheaval. He also expects that AI will complement workers in other jobs, but in ways that produce only modest increases in productivity.

39. On the other hand, researchers who believe that AI has the potential to boost productivity significantly (along the lines of a GPT, as explained in section 2.2) attribute the productivity paradox primarily to lags in AI implementation and restructuring, which can result in it taking years or even decades before substantial economic gains of GPTs are seen (Brynjolfsson, Rock and Syverson, 2017[6]; Brynjolfsson, Mitchell and Rock, 2018[25]).[11] OECD analysis confirms that uneven uptake and diffusion of digital technologies throughout the economy is an important source of the productivity slowdown (Andrews, Criscuolo and Gal, 2016[36]) and suggests that digitalisation may have contributed to the widening performance gap between more and less productive firms (Gal et al., 2019[38]), as less productive firms can find it harder to attract workers with the right skills to help them adopt digital technologies efficiently.

40. Other factors that may have contributed to the productivity paradox include:

- Mismeasurement in the productivity statistics, due to difficulties in capturing improvements in the quality of high tech products (Byrne and Sichel, 2017[39]);
- The gains of AI accruing mostly to a small number of *superstar firms* in a "winner-takes-most" dynamic, whose market power enables them to engage in wasteful and potentially anti-competitive efforts to block others from accessing the technology (see (Brynjolfsson, Rock and Syverson, 2017[6]) and as discussed further in section 4.5). However, Schwellnus et al. (2018[40]) attribute the "winner-takes-most" dynamic to technological dynamism, rather than anti-competitive forces.
- Automation being introduced at an excessive rate, resulting in deployment of the *wrong types* of AI[12] and mismatches between skills and new technologies, thereby slowing productivity growth (Acemoglu and Restrepo, 2018[13]).

41. One challenge in weighing the relative merits of the arguments regarding AI's potential to increase productivity is that, at any point in time, it is difficult to forecast productivity growth a couple of years into the future – especially when a predicted productivity boost relies on the invention of an entirely new technology or an entirely new application of a technology. To highlight the challenge of relying on "our own limited imaginations" in this regard, Cowen (2016[41]) gives examples of past technological breakthroughs that have come as a surprise, among them: x-rays, radio and transistors. Cappelli (2020[42]) makes the point that claims reliant on future advances are easy to make but impossible to refute. Despite these challenges, some consultancies have attempted to put a value on the potential contribution of AI to economic growth (as detailed in Box 3.1), estimating that AI could deliver additional global economic output of up to $15.7 trillion by 2030 (PWC, 2018[43]).

[11] Indeed, a survey by Ransbotham et al. (2019[71]) shows that 40% of organisations that make significant investments in AI do not report business gains from it.

[12] As discussed in (Acemoglu and Restrepo, 2020[49]), ones which are only good enough to replace workers but not good enough to create new tasks and boost productivity sufficiently to raise demand for human labour.

42. What are the implications for future productivity growth? If Gordon's view holds true, then the impact of future AI developments will be modest. If, on the other hand, slow growth is due to lags in AI implementation and restructuring, this could still be consistent with projections of substantial economic growth. In other words, growth would follow an S-curve pattern with a slower start given the need to learn, invest and deploy the new technology, followed by an acceleration driven by competition and improvements in complementary technologies, and then a final period of slower growth again once the technology is widespread and market competition lowers the returns earned by early adopters[13].

Box 3.1. Estimates of the economic potential of AI

Studies by consultancies suggest that AI has enormous potential to contribute to global economic output, as shown in Table 3.1. Consultancies have generally tended to view AI as a revolutionary and transformative force, and one that can boost economic output by increasing productivity (by substituting workers and by complementing workers and capital), increasing consumption, enhancing the diffusion of innovation and creating a revenue stream for AI-producing firms. McKinsey's estimate of $13 trillion by 2030 corresponds to an additional 1.2% annual contribution to GDP, which is greater than the additional 0.4% contributed by robotisation during the 1990s and the additional 0.6% contributed by the spread of IT during the 2000s (2018[44]). Accenture's estimate of $14 trillion by 2035 is based on a projected increase in labour productivity of up to 38% in some countries (2017[45]). The studies that consider job loss generally assume it will be cancelled out by job creation in the long run.

Table 3.1. Estimated economic potential of AI

	Impact	Timeframe
(Accenture, 2017[45])	USD 14 trillion*	By 2035
(Analysis Group, 2016[46]) in a study funded by Facebook	USD 1.49-2.95 trillion	By 2026
(McKinsey, 2018[44])	USD 13 trillion	By 2035
(PWC, 2018[43])	USD 15.7 trillion	By 2030

Note: * based on 16 industries in 12 economies that make up 50% of global economic output. Estimation approaches differ, considering factors such as: productivity increases due to AI replacing workers and augmenting workers and capital, additional consumption, diffusion of innovation and returns to AI-producing firms.

These studies pay relatively little attention to the transition period, with the exception of McKinsey, who acknowledge potential negative externalities linked to displacement and wage polarisation, and net out the costs of transition to get their final estimate. PWC and McKinsey assume that adoption of AI follows an S-curve pattern, with a slower start followed by an acceleration.

3.2. Theoretical models are ambiguous on the impact of AI on employment and wages

43. This section explains why the impact of AI on employment and wages is ambiguous. While AI-facilitated automation is expected to reduce labour demand, it can increase it under specific circumstances.

[13] The assumption that new technologies follow an s-shape pattern is almost a stylised fact, according to Geroski (2000[124]).

3.2.1. AI-facilitated automation is expected to reduce labour demand and decouple wages from productivity gains

44. Economists have proposed a theoretical framework centred on AI being an *automation technology* to explain how AI has the potential to enhance productivity while simultaneously reducing labour demand, wages and the labour share (Acemoglu and Restrepo, 2018[13]). One limitation of this framework is that, by treating automation technologies together, they assume that AI is similar to other automation technologies, such as industrial robots and other automated machinery – an assumption which has yet to be proven (Naudé, 2019[47]) – and do not pay attention to the inherent capabilities of AI. This limitation is discussed in section 3.2.3.

45. The key feature of an automation technology is that it expands the set of tasks within the production process that can be performed by capital, so that the share of tasks performed by capital increases and the share of tasks performed by labour decreases (Acemoglu and Restrepo, 2019[48]). This may give firms the possibility to replace labour with cheaper capital, resulting in productivity gains. The displacement *effect* describes capital taking over tasks previously performed by labour. This reduces labour demand, and puts downward pressure on employment and wages. Additionally, because displacement increases output at the same time, it tends to have the impact of reducing the share of labour in national income[14] and decoupling wages from any productivity gains. This is one reason why productivity may increase but workers may not see their wages increasing at the same rate. This is also why treating AI as a purely factor-augmenting technological change, i.e. a force which increases the productivity of labour or capital while ignoring the displacement effect, can lead to misleading conclusions (Acemoglu and Restrepo, 2019[48]).

3.2.2. However, the creation of new labour-intensive tasks can increase the demand for labour in the long run

46. Even though the displacement effect may put downward pressure on employment and wages, there are other countervailing forces at play (Acemoglu and Restrepo, 2018[13]):

- The *productivity effect*, whereby cost savings generated by automation increase consumer demand (in the same sectors experiencing automation[15] and/or in other sectors[16]), which increases the demand for labour in non-automated tasks;

[14] Schwellnus et al. (2018[40]) show that technological progress and (to a lesser extent) globalisation can explain most of the contraction in the labour share over the last two decades. Capital-augmenting technological progress or technology-driven declines in relative investment prices reduce the labour share by fostering labour-capital substitution and increasing overall capital intensity.

[15] Similar to how the introduction of ATMs in the banking industry in the 1970s produced cost savings and additional consumer demand, which led banks to open additional branches, thereby offsetting the original displacement of bank tellers (Bessen, 2015[120]). Bessen (2018[117]) shows that a number of industries, including textiles, steel and automotive, experienced strong employment growth during periods of rapid technological progress and productivity growth, which could have been feared to cause a net job loss.

[16] By increasing productivity and reducing prices, certain technologies have a positive impact on employment in industries other than the ones where they are deployed (Autor and Salomons, 2018[119]). An example is a large supermarket chain introducing a new business model that generates

- The *capital accumulation effect*, whereby automation increases the capital intensity of production, triggering accumulation of capital, which also raises the demand for labour (in tasks where AI and automation are complementary to human labour)[17];
- The *deepening of automation*, whereby technological improvements increase the productivity of existing machines (i.e. with no additional displacement of labour), boosting the productivity effect and further increasing the demand for labour; and
- The *creation of new high-productivity, labour-intensive tasks*, which increases the labour share (potentially in the longer term), counteracting the impact of automation[18].

47. Acemoglu and Restrepo highlight an important dynamic within their model. While the productivity effect, capital accumulation effect and deepening of automation are important forces in counteracting the downward pressure on labour demand, employment and wages, these forces are unlikely to be large enough to counter the displacement effect in the short term. This is because, as automation continues, a falling share of the productivity gains accrues to labour.[19,20] However, in the longer term, through the creation of new high-productivity, labour-intensive tasks (i.e. ones that “reinstate labour as a central input into the production process” (Acemoglu and Restrepo, 2020[49])), a *reinstatement effect* can increase the labour share and directly counteract the *displacement effect*. This can ultimately set the growth process on a more balanced path, in which AI increases productivity, employment and wages overall.

48. The creation of new labour-intensive tasks is thus a critical mechanism for adjustment, but one that can be slow and one that depends crucially on the nature of AI being deployed. Not all AI applications will create new labour-intensive tasks. For instance, Acemoglu and Restrepo (2019[48]) decompose the change in the task content of production in the US and find stronger displacement effects and considerably weaker reinstatement effects during the last three decades than the decades before. They draw attention to the need to develop the *right types* of AI, i.e. AI that creates new tasks and boosts productivity sufficiently to raise demand for human labour (as opposed to the *wrong types*, which are only just good enough to replace workers) (Acemoglu and Restrepo, 2020[49]).

3.2.3. How does this framework apply to AI specifically?

49. In their paper “Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction” (2019[5]), Agrawal et al. adapt Acemoglu and Restrepo’s

considerable economies of scale and leads to lower prices, allowing consumers to increase their spending in other industries.

[17] Acemoglu and Restrepo (2018[13]) suggest that this effect may have mitigated the impact of the rapid accumulation of tractors in the American economy in the first half of the 20th century, citing Olmstead and Rhode (2002[121]).

[18] Along the lines of how the Industrial Revolution spurred new jobs such as engineers, machinists, repairmen, conductors, back-office workers and managers to support emerging technologies (Acemoglu and Restrepo, 2018[13]).

[19] It is this aspect in particular that encourages Acemoglu and Restrepo to reject the idea that automation always leads to greater employment and wages.

[20] When labour income does not reflect productivity gains, this may also suppress consumer demand and dampen the productivity effect (Gries and Naudé, 2018[28]).

framework to hone in specifically on the impact of machine learning using a task-based approach. They view machine learning as an advance in the field of prediction, which can therefore substitute for human prediction tasks (i.e. displacement effect) as an input to decision-making tasks (e.g. screening CVs for potential hires). By reducing uncertainty in prediction, machine learning can increase the relative returns to labour (e.g. a surgeon complemented in their work by an automated scan for cancer cells) or the returns to capital, if it encourages the automation of the decision task also (e.g. once the prediction of obstacles is automated, there is more reason to automating vehicle control). Machine learning may also create new decision tasks, which can be performed by capital or labour (in which case reinstatement can occur), although Agrawal et al. say that there are few tangible examples of this at this stage.

50. The work by Agrawal et al. suggests that the framework developed by Acemoglu and Restrepo can be reconciled with the concept of AI as a tool to enhance prediction, beyond simply treating AI as an automation technology. In either case, the theory is ambiguous on whether AI increases or decreases employment and wages. The ultimate impact will depend on the type of AI being developed and deployed, how it is developed and deployed, in addition to market conditions (Caselli and Manning, 2017[50])[21] and policy and institutions (OECD, 2019[16]; Aghion, Antonin and Bunel, 2020[51]; Acemoglu and Restrepo, 2018[13]). Additionally, the impacts on inequality should not be underestimated as there is no reason to believe that the displacement effects, productivity effects and emergence of new labour-intensive jobs will be distributed evenly across industries, regions, and socio-demographic groups.

3.3. The limited empirical evidence does not support the idea that AI has reduced employment and wages

51. Given the ambiguity surrounding the impact of AI on employment and wages in theoretical models, what does the empirical literature say? The body of literature on this topic is not large (see (Seamans and Raj, 2018[52]) and (McElheran, 2018[53]) for discussion of the related challenges) but this review has identified a few studies that examine recent historical data in the United States[22] for the impact of AI (or more specifically, machine learning, which the measures tend to capture) as opposed to broader automation or technological progress.

52. These studies do not support the idea of an overall decline in employment and wages. Some studies suggest a positive impact of AI on wage growth, with larger increases experienced by individuals in higher wage occupations and/or with higher educational attainment.

[21] Caselli and Manning (2017[50]) show that average wages will rise with the introduction of a new technology given certain conditions: that the price of investment goods falls compared to more labour-intensive consumer goods and that market competition is not reduced. As always, there are winners and losers but one implication of average wages rising is that if workers can switch jobs easily and/or redistribution is happening, all workers can benefit.

[22] The fact that the empirical studies identified in this review analyse only employment trends in the United States is likely due to the reliance of the measures of exposure to AI on the US-based O*Net database of occupations and tasks.

53. Felten et al. (2019[24]) examine AI advances and US labour market trends at occupation-state level between 2010 and 2015. They show that an occupation's exposure to AI (specifically, the areas of AI that have seen most advances in recent years) has a small positive link with wages but no link with employment. The positive relation is mostly driven by occupations that require a high level of familiarity with software and high-income occupations[23].

54. Fossen and Sorgner (2019[32]) apply the same measure to US individual-level panel data from 2011 to 2018 and find that exposure to advances in AI is associated with greater job stability (as indicated by an individual becoming non-employed or switching to a new occupations) and wage growth overall. They interpret this result as indicating that AI is predominantly complementary to human labour. The effects are even stronger for those with higher levels of formal education and more experience (as indicated by age), suggesting that these workers are more able to use AI to complement their own labour and boost their productivity. In contrast, the authors find that measures representing exposure to computerisation (as developed by Frey and Osborne (2017[26])) are associated with lower job stability and job growth.

55. Acemoglu et al. (2020[54]) examine changes in US job postings between 2010 and 2018 across establishments and occupations according to their exposure to AI. The study uses the exposure measures developed by Felten et al, Brynjolfsson et al, and Webb. Within establishments most exposed to AI (but not producing and supplying AI themselves), they observe a shift in the composition of job postings away from occupations most exposed to AI to occupations least exposed, although effect sizes are modest and results are not robust across specifications. They interpret this as suggesting any productivity and/or complementary effects of AI in these establishments are small and lower than substitution effects, although they acknowledge that it may simply be too early to observe an impact of AI in overall employment patterns (i.e. outside the market for AI talent). Overall, they find no significant impact on job quantity and no significant impact on the sets of skills required in exposed occupations (i.e. representing either a need for new skills or obsolescence of previously common skills).

56. None of these studies finds evidence to support the idea of an overall decline in employment due to recent advances in AI. The studies by Felten et al. and Fossen and Sorgner find a positive impact of AI on wage growth, with larger increases experienced by individuals in higher wage occupations and/or with higher educational attainment. Felten et al. note the possible implication that AI adoption could exacerbate income inequality.

57. While these backward-looking studies shine a light on the impact on employment and wages of developments in AI over the last decade, it is unclear to what extent future developments in AI will produce similar results. This question poses a substantial challenge for researchers, who must attempt to predict the impact of entirely new technologies and entirely new applications of existing technology, and for policymakers who may wish to devise policy around this impact.

[23] Exposure to AI was not related to employment growth or wage growth for low- or middle-income occupations.

3.4. Firms are divided in their expectations about AI's impact on overall labour demand

58. Surveys of employers show that opinions are divided about whether they think that AI will increase or decrease employment in future. In a survey of executives whose companies have adopted AI (McKinsey, 2019[12]) the results pointed to an expected decrease in the number of employees over the subsequent three years due to AI, despite showing that AI had led to job growth in the preceding year. The reasons for this outlook were not probed further, for instance whether it derives from expectations that upcoming developments in AI would be more suited to substituting labour. In a survey of both tech executives and the general population (Edelman, 2019[55]), two thirds of tech executives surveyed believed that AI could increase employment. A minority within the general population surveyed agreed, although a majority did agree that AI could produce an increase in employment in the long term. Business surveys by Bessen et al. (2018[11]) and McKinsey (2019[12]) suggest that businesses support the view that the impact of AI on jobs is much more about the shifting of work from some occupations to others than about eliminating labour overall.

59. Furthermore, there appears to be consensus that the impact will differ by occupation and industry. The surveys by Bessen et al. (2018[11]) and McKinsey (2019[12]) suggest job creation is likely to be experienced in sales and marketing (occupations which, Bessen et al. note, involve the complementary use of AI) and that job loss is likely to be experienced in manufacturing and some clerical occupations. The survey by Bessen et al. shows that startups that sell AI products to customers in the agriculture, manufacturing, utilities and transportation industries are much more likely to say that their products reduce labour costs and/or automate routine tasks.

4. The AI transition

60. The impact of AI on the labour market is likely to run much deeper than changes in employment and wages. The mechanisms underlying these changes could transform the way we work, reorganising tasks within any given occupation. The adoption of AI may result in the emergence of new tasks and occupations, which only humans can perform.

61. Workers may need to re-skill or up-skill in order to adapt to the reorganisation of tasks and the emergence of new tasks, and to weather potential job loss and navigate transitions to new jobs. Certain workers may be more capable or better positioned to do so, potentially exacerbating already existing inequality. For instance, workers in high-skilled occupations may have greater ability to learn new information, tend to possess skills which cannot be easily automated and have greater access to lifelong learning. Inequalities may also arise if the gains of AI are captured by the owners of capital and superstar firms, rather than workers.

4.1. Much of the impact of AI will be seen through the reorganisation of tasks

62. Many researchers share the view that the impact of AI must be understood not only in terms of its potential to destroy jobs, but also in terms of its potential to substantially transform the nature and content of jobs that remain (OECD, 2019[16]).[24] According to Autor (2015[56]), failing to understand this is what leads to exaggerated claims of mass unemployment. Combining Acemoglu and Restrepo's theoretical framework with Autor et al.'s task-based approach, AI adoption may result in a worker being displaced from a certain task. Rather than their entire job being eliminated entirely, there may then be a reorganisation of tasks within the job profile (with some tasks added and others removed) so that AI is ultimately complementary to the worker. These dynamics reflect the interplay between the displacement, productivity and reinstatement effects, which will determine the overall impact on AI on demand for labour (and the related impact on employment and wages).

63. A study by Brynjolfsson et al. (2018[25]) supports the idea of the reorganisation of tasks, as they find very few jobs that can be fully automated by machine learning. Instead, they find that many occupations comprise both tasks with high and low suitability for machine learning. They observe lower variance in the AI-suitability scores between occupations than between tasks, suggesting that suitability to AI is highly sensitive to the task being performed and that some of this sensitivity is dulled when tasks are bundled into an occupation. In their view, this supports the idea that the unleashing of the potential of machine learning is reliant on the reengineering of processes and the reorganisation

[24] Such transformations are typical of technological change and automation: Acemoglu and Restrepo (2018[123]) suggest that about half of employment growth between 1980 and 2015 was in occupations in which job titles or tasks performed by workers changed. In the case of automation, OECD analysis (2018[125]) found that while 82% of regions across Europe and North America had experienced employment decline in occupations at high risk of automation, 60% of regions had experienced an employment increase in occupations at low risk of automation and these increases actually accounted for a higher share of total employment than the decline. This supports the idea that automation shifts the mix of occupations, rather than driving down overall employment.

(unbundling and rebundling) of tasks.[25] They argue that this reorganisation of tasks should be the focus of the debate about the impact of AI on labour markets, instead of the focus on full automation of occupations.

64. An empirical study of how stock analysts have reacted to the introduction of AI (Grennan and Michaely, 2017[57]) provides a useful demonstration of how AI can produce both substitution and complementary effects, and results in a reorganisation of tasks. Firstly, AI produces a substitution effect as it is able to outperform high-skilled sell-side equity analysts in prediction tasks where sufficient data are available (in part because analysts' predictions can be subject to bias, due to conflicts of interest). The researchers find that analysts who cover stocks with the most data available (and therefore most suited to AI-based prediction) are more likely to leave the profession, representing the substitution effect. At the same time, the analysts who stay in the profession tend to shift their attention towards the types of stocks that are less suited to AI-based prediction, indicating a further substitution effect at the task level. The researchers find evidence that these analysts book more meetings with management teams, suggesting that the use of AI frees up time for them to use their interpersonal skills to gather soft information on the stocks. This represents a reorganisation of tasks and, in the researchers' view, the new focus of analysts on tasks that AI cannot perform reflects the complementary of AI to high-skilled labour.[26]

65. Ernst et al. (2018[58]) make the point that the decision to reorganise tasks will depend in part on workers' ability to adapt to the redesigned jobs. Crucially, the decision will primarily rest with the management of a company, and will depend on the profitability of doing so[27], the company's interest in supporting workers through this transition (e.g. through training), and institutional factors, such as the general infrastructure for training and job-search help available in the country, tax incentives and social benefit systems (Ernst, Merola and Samaan, 2018[58]) citing (Sengenberger, 1987[59])and (Albertini et al., 2017[60])).

4.2. The impact of AI will also result in the creation of new tasks

66. As established in previous chapter, AI's potential to create labour-intensive tasks (i.e. tasks that only humans can perform) is a critical mechanism for adjustment, counteracting the displacement effect and ensuring that the productivity benefits of AI are shared with workers. Most directly, AI will create jobs in entirely new occupations and fields related to its own development and deployment. However, this is not sufficient to ensure positive labour market outcomes. AI must also create new high-productivity tasks for human labour as noted in section 3.2.2. New jobs may also be created due to innovations enabled by AI and to spillovers from the AI industry.

[25] Brynjolfsson et al. (2017[6]) point out that firms implementing large enterprise planning systems almost always spend several times more on redesigning business processes and on training than they do on the hardware and software. Considerable changes to hiring and other HR practices may also be necessary to match human capital to the new structure.

[26] The researchers also find that the accuracy of earning forecasts produced by stock analysts declines in relation to the stocks that are more suitable for AI, but this decline in quality is attributed to compositional effects: it is the better performing stock analysts who leave the profession.

[27] This in turn depends on the impact on demand for the products and services linked to these jobs (citing (Bessen, 2018[117])).

4.2.1. New tasks for humans will be created in developing and deploying AI

67. As with other technologies, the deployment of AI will create jobs through its own need for further development, maintenance, operation and regulation (PWC, 2018[43]). In a study of companies already using or testing AI and machine-learning systems, (Wilson, Daugherty and Morini-Bianzino, 2017[61]) identified three different types of jobs that will emerge thanks to AI development and that will be performed by humans:

- *Trainers*, who will train AI systems, e.g. reducing the error rate of language translators, tagging data in a training dataset, adapting a chatbot to mimic human behaviour or match the culture of a company;
- *Explainers*, who will interpret the outputs generated by AI systems to improve accountability, e.g. explaining how an AI system arrived at a decision, inform decision-makers about appropriate uses of AI throughout an organisation;
- *Sustainers*, who will monitor the work of AI systems to ensure they are working as intended, e.g. monitoring a CV-screening process for bias, installing content filters in machine learning for a chatbot.

68. In certain AI systems, the need for human intervention in development and deployment is clear. For instance, trainers and sustainers may be required to ensure that AI-enabled sentiment analysis tools are producing accurate results. Knowing what people mean when they are giving feedback, and not necessarily what they say in that feedback, is a very human skill (Ultimate Software, 2018[62]). Sentiment analysis tools can classify content as "good, neutral, or bad", but human intervention may be needed to detect sarcasm.

69. The use of AI could also lead to the creation of brand new service activities. For instance, Guszcza et al. (2018[63]) anticipate that emerging AI regulation could create an industry around algorithmic auditing, wherein independent auditors ensure accountability in the "black box" of AI. They argue that algorithm auditing should become a profession in its own right, with proper credentialing, standards of practice, disciplinary procedures, ties to academia, continuing education, and training in ethics, regulation, and professionalism. Independent bodies could be formed to deliberate and issue standards of design, reporting and conduct, regarding AI systems that companies and organisation are developing and deploying.

4.2.2. The creation of new tasks beyond those that enable AI is crucial for ensuring positive labour market outcomes

70. Acemoglu and Restrepo (2020[49]) point out that the jobs created in the AI industry will not be enough to compensate for job loss if AI automates jobs in every other industry. This situation would lead to gross inequalities across sectors and transitions would be challenging. In their view, in order to lead to positive economic and social outcomes, the new tasks created must extend beyond those that enable AI. They give some examples of applications of AI that would create new high-productivity tasks for human labour:

- Individualised teaching: AI could use real-time data to determine students' individual learning styles and problem areas and then generate recommended teaching methods to enable teachers to teach in a way that is adapted to each student or small subset of students. This could enhance the productivity within teaching, benefiting society and potentially increasing demand for teachers with diverse skills to perform the individualised teaching.

- High-precision production: Using AI-enabled virtual reality in production processes could enable workers and robots to work together safely via interactive interfaces that augment human precision and perception.

71. In addition to this, AI has some characteristics that may lead to even more job creation than recent technological advances, specifically its potential to produce further innovations, enable scientific breakthroughs and generate entirely new industries (OECD, 2018[64]; Gartner, 2017[65]).[28] Predicting the scale of future job creation, particularly when the jobs rely on further technological breakthroughs or entirely new applications of the technology, is just as challenging (if not more) as predicting the scale of future job loss. However, one study has estimated that AI could lead to a net job creation of 2 million worldwide by 2025 (Gartner, 2017[65]).

72. The development of the AI industry may induce an even larger indirect job creation effect. Empirical work by Moretti (2010[66]; 2012[67]) shows that the creation of jobs in the ICT sector can have large multiplier effects in local labour markets. For each additional job in a high tech company in a local community, five additional jobs outside high-tech are created in the same community.

4.3. Workers may need to re-skill or up-skill in order to adapt to AI-induced changes in the labour market

73. Workers may need to re-skill or up-skill in order to adapt to the reorganisation of tasks and the emergence of new tasks, and to weather potential job loss and navigate transitions to new jobs. Some may choose to acquire AI-related skills so that they can take advantage of opportunities in AI development and deployment. However, not all jobs where AI is complementary to human labour will require specialised AI skills. Some of these jobs will require skills in areas that AI cannot do so well, such as creative and social intelligence, reasoning skills, and critical thinking.

4.3.1. The demand for AI-related skills is increasing

74. A range of different skill profiles will be required in order to develop and implement AI. Focusing at the top end of the AI talent market , the venture capital fund MMC Ventures (2019[68]) identified that in addition to a doctoral degree in mathematics, statistics or programming, AI professionals are increasingly expected to have sector-specific, engineering and commercial competencies, which further limits the potential AI talent pool. They estimate that demand for AI talent nearly doubled between 2016 and 2018 with two roles are open for every AI expert available, signalling a shortage of skills. However, they say that supply is growing with universities and companies increasingly providing the necessary training and with AI firms providing free educational resources.

75. While developing novel AI concepts and techniques will generally be the domain of those educated to doctoral level, a much broader landscape of talent will be needed to integrate these concepts into technologies and systems (Toney and Flagg, 2020[69]). Toney et al. suggest that demand is rising even more quickly for other types of AI talent that do

[28] To demonstrate the scale of the potential impact, the OECD (2018[64]) gives the example of the discovery of DNA structure in the 1950s leading to a revolution in industrial biotechnology and the creation of vast economic value (the global market for recombinant DNA technology has been estimated at around USD 500 billion).

not require a PhD (including for example, software engineers and database architects) relative to AI talent that does require a PhD. The researchers show that 80% of job postings considered AI-adjacent require a minimum education level of a bachelor's degree, with more than half of these stating no preference for a more advanced degree.

76. AI skills do appear to attract a pay premium. One analysis suggests that postings demanding AI skills offer on average 11% higher salary compared to job postings with no such demands (and compared to a 6% premium for software skills), even when controlling for unobserved firm characteristics (Alekseeva et al., 2019[70])).

77. A firm's need for AI professionals will likely depend on whether they are developing AI internally or simply buying and using an AI product, and the decisions they make around training, outsourcing and recruitment. One business survey (Ransbotham et al., 2019[71]) suggests that companies invest in AI talent internally (rather than relying on AI vendors) in addition to bringing in experienced AI talent from outside for technical leadership roles, and upskill their existing workforce to be able to work with AI, in order to capture value from AI. In another survey (Bessen et al., 2018[11]), AI startups suggest that most of their products require only general familiarity with computers within their client companies, claiming that the need for specialised computer skills or specific training among the workers who will use (and be complemented by) AI is modest. One survey (Accenture, 2018[35]), which surveyed both employers and workers, suggests that employers tend to underestimate the willingness of employees to acquire the skills necessary to work with intelligent technologies. In fact, a majority of the employees surveyed are positive about the impact of AI on their work (high-skilled employees are more positive than low-skilled employees) and consider it important to develop their own skills.

4.3.2. As smart as AI is, there are uniquely human skills it cannot replicate

78. Not all jobs that emerge in the AI transition will require AI-related skills. There are human skills that AI cannot replicate, which means that certain applications of AI will require human assistance.

79. One analysis (Sage-Gavin, Vazirani and Hintermann, 2019[72]) based on the U.S. Department of Labor's O*Net database, which ties abilities, skills, tasks and working styles to occupations, shows that skills such as creativity, complex reasoning, and social and emotional intelligence are growing in importance in many jobs. Many of these skills are the same ones that the OECD Future of Education and Skills 2030 project (OECD, 2019[73]) has encouraged individuals to develop, on the basis that AI cannot do them so well (at least currently), for example: creativity and originality[29], complex social interaction and dealing with uncertainty. The authors point out that humans can handle uncertainty better than AI, through their ability to develop their beliefs and understanding of what is happening in the world, and to discard beliefs when they are inaccurate, irrelevant or damaging. AI can complete specific tasks efficiently, and respond effectively to complexity and to some characteristics of uncertainty, but if the goals and context of the task are ambiguous or change, then a "breakdown" often occurs. The OECD report also highlights the importance that lifelong learning is responsive to the changing demands of the labour market, although

[29] Additionally, given the malleability of AI and its large range of applications, it is the creativity and imagination of the human users and designers of AI that will unlock its full benefits (Berkowitz and Miller, 2018[126]).

low skilled individuals and workers at high risk of automation are much less likely to be engaged in training (OECD, 2019[16]).

80. Not only will these skills help workers to use new technologies such as AI, but workers can also use AI to augment these skills so that human-machine collaboration can add up to more than the sum of its parts (Sage-Gavin, Vazirani and Hintermann, 2019[72]). Thus, enhancing skills in these areas that AI cannot emulate will allow AI to be complementary to human labour (OECD, 2019[73]).

4.4. Certain workers will be more capable of adapting to change

81. The evidence presented in the previous chapter showed that some high-skilled occupations involving non-routine cognitive tasks are among the most exposed to AI, suggesting that workers in these occupations are more likely to see their work substituted, complemented and/or transformed by AI. If these workers (including lab technicians, engineers and actuaries) can adapt to these changes, they may be able to benefit from the AI transition.

82. The empirical studies presented in section 3.3 (Felten, Raj and Seamans, 2019[24]; Fossen and Sorgner, 2019[32]) found larger positive wage effects of AI adoption among individuals with higher educational attainment and in higher wage occupations, suggesting that these individuals have been most able to use AI in a complementary fashion. At the same time, Acemoglu et al. (2020[54]) find that individuals in lower wage occupations have been more likely to be substituted by AI. Fossen and Sorgner also found that the positive wage effects were stronger for older, more experienced workers, suggesting that these workers are more able to use AI to complement their own labour and boost their productivity. In this case, AI adoption could increase inequality.

83. Explaining why workers in high-skilled occupations might be more capable of adapting to such changes, Fossen and Sorgner (2019[32]) point to their greater ability to learn new information and adapt to new technologies, as well as their tendency to possess skills which cannot be easily automated, such as creative and social intelligence, reasoning skills, and critical thinking. They suggest that the potential for AI to substitute labour depends on the extent to which an occupation consists of non-routine cognitive tasks, which is more likely in high-skilled occupations in their view.[30]

84. It has also been suggested that adjustments to white-collar jobs due to AI might be slower than adjustments to blue-collar jobs due to automation (Wright, 2019[74]), because of the greater need to adjust processes around reporting or controls, the value attached to relationships and to expert judgment in complex decision-making, and the unlikeliness of a situation in which an entire department (e.g. accounting) is dismissed all at once. The article provides the example of Zurich Insurance piloting the use of machine learning in the assessment of insurance claims for car crashes or burglaries. Zurich Insurance ultimately decided not to roll the pilot out in full due to the frequency with which humans had to step in to override the computer's decision.

[30] Agarwal et al. (2019[5]) present a similar argument in relation to the impact of machine learning but one that does not tie the impact to skill level. Instead, the impact of machine learning on an occupation is related to the extent to which the core skill of the occupation is prediction. In their view, the HR professional whose core skill is screening CVs for potential hires may find the value of this skill diminished whilst a surgeon using AI imaging to operate more precisely on a tumour may find the value of their operating skills enhanced.

85. Some expect AI advancements in problem solving, logical reasoning and perception to open up specialised AI tools to non-experts, thus complementing low-skilled workers while substituting high-skilled workers, e.g. agricultural systems that provide guidance what and when to plant, and construction systems that plan maintenance activities (Ernst, Merola and Samaan, 2018[58]). A similar example is the use of AI-enabled on-the-spot training programmes enabled by glasses or tablets with virtual or augmented reality functionality in manufacturing processes that require the worker to adapt to each specific order (Moore, 2019[75]). While the use of these devices means that workers need less pre-existing knowledge or training, Moore points out that this also means that workers do not learn long-term skills and do not specialise.

86. There may be a mix of factors influencing older workers' ability to adapt. On the one hand, the idea of age-biased technological change, whereby the adoption of technology disadvantages older workers, is well established ((Behaghel, Caroli and Roger, 2011[76]) and elsewhere). Webb (2020[23]) points out that older workers are likely to find it more difficult to adapt to changes in the labour market due to AI. They are generally less mobile and may have less incentive to retrain (due to fewer remaining years of working life). On the other hand, Webb considers that the impact of AI on employment may be felt via the entry margin rather than the exit margin (i.e. fewer young workers joining the occupation, rather than more older workers leaving it), which would result in a higher impact on younger workers.

4.5. Does AI favour owners of capital and superstar firms?

87. Just as changes in relative demand for different groups of workers can result in inequality, so can changes in relative demand for different factors of production. When AI replaces labour in a production process and complements other factors of production (say, land or capital), what workers lose in terms of wages, the owners of land and capital gain as a kind of unearned windfall (Korinek and Stiglitz, 2017[77]).

88. Korinek and Stiglitz (2017[77]) identify a further channel through which AI (and other technologies) may increase inequality. Specifically, the excludable nature of technology (e.g. through intellectual property rights) may enable innovators to build up market power in a "winner-takes-most" dynamic[31] (potentially to the point where they reach *superstar* status, as mentioned in previous section), which they can then use to earn a surplus in excess of the costs of innovation. This would create not only inequality among innovators[32], but also between innovators and workers.

89. Since technological progress can increase productivity and drive economic growth, there is reason to explore how AI can be implemented in an inclusive way, without increasing inequalities and societal resistance to technological progress. Korinek and Stiglitz (2017[77]) consider the scope for redistribution in a situation where AI is introduced as a labour-replacing technology, producing winners and losers (via the channels described

[31] Schwellnus et al. (2018[40]) demonstrate the existence of the "winner-takes-most" dynamic but attribute it to technological dynamism, rather than anti-competitive forces.

[32] Inequalities could also arise between workers in superstar firms and workers in firms struggling to keep at pace with digitalisation (OECD, 2019[16]).

above). Korinek and Stiglitz find that redistribution[33] (e.g. via a tax on capital inputs) can still produce a Pareto improvement whereby all parties are better off as a result of AI (even in the case of a *singularity*), as long as the costs of redistribution are sufficiently low. Korinek and Stiglitz also point out that technology that is privately optimal may not be socially optimal, and hint at potential intervention in the innovation process in order to make AI less likely to substitute labour.

[33] Korinek and Stiglitz suggest achieving redistribution via a tax on capital inputs that earn windfall gains (particularly on those that are fixed in supply, such as land or energy, as they would be less distortionary). If this type of redistribution is not feasible, Korinek and Stiglitz suggest shortening the term of patent protection, resulting in the lower prices for consumers/workers after expiration of the patent and thereby some redistribution of the innovation surplus.

5. AI and the work environment

90. Work not only rewards people financially, it also provides them with a chance to fulfil their ambitions, feel useful in society and build self-esteem. Work can be either good or bad for health, fulfilling or meaningless, depending on factors such as the tasks completed, work organisation and management practices, amongst others.[34] AI has the potential to reshape the work environment of many people, by changing the content and design of their jobs, the way they interact with each other and with machines, and how work effort and productivity are monitored. Deployment of AI-enabled technologies in the workplace is still at an early stage, and at this moment, it is an open question whether AI will improve or worsen the work environment overall, and how this might differ across different types of AI, different workers and different modes of implementation.

91. The quality of the work environment is an important element of overall job quality, in addition to earnings and labour market security (OECD, 2018[78]). The concept refers to the setting in which workers operate, reflecting the interplay between job *demands* such as physical risk factors, emotional demands and work intensity, and job *resources* such as task organisation, work autonomy, learning opportunities, workplace relationships and good management practices (OECD, 2017[79]).

92. This chapter first examines how the adoption of AI and the reorganisation of tasks can improve or worsen the work environment, to the extent that it steers workers towards or away from safe and fulfilling tasks. The discussion then moves to explore how AI-enabled technologies might change the interaction between worker and machine via the introduction of collaborative robots (or *cobots*).

93. This chapter also explores the multiple potential applications of AI in the field of human resource management and recruitment, enabling workers to advance their careers, helping managers to manage, and supporting career guidance and training. These applications demonstrate that AI can complement human capabilities and support management practices and career development. However, some of the same features that make AI algorithms so powerful in these respects may diminish the quality of the work environment in other ways or for other workers, generating new concerns as well as amplifying existing concerns. This chapter discusses how the collection and use of vast amounts of data and the lack of transparency and low explainability due to complex inner workings, may generate stress and increase psychosocial risks at work. Even AI technologies with potential to improve the work environment may have the opposite effect if applied badly or with the sole objective to increase productivity (even if driven by genuine business need) at the expense of other factors.

[34] This is well documented in various strands of literature, from occupational health studies that identify major risks for both physical and mental health in the workplace, to occupational psychology and behaviour research, to people management research which follows a more positive perspective under the basic premise that people are more productive when they enjoy their work and workplace (Saint-Martin, Inanc and Prinz, 2018[82]).

5.1. The jury is out on whether the reorganisation of tasks as a result of AI adoption improves the work environment

94. One of the most direct ways AI can affect the quality of the work environment is through the automation of tasks and the resulting reorganisation of tasks within an occupation. To the extent that AI can facilitate the automation of hazardous, repetitive or demeaning tasks and steer workers toward safer and more fulfilling ones, it can enhance the work environment. On the other hand, if the reorganisation has the effect of removing safe and fulfilling tasks from workers, the work environment will deteriorate.

95. One survey of workers in Japan (Yamamoto, 2019[80]) suggests that the reorganisation of tasks in the wake of AI adoption contributes both to greater job satisfaction and increased stress. The authors suggest that AI allows workers to concentrate on more complex tasks that can only be performed by humans. These more complex tasks may intensify work-related stress but may also provide a greater sense of satisfaction once accomplished.

96. Occupational Safety and Health (OSH) agencies have already identified the potential for robots to replace workers in strenuous work activities and dangerous work environments (e.g. chemical or ergonomic hazards), thereby reducing OSH risks (EU-OSHA, 2018[81]). A new generation of robots, powered by AI systems (instead of traditional programming algorithms) opens up even more opportunities. Many people are still exposed to risk factors for physical health at work, even though many tasks have been automated that formerly required hard physical labour (Saint-Martin, Inanc and Prinz, 2018[82]). Of particular concern is the high prevalence of risk factors for work-related musculoskeletal injuries in manufacturing and construction, but also in a number of service activities such as healthcare and retail.

97. In manufacturing and warehousing environments, AI may offer some solutions, but may also introduce some new risks. First, AI-enabled smart robots can perform a much wider range of tasks, including some physically onerous tasks that less advanced technologies left to human workers. Second, even when full automation may not be feasible, smart robots (including the cobots described in the next section) can work alongside operators to reduce the health consequences of physical efforts, repetitive movements or awkward postures, which are key risk factors for musculoskeletal injuries. However, the same technologies may produce psychosocial risks if people are driven to work at the robot's pace, as well as physical risks due to potential collisions. In addition, there may be questions about liability and responsibility in the case of injury or damage (Moore, 2019[75]).[35]

98. As established in previous chapters, AI's problem solving, logical reasoning and perception capabilities could lead to high-skilled workers (including lab technicians, engineers and actuaries) seeing substantial change in the tasks they perform and to their work environment. However, there does not appear to be much discussion in the literature

[35] A set of case studies (Jaehrling et al., 2018[107]) illustrates some additional risks, in this case following the introduction of an automatic sorting system in warehouses. The resulting reorganisation of the job of "manual picking" into two jobs ("feeding" and "palletising") made tasks less varied and work more repetitive as the tasks left to workers were those routine tasks that were too costly to automate. Workers expressed a sense of alienation, as if they were a "mere appendage of a machine". Even though the automatic sorting systems covered by the case studies did not appear to have involved AI, similar results might be expected with systems that do rely on AI.

on how the reorganisation of tasks due to AI for high-skilled workers could improve or deteriorate the quality of their work environment. One rare example is the discussion by Jha and Topol (2016[83]) of the potential for visual fatigue among radiologists as their profession becomes more data-rich due to the requirements of AI technology, and as their activities depend less on inference and more on detection. This gap in the literature may be due to lower levels of concern about the quality of the work environment among those in higher skill jobs (who are, on average, more likely to work in high quality working environments (OECD, 2017[79])). Those highly skilled workers who are exposed to AI may also have greater say in how AI is adopted, given that they are more likely to possess specialist knowledge essential for the functioning of the organisation, implying that the withdrawal of their co-operation could be costly.

5.2. AI can promote close human-robot collaboration

99. One factor that has traditionally limited human-robot collaboration in manufacturing or warehousing environments is the physical danger associated with humans and robots sharing the same space. Some point to AI-enabled technologies as a way to allow humans and robots to work in close collaboration while safeguarding the health and well-being of workers (Daugherty and Wilson, 2018[84]; [85]). One example[36] is AI-enabled *cobots*.

100. Cobots allow firms to combine a robot's strength and endurance with a human's tacit knowledge and agile decision-making (Knudsen and Kaívo-Oja, 2020[86]), thereby complementing and augmenting human capabilities (rather than replacing them) (Daugherty and Wilson, 2018[84]; [85]), and enhancing performance compared to purely robotic processes. Collaborative robotics has been described as one of the fastest-growing sectors of the robotics market (Goldberg, 2019[87]). Villani et al. (2018[88]) identify the industrial applications where cobots are most advantageous, according to the literature: handling; welding; assembly; and applications in the automotive industry (where demand is currently the greatest). In these applications, cobots generally assist the operator by performing mundane and or physical tasks such as moving materials, holding heavy objects or performing sample tests.

101. Despite these advantages, when AI-enabled cobots work in close proximity to a worker, new physical and psychosocial risks are likely to arise. This is why robots have typically been sectioned off from human workers in industrial environments, with little physical interaction.[37] Indeed, collaborative robotic assembly tasks have been shown to produce mental strain as evidenced by the monitoring of psychological and physiological (e.g. sweating) responses, which are more pronounced when the cobot is within 2 metres of the worker and moves quickly and without warning (Arai, Kato and Fujita, 2010[89]).

[36] Another example, mentioned in section 4.2.2, is the use of AI-enabled virtual reality in production processes enabling workers and robots to work together safely via interactive interfaces that augment human precision and perception (Acemoglu and Restrepo, 2020[49]).

[37] For decades, robots have typically been large pieces of machinery, usually sectioned off from human workers, that would perform a dedicated task – unloading a stamping press, for example (Daugherty and Wilson, 2018[84]). That specific task was part of a rigid, fixed chain of work that would generally include humans doing other predefined tasks – for instance, inspecting the stamped metal parts in order to discard defected parts.

102. However, some believe that these risks can be mitigated through the use of intelligent navigation systems. Cobots can be equipped with AI-powered intelligent navigation systems, which allow them to navigate a shared workspace with the human element in mind (e.g. human field of vision and human motion patterns) (Lasota and Shah, 2015[90]). The aim is not only to avoid collision but also to achieve fluid human–robot interactions so that the individual feels safe and comfortable working with a robot teammate. In one experiment, Lasota and Shah (2015[90]) showed that individuals felt more satisfied, safer and more comfortable working in a shared workspace with an AI-enabled robot than with a standard robot, in addition to performing the task more quickly[38].

103. While close collaboration facilitated by cobots may enhance performance in certain settings, there is also concern about increased work intensity if the worker is driven to work at the robot's pace rather than the reverse (Moore, 2019[75]). As more autonomy is given to the cobot, there are questions about whether this diminishes the operator's task discretion and autonomy. These factors have been shown to be closely associated with workers' job satisfaction, physical and psychological well-being, and to act as a buffer against the damaging effect of high work intensity ((OECD, 2017[79]) citing ((Karasek, 1979[91]; Karasek and Theorell, 1990[92])).

104. Some experiments have suggested that there may be particular circumstances in which a cobot equipped with an AI-powered plan execution system is well suited to act as a team leader and to allocate tasks among human team members. One experiment (Gombolay et al., 2015[93]), in which 24 pairs of human participants collaborated with a cobot equipped with a plan execution system to build Lego kits, found that participants preferred when the cobot was given full authority over team coordination compared to when one participant was given authority or authority was shared with the cobot. The results surprised the researchers who expected that participants would prefer to keep some control over team coordination. It could be that the participants found the process of scheduling to be burdensome, especially given the tight deadlines, and preferred to be part of an efficient team rather than play a role in the team coordination process.

105. The potential of AI to enhance performance by enabling close human-robot collaboration through cobots has been an active area of research and development. A substantial amount of this literature has examined the impact of human-robot collaboration on operators' feelings of trust, safety and stress (e.g. (Villani et al., 2018[88]), (TNO (Netherlands Organisation for Applied Scientific Research), 2018[94]), (Hancock et al., 2011[95])). For instance, the literature review performed by Villani et al. (2018[88]) identifies safety issues as the primary challenges for developing cobots and calls for developers to prioritise safety over performance. They suggest that certain advances in collaborative robotics that would improve human-robot interaction (e.g. human-friendly interfaces) have not yet transferred from the laboratory to industrial settings. As such, it is not clear that the promise of cobots to safeguard the health and well-being of workers is yet being fully realised.

5.3. AI can support human resource management and career development

106. AI has a few features that make it particularly attractive to firms that wish to employ more modern, participative and engaging human resource management models and to workers wishing to advance their careers. However, potential benefits for workers are very

[38] The study did not make comparisons with a work environment consisting of only human workers.

much dependent on how employers will use these new technologies, which have the potential to collect and produce vast amount of data on work performance, and therefore, may increase work pressure (see section 5.4). With these caveats in mind, Table 5.1 presents some applications that demonstrate how AI can enable personalised coaching for individuals, help managers to manage, match skills to jobs, and improve training tools and programmes.

Table 5.1. AI applications in Human Resource Management (HRM) and career development

Application	What does it offer?	How does it use AI?
Humu's Nudge Engine	Ongoing and personalised coaching for employees and managers using insight from behavioural sciences and occupational psychology	Uses machine learning to customise hints and suggestions. e.g. what timing, messaging, and motivational techniques are effective for each employee
Dristi's video-enabled productivity monitoring	Increases efficiency along assembly lines by identifying weaknesses and inefficiencies on the factory floor	Image recognition software converts videos of workers along the assembly line to data points for use in a user-friendly app
Humanyze's wearable devices	Employees wear "sociometric" badges that record communication patterns so that feedback on teamwork can be given	AI-enabled analytics identify weaknesses in communication patterns. e.g. based on tone of voice, gesturing, frequency of interruption
HireVu's facial recognition software	Analyses recorded interviews to make the hiring process more efficient	Image recognition software analyses facial expression, body language and word choice filter to assist with selection
IBM's predictive attrition program	Predicts whether an employee is likely to leave the company so that managers can take strategic action	IBM's AI platform, Watson, makes predictions based on a wide variety of data points
U.S. Army's chatbot recruiter	Answers questions about the army's recruiting process and refers users to human recruiters when necessary	NLP-enabled chatbot speaks with potential recruits using the same language and style as an army recruiter
Jobiri's resume builder	Builds CVs and cover letters for jobseekers	AI algorithm evaluates CVs and provides customised feedback
Instant Coach Flight Simulator	Enables individuals to practice skills in between training sessions	A chatbot provides a private setting for individuals to practice skills, including difficult, dangerous or embarrassing ones
IBM's Blue Matching	Delivers personalised internal job recommendations to IBM employees on a voluntary basis	Predictive analytics generate recommendations that fit employees' qualifications, aspirations and AI-inferred skills

Note: This table is intended to illustrate a variety of applications of AI in HRM and career development tools and is not intended to be comprehensive. Information in the table was collected from developers' websites.

107. AI's ability to process large amounts of data and learn in real time could make it particularly suitable for supporting continuous feedback and development (e.g. Ultimate Software's UltiPro Perception). Rather than waiting for the results of an annual employee engagement survey, regular feedback helps managers take timely actions to ensure that employees' needs and goals are being met (Nielsen et al., 2016[96]; Kark, Van Dijk and Vashdi, 2018[97]).

108. AI's capabilities in the collection and analysis of data may make it an attractive tool to support management decision-making, from monitoring worker productivity (e.g. Dristi's video-enabled solution) to communications (e.g. Humanzye's wearable devices). Human resource management (HRM) professionals may be attracted to AI-enabled technologies on the basis that they offer a more data-driven approach to recruitment (e.g. HireVu's facial recognition software) or retention (e.g. IBM's predictive attrition program), or that they are time-saving (e.g. US Army chatbot recruiter).

109. AI may offer advantages for workers who wish to advance their careers, from helping jobseekers to draft their CVs (Jobiri's resume builder) to enhancing training programmes (Instant Coach Flight Simulator). AI-enabled data analytics (such as IBM's Blue Matching) could improve matching between skills and jobs, which has been shown to be a key driver of job satisfaction and performance (Saint-Martin, Inanc and Prinz, 2018[82]).

110. Some AI applications complement sophisticated data analytics with insights from neuroscience, behavioural science and applied research in various fields, such as communication and organisational psychology (such as Humu's Nudge Engine). These kinds of knowledge can help develop a positive workplace culture, but all too often, they remain outside the range of skills and competencies that employers are focusing on to run their core business activities. In this regard, AI-enabled technologies may offer cost efficiencies and scalability relative to a human coach (Bersin, 2018[98]).

111. For companies wanting to improve workplace culture and the quality of the work environment, such technologies can be particularly appealing. However, they may have the opposite effect if they enable excessive monitoring on behalf of the firm, undermine data privacy or lack transparency and explainability (as discussed in section 5.4).

112. Evidence on the current prevalence of AI applications within HRM functions is mixed but points to the potential for this to grow in the future. One report (PWC, 2018[99]) suggests that 40% of HRM functions in international companies (mostly US-based) are currently using AI applications, mostly for the recruitment and hiring process. HR practitioners participating in a roundtable (Mathis, 2018[100]) agreed that this was the main application, while a few also mentioned using AI to customise e-learning content. The researchers note that HRM applications represent a very small share of the total investment in AI development, compared to other industries such as health, robotics and marketing, sales and customer relationship management (citing (HRWins, 2018[101])) but that the number of HR-related AI sales increased considerably from 2013 to 2018 (citing (CB Insights, 2018[102])). Another recent survey across various industries in more than 30 countries showed that a vast majority of HR professionals surveyed believed that AI could improve internal matching and visibility of opportunities (Zhang, Feinzig and Hemmingham, 2018[103]). However, the same survey suggested that adoption levels are still modest: almost two thirds of HR professionals surveyed had not yet adopted such tools while only 6% of them report using AI solutions moderately or to a great extent.

5.4. AI may also entail risks for the work environment

113. Some of the same features that make AI algorithms so powerful may also entail risks for the quality of the work environment. Excessive monitoring may generate psychosocial risks, increasingly recognised as an important component of occupational safety and health (Leka and Jain, 2010[104]; ILO, 2016[105]). Concerns about data privacy, transparency and explainability may exacerbate these risks, in addition to raising questions about the ethics[39] of introducing AI to the workplace. AI can also amplify some of the psychosocial risks associated with digitalisation more generally[40] as AI is embedded in

[39] A forthcoming OECD publication separately explores these ethical questions in more detail. This literature review focuses on the impact on the work environment and the quality of jobs only.

[40] e.g. stress, discrimination, heightened precariousness, musculoskeletal disorders, and the possibilities of work intensification and job losses

pre-existing tools or new tools for workplace management and design (Moore, 2019[75]). However, Moore notes a general lack of discussion in high-level governmental and organisational reports about the implications for OSH of introducing AI into the workplace.

114. Even those who warn of the risks associated with the use of AI in the workplace, point out that the use of such tools to supervise work activities is not necessarily harmful (Moore, 2019[75]; De Stefano, 2018[106]). According to Moore (2019[75]), it is the implementation rather than the technology itself that creates a negative or positive impact on working conditions. Jaehrling et al. (2018[107]) note the importance of mediating factors such as management attitudes and perceptions as well as employee bargaining power, in determining the impact of technological innovations on the work environment.

5.4.1. Enable excessive monitoring on behalf of the firm

115. Excessive monitoring of employees, in the form of data collection and processing, may cause stress and undermine well-being. Surveillance at work is not necessarily new[41], but AI tools can only exacerbate the situation, not least because it is the very way those tools perform – every bit of data is potentially valuable (Van den Broek, 2017[108]).

116. Many of the HRM-related applications mentioned in Table 5.1 require additional data to be collected in the workplace. Even cobots – which are not intended to monitor employees' behaviours but rather are geared towards helping them execute work tasks – produce a myriad of granular data on work performance (e.g. workers' and machines' idle times). In addition, some innovative approaches to put human psychosocial risks at the heart of human-robot collaboration involve the operator wearing a smart-watch that monitors stress levels (Landi et al., 2018[109])

117. Even if effectively anonymised and aggregated, data collection can be highly invasive and may capture personal elements, including the level of interaction with colleagues and the mood of workers (De Stefano, 2018[106]). Moore (2019[75]) describes the potential for AI tools to increase the degree of monitoring in call centre work, already considered repetitive, demanding and subject to high levels of monitoring (citing (Woodcock, 2016[110])). While AI tools to analyse sentiment or facial expressions could be employed to identify and combat overwork or stress, the requirement for invasive data collection could equally exacerbate the issue of monitoring and create new sources of stress.

118. How AI tools impact managerial practices is also important. If these tools are used to implement micromanagement and other practices that increase pressure on workers, they may cause stress and anxiety (Moore, 2019[75]), and may even cause efficiency and productivity to decline ((De Stefano, 2018[106]) citing (Moore, Akhtar and Upchurch, 2018[111])).

5.4.2. Data privacy and protection issues: is "Big Brother" watching you?

119. Data privacy and protection issues come to the fore where AI-enabled technologies rely on data in the individual's private sphere. For instance, sentiment analysis may rely on capturing and analysing a worker's written exchanges, from e-mails, to instant messages, to blogs and communications on various social networks.

[41] For instance, computer monitoring that measures employee keystroke speed and accuracy, or video surveillance that detects safety issues but also employee misconduct, have been used for some time now, well before the deployment of AI technologies in the work environment.

120. Data privacy and protection issues cut across all AI-enabled technologies, from cobots to individual virtual coaches, to smart apps and platforms that support decision-making in sensitive areas of HR management, such as hiring and performance management processes. Collection, storage, processing and analysis of large amounts of data are the very essence of these technologies. In a recent white paper (2020[112]), the European Commission stated its intention to examine on a continuous basis any additional risks posed by AI systems and the application of General Data Protection Regulation (GDPR) (European Commission, 2018[113]) to these risks.

5.4.3. Lack of transparency, explainability and fairness

121. Many of the concerns discussed above can be exacerbated when there is no transparency about what AI technologies are being used in the workplace and how they feed into decision-making. This lack of transparency and explainability could result in the misuse of AI and the use of inaccurate and/or biased AI; it could also reinforce ethical and privacy concerns and pose a barrier for workers wishing to have a say on how AI is used in the workplace. AI has the potential to produce results that are inaccurate and/or biased and therefore lead to unfair and discriminatory decisions.

122. HR professionals may be attracted to AI-enabled technologies on the basis that they will overcome individual biases of supervisors and replace them with more objective and neutral metrics, but may find instead that one set of biases has been replaced by another (De Stefano, 2018[106]). For instance, if a system learns which job applicants to accept for an interview by using a dataset of decisions made by human recruiters in the past, it may inadvertently learn to perpetuate their racial, gender, ethnic, or other biases (Brynjolfsson and McAfee, 2017[31]). For instance, in 2018, Amazon had to scrap an experimental AI-enabled recruitment tool, which was discovered to be biased against female candidates (Dastin, 2018[114]). Due to the prevalence of men already in technical roles, the system downgraded CVs that mentioned all-women's colleges or female-indicating phrases like "women's chess club." A recent study shows that, to find the best workers (and simultaneously overcome bias, even if this may not be a specific goal), hiring algorithms must find a balance between selecting from groups with proven track records and selecting from under-represented groups to learn about quality (Li, Raymond and Bergman, 2020[115]).

123. Similarly, AI-enabled performance management systems shaped by subjective assessments of intangibles, such as engagement and cultural fit, risk introducing racial stereotypes into decision-making and harming diversity (Bodie et al., 2017[116]). Moreover, these biases may not appear as an explicit rule but, rather, be embedded in subtle interactions among the thousands of factors considered, so that diagnosing and correcting the problem can be a challenging task (Brynjolfsson and McAfee, 2017[31]).[42] De Stefano points to the importance of workers being able to "negotiate the algorithm" (including through collective bargaining) when AI is used in performance management systems, a task which is more challenging when transparency is low.

[42] Technical solutions do appear to be emerging, like the Local Interpretable Model-Agnostic Explanations (LIME) (Daugherty and Wilson, 2018[84]). For instance, if an expert HR system has identified the best candidate for a particular job, LIME can identify the variables that led to that conclusion (such as education and deep expertise in a particular narrow field) as well as the evidence against it (such as inexperience in working on collaborative teams).

124. Employers need to learn how to correctly use the data provided by monitoring technologies, as information should be placed in context before proper sense-making can be applied (Van den Broek, 2017[108]). Even though today's technologies are getting increasingly smarter, context remains very hard to grasp and interpret for a machine. Therefore, when combined with algorithmic decision-making, data-driven performance management may increase psychosocial risks and stress significantly, unless it is backed up with ethical consideration and adequate human intervention (Moore, 2019[75]). Risks of stress and anxiety arise when workers feel that decisions are being made through automated processes based on numbers and data that they have neither access to nor control over. This may generate great uncertainty as to the accuracy and fairness of the decision-making process, especially if the latter determines promotion and remuneration, job description changes, and hiring and firing.

125. For companies operating in the EU area, the GDPR already establishes the right for people not to be subject to an automated individual decision-making (including profiling with respect to the individual's performance at work), therefore requiring some forms of human intervention in decision-making processes. Guszcza et al. (2018[63]) anticipate that emerging regulations might lead to the creation of brand new service activities such as algorithmic auditing. According to Guszcza et al., it may require no less creativity, hard work, and innovation for companies to improve transparency and explainability around AI-enabled technologies (including those that affect their employees) than to develop the AI technologies themselves.

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