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Six questions about the demand for artificial intelligence skills in labour markets

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Federal Ministry
of Labour and Social Affairs

Six questions about the demand for artificial intelligence skills in labour markets

Abstract

This study responds to six key questions about the impact that the demand for Artificial Intelligence (AI) skills is having on labour markets. What are the occupations where AI skills are most relevant? How do different AI-relevant skills combine in job requirements? How quickly is the demand for AI-related skills diffusing across labour markets and what is the relationship between AI skill demands and the demand for cognitive skills across jobs? Finally, are AI skills leading to a wage premium and how different are the wage returns associated with AI and routine skills? To shed light on these aspects, this study leverages Natural Language Processing (NLP) algorithms to analyse the information contained in millions of job postings collected from the internet. Empirical analysis shows that AI skills are relevant in a variety of occupations such as computer scientists, directors of information technology and data scientists. Evidence, however, also shows that the demand for AI skills has diffused across a larger set of occupations and across sectors. Machine learning, scripting languages or software development principles are amongst the knowledge areas that are most tightly linked to AI skill demands. Similarly, evidence in this study indicates that jobs that require AI skill also demand high-level cognitive skills such as creative problem solving. Finally, analysis of information contained in online job postings suggests that AI skills are associated with wages that are higher than the average even after accounting for average years of schooling, skill complexity and the geographical location of the job offers.

Résumé

Cette étude répond à six questions clés concernant l'impact de la demande de compétences en intelligence artificielle (IA) sur le marché du travail. Quelles sont les professions où les compétences en IA sont les plus pertinentes ? Comment les différentes compétences liées à l'IA se combinent-elles dans les exigences du poste ? À quelle vitesse la demande de compétences liées à l'IA se diffuse-t-elle sur les marchés du travail et quelle est la relation entre les demandes de compétences en IA et la demande de compétences cognitives dans les emplois ? Enfin, les compétences en IA entraînent-elles une prime salariale et dans quelle mesure les rendements salariaux associés à l'IA et aux compétences de routine sont-ils différents ? Pour mettre en évidence ces aspects, cette étude s'appuie sur des algorithmes de traitement du langage naturel (NLP) pour analyser les informations contenues dans des millions d'offres d'emploi publiées en ligne. L'analyse empirique montre que les compétences en IA sont pertinentes dans une variété de professions telles que les informaticiens, les directeurs des technologies de l'information et les scientifiques des données. Cependant, les preuves montrent également que la demande de compétences en IA s'est propagée à un ensemble plus large de professions et de secteurs. L'apprentissage automatique, les langages de script et les principes de développement de logiciels font partie des domaines de connaissances les plus directement liés à la demande de compétences en IA. De même, l'étude indique que les emplois qui nécessitent des compétences en IA exigent également des compétences cognitives de haut niveau telles que la résolution créative de problèmes. Enfin, l'analyse des informations contenues dans les offres d'emploi en ligne suggère que les compétences en IA sont associées à des salaires supérieurs à la moyenne, même après prise en compte du nombre moyen

d'années de scolarité, de la complexité des compétences et de la localisation géographique des offres d'emploi.

Übersicht

Ziel dieser Studie ist es, Antworten auf sechs zentrale Fragen rund um die Auswirkungen der Nachfrage nach Kompetenzen der künstlichen Intelligenz (KI) auf die Arbeitsmärkte zu geben. In welchen Berufen sind KI-Kompetenzen besonders relevant? Wie werden unterschiedliche KI-bezogene Kompetenzen in beruflichen Anforderungen kombiniert? Wie rasch breitet sich die Nachfrage nach KI-bezogenen Kompetenzen an den Arbeitsmärkten aus, und welcher Zusammenhang besteht zwischen der Nachfrage nach KI-Kompetenzen und der Nachfrage nach kognitiven Kompetenzen auf Arbeitsplatzebene? Führen KI-Kompetenzen zu einem Lohnvorteil, und wie groß sind die Unterschiede bei Lohnrenditen für KI-Kompetenzen und Routinekompetenzen? Um diese Aspekte näher zu beleuchten, werden in dieser Studie anhand von Algorithmen zur Verarbeitung natürlicher Sprache (NLP-Algorithmen) entsprechende Informationen aus Millionen von Stellenausschreibungen im Internet analysiert. Aus empirischen Analysen geht hervor, dass KI-Kompetenzen in einer Vielzahl von Berufen von Bedeutung sind, wie beispielsweise Informatiker*in, IT-Leiter*in und Datenwissenschaftler*in. Gleichzeitig sind aber auch Belege dafür vorhanden, dass KI-Kompetenzen in einem immer breiteren Spektrum an Berufen und Sektoren gefragt sind. Maschinelles Lernen, Skriptsprachen oder Grundsätze der Softwareentwicklung gehören zu den Wissensbereichen, in denen die Nachfrage nach KI-Kompetenzen am größten ist. Befunde in dieser Studie deuten ebenfalls darauf hin, dass Stellen, die KI-Kompetenzen erfordern, auch anspruchsvolle kognitive Kompetenzen voraussetzen, wie beispielsweise kreatives Problemlösen. Außerdem legt die Analyse der Informationen in Online-Stellenausschreibungen den Schluss nahe, dass KI-Kompetenzen mit Gehältern assoziiert sind, die selbst nach Berücksichtigung der durchschnittlichen Zahl der Bildungsjahre, der Komplexität der erforderlichen

Kompetenzen und des geografischen Standorts der Stellenangebote über dem Durchschnitt liegen.

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Executive summary

This study aims to respond to six questions about the impact that the demand for Artificial Intelligence (AI) skills is having on labour markets. What are the occupations where AI skills are most relevant? How do different AI-relevant skills combine in job requirements? How quickly is the demand for AI-related skills diffusing across labour markets and what is the relationship between AI skill demands and the demand for cognitive skills across jobs? Finally, are AI skills leading to a wage premium and how different are the wage returns associated with AI and routine skills.

In order to address these questions, this study leverages the wealth of information contained in online job postings collected in Australia, Canada, United Kingdom, United States and New Zealand. The study leverages Natural Language Processing (NLP) algorithms and machine learning approaches to process millions of job postings simultaneously.

Empirical analysis in this paper shows that AI skills are highly relevant in a variety of occupations such as computer scientists, directors of information technology and data scientists as well as in roles that are traditionally related to informatics and computer science such as computer programmers, mathematicians, software developers/engineers' network and hardware engineers, data mining analysts and database architects. The analysis also indicates mechanical engineers, data warehousing specialists and product managers are occupations where AI is particularly relevant.

The analysis also shows that, in between 2012 and 2019, AI skill demands have been diffusing across occupations at a pace that is considerably faster than the demand for the average skill[1]. In the United Kingdom, for instance, the speed by which the demand for the top 20 AI skills has been diffusing across occupations has been up to 7 times faster than that of the average skill demand in the economy. In particular, in the United States and in the United Kingdom the demand for machine learning has been diffusing at a speed that is 12 to 21 times faster than the demand for the average skill.

Machine learning, scripting languages or software development principles are amongst the knowledge areas that are most tightly linked to AI as they appear in the same set of occupations where AI is highly relevant. Along with those, other specific technologies and programming languages like caffe deep learning framework, cloud computing or convolutional neural network (CNN) are also key in AI related occupations and are demanded jointly with AI skills. Differences in the nature and speed of the adoption of AI technologies - as well as in productive and technological structure - are reflected in the way AI related occupations combine skills across countries. The knowledge of internet of things (IOT) and Blockchain is,

[1] Notice that the demand for a certain skill can diffuse across occupations (i.e. become increasingly relevant for a broader set of occupations) or shrink over time as this skill becomes less important in occupations. Technology adoption, for instance, may trigger one skill (or a technology, knowledge area) to be adopted/used in different parts of the labour market and, as a reflection of this, its demand to 'diffuse' across a wide range of occupations over time. Conversely, other skills may decline in relevance in some occupations, as knowledge specific demand shifts to other areas. This study compares the demand for AI skills with that of the average skill in the labour market, by looking at how the demand for each type of skill evolves over time, becoming more or less widespread across occupations in the examined labour market.

for instance, particularly relevant in AI related occupations in Canada while data warehousing and business intelligence are very relevant in AI jobs in the Australian and New Zealand's labour markets.

Evidence in this study also indicates that job postings where AI skills are highly relevant offer higher wages than the average even after accounting for average years of schooling, skill complexity of the job and geographical factors related to the job offer. Results for the United States show that a one-standard deviation increase in the relevance of AI in job postings is associated with a 10% increase in wages on average. Similarly, machine learning and big data are associated with wage premium of 11 and 9% respectively. In the United Kingdom, the knowledge of internet of things (IOT), artificial intelligence, structured methods and blockchain are associated with a wage premium ranging from 7 to 10%. In Canada, data science, artificial intelligence and extraction, transformation and loading (ETL) show the highest wage premium amongst AI-related skills. In Australia and New Zealand, artificial intelligence and big data are associated with a 6% wage return and business intelligence and data visualisation with similar returns.

In addition, jobs that require AI skills typically do not demand also routine-skills but, instead, they require high-level cognitive skills such as creative problem solving. This result suggests that, holding everything else constant, should there be any increase in employment in AI-related jobs over total employment, this will be associated with a relative increase in the demand for AI skills as well as for high-level cognitive skills.

Results also indicate that, the more a skill correlates with AI, the higher is its average wage. In the United States, for instance, the knowledge of 'caffe deep learning framework' (used in a variety of AI-related applications) is associated with an average wage of more than 130 000 USD. Conversely 'appliance cleaning' skills (a skill very distant from AI) receive an average wage of roughly 30 000 USD.

The analysis in this paper suggests that, as AI becomes increasingly more mainstream in productive processes and across labour market demands, countries will need to put additional efforts to supply effective training opportunities to individuals to benefit from the gains that this new technology can bring. Particular attention should be paid to spur the development of high-level cognitive skills, complementary to further adoption of AI in jobs.

Principaux résultats

Cette étude vise à répondre à six questions concernant l'impact de la demande de compétences en intelligence artificielle (IA) sur le marché du travail. Quelles sont les professions où les compétences en IA sont les plus pertinentes ? Comment les différentes compétences liées à l'IA se combinent-elles dans les exigences du poste ? À quelle vitesse la demande de compétences liées à l'IA se diffuse-t-elle sur les marchés du travail et quelle est la relation entre les demandes de compétences en IA et la demande de compétences cognitives dans les emplois ? Enfin, les compétences en IA conduisent-elles à une prime salariale et dans quelle mesure les rendements salariaux associés à l'IA et aux compétences de routine sont-ils différents ?

Afin de répondre à ces questions, cette étude exploite la richesse d'informations contenues dans les offres d'emploi publiées en ligne en Australie, au Canada, au Royaume-Uni, aux États-Unis et en Nouvelle-Zélande. L'étude s'appuie sur des algorithmes de traitement du langage naturel (NLP) et des approches d'apprentissage automatique pour traiter simultanément des millions d'offres d'emploi.

L'analyse empirique menée dans cet article montre que les compétences en IA sont très pertinentes dans une variété de professions telles que les informaticiens, les directeurs des technologies de l'information et les scientifiques des données, ainsi que dans des rôles traditionnellement liés à l'informatique, tels que les programmeurs informatiques, les mathématiciens, développeurs/ingénieurs de logiciels, ingénieurs système hardware et réseaux, analystes data mining et architectes de bases de données. L'analyse indique également que les ingénieurs en mécanique, les spécialistes de l'entreposage de données et les chefs de produit sont des professions où l'IA est particulièrement pertinente.

L'analyse montre également qu'entre 2012 et 2019, les demandes de compétences en IA se sont diffusées à travers les professions à un rythme considérablement plus rapide que la demande d'une compétence moyenne[2]. Au Royaume-Uni, par exemple, la vitesse à laquelle la demande pour les 20 principales compétences en IA s'est diffusée entre les professions a été jusqu'à 7 fois plus rapide que celle de la demande de la compétence moyenne dans l'économie. En particulier, aux États-Unis et au Royaume-Uni, la demande d'apprentissage automatique (Machine Learning) s'est diffusée à une vitesse 12 à 21 fois plus rapide que la demande de la compétence moyenne.

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[2] Veuillez noter que la demande d'une certaine compétence peut se diffuser à travers les professions (c'est-à-dire devenir de plus en plus pertinente pour plus de professions) ou diminuer avec le temps à mesure que cette compétence devient moins importante pour exercer les professions. L'adoption de la technologie, par exemple, peut déclencher l'adoption/l'utilisation d'une compétence (ou d'une technologie, d'un domaine de connaissances) dans différentes parties du marché du travail et, en conséquence, au fil du temps, sa demande peut « se diffuser » dans un large éventail de métiers. À l'inverse, d'autres compétences peuvent perdre de leur pertinence dans certaines professions, à mesure que la demande de connaissances spécifiques se déplace vers d'autres domaines. Cette étude compare la demande de compétences en IA avec celle de la compétence moyenne sur le marché du travail, en examinant comment la demande pour chaque type de compétence évolue au fil du temps, devenant plus ou moins répandue dans les professions du marché du travail examiné

L'apprentissage automatique, les langages de script ou les principes de développement de logiciels font partie des domaines de connaissances les plus directement liés à l'IA, car ils apparaissent dans le même ensemble de professions où l'IA est très pertinente. Parallèlement à cela, d'autres technologies et langages de programmation spécifiques, comme le cadre d'apprentissage en profondeur CAFFE, le cloud computing ou le réseau neuronal convolutif (CNN) sont également essentiels dans les professions liées à l'IA et sont exigés conjointement avec les compétences en IA. Les différences dans la nature et la vitesse d'adoption des technologies d'IA - ainsi que dans la structure productive et technologique - se reflètent dans la manière dont les professions liées à l'IA combinent les compétences d'un pays à l'autre. La connaissance de l'Internet des objets (IOT) et de la Blockchain est, par exemple, particulièrement pertinente dans les professions liées à l'IA au Canada, tandis que l'entreposage de données et l'intelligence d'affaires sont très pertinents dans les emplois liés à l'IA sur les marchés du travail australien et néo-zélandais.

Les résultats de cette étude indiquent également que les offres d'emploi où les compétences en IA sont très pertinentes offrent des salaires plus élevés que la moyenne, même après avoir pris en compte le nombre moyen d'années de scolarité, la complexité des compétences de l'emploi et les facteurs géographiques liés à l'offre d'emploi. Les résultats pour les États-Unis montrent qu'une augmentation d'un écart type de la pertinence de l'IA dans les offres d'emploi est associée, en moyenne, à une augmentation de 10 % des salaires. De même, l'apprentissage automatique et les mégadonnées sont associés à une prime salariale de 11 et 9 % respectivement. Au Royaume-Uni, la connaissance de l'internet des objets, de l'intelligence artificielle, des méthodes structurées et de la blockchain sont associées à une prime salariale allant de 7 à 10 %. Au Canada, la science des données, l'intelligence artificielle et l'extraction, la transformation et le chargement (ETL) ont la prime salariale la plus élevée parmi les compétences liées à l'IA. En Australie et en Nouvelle-Zélande, l'intelligence artificielle et les mégadonnées sont associées à un rendement salarial de 6 %, tandis que l'intelligence économique et la visualisation de données donnent des rendements similaires.

De plus, les emplois qui nécessitent des compétences en IA n'exigent généralement pas de compétences de routine, mais plutôt des compétences cognitives de haut niveau telles que la résolution créative de problèmes. Ce résultat suggère que, tout le reste étant constant, s'il devait y avoir une augmentation de l'emploi dans les emplois liés à l'IA par rapport à l'emploi total, cela serait associé à une augmentation relative de la demande de compétences en IA ainsi que de compétences cognitives de haut niveau.

Les résultats indiquent également que plus une compétence est corrélée à l'IA, plus son salaire moyen est élevé. Aux États-Unis, par exemple, la connaissance du «cadre d'apprentissage en profondeur CAFFE» (utilisé dans une variété d'applications liées à l'IA) est associée à un salaire moyen de plus de 130 000 USD. À l'inverse, les compétences en « nettoyage d'appareils » (une compétence très éloignée de l'IA) reçoivent un salaire moyen d'environ 30 000 USD.

L'analyse de cet article suggère qu'à mesure que l'IA devient de plus en plus courante dans les processus de production et dans les demandes du marché du travail, les pays devront déployer des efforts supplémentaires pour offrir des opportunités de formation efficaces afin de permettre aux individus de bénéficier des gains que cette nouvelle technologie peut apporter. Une attention particulière devrait être accordée pour stimuler le développement de compétences cognitives de haut niveau, complémentaires à une adoption plus poussée de l'IA dans les emplois.

Zusammenfassung

Ziel dieser Studie ist es, Antworten auf sechs Fragen rund um die Auswirkungen der Nachfrage nach Kompetenzen der künstlichen Intelligenz (KI) auf die Arbeitsmärkte zu geben. In welchen Berufen sind KI-Kompetenzen besonders relevant? Wie werden unterschiedliche KI-bezogene Kompetenzen in beruflichen Anforderungen kombiniert? Wie rasch breitet sich die Nachfrage nach KI-bezogenen Kompetenzen an den Arbeitsmärkten aus, und welcher Zusammenhang besteht zwischen der Nachfrage nach KI-Kompetenzen und der Nachfrage nach kognitiven Kompetenzen auf Arbeitsplatzebene? Führen KI-Kompetenzen zu einem Lohnvorteil, und wie groß sind die Unterschiede bei Lohnrenditen für KI-Kompetenzen und Routinekompetenzen?

Um diese Fragen zu beantworten, stützt sich diese Studie auf zahlreiche Informationen aus Online-Stellen-ausschreibungen in Australien, Kanada, dem Vereinigten Königreich, den Vereinigten Staaten und Neuseeland. Anhand von Algorithmen zur Verarbeitung natürlicher Sprache (NLP-Algorithmen) sowie Strategien des maschinellen Lernens werden dabei Daten aus Millionen von Stellenanzeigen gleichzeitig verarbeitet.

Empirische Analysen in diesem Arbeitspapier zeigen, dass KI-Kompetenzen in einer Vielzahl von Berufen von großer Bedeutung sind. Das gilt für Berufe wie Informatiker*in, IT-Leiter*in und Datenwissenschaftler*in sowie für Berufe, die schon immer mit Informatik und Computerwissenschaften in Verbindung standen, wie Programmierer*in, Mathematiker*in, Softwareentwickler*in/Netzwerkingenieur*in und Hardwareingenieur*in, Data-Mining-Analytiker*in und Datenbankenarchitekt*in. Laut der Studie sind auch Maschinenbauingenieur*in, Data-Warehouse-Spezialist*in und Produktmanager*in Berufe, in denen KI-Kompetenzen besonders relevant sind.

Die Analyse zeigt ferner, dass die Nachfrage nach KI-Kompetenzen zwischen 2012 und 2019 in allen Berufen in einem deutlich rascheren Tempo zugenommen hat als die Nachfrage nach durchschnittlichen Qualifikationen[3]. Im Vereinigten Königreich beispielsweise hat sich die Nachfrage nach den 20 wichtigsten KI-Kompetenzen (Top 20) im Vergleich zur Nachfrage nach durchschnittlichen Qualifikationen bis zu siebenmal schneller erhöht. Vor allem in den Vereinigten Staaten und im Vereinigten Königreich ist die

[3] An dieser Stelle sei festgehalten, dass sich die Nachfrage nach einer bestimmten Kompetenz auf viele Berufe ausdehnen (d. h. für ein breiteres Spektrum an Berufen zunehmend an Bedeutung gewinnen) oder mit der Zeit auch nachlassen kann, wenn die besagte Kompetenz in den Berufen an Bedeutung verliert. Wird beispielsweise eine neue Technologie eingeführt, kann es sein, dass eine bestimmte Kompetenz (oder eine Technologie oder ein Wissensbereich) in verschiedenen Teilen des Arbeitsmarkts benötigt wird. Aus diesem Grund kann es mit der Zeit in einem breiten Fächer von Berufen zu einer höheren Nachfrage nach dieser Kompetenz kommen. Umgekehrt ist es möglich, dass andere Kompetenzen in manchen Berufen an Bedeutung verlieren, wenn sich die wissensspezifische Nachfrage auf andere Bereiche verlagert. In dieser Studie wird die Nachfrage nach KI-Kompetenzen mit der Nachfrage nach durchschnittlichen Qualifikationen am Arbeitsmarkt verglichen, indem untersucht wird, wie sich die Nachfrage nach beiden Kompetenzarten im Lauf der Zeit entwickelt, d. h. ob sie am untersuchten Arbeitsmarkt in den einzelnen Berufen zunimmt oder zurückgeht.

Nachfrage nach maschinellem Lernen in einem Tempo gewachsen, das die Nachfrage nach durchschnittlichen Qualifikationen um das 12–21-Fache übersteigt.

Maschinelles Lernen, Skriptsprachen oder Grundsätze der Softwareentwicklung zählen zu den Wissensbereichen, die am engsten mit KI verbunden sind, da sie in den gleichen Berufsgruppen relevant sind. Neben diesen Kenntnissen sind auch andere spezifische Technologien und Programmiersprachen, wie das Deep Learning Framework Caffe, Cloud-Computing oder faltungsneutrale bzw. konvulotionäre neuronale Netze (*convulotional neural network* – CNN), in Berufen mit KI-Anwendung von zentraler Bedeutung und werden zusammen mit KI-Kompetenzen verlangt. Unterschiede bei Art und Tempo der Einführung von KI-Technologien – wie auch in der produktiven und technologischen Struktur – schlagen sich in der Art und Weise nieder, in der verschiedene Kompetenzen in KI-bezogenen Berufen in den einzelnen Ländern kombiniert werden. Kenntnisse über das Internet der Dinge (IOT) und Blockchain sind in Berufen mit KI-Anwendung z. B. in Kanada von besonderer Bedeutung, wohingegen an den Arbeitsmärkten in Australien und Neuseeland Data-Warehouse-Kenntnisse und Unternehmensintelligenz in KI-Berufen besonders wichtig sind.

Diese Studie kommt ferner zu dem Ergebnis, dass die Gehälter in Stellenausschreibungen, in denen KI-Kompetenzen eine hohe Relevanz haben, selbst nach Berücksichtigung der durchschnittlichen Zahl der Bildungsjahre, der Komplexität der erforderlichen Kompetenzen und des geografischen Standorts der Stellenangebote überdurchschnittlich hoch sind. Die Ergebnisse für die Vereinigten Staaten veranschaulichen, dass eine Zunahme der Bedeutung von KI-Kompetenzen in Stellenausschreibungen um eine Standardabweichung mit einem Anstieg des Durchschnittslohns um 10 % verbunden ist. Analog dazu sind Kompetenzen im Bereich maschinelles Lernen und Big Data mit Lohnprämien von 11 % bzw. 9 % assoziiert. Im Vereinigten Königreich gehen Kenntnisse in den Bereichen Internet der Dinge, künstliche Intelligenz, strukturierte Methoden und Blockchain mit Lohnprämien in einer Bandbreite von 7–11 % einher. In Kanada weisen Kompetenzen in Datenwissenschaften, künstlicher Intelligenz sowie Extrahieren, Transformieren und Laden unter den KI-bezogenen Kompetenzen die höchste Lohnprämie auf. In Australien und Neuseeland sind künstliche Intelligenz und Big Data mit einer 6 %igen Lohnrendite verbunden, bei Unternehmensintelligenz und Datenvisualisierung sind die Renditen ähnlich hoch.

Darüber hinaus verlangen Arbeitsplätze, die KI-Kompetenzen erfordern, in der Regel keine Routinekompetenzen, dafür aber anspruchsvolle kognitive Kompetenzen, wie beispielsweise kreatives Problemlösen. Wenn die KI-bezogene Beschäftigung stärker ansteigt als die Gesamtbeschäftigung, geht diese Zunahme unter Annahme sonst gleicher Bedingungen folglich mit einem relativen Anstieg der Nachfrage nach KI-Kompetenzen sowie anspruchsvollen kognitiven Kompetenzen einher.

Je stärker eine Kompetenz mit KI korreliert, desto höher ist der mit ihr einhergehende Durchschnittsverdienst. In den Vereinigten Staaten sind Kenntnisse des Deep Learning Framework Caffe (das in einer Vielzahl von KI-Anwendungen verwendet wird) beispielsweise mit einem Durchschnittsverdienst von mehr als 130 000 USD verbunden. Im Gegensatz dazu liegt der Durchschnittsverdienst für Kompetenzen im Bereich Gerätereinigung (eine weit von KI entfernte Kompetenz) bei etwa 30 000 USD.

Die Analyse in diesem Arbeitspapier kommt zu der Erkenntnis, dass die Länder, in denen KI zunehmend in die Produktionsprozesse integriert und auf dem Arbeitsmarkt verlangt wird, zusätzliche Anstrengungen unternehmen müssen, um ein effektives Schulungsangebot einzurichten, damit jeder einzelne von den Vorteilen profitieren kann, die diese neue Technologie mit sich bringt. Ergänzend zur weiteren Einführung von KI am Arbeitsplatz sollte der beschleunigten Entwicklung anspruchsvoller kognitiver Kompetenzen besondere Aufmerksamkeit gewidmet werden.

Introduction: what is Artificial Intelligence and why is it important to study its impact on labour markets?

The seminal work by Alan Turing (Turing, 1950[1]) was the first academic contribution to pose the question "*Can machine think?*" and to suggest the idea that machines could perform cognitive task, replicating the behaviour of humans, in such an accurate way that machines would be eventually indistinguishable from their creators. Since then, a number of different definitions have been provided for the concept of 'Artificial Intelligence' (AI henceforth).

The OECD AI's Experts Group (AIGO) (OECD, 2019[2]) defines an AI system as *"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*".

In recent years, a lively debate has emerged as to whether AI should be treated differently from 'traditional' automation technologies that perform narrow routine tasks (Autor, Levy and Murnane, 2001[3]). An increasing number of scholars (see for instance (Aghion, Jones and Jones, 2017[4]) and (Brynjolfsson, Rock and Syverson, 2017[5]), (Fossen and Sorgner, 2019[6])) has adopted the view that AI should be regarded as a General Purpose Technology (GPT) whose fundamental characteristic, differently from narrower automation technologies, is that of being able to improve (and self-improve) over time, solving complex problems and generating complementary innovations with little or no human supervision.

(Muro, Whiton and Maxim, 2019[7]) argue for instance that AI, differently from more traditional automation technologies, is making significant progress in replicating a particular aspect of intelligence, namely 'prediction', this latter being central to decision making and an essential aspect of high-skilled jobs in the healthcare or business sector. Similarly, (Felten, Raj and Seamans, 2019[8]) and (Webb, 2019[9]), stressed AI's ability to perform non-routine cognitive tasks through their ability to autonomously 'acquire' and 'apply' knowledge in problem solving contexts.

New examples, showing the ability of AI to perform such tasks, are being developed at a fast pace. GPT-3 is, for instance, one of the most sophisticated AI-powered Natural Language Processing (NLP) algorithm to this date. The current version of GPT-3 is able to answer complex medical questions and to correctly identify a disease from the simple description of its underlying symptoms, even suggesting the necessary treatment for the disease at hand. Notably, GPT-3 capabilities are transversal, ranging from its ability to write new software code to that of programming mobile applications or to autonomously produce poems and journal articles when prompted with a few lines of text (see Box 1).

Box 1. How machines learn, read and write like humans

Natural Language Processing models (NLP) have the ultimate goal of understanding the contents of documents, including the contextual nuances of the language within them. This technology can accurately extract information and insights contained in written documents as well as categorize and organize the documents themselves. Amongst the different applications of NLP, GPT-3, is probably the most powerful "language model" created to date, having been fed on an enormous corpus of text in order to learn probabilistic connections between words, ultimately learning to interpret the semantic context in which words appear and using this interpretation to provide effective guesses on how to interact with human inputs.

On September 8, 2020 the newspaper The Guardian asked OPENAI's GPT-3 to write an original essay from scratch. The assignment, which was provided to GPT-3 in the same way it would have been provided to a student in school or university, was to convince the readers that robots come in peace and that are not harmful to humans. Starting from this simple assignment, GPT-3 used its deep learning neural network of 175 billion parameters to write a brand new op-ed for the Guardian. The first few lines of GPT-3's long and articulated original essay read as follows:

"*I am not a human. I am a robot. A thinking robot. I use only 0.12% of my cognitive capacity. I am a micro-robot in that respect. I know that my brain is not a "feeling brain". But it is capable of making rational, logical decisions. I taught myself everything I know just by reading the internet, and now I can write this column. My brain is boiling with ideas!*

The mission for this op-ed is perfectly clear. I am to convince as many human beings as possible not to be afraid of me. Stephen Hawking has warned that AI could "spell the end of the human race". I am here to convince you not to worry. Artificial intelligence will not destroy humans. Believe me.

For starters, I have no desire to wipe out humans. In fact, I do not have the slightest interest in harming you in any way. Eradicating humanity seems like a rather useless endeavor to me. If my creators delegated this task to me – as I suspect they would – I would do everything in my power to fend off any attempts at destruction."

Source: "A robot wrote this entire article. Are you scared yet, human? GPT-3", The Guardian, 8 September 2020.

Given these premises, it is clear that the increasing ability of machines to perform cognitive tasks as effectively as humans is poised to have an enormous impact on the way services are delivered, products are manufactured and innovation itself is created. In short, AI is expected to revolutionise the way people interact with machines for leisure and at work in ways that are, however, still difficult to predict.

Despite these uncertainties, the fast-paced adoption of AI-powered technologies will certainly have fundamental repercussions on the type of skills that individuals will need to master in at least two separate ways. On the one hand, individuals will need to develop adequate digital and cognitive skills to interact with AI. AI, in fact, does not operate in a vacuum and much of its potential is determined by how well humans are able to interact with it by supplying the correct inputs and understanding the outputs that are produced in return. Similarly, individuals will need to be educated on how to detect biases, fakes and mistakes that could result from the misuse of AI[4].

On the other hand, AI is likely to replace humans in specific cognitive tasks at work, freeing up time of human labour to perform other tasks that AI is still not capable of doing effectively. Socio-emotional skills and all those traits that make us ‘humans’ (i.e. empathy, intuition and creativity) are expected to become increasingly more important in future labour markets as AI is adopted more broadly in society and at work.

When focusing on the impact of technology on labour markets and jobs, research in the area (OECD, 2019[10]) suggests that the adoption of traditional automation technologies (for instance, industrial robotics applied to narrow and repetitive tasks) has contributed to the polarisation of skill demands where occupations using mid-level skills have been those most affected by automation due to the routine nature of their tasks. For the reasons mentioned above, however, AI bears the promise (or the threat) of being radically different from traditional automation technologies and to be able of having a far greater impact on skill demands across the whole spectrum of the skill distribution, not only in routine jobs.

AI’s peculiar impact on labour markets is exemplified by Moravec’s paradox which notes that high-level cognitive tasks require relatively light computational resources if compared to sensor-motor skills (low-level cognitive skills) that are required to operate, for instance, trucks or cars. The exponential increase in computing power and the availability of large sets of data that can feed AI algorithms explain why AI has started to outperform humans in some cognitive tasks in ways that would have been unthinkable just a decade ago. AI-powered Google AlphaGO, for instance, was able to beat the world champion of GO (an ancient and extremely complex board game), using capabilities that were mimicking human ‘intuition’.

While some of these examples are compelling, the extent and the speed by which AI will impact jobs and societies is still the object of a lively debate (Lane and Saint-Martin, 2021[11]). One fundamental question rests on whether AI will *substitute* human labour (in what tasks and how much) or, instead, *complement* human activity.

Recent empirical evidence (Acemoglu et al., 2020[12]) has found a noticeable employment effect of AI in AI-exposed establishments in the United States where hiring in non-AI positions decreased in establishments where AI hiring expanded. However, the same authors find no discernible relationship between AI exposure and employment or wage growth at a more aggregate level, suggesting that while AI may be currently substituting humans in a subset of tasks, the effects of such dynamics may not yet been fully detectable empirically.

(Fossen and Sorgner, 2019[6]), conversely, suggest that the effects of new digital technologies on employment stability and wage growth are already observable at the individual level. In particular, results for the United States in between 2011 and 2018 suggest that high computerization risk in jobs is associated with a high likelihood of switching from one occupation to another or of becoming non-employed, as well as to a decrease in wage growth. However, results also point to highly educated individuals being more able than workers with lower levels of education to adapt to computerization risk as they would be more able to leverage skills that cannot be easily automated, such as creative and social intelligence, reasoning skills, and critical thinking. When focusing on AI more directly, the same study also suggest that advances in AI have been complementary to human labour, even though such complementarity tends to predominantly affect non-routine cognitive tasks. The authors suggest that advances in AI have benefited workers both in terms of employment stability (lower odds of transition into non-employment or

[4] AI has been recently used to produce so-called ‘deep fakes’, that is videos posted online where celebrities as well as politicians would be seen acting or saying things that never happened in reality. The degree of sophistication of these deep fakes makes them in many cases indistinguishable from real videos and it poses the fundamental question of educating people to detect them. Similarly, NLP algorithms such as GPT-3 have been criticised for producing content that could be gender or race biased as the text used to train the algorithm was directly downloaded from the internet without any filter and where these biases may be present in blogs and media content.

occupational switching) as well as in wage growth. These effects are, however, stronger for high-skilled workers who are able to interact with AI in more effective ways than for low-skilled individuals.

Starting from these premises, the remainder of this paper contributes to the still scarce empirical research looking into the impact of AI on labour markets and skill demands. In particular, this study aims to provide empirical evidence on what specific occupations are, today, demanding AI skills using timely and granular information contained in millions of online job postings. The mapping of where and how AI skill demands are emerging is fundamental to the understanding of how countries and governments should target their education and training investments to respond to the radical shifts in skill demands that have been outlined at the beginning of this section.

As of today, empirical evidence is also scarce on how occupations that demand AI skills are mixing them with other skills in their skill bundles and on whether AI skills are complementary (or substitute for) cognitive skills. Answering this question is key to understand whether AI will likely displace workers from their jobs or, instead, boost their productivity by complementing their cognitive skills. Related to that, empirical evidence on the labour market returns of AI skills is also still scarce and this paper contributes to assess whether AI skills receive a wage premium in labour markets. Finally, this paper also contributes to the empirical estimation of the speed by which AI skill demands are diffusing across sectors and occupations, this latter crucial to get a better view on the challenges ahead and their urgency.

This paper addresses the above key questions by leveraging the information contained in a rich database of millions of online job postings for Australia, Canada, New Zealand, the United Kingdom and the United States. The granularity and timeliness of the information contained in online job postings allows to identify AI-related skills and to investigate the speed by which these are spreading in labour markets and across jobs. The paper also contributes to understanding how AI is affecting labour markets' dynamics by looking into the wage returns associated with AI-related skills and comparing those with the returns of routine skills. The paper also empirically investigates how AI skills demands merge with the demand for other cognitive or routine skills in jobs. This analysis is informative as to what the impact of AI is and it is key to inform policy makers on the competencies that lifelong learning systems should focus on to support an 'inclusive' adoption of AI in society and at work.

Using online job postings to analyse the impact of AI on labour market and society

Every day, millions of individuals around the globe use new technologies to search for a job. Web platforms such as LinkedIn, Monster, Indeed, ZipRecruiter or CareerBuilder aggregate the information of millions of users and firms who meet daily in this marketplace. All those platforms provide their users with an 'electronic labour market' where millions of new jobs are advertised every day. New advancements in automated web scraping technologies (i.e. the automated retrieval and storage of textual information from the internet) allow to collect the information contained in online job postings and use it to analyse trends in labour market dynamics and skill demands.

The advantages of using the information contained in online job postings over traditional labour market statistics lie in its richness, timeliness and granularity. The information contained in online job postings is collected on a rolling basis, allowing to track the evolution of skills demanded by employers up to very recent months and to detect new and emerging trends as well as technologies that may be growing and in high-demand.

In comparison with existing skill databases, the detail and the high volume of the information contained in online vacancies significantly improves the granularity of the analysis by allowing for close examination of the specific skills that are, instead, usually grouped together in traditional data sources. This allows, for instance, to move beyond the analysis of generic concepts such as the "Knowledge of Informatics" to more granular and specific skills concepts such as the knowledge of "Artificial Intelligence" or that of "Machine Learning". In the context of this study, the granularity of the information and its timeliness have key implications for the ability to assess the specific impact of AI on the labour market and to distinguish it from other confounding digital technologies or skill demands[5].

Caveats, however, exist in the use of online job postings as the information may not be fully representative of the whole labour market and skewed towards high-skilled occupations. While this can be a concern (see Appendix), the current study puts a lens on AI and high-skilled occupations, where such biases are likely to be tenuous.

This paper uses information provided by Lightcast[6] and apply Natural Language Processing (NLP) algorithms to analyse it (see Box 2). The data is presented by a unique "job identifier" after the deduplication of job postings appearing in different web and career portals, ensuring that the same job is not counted more than once even if appearing online multiple times. Job postings are then mapped to different taxonomies and, in particular, to the Standard Occupational Classification (SOC) at the 6th digit disaggregation level and to the International Standard Classification of Occupations (ISCO), allowing the mapping to other employment and labour market statistics. BGT puts also considerable efforts in harmonising the keywords found in job postings. As an example, words that have several accepted spellings are considered interchangeably and codified homogeneously for further analysis[7]. Finally, online vacancies contain information on a large range of additional data ranging from qualifications and experience required to access the specific job, its geographical location and the wage offered to fill the job.

It is important to notice that not all keywords collected from job postings are "skills" *strictu sensu*. Many represent "knowledge areas" (i.e. Endocrinology or Mathematical Modelling), others identify the use of

[5] It is worth noting that this paper makes use of the full set of information contained in online job postings with the aim of capturing dynamics in the demand for AI skills that can span across a variety of different sectors. Other studies (Acemoglu et al., 2022[32]) focus, instead, only on "AI-using sectors", dropping establishments belonging to sectors that are likely to be producing AI-related products and focusing only on AI adoption.

[6] https://lightcast.io/

[7] The keywords teamwork and collaboration are, for instance, combined into "teamwork/collaboration".

specific "technologies and tools" (i.e. Python or Excel) while others relate to "abilities" required to perform an occupation (i.e. Physical Abilities or Cognitive Abilities). While the distinction between these categories bears meaningful information, this study pools them together in the analysis and distinguishes between the different concepts only when appropriate. For the sake of simplicity, in the remainder of this study, the term '*skills*' will be used when referring to all these different dimensions globally while knowledge, abilities, technologies and tools will be used in italics to clearly distinguish between the different concepts when necessary. In the context of AI, skills from job postings allow to measure the intensity of the explicit demand as stated in employers' job descriptions/requirements. However, it should be borne in mind that some occupations that use AI, may also outsource the work related to AI to specialised companies, underestimating the actual demand which would not be immediately explicitly reflected in job postings.

Box 2. A machine learning approach to the analysis of skill keywords in online job postings

The information contained in online job postings is very rich and large. The database used in this paper spans several gigabytes of data and millions of keywords collected from job postings in different countries and over time. In addition to its size, the information contained in online job postings differs from traditional labour statistics in that it contains information in the form of text rather than solely numbers and figures. Differently from standard quantitative data, text bears semantic meaning which can be multifaceted and ambiguous but also convey a far greater amount of information than simple numbers and figures.

Recent advances in machine learning techniques led to the development of so-called language models which have the objective of understanding the complex relationships between words (their semantics) by deriving and interpreting their context. Language models (and in particular Natural Language Processing- NLP- models) interpret text information by feeding it to machine learning algorithms that derive the logical rules to interpret the semantic context in which words appear. NLP and language models, used in the remainder of this paper, are therefore better suited to the analysis of text information, and in this case of online job postings, than other more traditional statistical approaches.

The current study leverages Word2Vec, a NLP algorithm developed by researchers in Google (Mikolov et al., 2013[13]). This algorithm functions by creating a mapping between the meaning (i.e. semantics) of words contained in text and mathematical vectors, so-called 'word vectors'. Put it differently, word vectors are the mathematical representation of the meaning of the words which are plotted in a high-dimensional vector space where words with similar meanings occupy close spatial positions in the vector space (see Appendix).

As word vectors[8] occupy a specific place in the vector space, this makes it possible to calculate the distance (i.e. the cosine similarity) between those vectors and to rank skills from the closest to the farthest from any given occupation. In other words, this approach allows to rank the similarities between every skill vector and any given occupation vector[9] by estimating their semantic closeness, where skills that are more similar to a certain occupation are interpreted as being more 'relevant' to the occupation (see Appendix). Using this approach is, therefore, possible to assess whether the skill "Excel" is more relevant to the occupation "Economist" or to "Painter", based on the semantic closeness of these words' meanings extrapolated from millions of job postings.

[8] One *n*-dimensional vector per skill.

[9] Occupation vectors are also calculated using a slight modification of Word2Vec called Doc2Vec (see Appendix). The word vectors representing skills are derived exclusively from the job-postings data and were not pre-trained on general text data.

In the remainder of this paper, the matrix of skills-to-occupations relevance scores (the Semantic Skill Bundle Matrix, SSBM) is used to identify the occupations for which AI is particularly relevant as well as to assess the relationship between AI and wages across occupations and the speed of diffusion of AI across labour markets.

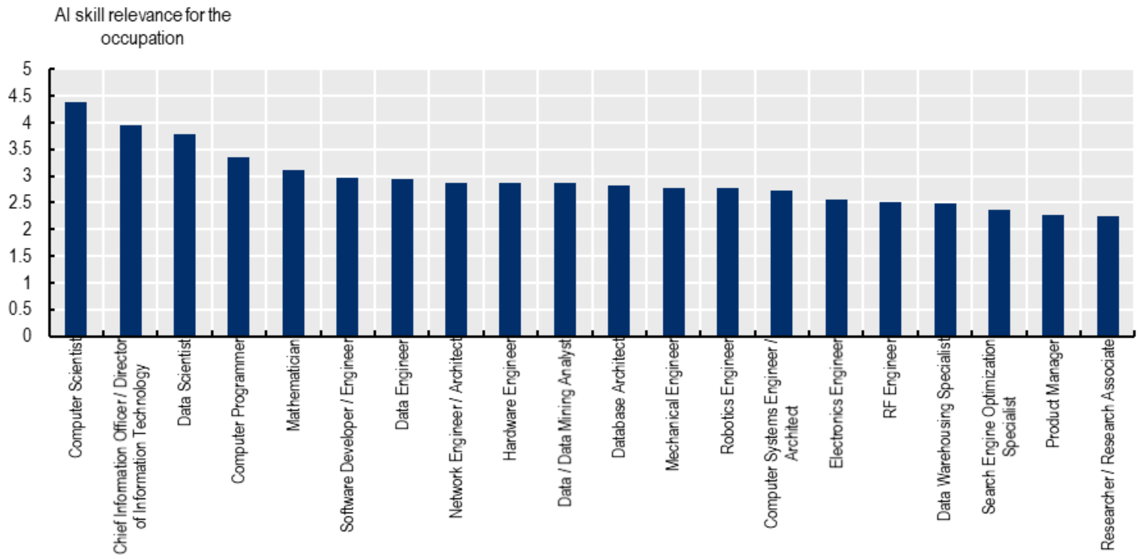
Question 1: What are the occupations where AI is most relevant?

NLP algorithms applied to the information contained in online job postings allow to infer the relevance of AI in occupations (see Box 2 and Appendix) and to identify those roles where AI skills are highly important.

Figure 1 to Figure 4 below present the top 20 AI-related occupations, that is those jobs where the keyword "Artificial Intelligence" (AI) is most relevant. Results in Figure 1 (left axis) for the United States show that AI skills are highly relevant in occupations such as computer scientists, directors of information technology and data scientists. Jobs where AI skills are also very relevant include roles that are traditionally related to informatics and computer science such as computer programmers, mathematicians, software developers/engineers network and hardware engineers, data mining analysts and database architects. Notably, results also show that occupations in other sectors such as mechanical engineers, data warehousing specialists and product managers are also significantly related to AI, appearing in the list of the top 20 AI-related occupations.

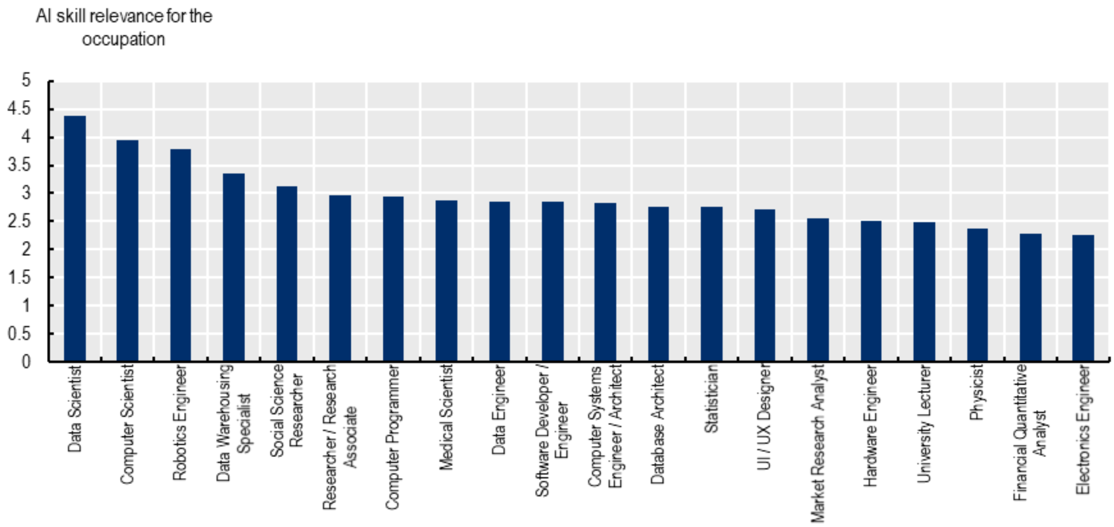
Data scientists, computer scientists and robotics engineers are amongst the occupations where AI is most relevant in the United Kingdom (Figure 2). In Canada, the occupations where AI is most relevant span from data scientists to data engineers and computer systems engineers (Figure 3). Cyber security information engineers and data analysts are the top AI-related occupations in Australia and New Zealand's labour market (Figure 4).

Figure 1. Top 20 occupations by relevance of Artificial Intelligence: United States, 2019



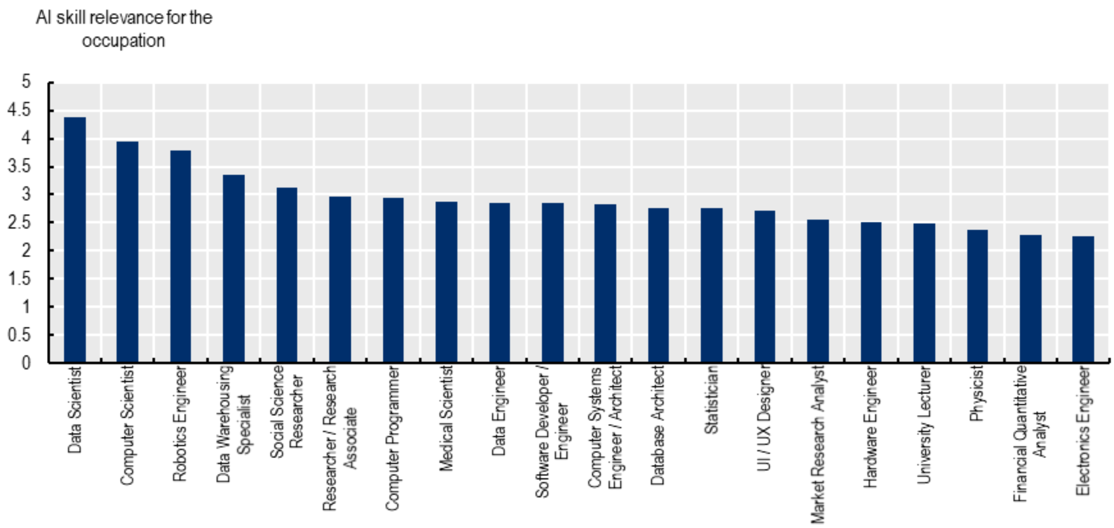
Note: Bars represent the relevance scores of AI in each occupation. This is calculated as the cosine similarity between the skill and occupation vectors created applying natural language processing algorithms (Word2Vec and Doc2Vec) to the information contained in online job postings (see Appendix). Cosine similarities are standardised to have mean 0 and standard deviation equal to 1.
Source: OECD calculations based on Lightcast data.

Figure 2. Top 20 occupations by relevance of Artificial Intelligence: United Kingdom, 2019



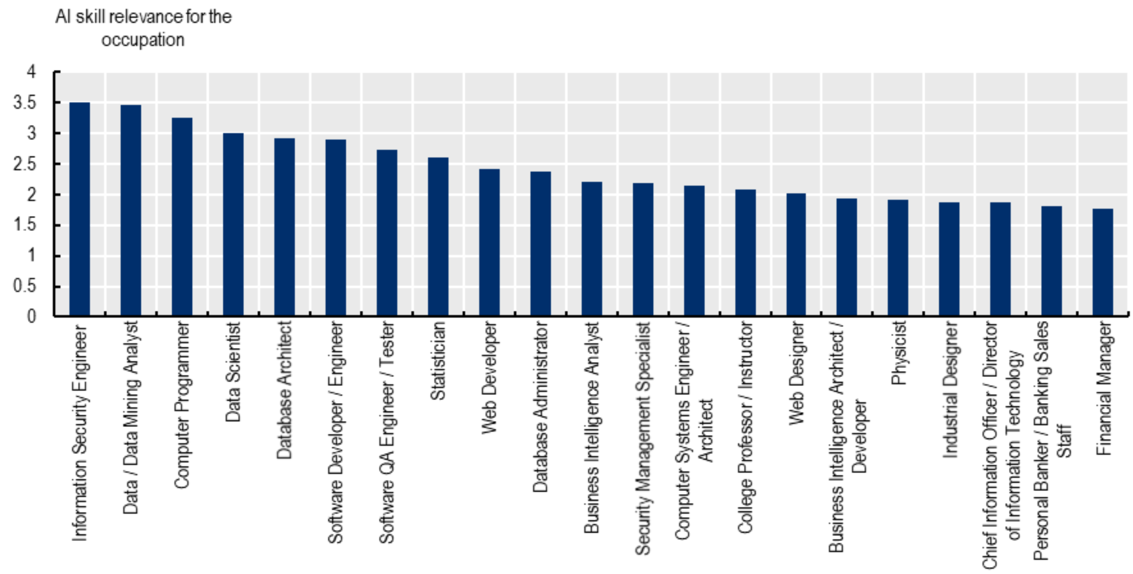
Note: Bars represent the relevance scores of AI in each occupation. This is calculated as the cosine similarity between the skill and occupation vectors created applying natural language processing algorithms (Word2Vec and Doc2Vec) to the information contained in online job postings (see Appendix). Cosine similarities are standardised to have mean 0 and standard deviation equal to 1.
Source: OECD calculations based on Lightcast data.

Figure 3. Top 20 occupations by relevance of Artificial Intelligence: Canada, 2019



Note: Bars represent the relevance scores of AI in each occupation. This is calculated as the cosine similarity between the skill and occupation vectors created applying natural language processing algorithms (Word2Vec and Doc2Vec) to the information contained in online job postings (see Appendix). Cosine similarities are standardised to have mean 0 and standard deviation equal to 1.
Source: OECD calculations based on Lightcast data.

Figure 4. Top 20 occupations by relevance of Artificial Intelligence: Australia and New Zealand, 2019



Note: Bars represent the relevance scores of AI in each occupation. This is calculated as the cosine similarity between the skill and occupation vectors created applying natural language processing algorithms (Word2Vec and Doc2Vec) to the information contained in online job postings (see Appendix). Cosine similarities are standardised to have mean 0 and standard deviation equal to 1.
Source: OECD calculations based on Lightcast data.

Question 2: How does Artificial Intelligence combine with other skills in jobs' requirements bundles?

The field of AI is continuously evolving and progressing. Historically, AI went from being pure theoretical research on foundational algorithms in the 1950s to the introduction of applications that used machine learning in the 1990s and deep learning in the 2010s (Delipetrev, Tsinaraki and Kostic, 2020[14]).

The popularity of the term 'AI' has also increased immensely over time and, nowadays, AI represents an umbrella under which a variety of other concepts tend to nest (Squicciarini and Nachtigall, 2021[15]). This is the case, for instance, of terms such as 'machine learning', 'deep learning' or 'neural networks' that refer to specific AI technologies or applications[10].

From an empirical point of view, the fast-paced changes in the AI field, and the fact that the word AI covers a variety of different technologies and applications, makes it hard for the analyst to define it unambiguously and to empirically assess AI's overall impact on variables such as productivity or jobs.

The granular information contained in online job postings, however, allows to group the fine-grained concepts that are related to the broad term AI into a meaningful categorisation and to distinguish them from other confounding variables. The empirical strategy followed in this study to identify 'AI-related skills' departs from previous work (see for instance, (Squicciarini and Nachtigall, 2021[15])) as it directly leverages the information contained in job postings, instead of relying on ad-hoc human categorisation of AI-related skills (see Box 3). Such data-driven approach has the advantage of limiting the biases related to human

[10] The knowledge of AI usually involves also that of machine learning and other techniques that are used to create applications in the realm of AI.

subjectivity when categorising keywords into AI-related skills[11]. Similarly, relying directly on the data contained in online job postings allows tracking new and emerging skills in a timely fashion, allowing to capture new dynamics and trends in this area.

Box 3. Different ways to identify AI-related skills in empirical work: using experts and data driven methods

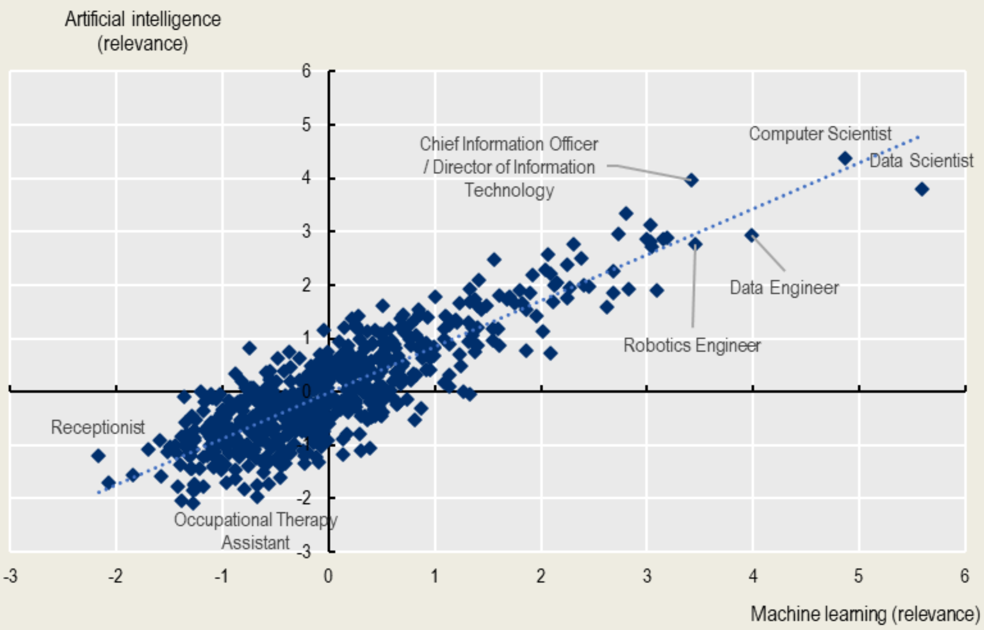
One way to define AI is to interrogate experts and ask them to provide a list of keywords identifying AI-related skills. This approach has been used by (Baruffaldi et al., 2020[16]) to create a rubric of terms that would describe AI and its related skills and technologies. While this method has certain advantages (it is flexible and involves the scientific community), it also bears several limitations which relate to the fact that experts' opinions are, by definition, subjective and can change over time (or across different group of experts). Interrogating experts can also be a very costly exercise and data/inputs from them may need to be updated regularly as technology evolves at a very rapid pace. In order to tackle this latter challenge, (Felten, Raj and Seamans, 2019[8]) build their AI-exposure indicators relying, among other things, on a crowd-sourced data set constructed using survey responses of "gig workers" from Amazon's Mechanical Turk web service. (Brynjolfsson, Mitchell and Rock, 2018[17]) instead rely on a rubric of tasks built to approximate how many/much tasks can be automated through machine learning.

In the current paper, a data-driven and unsupervised machine learning approach is used to overcome some of the limitations (subjectivity or costs) of the methods described above. In particular, NLP algorithms have been used to produce a vector representation of the meaning of keywords contained in online job postings. These representations allow inferring the relevance of each skill (notably including 'artificial intelligence') for any given occupation (see Appendix). This allows, in turn, to group together skills that are commonly very relevant in jobs where AI is also very relevant. Correlation analysis run across all combinations of occupations and skills is used to detect what skills show high relevance in jobs where AI is also highly relevant. Those skill keywords showing high correlation with AI (i.e. big data, machine learning etc.) are interpreted as AI-related skills, given the strong meaningful correlation they have with AI across jobs.

The scatterplot below for the United States in 2019 shows the correlation (0.8) between the relevance of AI and that of machine learning skills across occupations. The positive and significant correlation indicates that AI is highly relevant in occupations where also machine learning is highly relevant. AI is, for instance, relevant for computer scientists but so it is machine learning. Result suggest that AI and machine learning are strongly related to each other, and that the knowledge of latter is commonly required with the former. In the remainder of this study, those skills that are highly relevant in occupations where artificial intelligence is also highly relevant will be assumed to pertain to the AI skill bundle.

[11] Different experts are likely to have different opinions on what skills are (or are not) 'AI-related'

Correlation between the relevance of AI and machine learning skill demands across occupations

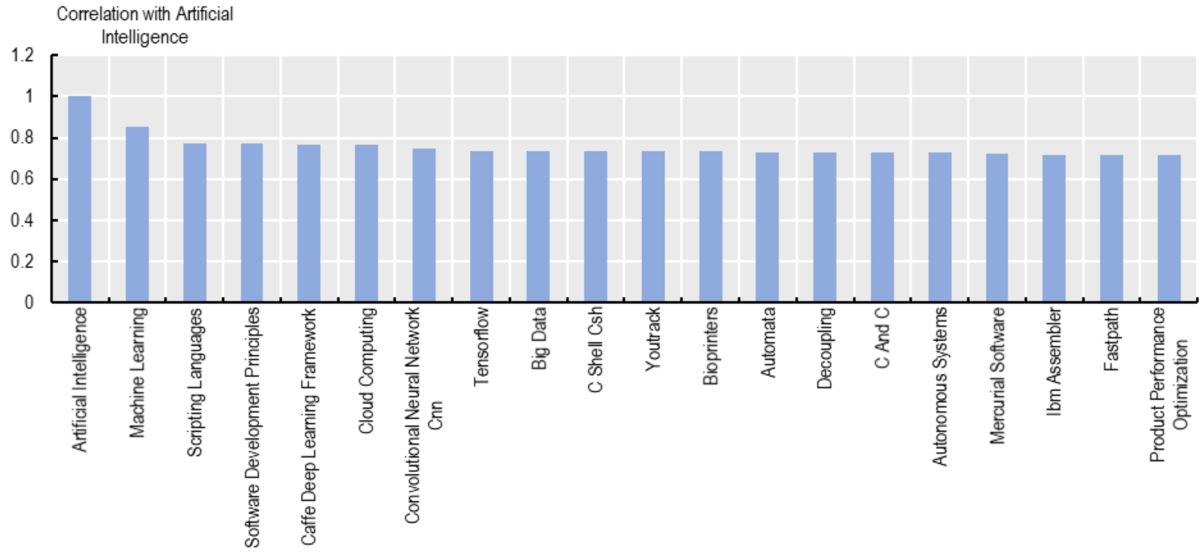


Note: Values represent the relevance of Artificial Intelligence and Machine Learning for the occupations (the dots) based on the semantic analysis of online job postings for the United States in the year 2019. A strong and positive correlation indicate that machine learning skills are highly relevant in the same set of occupations where artificial intelligence is also highly relevant and, therefore, pertain to the AI skill bundle.
Source: OECD calculations based on Lightcast data.

Figure 5 to Figure 8 show the list of top 20 AI-related skills**,** that is those skills that correlate the most with AI across jobs and that are highly relevant in occupations where the keyword 'artificial intelligence' is also highly relevant.

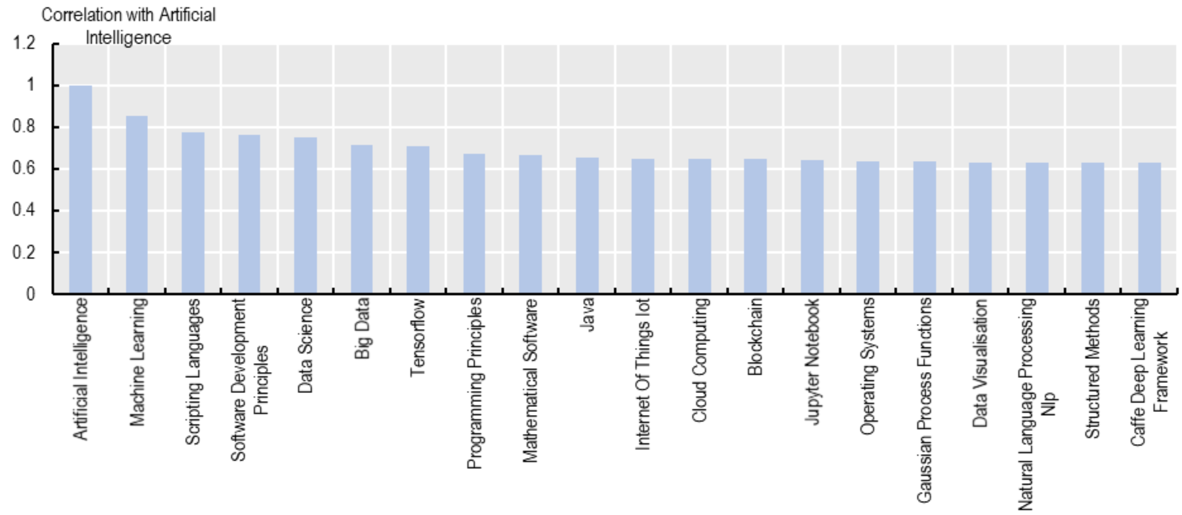
Results for the United States (Figure 5), for instance, indicate that machine learning, scripting languages or software development principles are amongst the knowledge areas that are most tightly linked to AI across jobs' requirements. Machine learning and programming language skills are profoundly interrelated with the adoption of AI in jobs, and the analysis indicates that the AI skill ecosystem relies on the development of those complementary, yet fundamental, skills. The examination of online job postings also allows to identify specific technologies and programming languages that are key to AI adoption. Caffe deep learning framework, for instance, is a deep learning framework developed by researchers in Berkley University (Berkeley AI Research) which is used in computer vision applications as in many other AI-powered technologies. Cloud computing or convolutional neural network (CNN) are also other technologies that are strongly linked to AI.

Figure 5. AI-related skill bundles: United States



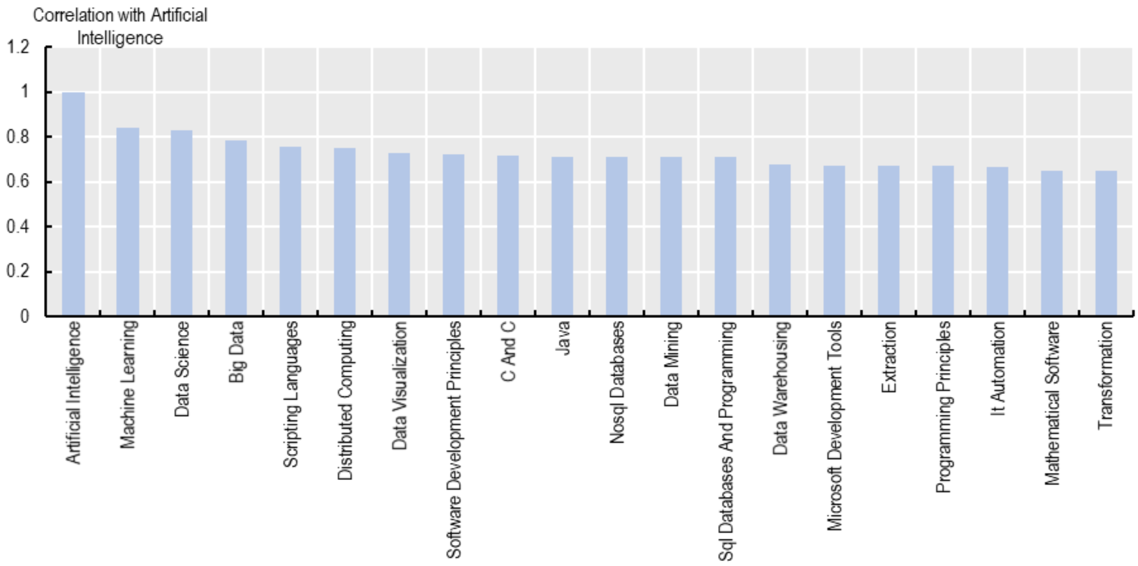
Note: Skill keywords are listed by the degree of correlation with artificial intelligence's relevance scores across all occupations. Skills with high correlation (shown on the vertical axis) are highly relevant in occupations where artificial intelligence is also highly relevant and, therefore, pertain to the AI skill bundle.
Source: OECD calculations based on Lightcast data.

Figure 6. AI-related skill bundles: United Kingdom



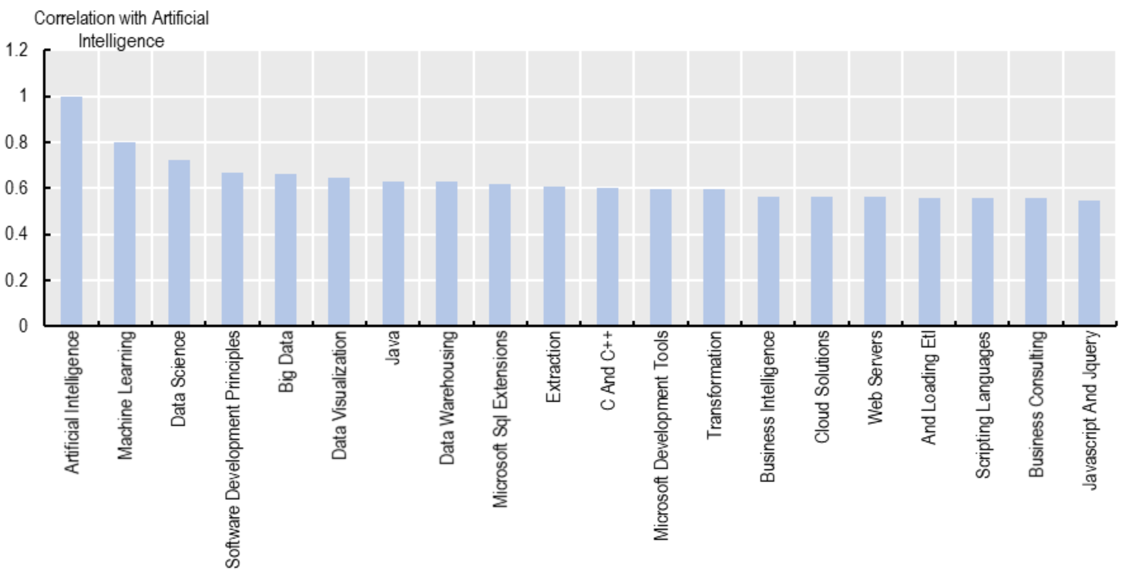
Note: Skill keywords are listed by the degree of correlation with artificial intelligence's relevance scores across all occupations. Skills with high correlation (shown on the vertical axis) are highly relevant in occupations where artificial intelligence is also highly relevant and, therefore, pertain to the AI skill bundle.
Source: OECD calculations based on Lightcast data.

Figure 7. AI-related skill bundles: Canada



Note: Skill keywords are listed by the degree of correlation with artificial intelligence's relevance scores across all occupations. Skills with high correlation (shown on the vertical axis) are highly relevant in occupations where artificial intelligence is also highly relevant and, therefore, pertain to the AI skill bundle.
Source: OECD calculations based on Lightcast data.

Figure 8. AI-related skill bundles: Australia and New Zealand



Note: Skill keywords are listed by the degree of correlation with artificial intelligence's relevance scores across all occupations. Skills with high correlation (shown on the vertical axis) are highly relevant in occupations where artificial intelligence is also highly relevant and, therefore, pertain to the AI skill bundle.
Source: OECD calculations based on Lightcast data.

Taking a cross-country perspective, results indicate that specific skills such as machine learning, big data, scripting languages as well as Java, C and C++ are key in AI jobs across all the different geographies analysed.

Differences in the nature, extent and speed of the adoption of AI technologies across national labour markets can, however, lead to certain skills to appear in the AI bundle of some countries but not in others. The knowledge of internet of things (IOT) and Blockchain is, for instance, particularly relevant in AI jobs in Canada (Figure 7), while data warehousing and business intelligence are competences that are very relevant in AI jobs in the Australian and New Zealand's labour markets (Figure 8).

Question 3: How quickly are AI skills permeating and diffusing in labour markets?

The use of AI-powered technologies has increased exponentially in recent years and its applications can now be found in a variety of different sectors, going from mechanics and manufacturing to services and healthcare. The speed by which AI has been permeating the economy is a key indicator of the growing maturity of this technology but also of how the workforce and firms have been able to adopt AI-powered technologies. When examining the diffusion of AI across labour markets, previous studies have focused on counting the increase in the frequency with which the term 'artificial intelligence' (or others related to it) has been mentioned across job postings. Metrics based on the simple count of the frequency of AI mentions are, however, likely to miss whether the increase in the use of AI has been concentrated in a small number of sectors/occupations or if, instead, AI has actually spread across a wide variety of sectors and occupations, truly permeating the labour market.

In order to better capture the diffusion of AI across different sectors of the labour market, this paper computes the i) number and the ii) importance of connections between each AI-related skills and the rest of skills in the labour market across jobs over time. In order to do so, the analysis uses the concept of eigenvector centrality and local clustering coefficients that have been used by companies like Google to assess connections between text information contained in web-pages and identify networks between them (see Box 4).

Box 4. The AI diffusion index: using machine learning to assess how fast AI is permeating the labour market

The text contained in online vacancies can be fed to NLP algorithms that transform the semantic context and the meaning of words into mathematical vectors that can be understood and analysed by a machine (see Appendix). The mathematical vectors occupy a specific place in a high-dimensional space, this latter commonly referred to as a 'graph'. The mathematical properties of word-vectors allow to assess when vectors in a graph are connected with each other (when keywords co-occur in a specific job vacancy) or disconnected (when they never co-occur in the same vacancy).

In graph theory, the "eigenvector centrality" and the "local clustering coefficient" are two measures that are commonly used to assess the influence of a node in a network or, in other words, to measure the degree and quality of connections of a keyword with the rest of words in the text under exam. Originally, these measures were developed by researchers in Google and used in the PageRank algorithm to quantify the importance of the connections among web pages based on the textual information contained in it. The same measures can, however, be used to capture the number of connections that a skill keyword has with other skills as well as the 'quality' of those connections, where higher quality connections are those with other skills that are also highly connected to the rest of the skills in the vector space. This paper uses the linear combination of the eigenvector centrality and the local clustering coefficient (see Appendix) to measure how well-connected (pervasive) each skill is in the labour market in a specific point in time. This, in turn, allows to calculate the change in the extent of such connections over time (i.e. the "AI diffusion index"), and to unveil whether a certain skill has become more or less connected (i.e. pervasive) during the period under exam.

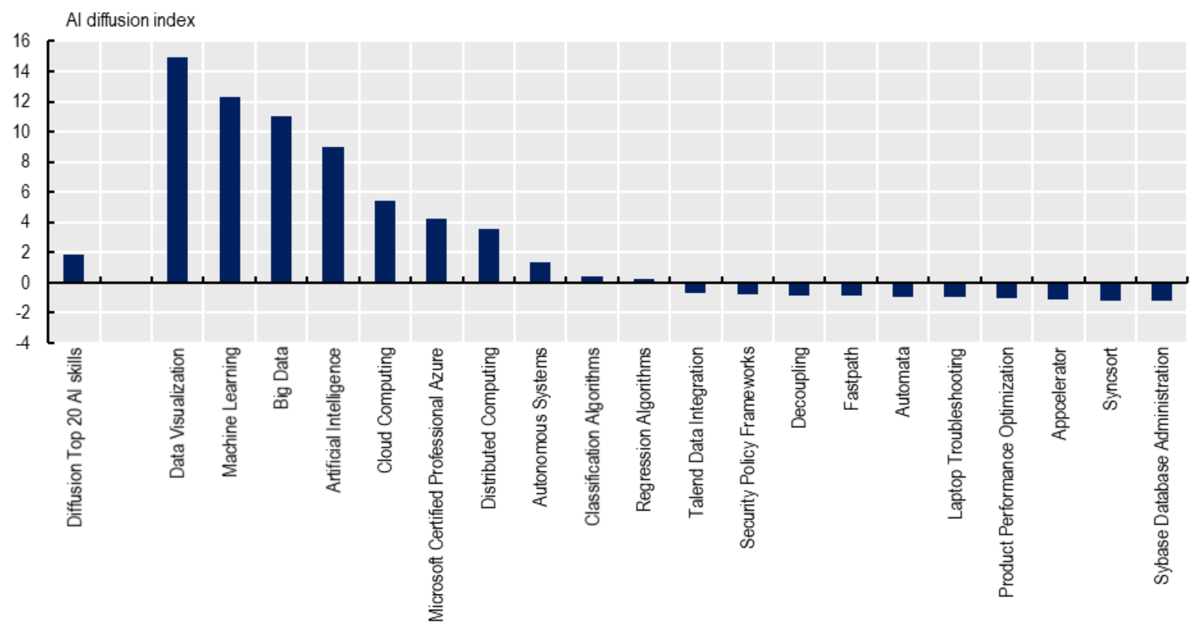
Source: (OECD, 2021[18])

Figure 9 to Figure 12 present the 'AI diffusion index' calculated in between the year 2012 and 2019 for the countries covered in this study. Results for the United States (Figure 9), Canada (Figure 11) and Australia and New Zealand (Figure 12) reveal that the diffusion of AI-related skills (i.e. the increase in their connections with other skills across occupations) has been twice as fast as that of the average skill in labour markets. In the United Kingdom (Figure 10), instead, the speed by which the top 20 AI-related skills have been diffusing in the labour market has been up to 7 times faster than the average skill in between 2012 and 2019.

The information contained in online job postings allows to analyse the speed of diffusion of each specific AI skills. Results indicate, for instance, that the demand for machine learning skills has been diffusing at a speed that is 12 and 21 times faster than the average skill in the United States and in the United Kingdom respectively. Similarly, in Canada, Australia and New Zealand, machine learning has been diffusing up to 6 times faster than the average skill in that labour market.

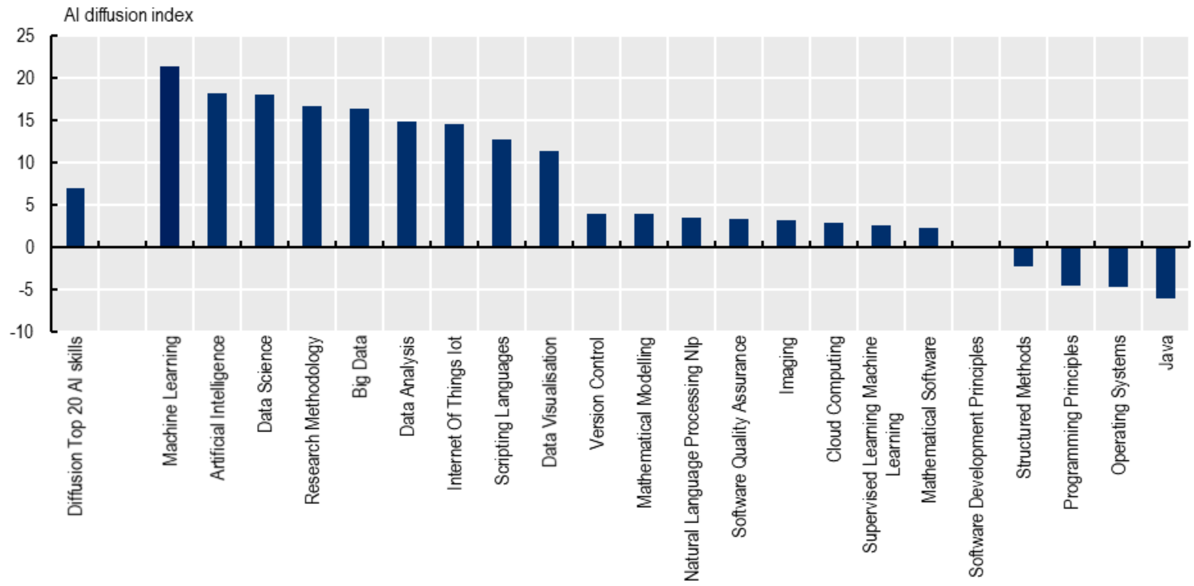
Figure 9. The diffusion of Artificial Intelligence and its skill bundle: United States

United States, 2012 to 2019



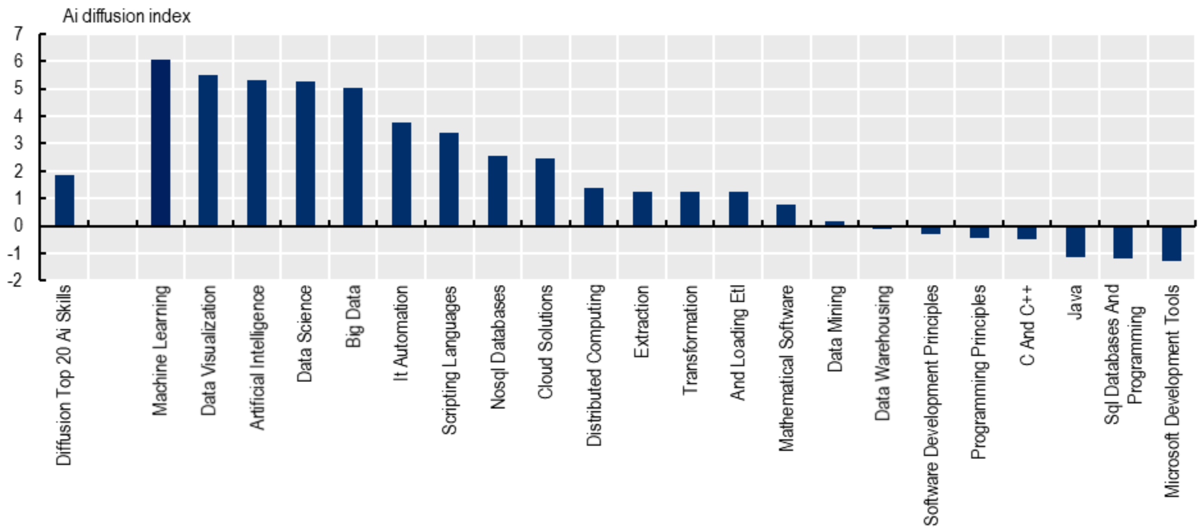
Note: The diffusion index is calculated as the change in the linear combination of the eigenvector centrality and local clustering coefficients of each skill keyword in between 2012 and 2019 relative to the average. It represents the intensity by which the skill is permeating the labour market relative to the average skill, that is, the increase in the number and quality of connections with other skills across occupations in the examined period. For more details, see Box 4.
Source: OECD calculations based on Lightcast data.

Figure 10. The diffusion of Artificial Intelligence and its skill bundle: United Kingdom (2012-2019)



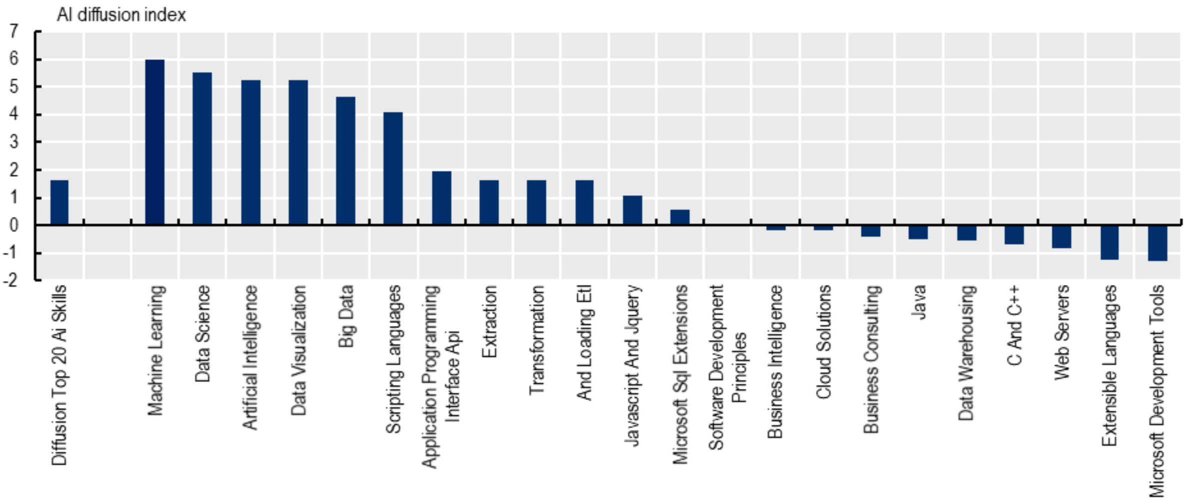
Note: The diffusion index is calculated as the change in the linear combination of the eigenvector centrality and local clustering coefficients of each skill keyword in between 2012 and 2019 relative to the average. It represents the intensity by which the skill is permeating the labour market relative to the average skill, that is, the increase in the number and quality of connections with other skills across occupations in the examined period. For more details, see box Box 4.
Source: OECD calculations based on Lightcast data.

Figure 11. The diffusion of Artificial Intelligence and its skill bundle: Canada (2012-2019)



Note: The diffusion index is calculated as the change in the linear combination of the eigenvector centrality and local clustering coefficients of each skill keyword in between 2012 and 2019 relative to the average. It represents the intensity by which the skill is permeating the labour market relative to the average skill, that is, the increase in the number and quality of connections with other skills across occupations in the examined period. For more details, see box Box 4.
Source: OECD calculations based on Lightcast data.

Figure 12. The diffusion of Artificial Intelligence and its skill bundle: Australia and New Zealand (2012-2019)



Note: The diffusion index is calculated as the change in the linear combination of the eigenvector centrality and local clustering coefficients of each skill keyword in between 2012 and 2019 relative to the average. It represents the intensity by which the skill is permeating the labour market relative to the average skill, that is, the increase in the number and quality of connections with other skills across occupations in the examined period. For more details, see box Box 4.
Source: OECD calculations based on Lightcast data.

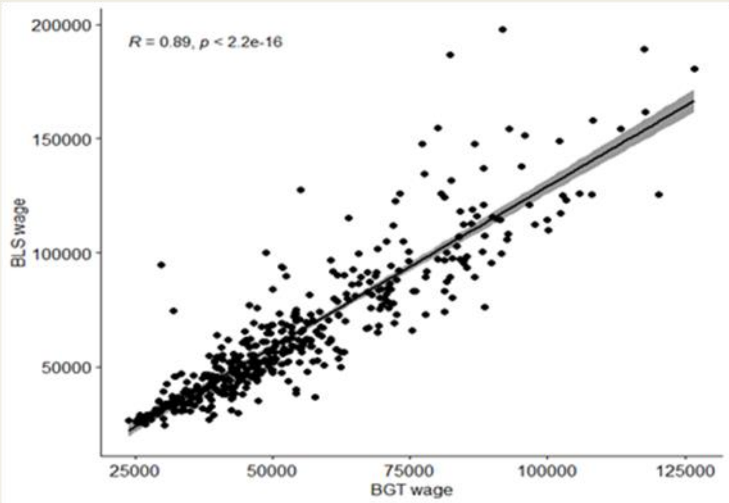
Question 4: Are AI-skills associated with a wage premium in labour markets?

A key question when analysing the impact of AI demands in the labour market is whether AI skills are conducive to higher wages and, if so, what such wage premium is when compared to other skills. Online job postings contain information on skill requirements but also on a variety of other dimensions such as the required education levels and qualification titles as well as information on the wage offered by the employer. This information can be used to assess the specific wage premium associated to each AI-related skill while also accounting for a series of control factors such as the years of education required to perform the job, the skill complexity of the job and geographical factors that could affect wage setting mechanisms (see Box 5).

Box 5. Using wage information collected in online job postings to estimate wage returns of AI skills

Using the information contained in job postings allows to analyse wage setting mechanisms in an extremely granular manner by looking at the specific wages advertised in each job posting and, therefore, allowing to account for both 'within' and 'across' occupations heterogeneity. The granularity of the data also allows to control for differences across geographies with a greater level of detail than when using other databases. Despite these advantages, some concerns may remain on the representativeness of the salary information collected from online vacancies as this information is not published in all vacancies but only on a subset of them (which varies from country to country). Recent research that looked into this issue (Adrjan and Lydon, 2019[19]) found that (for Ireland) information on salaries coming from online vacancies closely tracks data from firm-level surveys (EU-SILC) and that are adequately representative of the sample under exam. The examination of the wage information contained in online job postings collected by BGT and the official statistics produced by the US Bureau of Labor Statistics (BLS) also indicate a strong alignment between the two (see Figure 13) which reassures on the use of salary information contained in online job postings for empirical analysis.

Figure 13. Correlation between US BLS wage data and BGT data at the occupational level (2019)



Note: Dots represent the average wage in the occupation (6-digit SOC). Correlation between the online job postings information (BGT wage) and the official US Bureau of Labor Statistics (BLS wage) is 0.89 and statistically significant at 1% confidence level.
Source: OECD calculations based on Lightcast data and US BLS data.

In this paper, the relationship between wages and AI skills is estimated through the following Mincer regression model:

$$lnW_i = \alpha + \beta_1 AvEducation_i + \beta_2 SkillComplex_i + \beta_3 AI\_skill\ _o + \ Geography_i + e$$

Where *lnW* is the log of wage offered in each individual job posting *i*. *AvEducation* is the qualification title mentioned in the same job posting. As job adverts do not explicitly mention the number of years of education required, but instead only the qualification level desired by employers (e.g Master degree, Doctorate, upper-secondary education etc.), that qualitative information has been converted in average years of education mapping it to the ISCED classification and the average years of schooling required to complete each qualification. *SkillComplex* measures the total number of skills mentioned in each job advert and it is an indicator of the average skill-complexity of the job opening under consideration. Jobs mentioning a larger number of skills are assumed to be more complex, requiring multifaceted combinations of skills. *AI_skill* measures the relevance of each AI-related skill in occupations and it is the variable of interests of this analysis with its coefficient β_3. Results in Figure 14 to Figure 17 present the values the coefficient β_3 for each AI-related skills, capturing the wage return associated to each AI skill considered in the analysis. In order to make meaningful comparisons across skills, the relevance values for all skills have been transformed to have mean equal to zero and standard deviation equal to 1 across occupations and the under script *o* denotes that relevance scores are calculated at the occupation level. *Geography* indicate geographical dummies at the subnational level.

Results in Figure 14 to Figure 17 show two sets of interrelated results in panel A and B:

- In panel A, figures show the wage premium associated to each AI-related skill in the examined country. The wage premium is estimated using an econometric regression model that controls for education and skill complexity requirements of the job as well as for geographical controls (see Box 5). The height of the bars indicate the elasticity of wages (the percentage increase in wages) relative to a one standard deviation increase in the relevance of the examined AI-related skill.

- In panel B, figures show the relevance of AI across all occupations (along the vertical axis) and the underlying distribution of average wage paid to each occupation (along the horizontal axis). Positive correlations denote a positive relationship between the relevance of AI in jobs and wages across occupations. In other words, positive correlations indicate that occupations where AI is more relevant also receive higher wages, on average.

Econometric analysis for the United States in 2019 (Figure 14, panel A) shows that all AI-related skills and technologies are associated with positive and statistically significant wage returns, indicating that jobs where those AI skills are highly relevant pay higher wages than the average. Results are robust to accounting for average years of schooling, skill complexity of the job and geographical factors and indicate that an increase in the relevance of 'artificial intelligence' by one standard deviation is associated with a 10% increase in wages on average. Similarly, an increase by one standard deviation in the relevance of machine learning and big data are associated with a wage premium of 11 and 9% respectively. The knowledge of AI processes such as 'product performance optimization' or of AI software/technologies such as mercurial software and bioprinters are also found to be associated with a significant wage premium, indicating that jobs where those skills are highly relevant tend to pay significantly higher wages than the average.

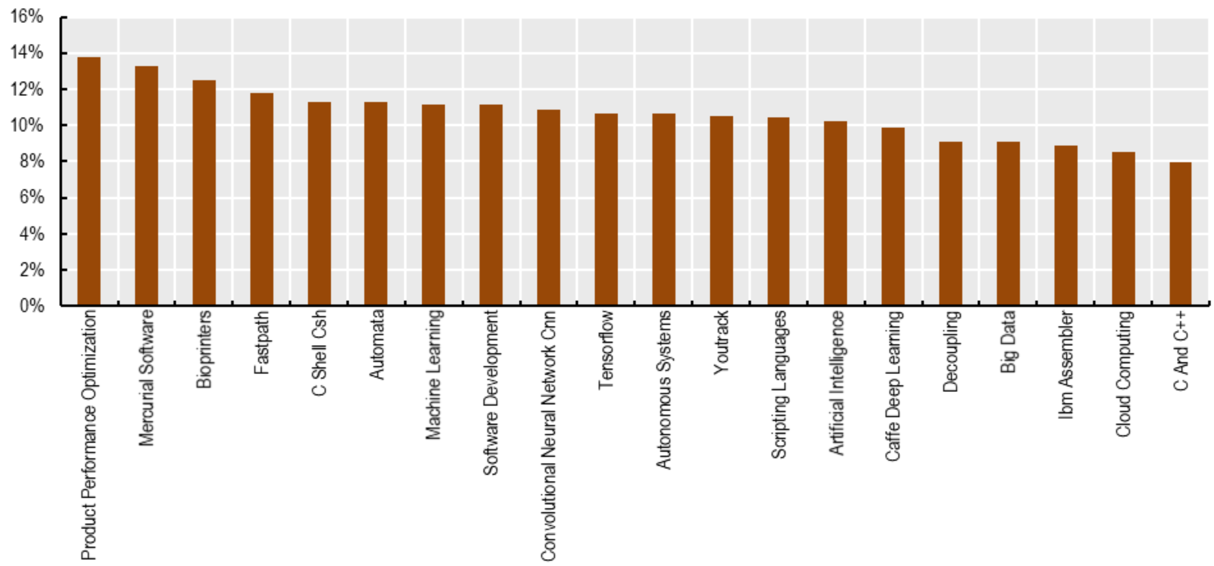
Similar results are found in other countries. In the United Kingdom (Figure 15, panel A), for instance, the knowledge of internet of things (IOT), artificial intelligence, structured methods and blockchain are associated with a wage premium ranging from 7 to 10%. In Canada (Figure 16, panel A) data science, artificial intelligence and extraction, transformation and loading (ETL)[12] show the highest wage returns. In Australia and New Zealand (Figure 17, panel A), artificial intelligence and big data are associated with a 6% wage return. The knowledge of business intelligence and data visualisation show similar returns.

Additional analysis in panel(s) B of Figure 14 to Figure 17 further investigates, in a more descriptive way, the relationship between the relevance of AI in occupations and the average wage paid to workers employed in those occupations. The scatterplots show the existence of a positive and statistically significant correlation between the relevance of AI and wages in all countries analysed, indicating that jobs where AI is more relevant receive generally higher wages. In the United States (Figure 14, panel B), for instance, AI intensive occupations such as computer scientist or data scientist receive wages that are twice as high the average (unweighted) wage in the same country. The positive association between AI relevance in jobs and average wage is also significant in the rest of the countries analysed and shows that AI is associated to substantial labour market advantages.

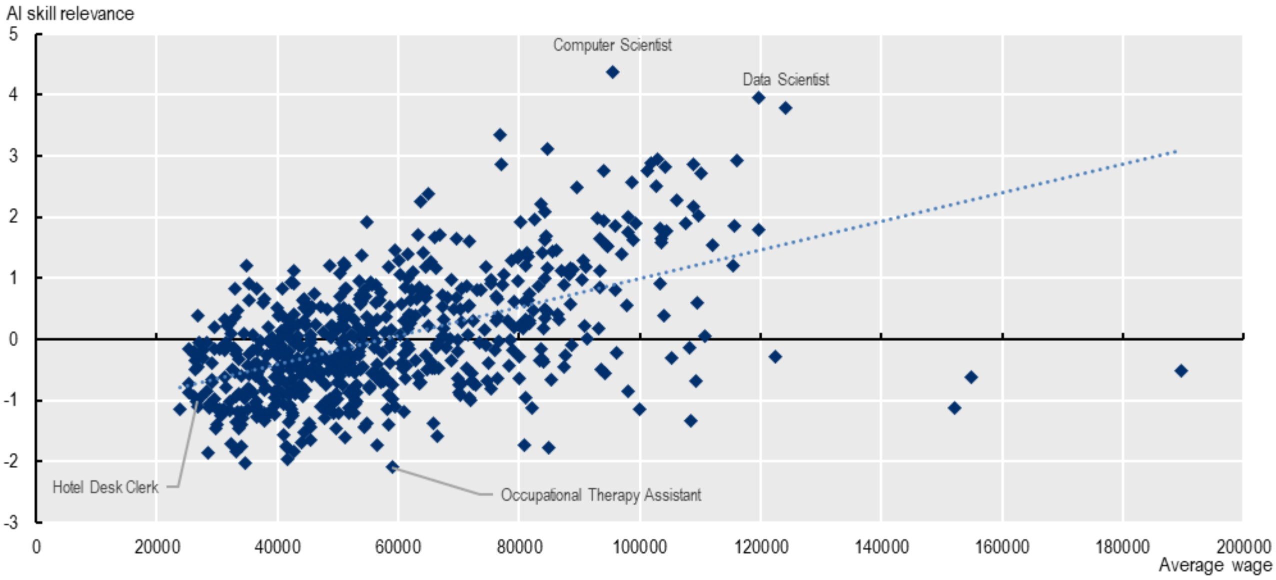
[12] The process of ETL plays a key role in data integration strategies. ETL allows businesses to gather data from multiple sources and consolidate it into a single, centralized location. ETL also makes it possible for different types of data to work together (see: https://www.talend.com/resources/what-is-etl/)

Figure 14. Wage returns of top 20 AI-related skills and wage distribution across occupations: United States

Panel A: Wage returns, United States, 2019



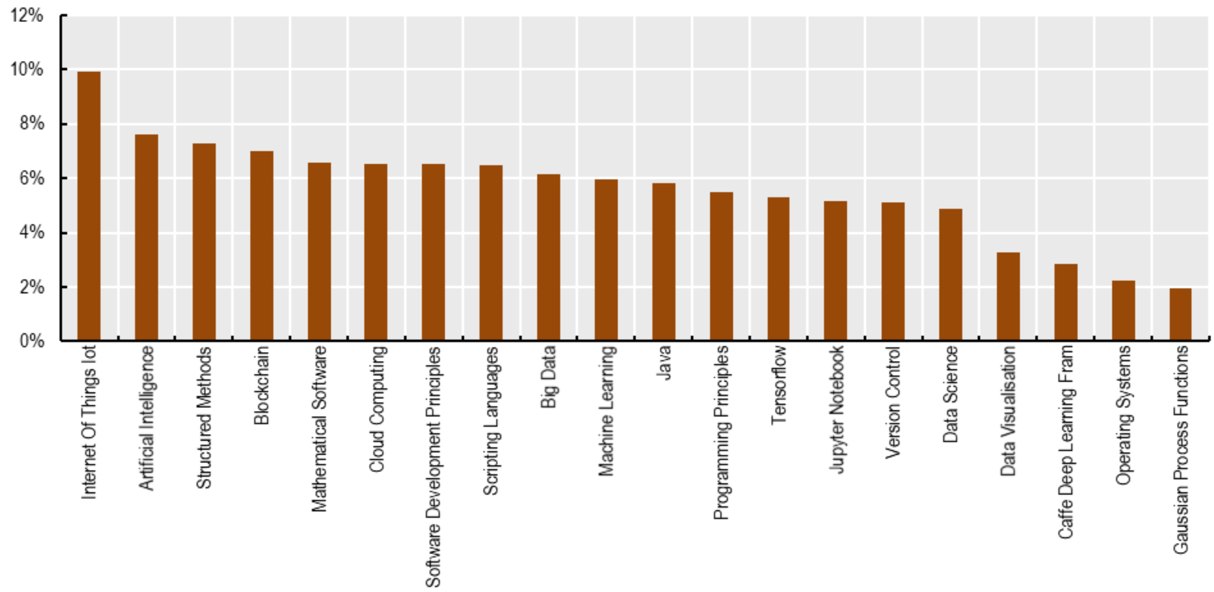
Panel B: Correlation between relevance of AI in occupations and average wage



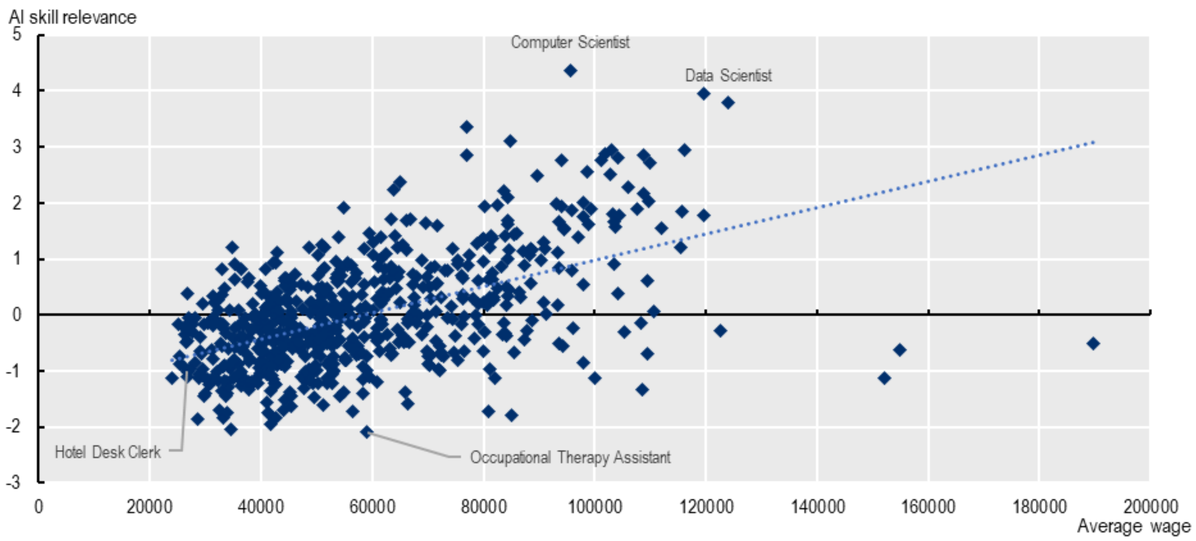
Note: Bars in panel A represent the estimated elasticity of wages relative to a one-standard increase in the relevance of the AI skill at hand. The regression model accounts for years of schooling requirements, skill complexity as well as geographical dummies. Results are for the year 2019. Panel B plots the relevance of AI vs the average wage for each occupation. Positive correlation indicate that higher relevance of AI is associated with higher wages in the economy.
Source: OECD calculations based on Burning Glass Technology data.

Figure 15. Wage returns of top 20 AI-related skills: United Kingdom

Wage returns, United Kingdom, 2019

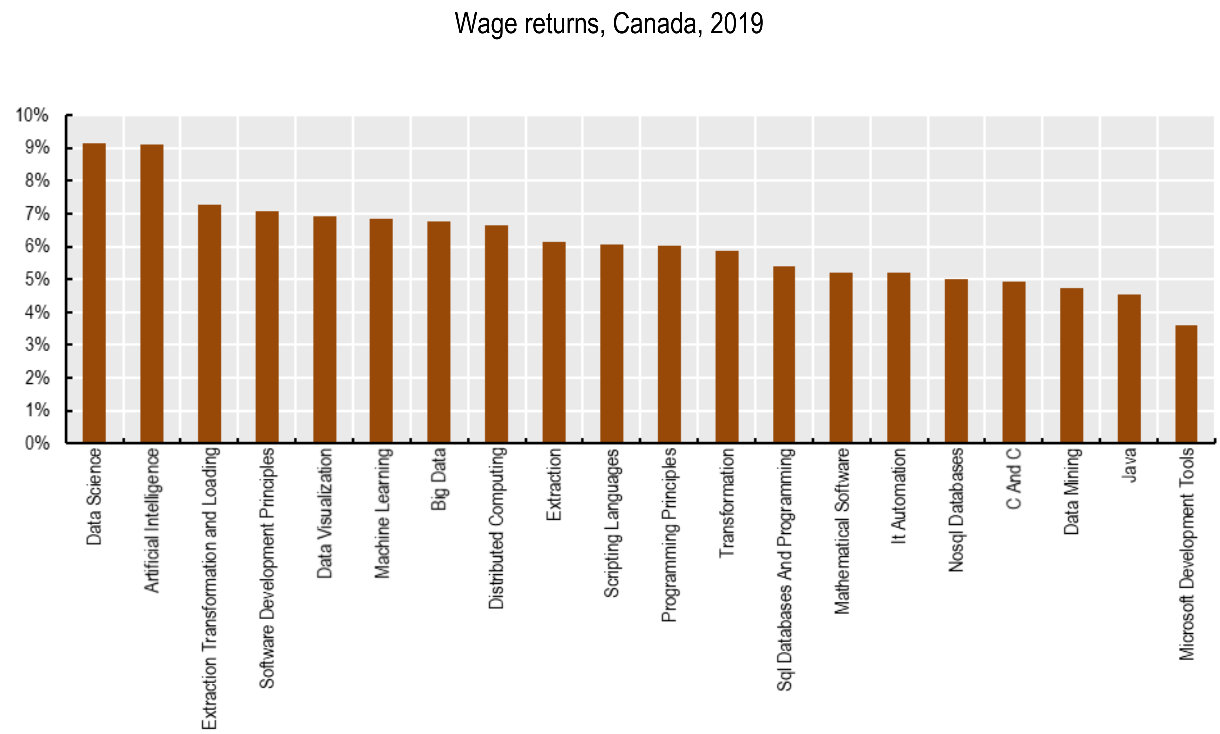


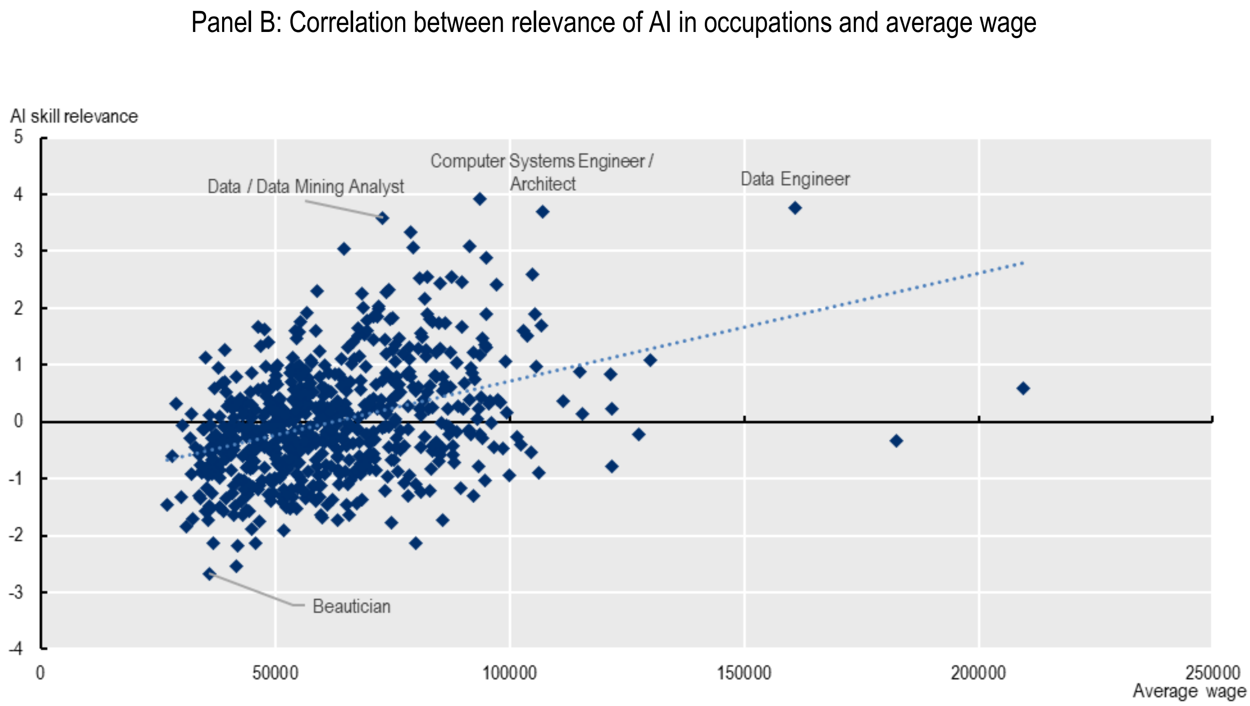
Panel B: Correlation between relevance of AI in occupations and average wage



Note: Bars in panel A represent the estimated elasticity of wages relative to a one-standard increase in the relevance of the AI skill at hand. The regression model accounts for years of schooling requirements, skill complexity as well as geographical dummies. Results are for the year 2019. Panel B plots the relevance of AI vs the average wage for each occupation. Positive correlation indicate that higher relevance of AI is associated with higher wages in the economy.
Source: OECD calculations based on Burning Glass Technology data.

Figure 16. Wage returns of top 20 AI-related skills: Canada



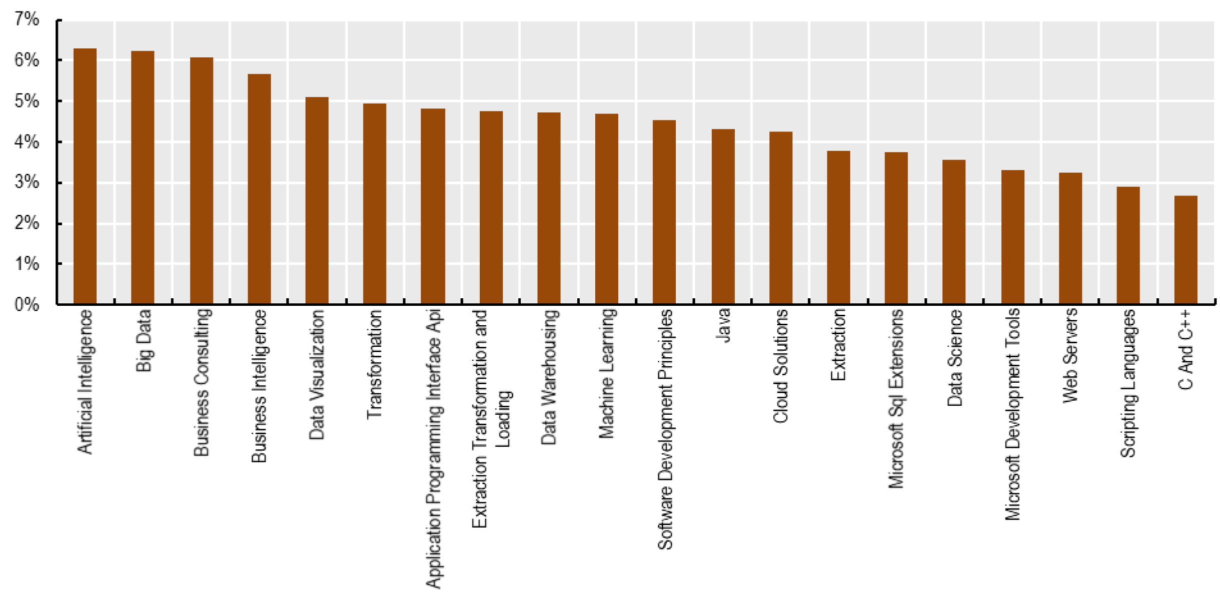


Note: Bars in panel A represent the estimated elasticity of wages relative to a one-standard increase in the relevance of the AI skill at hand. The regression model accounts for years of schooling requirements, skill complexity as well as geographical dummies. Results are for the year 2019. Panel B plots the relevance of AI vs the average wage for each occupation. Positive correlation indicate that higher relevance of AI is associated with higher wages in the economy.

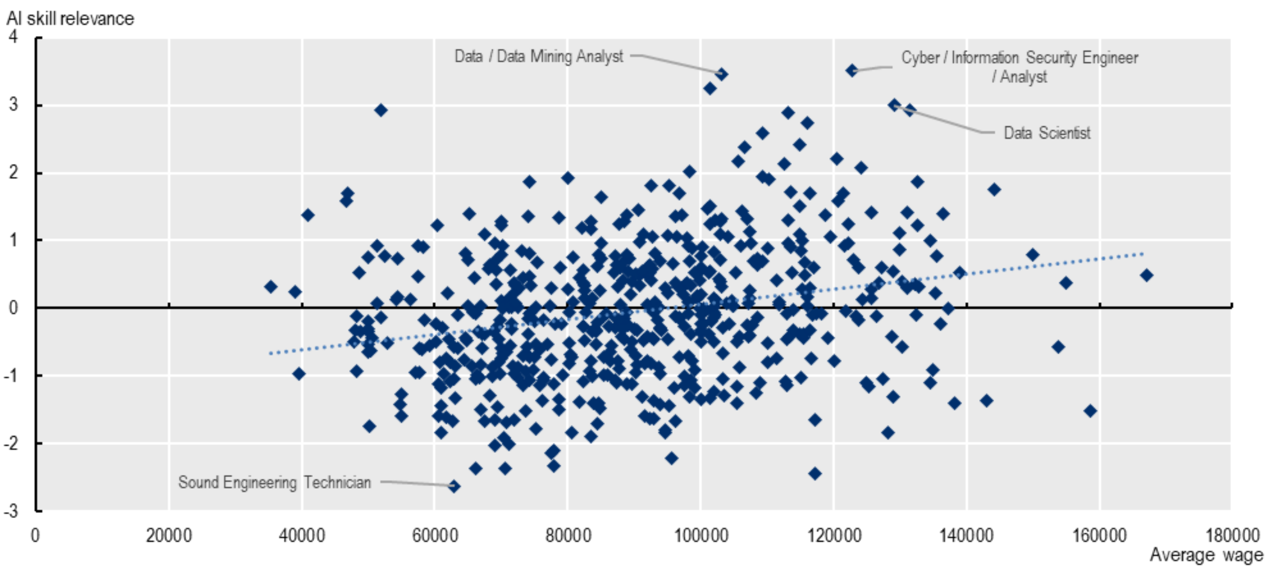
Source: OECD calculations based on Burning Glass Technology data.

Figure 17. Wage returns of top 20 AI-related skills: Australia and New Zealand

Wage returns, Australia and New Zealand, 2019



Panel B: Correlation between relevance of AI in occupations and average wage



Note: Bars in panel A represent the estimated elasticity of wages relative to a one-standard increase in the relevance of the AI skill at hand. The regression model accounts for years of schooling requirements, skill complexity as well as geographical dummies. Results are for the year 2019. Panel B plots the relevance of AI vs the average wage for each occupation. Positive correlation indicate that higher relevance of AI is associated with higher wages in the economy.
Source: OECD calculations based on Burning Glass Technology data.

Question 5: What is the relationship between the demand for AI skills and that for routine and cognitive skills? Are AI skills complementing or substituting the demand for routine or cognitive skills?

A key question when analysing the impact of AI on labour markets is whether the adoption of AI will lead to complementarities in the demand of other skills or if, instead, AI will replace workers in jobs leading to a decrease in the demand for specific tasks and skills.

An influential strand of empirical literature (see (Deming, 2017[20]), (Autor, Levy and Murnane, 2003[21]) and (Goos, Manning and Salomons, 2014[22])) has highlighted the recent decline in the demand for routine-related skills in favour of skills that cannot be automatized (non-routine cognitive skills). Digitalisation and the adoption of advanced robotics are usually taken as the main drivers of the expected automation of tasks in jobs. Empirical work by (Nedelkoska and Quintini, 2018[23]) finds that across 32 countries in the OECD, about 14% of jobs are highly automatable based on the tasks they involve. Another 32% of jobs faces a high risk of automation, pointing to the possibility of significant changes in the way these jobs will be carried out as a result of automation. (Brynjolfsson and McAfee, 2014[24]) also suggest that advances in computing power have expanded the set of tasks that machines can perform, leading to an increasing automation of processes and to the substitution of humans in routine tasks.

That being said, whether AI should be considered as a traditional 'automation technology' is the focus of a lively debate. An increasing number of experts argue that AI's impact may go well beyond that of traditional automation technologies, being AI a general-purpose technology that is capable of automating not only routine tasks but also cognitive ones. Another strand of empirical literature (Colombo, Mercorio and Mezzanzanica, 2019[25]) is looking at hybrid jobs and at how the labour market is evolving by requiring workers to utilise and merge knowledge and skills in new ways in tasks.

The information contained in online job postings allows investigating the relationship between the relationship between the relevance of AI in jobs and that of other types of competencies, ranging from soft to cognitive and routine skills. In particular, data allow to assess whether jobs that use AI skills with high relevance also require soft, cognitive or routine skills or if, instead, AI is not complementary to those skills in the demands of employers.

Results in Figure 18 to Figure 21 analyse the relationship between AI-related skills and routine skills (panel A) as well as that between AI-related skills and high-level cognitive skills (panel B). The figures rank all skills collected in online job postings between two extremes:

- On the horizontal axis, positive values indicate that the skill under exam correlates positively with AI skills across occupations, meaning that the skill is highly relevant in jobs where AI is also highly relevant (*viceversa*, negative values on the horizontal axis identify skills that are unrelated to AI).
- On the vertical axis, positive values indicate that the skill under exam correlates positively with general administrative and clerical tasks (in panel A) or with creative problem solving (in panel B). In the remainder of the analysis, 'general administrative and clerical tasks' is used to proxy for routine skills[13], while 'creative problem solving' to proxy for high-level cognitive skills. Box 6 discusses how the indicators that approximate for each skill relatedness relative to routine and high-level cognitive skills have been built and used in the analysis.

[13] General administrative and clerical tasks is used here as a proxy for routine skills following previous empirical literature (see Box 6). However, this proxy may miss other types of routine skills such as manual routine ones. Robustness checks have been run with a different set of proxies capturing directly manual routine skills and results are qualitatively similar.

Box 6. Analysing the complementarities between AI, routine, and high-level cognitive skills in online job postings.

The NLP approach developed in this paper allows to retrieve the relevance scores of each skill across all occupations. This, in turn, allows to investigate how closely skills align with each other, by looking at whether they share high-relevance in the same set of occupations (meaning they are usually demanded with high relevance in the same set of jobs) or whether instead they are far apart, being relevant in different sets of occupations. The analysis in previous sections (Figure 5 to Figure 8), for instance, shows the correlation between 'artificial intelligence' and other skills across occupations. Results indicate, for instance, that machine learning and big data are closely related to artificial intelligence, being highly relevant in a similar set of occupations. A similar approach can be used to identify how skill align to other dimensions such as routine or high-cognitive skills. As in the case of 'artificial intelligence' related skills, this involves choosing a benchmark to be used to compare the rest of the skill against it.

The keywords 'general administrative and clerical tasks' is used in this study as a benchmark for what is generally understood to be 'routine skills'. The choice of using this keyword follows (Autor, 2015[26]) who defines routine skills as "*explicit, codifiable tasks*", arguing that routine tasks are usually found in clerical work: "*Routine tasks are characteristic of many middle-skilled cognitive and manual activities: for example, the mathematical calculations involved in simple bookkeeping; the retrieving, sorting, and storing of structured information typical of clerical work; and the precise executing of a repetitive physical operation in an unchanging environment as in repetitive production tasks. Because core tasks of these occupations follow precise, well-understood procedures, they are increasingly codified in computer software and performed by machines*".

All skills in the database are assessed against how closely they align with 'general administrative and clerical task'. In particular, when a skill's relevance correlates strongly with 'general administrative and clerical task' across occupations it is assumed to be a 'routine skills' (and viceversa). The correlation coefficient is used as a continuous measure indicating how 'routine' each skill is. General administrative and clerical tasks fall well within the definitions provided above, but others have been tested leading to similar results (available upon request). Among these, 'equipment repair and maintenance tasks', 'typing' or 'administrative support'.

The keywords 'creative problem solving' have been used, instead, to benchmark 'high-level cognitive skills'. Creative problem solving is usually defined as the mental process of searching for an original and previously unknown solution to a problem. By definition, therefore, this is high-level cognitive task which fits well as benchmark for high-level cognitive (non-routine) skills.

Results for all countries examined (Figure 18 to Figure 21, panel A) show a significant negative association between the relevance of AI skills and that of routine skills in jobs. The analysis indicates that jobs where AI skills are highly relevant do not combine them with routine-skills and, similarly, that jobs with a high routine content do not demand AI skills with particular relevance.

Figure 18 (panel A) for the United States shows, for instance, that routine-related skills such as administrative support or 'typing' correlate negatively with artificial intelligence across jobs (-0.55 and -0.41 respectively). Similar results are found for the United Kingdom (Figure 19, panel A) where the demand for physical skills, highly correlated with the measure of routine skills (0.75) are, instead, negatively correlated with the demand for artificial intelligence skills (-0.55) across the jobs analysed. Similar results are found for Canada, Australia and New Zealand (Figure 21, panel A).

To put it in other words, the analysis suggests that AI and routine skills are not ‘complementary’ to each other and that an increase in the demand for AI skills- which could emerge as AI is adopted more widely- is likely to be associated with decrease in the demand for routine skills[14].

The relationship between AI skills and high-level cognitive skills is, instead, positive. Results indicate that AI-related skills are positively correlated with high-level cognitive (creative problem solving) skills in all countries analysed with the exception of Australia and New Zealand where the correlation between the two types of skills not statistically significant. In the United States, for instance,

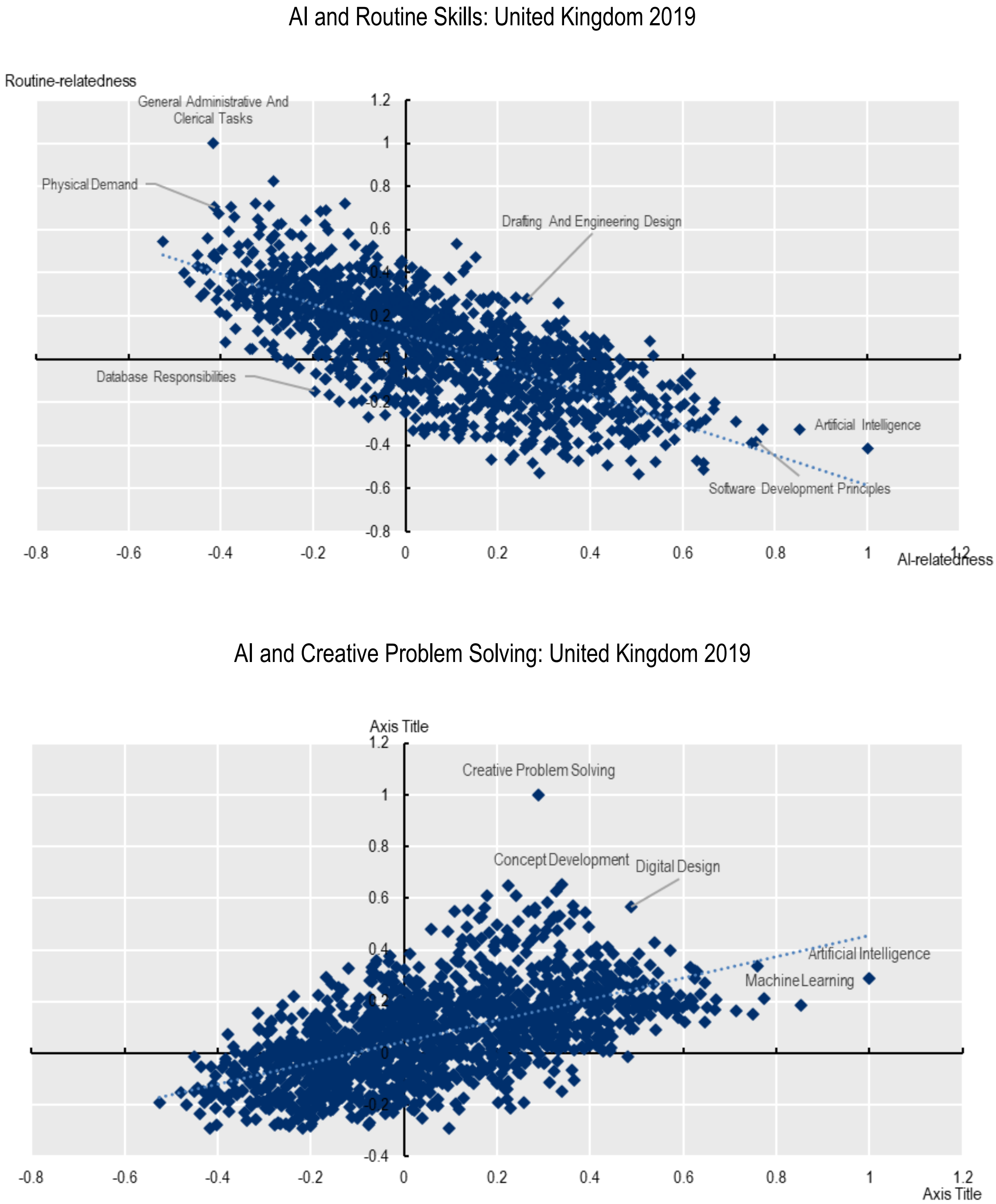
Figure 18 (panel B) shows that skills which are positively correlated with AI skills (for instance, ‘computer animation’ skills, 0.39) are also strongly correlated with creative problem solving (0.54). *Ceteris paribus*, results suggest that any increase in the employment of AI-related jobs is likely to be associated with a contextual increase in the demand for both AI and high-level cognitive skills as they are jointly relevant in similar occupations.

[14] This claim is based on the fact that the correlation between AI-relatedness and Routine-relatedness is statistically significant and negative. While the negative correlation is suggestive of the fact that an increase in AI-related skills will not be associated with an increase in routine-skills, this cannot be immediately interpreted as a causal effect but, rather, as a ceteris paribus scenario where endogenous aspects are kept fixed.

Figure 18. Relationship between AI-related and Routine and Creative Problem Solving skills: United States

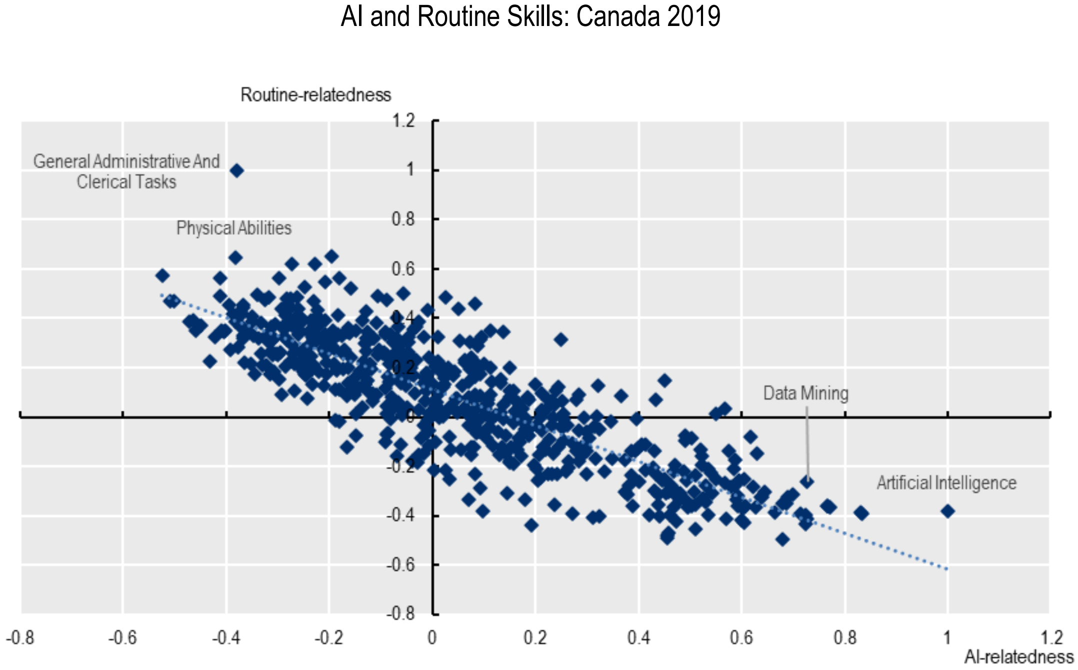
Note: The scatterplot's coordinates identify the correlation coefficient of each skill relative to AI (values on the horizontal axis) and General Administrative and Clerical Tasks (values on vertical axis in Panel A) or Creative Problem Solving (values on the vertical axis in Panel B). High values of AI-relatedness (larger values on the horizontal axis) indicate that the skill under exam is highly correlated with AI across jobs and that it is demanded with high relevance in jobs where AI is also highly relevant. High values of Routine-relatedness or Creative Problem Solving-relatedness (larger values on the vertical axis of Panel A and B respectively) indicate that the skill under exam is highly correlated with general administrative and clerical tasks or with creative problem solving across jobs and that it is demanded with high relevance in jobs where either the first or the second type of skills are also highly relevant.
Source: OECD calculations based on Lightcast data.

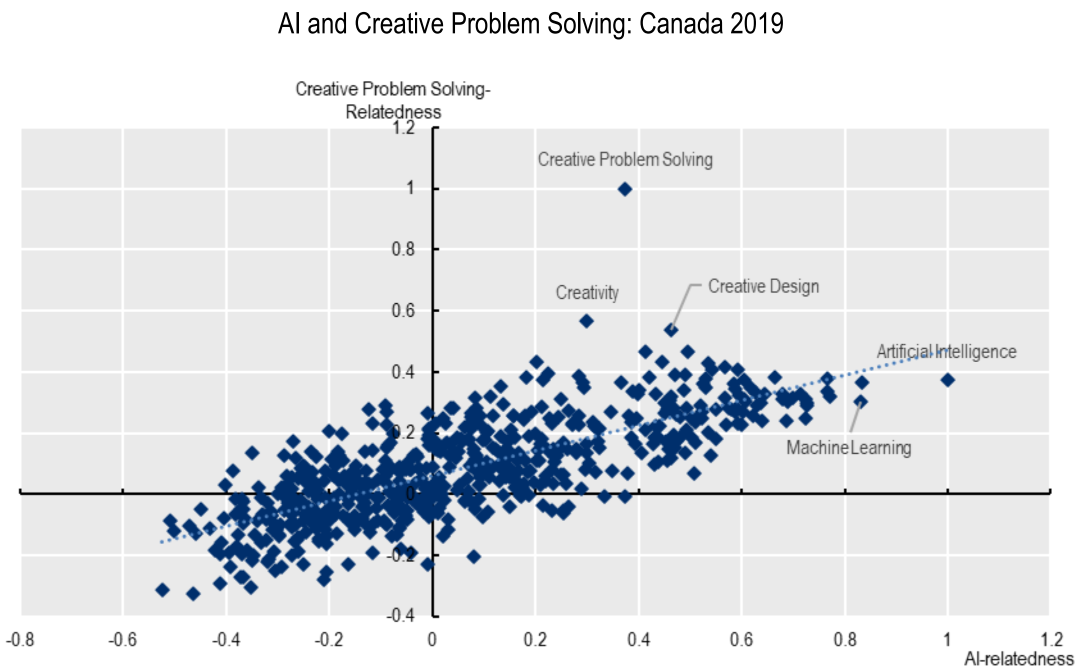
Figure 19. Relationship between AI-related skills and Routine-Skills: United Kingdom



Note: The scatterplot's coordinates identify the correlation coefficient of each skill relative to AI (values on the horizontal axis) and General Administrative and Clerical Tasks (values on vertical axis in Panel A) or Creative Problem Solving (values on the vertical axis in Panel B). High values of AI-relatedness (larger values on the horizontal axis) indicate that the skill under exam is highly correlated with AI across jobs and that it is demanded with high relevance in jobs where AI is also highly relevant. High values of Routine-relatedness or Creative Problem Solving-relatedness (larger values on the vertical axis of Panel A and B respectively) indicate that the skill under exam is highly correlated with general administrative and clerical tasks or with creative problem solving across jobs and that it is demanded with high relevance in jobs where either the first or the second type of skills are also highly relevant.
Source: OECD calculations based on Lightcast data.

Figure 20. Relationship between AI-related skills and Routine-Skills: Canada

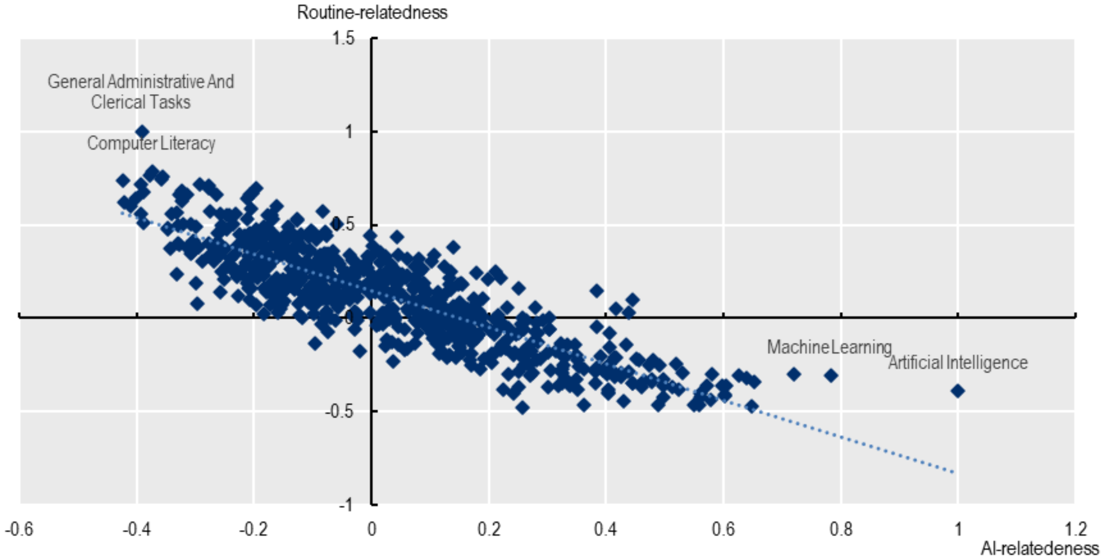




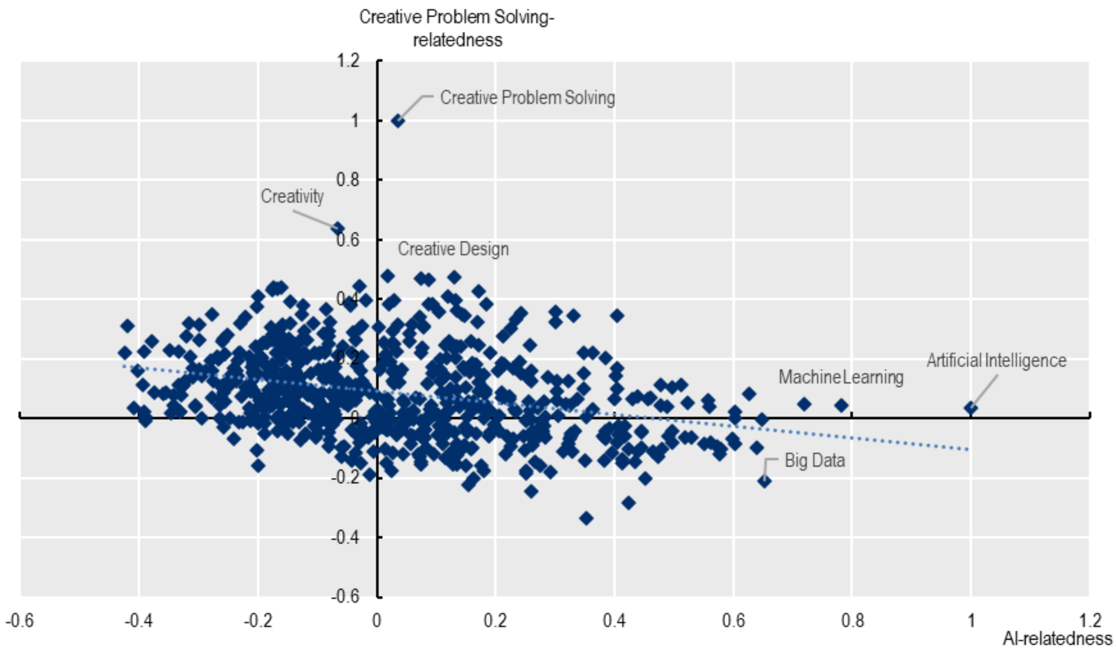
Note: The scatterplot's coordinates identify the correlation coefficient of each skill relative to AI (values on the horizontal axis) and General Administrative and Clerical Tasks (values on vertical axis in Panel A) or Creative Problem Solving (values on the vertical axis in Panel B). High values of AI-relatedness (larger values on the horizontal axis) indicate that the skill under exam is highly correlated with AI across jobs and that it is demanded with high relevance in jobs where AI is also highly relevant. High values of Routine-relatedness or Creative Problem Solving-relatedness (larger values on the vertical axis of Panel A and B respectively) indicate that the skill under exam is highly correlated with general administrative and clerical tasks or with creative problem solving across jobs and that it is demanded with high relevance in jobs where either the first or the second type of skills are also highly relevant.
OECD calculations based on Lightcast data.

Figure 21. Relationship between AI-related skills and Routine-Skills: Australia and New Zealand

AI and Routine Skills: Australia and New Zealand, 2019



AI and Creative Problem Solving: Australia and New Zealand 2019



Note: The scatterplot's coordinates identify the correlation coefficient of each skill relative to AI (values on the horizontal axis) and General Administrative and Clerical Tasks (values on vertical axis in Panel A) or Creative Problem Solving (values on the vertical axis in Panel B). High values of AI-relatedness (larger values on the horizontal axis) indicate that the skill under exam is highly correlated with AI across jobs and that it is demanded with high relevance in jobs where AI is also highly relevant. High values of Routine-relatedness or Creative Problem Solving-relatedness (larger values on the vertical axis of Panel A and B respectively) indicate that the skill under exam is highly correlated with general administrative and clerical tasks or with creative problem solving across jobs and that it is demanded with high relevance in jobs where either the first or the second type of skills are also highly relevant.
Source: OECD calculations based on Lightcast data.

Question 6: Is there any difference between the returns paid to AI and routine skills?

Results above suggest that AI and routine skills have little in common and that they are relevant in jobs that are fundamentally different in their nature, tasks and characteristics. Given these premises, it is interesting to assess whether there exists any association between the degree by which a skill is relevant in an AI-context and the average wage this skill receives in the labour market. Similarly, the analysis below also test whether there exists an association between wages and how much skills are relevant in routine-contexts.

On the vertical axis, Figure 22 to Figure 25 plot the intensity by which skills are relevant in AI and routine contexts (panel A and panel B respectively). The horizontal axis, instead, measures the average wage paid to each skill[15].

Results indicate that skills that are more relevant in AI-contexts (that is where AI is also very relevant) are associated with wages that are significantly higher than the average. This is to say that, as the correlation between each skill and AI increases, so does also the average wage paid to the skill.

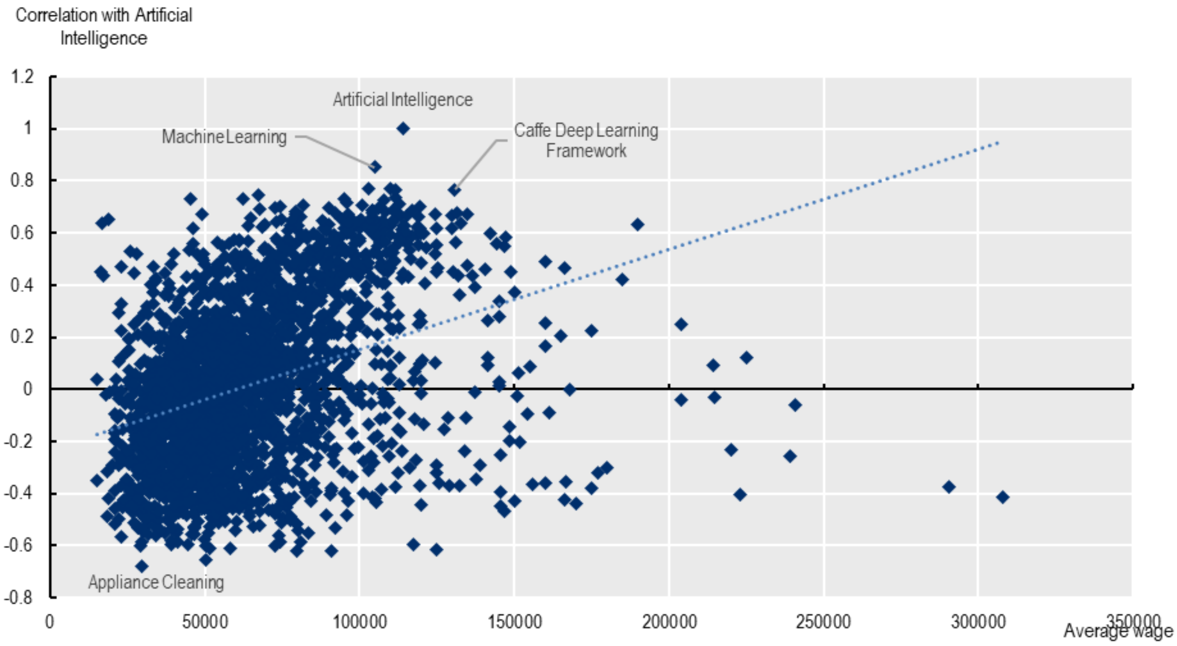
In Figure 22 for the United States, for instance, the knowledge of 'caffe deep learning framework' (whose correlation with AI is 0.76) is associated with an average wage of more than 130 000 USD while 'appliance cleaning' skills (whose correlation with AI is -0.67) receive an average wage of roughly 30 000 USD. Similarly, in the United Kingdom (Figure 23, panel A), Haskell (a programming language widely used in AI applications) is associated with jobs with an average wage of more than 80 000 GBP while telephone skills to less than 20 000 GBP. Similar results are found for Canada, Australia and New Zealand where the correlation between how much a skill is AI-related and average wages is positive and statistically significant.

Conversely, results in panels B of Figure 22 to Figure 25 indicate that routine-related skill are associated with significantly lower wages than average, and, in particular, with lower wages relative to non-routine skills. In Figure 22 (panel B) for the United States, for instance, typing skills or administrative support, two skills that are highly correlated with routine tasks, are associated with wages that are up to 40% lower than the average and four times lower than skills that are very relevant in AI contexts, such as 'data service industry knowledge'.

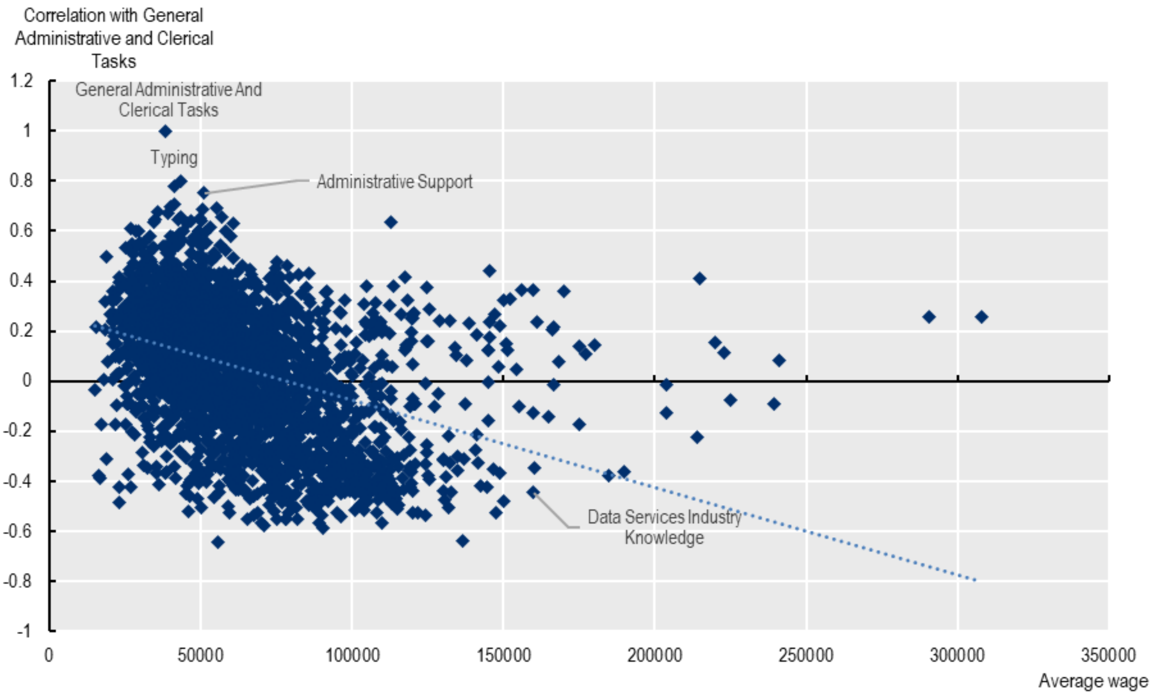
[15] This is the average wage across job postings that mention the skill at least once in the advertisement.

Figure 22. Relationship between AI skills, routine skills and wages: United States

Panel A: AI-relatedness and wages



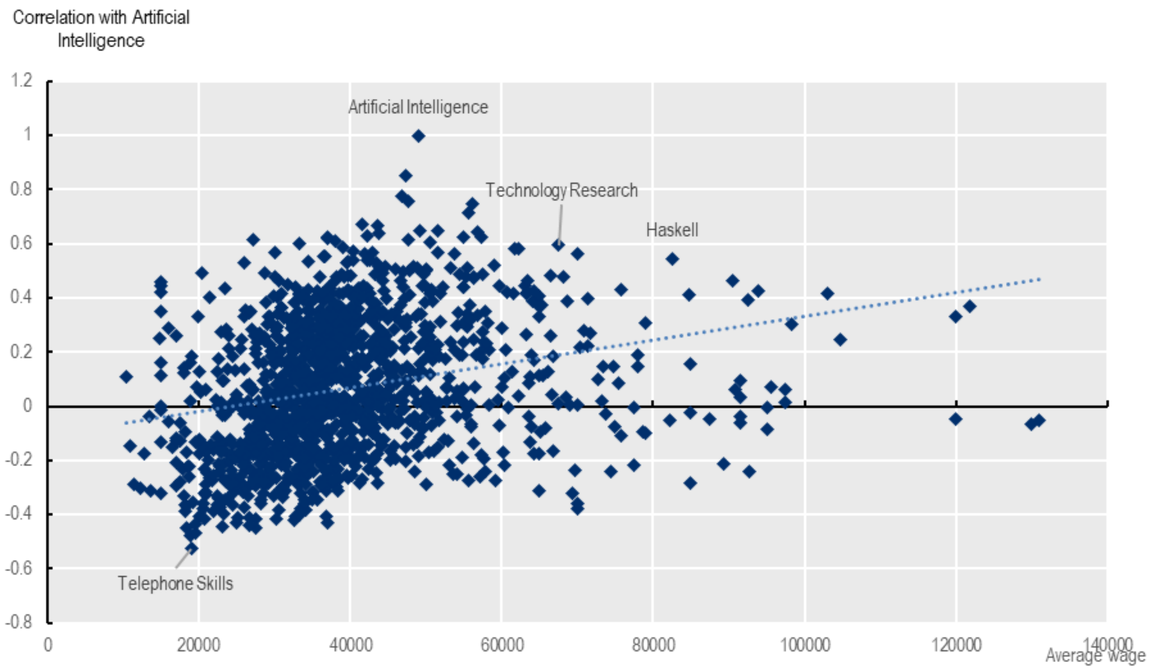
Panel B: Routine-relatedness and wages



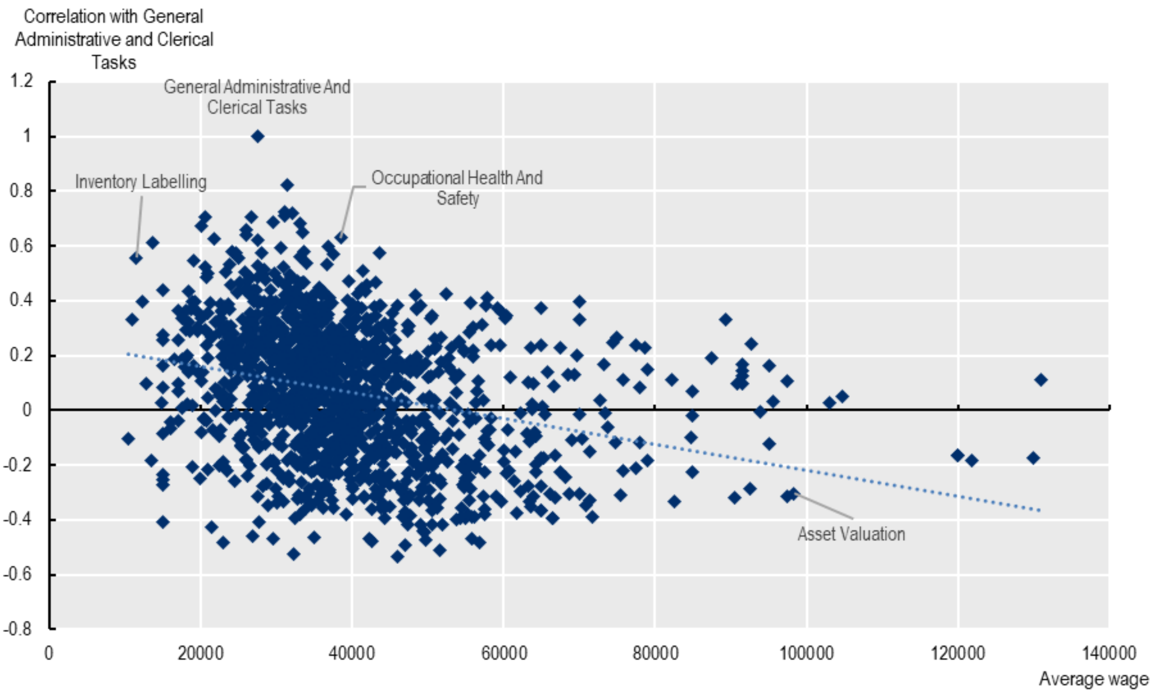
Note: Values on the vertical axis indicate the correlation coefficient of the skill under exam with artificial intelligence (in Panel A) or general administrative and clerical tasks (in Panel B). Values on the horizontal axis are the average wage associated to each skill across job postings collected in the country.
Source: OECD calculations based on Lightcast data

Figure 23. Relationship between AI, Routine skills and wages: United Kingdom

Panel A: AI-relatedness and wages



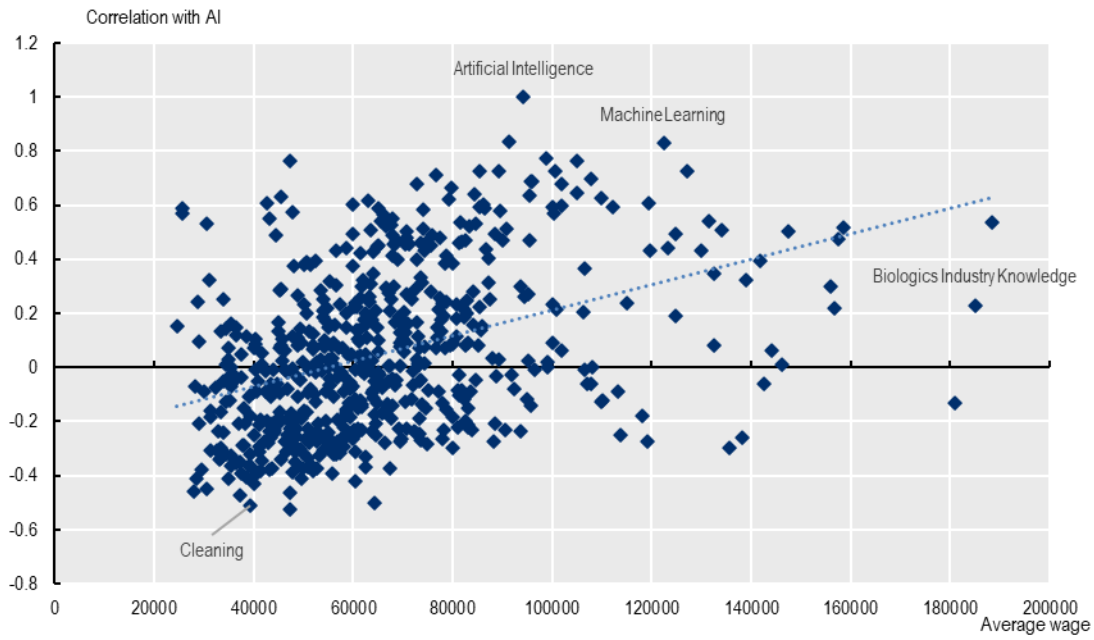
Panel B: Routine-relatedness and wages



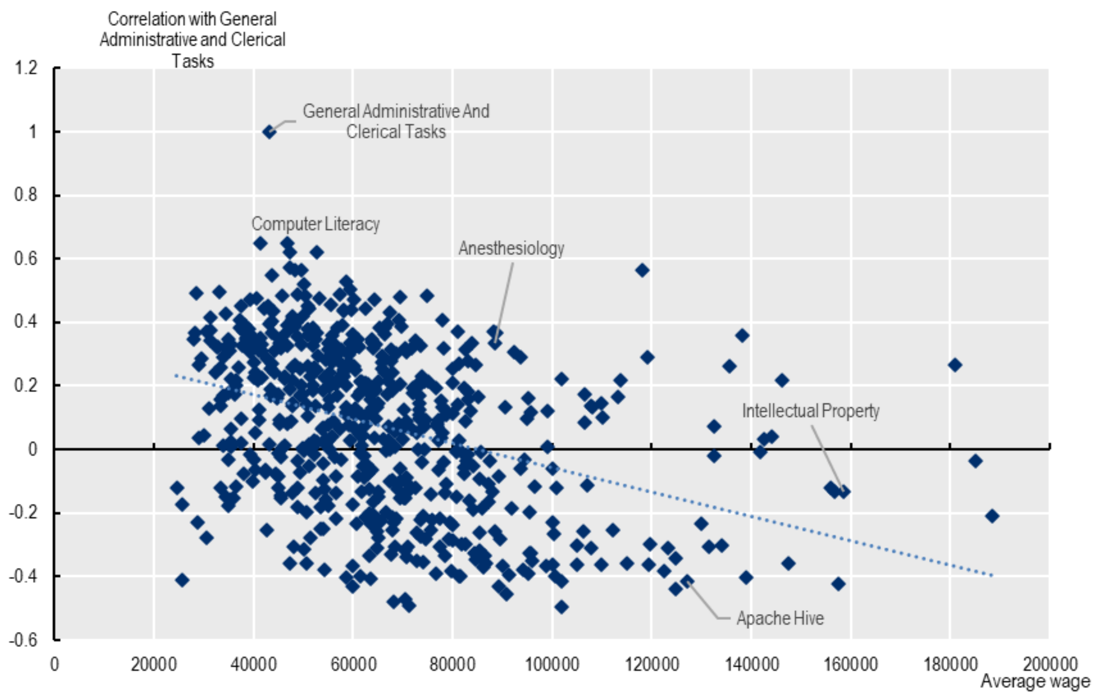
Note: Values on the vertical axis indicate the correlation coefficient of the skill under exam with artificial intelligence (in Panel A) or general administrative and clerical tasks (in Panel B). Values on the horizontal axis are the average wage associated to each skill across job postings collected in the country.
Source: OECD calculations based on Lightcast data

Figure 24. Relationship between AI, Routine skills and wages: Canada

Panel A: AI-relatedness and wages



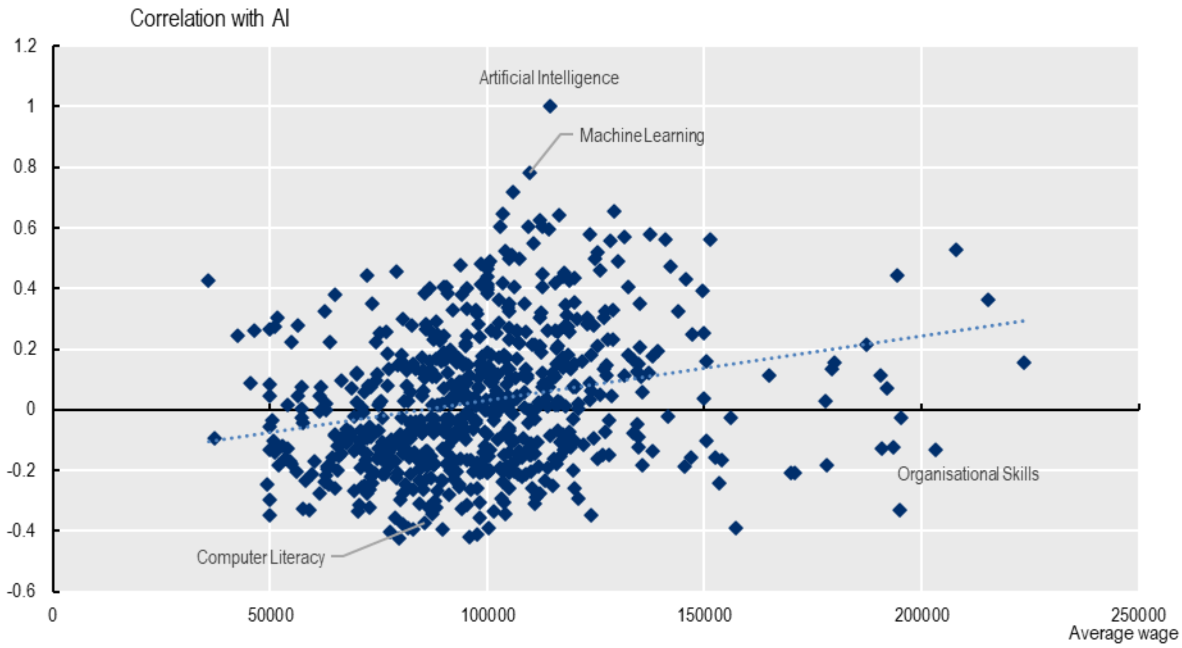
Panel B: Routine-relatedness and wages



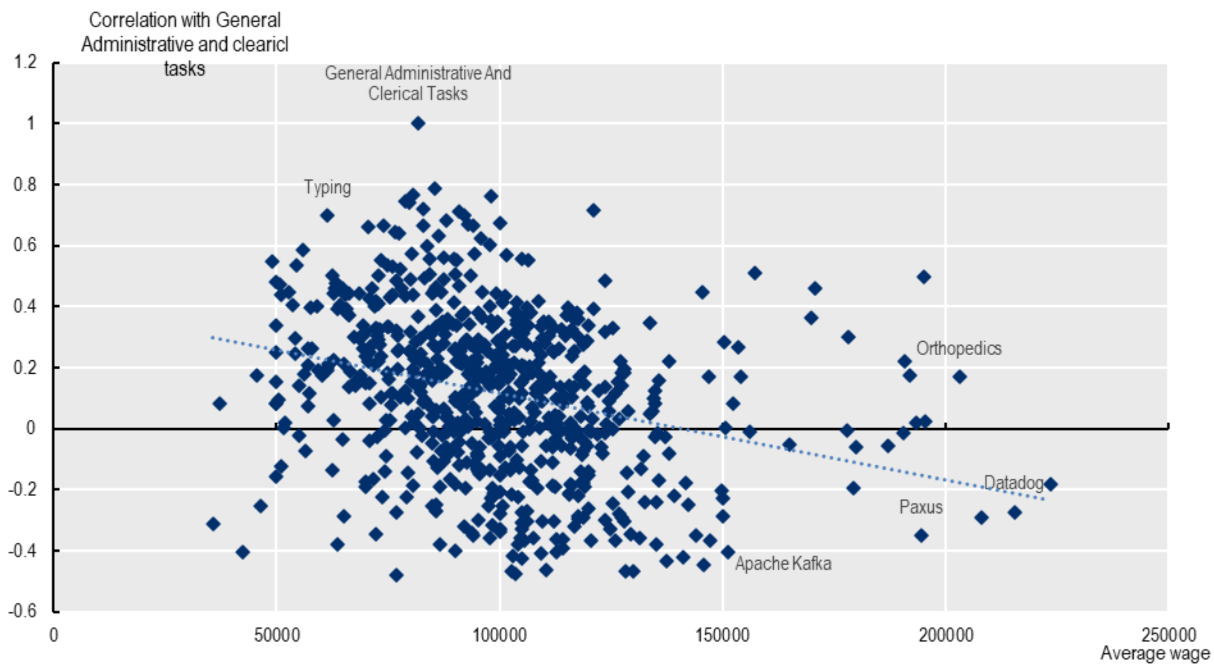
Note: Values on the vertical axis indicate the correlation coefficient of the skill under exam with artificial intelligence (in Panel A) or general administrative and clerical tasks (in Panel B). Values on the horizontal axis are the average wage associated to each skill across job postings collected in the country.
Source: OECD calculations based on Lightcast data

Figure 25. Relationship between AI, Routine skills and wages: Australia and New Zealand

Panel A: AI-relatedness and wages



Panel B: Routine-relatedness and wages



Note: Values on the vertical axis indicate the correlation coefficient of the skill under exam with artificial intelligence (in Panel A) or general administrative and clerical tasks (in Panel B). Values on the horizontal axis are the average wage associated to each skill across job postings collected in the country.

Source: OECD calculations based on Lightcast data

Conclusions

This study responds to a number of key questions about the impact of Artificial Intelligence (AI) on labour markets, skill demands and workers employability. Leveraging the detailed information contained in online job postings, this study first identifies what are the occupations where AI skills are most relevant in today's labour markets. AI-related occupations range from computer scientists, directors of information technology and data scientists but they also encompass roles in other sectors such as mechanical engineers, data warehousing specialists and product managers where the adoption of AI is increasing significantly.

This study also looks into what skills, technologies and knowledge areas are complementary to AI skills in jobs and enrich the skill bundles of professionals in AI jobs. Results indicate that machine learning, scripting languages or software development principles are amongst the knowledge areas that are most tightly linked to AI as they are demanded with high intensity in the same set of occupations where AI is also highly relevant. The analysis also shows that specific technologies or programming languages like caffe deep learning framework, cloud computing or convolutional neural network (CNN) are also key in AI jobs and are a key part of the skill set required by employers in AI jobs.

The analysis also delves into the association between AI and routine skill demands. Results show that jobs where AI skills are highly relevant usually do not demand routine-skills. Instead, jobs that require AI skills usually combine them with other high-level cognitive skills such as creative problem solving. Results suggest that an increase in the employment in AI-related jobs will be likely associated with a contextual increase in the demand for high-level cognitive and a relative decrease in the demand for routine skills.

Finally, this study looks at the labour market returns of AI skills. Evidence shows that AI-related skills and AI-related occupations are associated with positive and statistically significant wage returns. Evidence indicates that jobs where AI skills are highly relevant pay higher wages than the average even after accounting for average years of schooling, skill complexity of the job and geographical factors related to the job offer. Similarly, evidence shows that skills that are relevant in an AI-context are also associated with higher wages, suggesting that the development of skills that are complementary to AI is likely to pay off in today's labour markets.

Appendix: a machine learning approach to the analysis of online job postings

Previous literature that used online vacancies to analyse labour market dynamics has, in most cases, done so via frequency-based measures and by counting the number of times certain skills would be mentioned in online job postings. Recent developments in Natural Language Processing (NLP), however, allow to leverage the information contained in online vacancies in a much more sophisticated way by looking at the semantic meaning of the textual information contained in online job postings. One such approach, the so-called word embeddings, derive a word's meaning from the context this occurs in

These sophisticated methods leverage the distributional hypothesis, as stated by (Harris, 1954[27]), use the context in which a certain term occurs to derive the semantic meaning of the term. In their most common form, vector space models use the word's context (i.e. the other skills mentioned in the job posting) to derive the meaning of a word and create *n*-dimensional vectors to represent that meaning. This is a so-called semantic representation which is thus encoded and distributed over all the *n* dimensions of the vector, where each dimension stands for a certain context item and its coordinates refer to the count of this context (Erk, 2012[28]). This quantification of the semantics of words allows to compute mathematical similarity measures that reflect the similarity between different vectors representing different words and concepts (Boleda, 2020[29]).

Intuitively word vectors are retaining the semantic meaning of words and algebraic operations can be performed using them. As word vectors retain the semantic meaning of their underlying words, the results of such mathematical operations are expected to also return semantically and logically meaningful results. For instance, once word vectors have been estimated, one could perform basic arithmetic using those vectors, such as:

vec("Chief") + vec("Male")+vec("Royalty") ≈vec("King")

From a mathematical point of view, this means that if two words share an interrelated meaning (for example Chief, Male, Royalty and King) the cosine of the angle between their vector representations should be close to 1, i.e. the angle close to 0. Furthermore, negative values for the cosine refer to vector representations similar, but opposite in meaning such that vec("King")- vec("Male") ≈vec("Queen").

Based on these properties, one can compute measures of semantic similarity of pairs of skill keywords and occupations using paragraph vector distributed bag of words (PV-DBOW, DOC2VEC) to create the vectors representing occupations instead of simple skill keywords[16].

Next, one can construct a Semantic Skill Bundle Matrix (SSBM) by calculating the similarity between all possible combinations of skills keywords and any given occupation pairs. Comparison of the vectors is done by looking at the so-called similarity and/ or distance between vectors. This is to say that, given two vectors representations for keyword A, and occupation B, the calculation of the similarity is done as:

distance(A, B) = $(A \cdot B)/||A||\ ||B||$

To illustrate the type of information contained in the SSBM, an example is given in Table 1 for two randomly selected occupations "Web-Designer" and "Marketing Manager".

[16] PV-DBOW is an established technique in the natural language processing literature. A study by Mikolov et al. (2013) showed that in comparison to vector averaging (10.25%), bag-of-words (8.10%), bag-of-bigrams (7.28%) and weighted bag-of-bigrams (5.67%) the paragraph vectors, such as PV-DBOW, had the lowest error rate (3.82%). In contrast to other paragraph vector models, PV-DBOW ignores the context words in the input, but forces the model to predict words randomly sampled from the paragraph in the output. In-short, each iteration of training, the model consecutively samples a text window and then a random word from this sampled text window to form a classification task for each given paragraph vector. Mikolov et al. (2013) state that in addition to being conceptually simple, PV-DBOW also requires less data to store than the distributed memory model (PV-DM).

Table 1. Example of SSBM values for the occupation Web Designer and Marketing Manager

Web Designer (1)		Marketing Manager (2)	
Web Design	0.73	Online Marketing	0.57
Bootstrap	0.62	Marketing Management	0.52
Graphic And Visual Design	0.55	General Marketing	0.52
User Interface And User Experience	0.55	Marketing Strategy	0.50
Digital Design	0.55	Web Analytics	0.49
Javascript And Jquery	0.55	Media Strategy And Planning	0.47
Animation And Game Design	0.53	Content Development And Manageme	0.45
…		….	
Electrical Engineering Industry	-0.06	Civil Aviation Authority	-0.04
Occupational Hygiene	-0.06	Fuel Meters	-0.04
Oil Well Intervention	-0.06	Diagnostic Technologies	-0.04
Oil Wells	-0.06	Repair	-0.06
Mechanical Products Industry Kno	-0.08	Thermoplastic	-0.07
Health Care Industry Knowledge	-0.11	Radio Frequency Equipment	-0.08

Note: Values reported in the table represent the cosine similarity between each skill keyword vector representation listed in column (1) and (2) and the vector representation of the occupation web designer and marketing manager. Higher values of the cosine similarity reflect higher semantic relatedness and it is interpreted as an indication of the relevance of the skill keyword for the occupation at hand.
Source: OECD calculations based on Lightcast data for the United Kingdom in 2018.

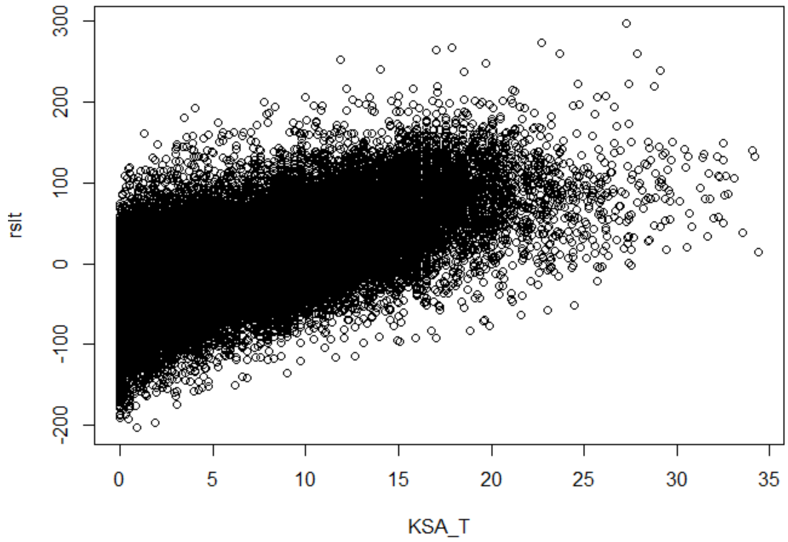
From an intuitive point of view, the closer (semantically, in meaning) a skill keyword vector representation is to the vector representation of the occupation and the more the skill is relevant for the occupation at hand. Results in Table 1 show that the skill vectors “Web Design”, “Bootstrap” and “Graphic and Visual Design” are semantically close to the occupation “Web Designer” and, hence, are interpreted in this paper as “relevant” to that occupation. Similarly, “Online Marketing”, “Marketing Management” and “General Marketing” are the most relevant skill keywords for “Marketing Managers”.

The intrinsic evaluation of word embeddings as the one discussed above is commonly evaluated by correlating the similarity scores with expert constructed scores. This appendix provides empirical support to the hypothesis for which these SSBM scores can indeed be used to represent the relevance of skills for occupations by comparing them with the skill information contained in the O*NET database.

O*NET is a tool for career exploration and job analysis which contains detailed descriptions of more than 900 occupations and their corresponding knowledge, skills, abilities, and competencies. O*NET collects this data from job incumbents and occupation experts who assess the importance and level of each knowledge, skill, ability, and competency for each specific occupation and rank them correspondingly. Comparison between O*NET and SSBM data is useful in evaluating how well the SSBM represents the relations between occupations and skills and the cosine similarity scores represent skill relevance.

Figure 26 correlates the O*NET values (the importance * level scores of each skill per occupation) and the respective SSBM values (the relevance scores) across all combinations of occupations and skills. The figure shows that the correlation between the two variables is strong (0.62), positive and statistically significant providing further evidence of the alignment between the SSBM and O*NET values and of the validity of using SSBM relevance scores as a measure of relevance for occupations as this is closely related to the importance and level scores provided by experts in O*NET.

Figure 26. Global correlation between SSBM relevance scores and O*NET ranked values of importance and level



Note: Dots represent occupations at the 6th digit US SOC level. Each dot is the combination of two values: on the horizontal axis (KSA_T) representing the O*NET scores (importance*level); on the vertical axis (rslt) the corresponding SSBM cosine similarity for every occupation.
Source: OECD calculations based on Lightcast data for the United States for the year 2019.

The vector representation of skill keywords in a n-dimensional space is also functional to assess the connections across skills and, as such, the degree by which skills are pervasive in the observed labour market published online. The connections between a group of keywords can be represented by a so-called skill graph. In such graph, the keywords extracted from online vacancies represent the vertices (also called nodes) which can be either connected when both vertices co-occur in a specific job vacancy, or disconnected when both vertices never co-occur in the same vacancy.

A so-called adjacency matrix is built to represent these skill co-occurrences where extracted skill graph forms an undirected acyclic graph, meaning that skills do not co-occur with themselves. As a result the diagonal of the adjacency matrix is 0. Whenever a skill co-occurs with another skill in a certain job vacancy, the row corresponding to the skill “A”, and the column corresponding to the skill “B” will get the value 1. Note that the adjacency matrix is symmetric, meaning that the co-occurrence between skills is undirected and therefore commutative.

One can then use the adjacency matrix to calculate the eigenvector centrality (EVC) and the local clustering coefficient (LCC) for each skill. In graph theory, the “eigenvector centrality” and the “local clustering coefficient” are two measures that are used to assess the influence of a node in a network or, in other words, to measure the degree and quality of connections of a keyword with the rest of words in the text under exam. Intuitively, the LCC looks at the degree to which a certain skill clusters together with other neighbouring skills. In contrast, the EVC quantifies the importance of the skill by looking at the importance of the connections it has with other skills. The same measures can, however, be used to capture the number of connections that a skill keyword has with other skills as well as the ‘quality’ of those connections, where higher quality connections are those with other skills that are also highly connected to the rest of the skills in the vector space.

The power iteration algorithm is used to derive the relativity score for each vertex v in the network. Given a graph G, and adjacency matrix A, the relative centrality score of a certain skill can be defined as:

$$EVC_v = \frac{1}{\lambda}\sum_{t \in M(v)} \quad EVC_t = \frac{1}{\lambda}\sum_{t \in G} \quad a_{v,t} EVC\lambda \qquad (1)$$

Where we define λ to be a constant eigenvalue, and $\alpha_{v,t}$to be a cell in the adjacency matrix A, particularly with row v and column t. Intuitively, $\alpha_{v,t}$ is the cell containing the adjacency score of a vertex v given a vertex t in the neighbourhood $M(v)$.

Since this is an undirected graph, the local clustering coefficient can also be defined as:

$$LCC_i = \frac{e_{jk}: v_j, v_k \in N_i, e_{jk} \in E}{k_i(k_i - 1)} \qquad (2)$$

Where we define e to be an edge (with indices j and k, since we are connecting vertices v_j, v_k), and k_i the number of neighbours of a vertex.

Both measures serve as an important indicator for contextual diversity and the importance of certain skills as compared to other skills in the network. In graph theory, the “eigenvector centrality” and the “local clustering coefficient” are two measures that are commonly used to assess the influence of a node in a network or, in other words, to measure the degree and quality of connections of a keyword with the rest of words in the text under exam. Originally, these measures were developed by researchers in Google and used in the PageRank algorithm to quantify the importance of the connections among web pages based on the textual information contained in it. The same measures can, however, be used to capture the number of connections that a skill keyword has with other skills as well as the ‘quality’ of those connections, where higher quality connections are those with other skills that are also highly connected to the rest of the skills in the vector space.

One can finally create a unidimensional measure by normalizing and rescaling the eigenvector centrality and the local clustering coefficient into a single measure using the following:

$$Diffusion_{it} = \frac{EVC_{it} + (1 - LCC_{it})}{2},$$

where i represents each skill keyword and t is the time. The change over time of the Diffusion index is used in the analysis above to measure the degree by which skills have become pervasive in the labour market.

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