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Demand for AI skills in jobs: Evidence from online job postings

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Abstract

This report presents new evidence about occupations requiring artificial intelligence (AI)-related competencies, based on online job posting data and previous work on identifying and measuring developments in AI.

It finds that the total number of AI-related jobs increased over time in the four countries considered – Canada, Singapore, the United Kingdom and the United States – and that a growing number of jobs require multiple AI-related skills.

Skills related to communication, problem solving, creativity and teamwork gained relative importance over time, as did complementary software-related and AI-specific competencies.

As expected, many AI-related jobs are posted in categories such as "professionals" and "technicians and associated professionals", though AI-related skills are in demand, to varying degrees, across almost all sectors of the economy.

In all countries considered, the sectors "Information and Communication", "Financial and Insurance Activities" and "Professional, Scientific and Technical Activities" are the most AI job-intensive. This analysis aims to inform the discussion on skills demand and the role that human capital may play in relation to technology development and diffusion, in firms and industries.

Keywords: Digital, Employment, Science & Technology

JEL codes: O32, J23, J24

Synthèse

Ce document présente des données entièrement nouvelles sur les professions nécessitant des compétences liées à l'Intelligence Artificielle (IA), en s'appuyant sur les publications d'offres d'emploi en ligne et sur de précédents travaux visant à étudier et mesurer l'évolution de l'IA.

Ces données montrent que le nombre total d'emplois liés à l'IA a augmenté au cours du temps dans les quatre pays considérés – Canada, États-Unis, Royaume-Uni, Singapour – et qu'un nombre croissant d'emplois requièrent des compétences multiples en IA.

Cependant, ces offres d'emploi nécessitant des compétences en IA demandent également de plus en plus des compétences complémentaires en communication, résolution de problèmes, créativité et travail d'équipe.

Comme on peut s'y attendre, la plupart des offres d'emplois liés à l'IA sont publiées dans des catégories telles que «Professions intellectuelles et scientifiques» et «Professions intermédiaires», même si des compétences en IA sont recherchées, à des degrés variables, dans presque tous les secteurs de l'économie.

Dans tous les pays considérés, les secteurs «Information et communication», «Activités financières et d'assurances» et «Activités professionnelles, scientifiques et techniques» sont ceux qui cherchent le plus activement à recruter des employés en lien avec l'IA.

Kurzfassung

Diese Studie enthält neue Erkenntnisse zu Berufen, die Kompetenzen im Zusammenhang mit künstlicher Intelligenz (KI) erfordern. Sie beruht auf online ausgeschriebenen Stellen und auf früheren Arbeiten, die der Identifizierung und Messung von Entwicklungen in der KI dienen.

Dabei ist festzustellen, dass die Zahl der KI-relevanten Jobs in den vier betrachteten Ländern - Kanada, Singapur, Großbritannien und den Vereinigten Staaten von Amerika - stets zugenommen hat und dass eine immer zunehmende Zahl von Jobs mehrere KI-bezogene Fähigkeiten erfordert.

Kompetenzen in Bezug auf Kommunikation, Problemlösung, Kreativität und Teamarbeit gewannen im Laufe der Zeit an relativer Bedeutung, sowie ergänzende Softwarefähigkeiten an Wichtigkeit.

Erwartungsgemäß werden viele KI-relevante Jobangebote unter Kategorien wie „Fachkräfte" und „Techniker und zugehörige Fachkräfte" gefunden, obwohl KI-relevante Kompetenzen in nahezu allen Wirtschaftssektoren in unterschiedlichem Maße gefragt sind.

In allen untersuchten Ländern sind die Sektoren, in denen am aktivsten nach Arbeitskräften mit KI-relevanten Fähigkeiten gesucht wird, „Information und Kommunikation", „Finanz- und Versicherungsaktivitäten" und „Professionelle, wissenschaftliche und technische Aktivitäten".

Executive summary

Artificial Intelligence (AI) is reshaping economies and societies. While often in their infancy and with much potential to be fulfilled, AI technologies promise to overhaul production by improving efficiency, reducing costs, multiplying product and service offerings, and supporting decision-making, among others.

As AI permeates economies and societies, it nevertheless raises questions and fuels anxieties, including around its impact on jobs. AI is expected to complement humans in some tasks, while replacing them in others; and to generate new types of jobs while transforming the way work is organised, the tasks to be performed and the skills needed in the world of work and, more generally, in life.

Managing the AI transition in a responsible and people-centred fashion is a major challenge for governments. It calls for evidence informing the design of policies able to foster the development of AI while making sure that its deployment across economies and societies contributes to improve individual and societal well-being.

This report offers first-time evidence about the job adverts requiring Artificial Intelligence-related competences, here called AI-related jobs, and the type of AI-related competences and skills demanded from workers.

It aims to inform the discussion on skills demand and the role that human capital may play in enabling the digital transformation of firms and industries - especially the diffusion of AI-related technologies -, and to provide evidence in support of policy-making regarding technology adoption and development, economic performance and skills needs.

The analysis relies on information from online job platforms and companies' websites collected by Burning Glass Technologies (BGT) for Canada, Singapore, the United Kingdom and the United States for the period 2012-18. It builds on the findings and AI-related keywords identified in WPIA work assessing AI-related developments in science and technology (Baruffaldi et al. (2020[1])). The analysis has further benefitted from expert advice from the UK Department for Business, Energy and Industrial Strategy (BEIS) about software packages and software repositories used in AI-related developments.

Key findings are:

- The total number of AI-related jobs advertised online increased over time, and reached almost 150 000 AI-related job postings in the US in 2018.
- In all countries, a growing number of AI-related jobs advertised online required multiple AI-related skills. In 2012, no AI-related job posted online required more than 7 AI-related skills in Canada and Singapore, or more that 9 AI-related skills in the UK and the US. In 2015 and 2018, online job adverts requiring 10 or more AI-related skills were observed in all countries.
- In all countries considered, between 2012 and 2018, the average share of AI software-related skills out of total AI-related skills sought in jobs advertised online increased. In 2018, such share amounted to about 30%.
- In 2012, a considerable part of the overall skill set of AI-related jobs advertised online was represented by skills not directly or solely related to AI, such as software engineering and development as well as operating systems. By 2018, however, software engineering and development seemed to have lost relative importance, while AI-related skills such as Natural Language Processing (NLP) and deep

learning emerged more prominently. Skills related to big data constituted a considerable part of the skills profiles of AI-related jobs advertised online, throughout the period considered, in all countries.

- Skills related to communication, problem solving, creativity and teamwork gained relative importance over time and complemented software-related skills as well as AI-specific competencies, although to different extents in different countries. Overall, a trend towards requiring a set of generic skills in AI-related jobs emerges from the data.
- Between 2012 and 2016, demand for “cluster analysis” skills experienced a sudden and marked increase (a “burst”) across all countries. Moreover, particularly in Canada, the UK and the US, many of the other skills that burst in this period related to data mining and classification, NLP and computational linguistics. In the same period, across all countries evidence showed bursting of skills related to machine vision, including image recognition and processing, pattern recognition as well as motion planning.
- The burst behaviours observed in Canada and the US, and to a lesser extent in the UK and Singapore, further confirm a growing trend in the demand for deep learning-related skills, most notably in 2017 and 2018.
- In terms of occupational groups under which AI-related jobs are advertised, many AI-related jobs belonged to the “Professionals” and “Technicians and associated professionals” categories.
- Moreover, with the exception of “Skilled agricultural, forestry and fishery workers”, which nevertheless are insufficiently represented in BGT data (see Cammeraat and Squicciarini (2021, forthcoming[2])), a growing number of AI-related jobs openings was posted online over time, in relation to all occupational groups.
- Skills related to AI appear to be in demand across almost all sectors of the economy, though to varying degrees. The group of sectors “Information and Communication” (J), “Financial and Insurance Activities” (K) and “Professional, Scientific and Technical Activities” (M) ranked at the top in terms of AI-job intensive sectors, in all countries considered.

Résumé

L'Intelligence Artificielle (IA) est en train de remodeler nos économies et nos sociétés. Quoique souvent encore à un stade immature, avec une grande marge de progression, les technologies de l'IA promettent une réorganisation de la production en augmentant l'efficacité, en réduisant les coûts, en accroissant l'offre de produits et de services, et en aidant à la prise de décision.

Alors que l'IA pénètre économies et sociétés, elle soulève néanmoins des questions et alimente les craintes, notamment au sujet de son impact sur l'emploi. L'IA promet d'assister les humains pour certaines tâches, voire de les remplacer pour d'autres ; et de générer de nouveaux types d'emplois tout en transformant la façon dont sont organisés le travail, les tâches à accomplir et les compétences requises dans le monde du travail, et plus globalement, dans la vie.

Une gestion responsable et centrée sur l'humain de la transition vers l'IA est un enjeu majeur pour les gouvernements. Cela nécessite des informations fiables pour aider à concevoir des politiques capables de favoriser le développement de l'IA tout en assurant que son déploiement au sein des économies et des sociétés contribue à améliorer le bien-être individuel et sociétal.

Ce rapport présente des données entièrement nouvelles sur les offres d'emplois nécessitant des compétences relatives à l'IA, nommés ici emplois liés à l'IA, et sur le type de qualifications et de compétences relatives à l'IA demandées aux travailleurs.

Son objectif est d'alimenter la discussion sur la demande de qualifications et sur le rôle que le capital humain pourrait jouer afin de permettre la transition numérique des entreprises et des industries – particulièrement la diffusion des technologies relatives à l'IA –, et de fournir des bases à l'élaboration de politiques concernant l'adoption et l'évolution technologiques, la performance économique et les besoins en compétences.

L'analyse repose sur l'information collectée par Burning Glass Technology (BGT) à partir des plateformes d'offres d'emploi en ligne et des sites internet des entreprises, pour le Canada, les États-Unis, le Royaume-Uni et Singapour, sur la période 2012-18. Elle est basée sur les résultats et les mots-clés relatifs à l'IA identifiés dans les travaux du Groupe de Travail sur l'Analyse de l'Industrie (GTAI) analysant le développement de l'IA dans la science et la technologie (Baruffaldi et al.,2020). L'analyse a de plus bénéficié d'avis d'experts du Ministère des entreprises, de l'énergie et de la stratégie industrielle du Royaume-Uni (BEIS) en ce qui concerne les logiciels liés à l'IA.

Les résultats principaux sont:

- Le nombre total d'emplois liés à l'IA proposés en ligne a augmenté dans le temps, et a atteint presque 150 000 offres d'emplois liés à l'IA aux États-Unis en 2018.
- Dans tous les pays, un nombre croissant d'emplois liés à l'IA proposés en ligne requièrent des qualifications multiples en IA. En 2012, aucun emploi lié à l'IA proposé en ligne ne demandait plus de 7 qualifications liées à l'IA au Canada et à Singapour, ou plus de 9 aux États-Unis et au Royaume-Uni. En 2015 et 2018, les annonces d'emploi demandant 10 qualifications ou plus en IA étaient présentes dans tous les pays.

- Dans tous les pays considérés, entre 2012 et 2018, la part des compétences liées à l'IA portant sur des logiciels spécifiques recherchées dans les offres en ligne a augmenté. En 2018, cette part s'élevait à 30%.
- En 2012, une part considérable des compétences demandées pour les offres d'emplois liés à l'IA publiées en ligne était constituée de compétences non directement ou non uniquement en relation avec l'IA, telles que l'ingénierie et le développement logiciels ou les systèmes d'exploitation. En 2018, en revanche, l'ingénierie et le développement logiciels semblaient avoir perdu de leur importance relative, alors que des compétences en IA telles que le traitement automatique du langage naturel (TALN) et l'apprentissage en profondeur («deep learning») ont émergé de façon apparente. Les compétences liées au big data ont constitué une part notable des profils de compétences des emplois liés à l'IA publiés en ligne, pendant toute la période, dans tous les pays.
- Les compétences en communication, résolution de problèmes, créativité et travail d'équipe ont gagné en importance relative dans le temps, et complètent des compétences en logiciel autant que des compétences spécifiques en IA, bien qu'à différentes échelles selon les pays. Généralement, une tendance à la demande d'un ensemble de qualifications génériques dans les emplois liés à l'IA apparait dans les données.
- Entre 2012 et 2016, la demande pour des compétences en « analyse de clusters » ont connu une croissance soudaine et marquée dans tous les pays. Au Canada, aux États-Unis et au Royaume-Uni, beaucoup d'autres compétences qui ont vu leur demande s'accélérer pendant cette période concernaient l'exploration et la classification de données, le TALN et la linguistique informatique. Pendant cette même période, tous les pays ont connu une accélération de la demande en compétences relatives à la vision artificielle, dont la reconnaissance et le traitement d'image, la reconnaissance de formes ainsi que la planification de mouvement.
- Cette accélération observée au Canada et aux États-Unis, et dans une moindre mesure au Royaume-Uni et à Singapour, confirme un peu plus une tendance croissante dans la demande de compétences liées à l'apprentissage en profondeur (deep learning), plus particulièrement en 2017 et 2018.
- En terme de catégories professionnelles, un nombre important d'annonces d'emplois relatifs à l'IA appartenait aux catégories «Professions intellectuelles et scientifiques» et «Professions intermédiaires».
- De plus, à l'exception des « Agriculteurs et ouvriers qualifiés de l'agriculture, de la sylviculture et de la pêche » qui de toute façon sont insuffisamment représentés dans les données BGT (voir Cammeraat and Squicciarini, 2021 forthcoming), un nombre croissant d'ouvertures de postes en relation avec l'IA ont été publiées en ligne au cours du temps dans toutes les catégories professionnelles.
- Les compétences en IA semblent recherchées dans presque tous les secteurs de l'économie, bien qu'à différents degrés. L'ensemble des secteurs «Information et communication» (J), «Activités financières et d'assurances» (K) et «Activités professionnelles, scientifiques et techniques» (M), sont les plus importants en termes d'intensité en emplois liés à l'IA, et ce dans tous les pays considérés.

Zusammenfassung

Künstliche Intelligenz (KI) verändert Wirtschaften und Gesellschaften. Obwohl KI-Technologien oft noch in den Anfängen mit viel Potenzial für die Zukunft stecken, versprechen sie bereits jetzt eine Veränderung der Produktion, indem sie unter anderem die Effizienz verbessern, Kosten senken, Produkt- und Serviceangebote vervielfachen und Entscheidungen unterstützen können.

Obwohl KI bereits Einzug in Wirtschaft und Gesellschaft gehalten hat, wirft sie Fragen auf und schürt Ängste, die auch ihre Auswirkungen auf Arbeitsplätze einschließt. Es ist zu erwarten, dass KI den Menschen bei einigen Aufgaben ergänzen und bei anderen ersetzen wird; dass sie neue Arten von Arbeitsplätzen schaffen und gleichzeitig die Organisation der Arbeit nach Art und Weise verändern kann. Das schließt die auszuführenden Aufgaben und Fähigkeiten, die in der Arbeitswelt und im Leben allgemein benötigt werden ein.

Das verantwortungsvolle und auf den Menschen ausgerichtete Management des KI-Übergangs ist eine große Herausforderung für die Regierungen. Es bedarf belastbarer Nachweise für die Gestaltung von Strategien, die die Entwicklung der KI fördern und gleichzeitig sicherstellen, dass ihr Einsatz in der Wirtschaft und der Gesellschaft zu einer Verbesserung des individuellen und gesellschaftlichen Wohlbefindens beiträgt.

Diese Studie liefert erstmals Nachweis über Stellenanzeigen, in denen KI-relevante Kompetenzen gefordert werden, hier als KI-relevante Jobs bezeichnet, sowie über die KI-bezogenen Kompetenzen und Fähigkeiten der Arbeitnehmer.

Ziel ist es, die Diskussion über den Kompetenzbedarf und die Rolle des menschlichen Kapitals bei der Ermöglichung der digitalen Transformation von Unternehmen und Industrien - insbesondere der Verbreitung von KI-relevanten Technologien - anzuregen und dem politischen Entscheidungsprozess in Bezug auf Technologiengestaltung und -entwicklung, wirtschaftliche Leistung und Kompetenzbedarf mit entsprechenden Erkenntnissen zu unterstützen.

Die Analyse beruht auf Informationen von Online-Jobplattformen und Unternehmenswebseiten, die von Burning Glass Technologies (BGT) für Kanada, Singapur, Großbritannien und die Vereinigten Staaten von Amerika für den Zeitraum von 2012 bis 2018 gesammelt wurden. Sie baut auf den Ergebnissen und KI-bezogenen Schlüsselwörtern auf, die in der WPIA-Arbeit zur Bewertung von KI-basierten Entwicklungen in Wissenschaft und Technologie identifiziert wurden (Baruffaldi et al. (2020)). Die Analyse profitiert ferner von Expertenratschlägen des britischen Ministeriums für Wirtschaft, Energie und Industriestrategie (Department for Business, Energy and Industrial Strategy, BEIS) zu Softwarepaketen und Softwarerepositorien, die bei Entwicklungen der KI Verwendung finden.

Die wichtigsten Ergebnisse sind:

- Die Zahl der online ausgeschriebenen KI-relevanten Jobs stieg im Laufe der Zeit stetig und erreichte 2018 in den Vereinigten Staaten fast 150 000 Stellenausschreibungen.
- In allen Ländern erforderte eine wachsende Anzahl von online ausgeschriebenen KI-relevanten Jobs auch mehrere KI-bezogene Fähigkeiten. Im Jahr 2012 verlangte kein derartiger Job mehr als 7 solcher Fähigkeiten in Kanada und Singapur und mehr als 9 dieser Fähigkeiten in Großbritannien und den Vereinigten Staaten. In

den Jahren 2015 und 2018 wurden in allen Ländern Online-Stellenanzeigen mit 10 oder mehr KI-bezogenen Fähigkeiten geschaltet.

- Zwischen 2012 und 2018 stieg in allen online ausgeschriebenen Stellen der betrachteten Länder der Software Anteil aller KI-relevanten Fähigkeiten kontinuierlich an. Im Jahr 2018 betrug dieser Anteil rund 30%.
- Im Jahr 2012 machte ein erheblicher Anteil der gesamten Fähigkeiten der online ausgeschriebenen KI-relevanten Jobs Kompetenzen aus, die nicht direkt oder ausschließlich mit KI zusammenhängen, wie z. B. Softwaretechnik und -entwicklung sowie Betriebssysteme. Bis 2018 schienen jedoch Softwaretechnik und -entwicklung an relativer Bedeutung verloren zu haben, während KI-relevante Fähigkeiten wie Natural Language Processing (NLP) und Deep Learning an Wichtigkeit gewannen. Kompetenzen im Zusammenhang mit Big Data machten im gesamten Betrachtungszeitraum in allen Ländern einen erheblichen Teil der Kompetenzprofile von KI-relevanten Jobs aus.
- Kompetenzen in Bezug auf Kommunikation, Problemlösung, Kreativität und Teamarbeit gewannen im Laufe der Zeit an relativer Bedeutung und ergänzten Software- sowie KI-spezifische Kompetenzen, wenn auch in unterschiedlichem Umfang in verschiedenen Ländern. Insgesamt ergibt sich aus den Daten der Trend, eine Reihe allgemeiner Fähigkeiten in KI-relevanten Jobs zu fordern.
- Zwischen 2012 und 2016 verzeichnete die Nachfrage nach Fähigkeiten zur „Clusteranalyse“ in allen Ländern ein plötzliches und deutliches Wachstum (eine „Beschleunigung“). Insbesondere in Kanada, den Vereinigten Staaten und Großbritannien "beschleunigten" sich in dieser Zeit Data Mining und Klassifizierung, NLP und Computerlinguistik. Im gleichen Zeitraum gab es in allen Ländern eine Beschleunigung des maschinellen Sehens, einschließlich Bilderkennung und -verarbeitung, Mustererkennung und Bewegungsplanung.
- Die in Kanada und den Vereinigten Staaten sowie in geringerem Maße in Großbritannien und Singapur beobachtete „Beschleunigung“ bestätigt insbesondere in 2017 und 2018, den weiterhin wachsenden Trend, Fähigkeiten im Bereich Deep Learning verstärkt nachzufragen.
- Viele KI-relevante ausgeschriebene Jobs waren unter den Berufsgruppen „Fachkräfte“ und „Techniker und zugehörige Fachkräfte“ zuzuordnen.
- Für alle Berufsgruppen ist im Laufe der Zeit ein Zuwachs der KI-relevanten Jobs zu beobachten. Davon ausgenommen sind „qualifizierten Land-, Forst- und Fischereifachkräften“, die in den BGT-Daten jedoch auch nicht ausreichend vertreten sind (siehe Cammeraat und Squicciarini (2021, forthcoming)).
- KI-relevante Fähigkeiten scheinen in fast allen Wirtschaftssektoren gefragt zu sein, wenn auch in unterschiedlichem Maße. Besonders die Sektoren „Information und Kommunikation“ (J), „Finanz- und Versicherungsaktivitäten“ (K) und „Professionelle, wissenschaftliche und technische Aktivitäten“ (M) lagen in allen der berücksichtigten Länder diesbezüglich an der Spitze.

1. Background

The work carried out by the Working Party on Industry Analysis (WPIA) in the context of the "Jobs and Skills" pillar of the Going Digital horizontal project, performed in the course of the Programme of Work and Budget 2017-18, provided evidence about the way in which the digital transformation is shaping jobs and skills.

In particular, joint work with the Directorate for Education and Skills (EDU) contributed to shed light on: the skill endowment of the workforce and the skill distances that emerge across occupations (STI Policy Paper n. 70/2019); the training required to move individuals across occupations (STI Policy Paper n 52/2018); and the cost that such re-qualification / upskilling may entail for countries (STI Policy Paper 61/2019).

Recognising the policy relevance of these analyses, the WPIA's parent Committee, the Committee on Industry, Innovation and Entrepreneurship (CIIE), expressed its support for WPIA to continue this work. In particular, the WPIA Secretariat was asked to inform the discussion on skills demand and the role that human capital may play in relation to technology development and diffusion, in firms and industries. It was recognised that, as the digital transformation unfolds, building human capacity is a critical policy area. It represents a necessary precondition for a fair labour market transformation as well as the cornerstone of technology diffusion and improved economic performance.

In line with this mandate, support from the German government has allowed setting up a dedicated Programme on "Artificial Intelligence (AI) in Work, Innovation, Productivity and Skills" (AI-WIPS) aimed at producing in depth analyses, measurement and knowledge in support of the international dialogue on the impact of AI on economies, labour markets and society.

In what follows we propose first-time evidence about the occupations requiring Artificial Intelligence-related competences. The analysis relies on information from online job platforms and companies' websites collected by a commercial data provider, Burning Glass Technologies (BGT), and on past WPIA work (Baruffaldi et al. (2020[1])) identifying and measuring developments in AI.

This work aims to inform the discussion on skills demand and the role that human capital may play in enabling the digital transformation of firms and industries - especially the diffusion of AI-related technologies -, and provide evidence to support policies addressing economic performance and skills needs.

2. Introduction

Artificial Intelligence (AI) is a term commonly used to refer to machines performing human-like cognitive functions (e.g. learning, understanding, reasoning and interacting)[1]. In recent years, AI has started to be considered as a general-purpose technology (Brynjolfsson, Rock and Syverson, 2017[3]) and is expected to generate productivity gains across all economic sectors and help address complex societal challenges, including aging, pandemics, health and the environment.

However, the extent to which AI will be developed and adopted and economic agents will be able to leverage it will depend on a number of factors. Among them, investment in AI itself, in (complementary) tangible and intangible assets, including IT infrastructure and business processes and, most importantly, the very knowledge and skills needed to work with AI. As AI develops and is adopted, it will likely change the way firms organise production and, with it, the nature of jobs and the skills that workers will need to perform them (OECD, 2017[4]) (Acemoglu and Restrepo, 2018[5]) (Brynjolfsson and Mitchell, 2017[6]).

While analysis related to these issues has been burgeoning recently, empirical evidence about the possible effects of AI on job and skills demand remains scant, also due to the difficulties inherent in operationally defining AI and the paucity of high-quality and representative data about job tasks and skills demand.

In the context of the Going Digital project performed over the biennium 2017-18, OECD work has provided evidence about the possible impact of the digital transformation on labour markets and skills. Among others, it has highlighted the role of training in helping workers move to different occupations, if made redundant by automation (see Bechichi et al. (2019[7]); the costs that such training may entail for countries (see Andrieu et al. (2019[8])); and a number of policy relevant implications (OECD, 2019[9]). In addition, recent studies have focused on the impact of AI on jobs and, in particular, on the very skills and tasks that AI may or may not replace (e.g. Brynjolfsson, Mitchell and Rock (2018[10]) Acemoglu and Restrepo (2019[11])). Finally, a complementary strand of work has investigated how AI can complement - instead of substituting - humans and create new types of work. Among the job areas identified as complementary to AI there are those that leverage skills such as critical thinking, creativity and empathy (see, e.g. (EOP, 2016[12]) (OECD, 2017[13]).

The present work contributes to shedding light on the skills needed to work with AI and the jobs requiring AI-related competences. Skills are at the core of the analysis, as only a deep understanding of skills demand by firms and sectors can help disentangle the way the digital transformation, and AI in particular, is shaping labour markets and the tasks to be performed on the job. Moreover, characterising skills demand patterns helps assessing the extent to which technologies such as AI diffuse, as firms and sectors adopting or developing AI will need a suitably skilled workforce.

The analysis relies on job openings related data collected from online platforms and companies' websites by a commercial provider, Burning Glass Technologies (BGT). AI-related vacancies are identified using the lists of AI-related keywords provided by Baruffaldi et al. (2020[1]) and a list of AI-related software and repositories validated by experts at the UK Department for Business, Energy and Industrial Strategy (BEIS).

AI-related jobs are identified as those postings containing in the online job description at least two AI-related skills belonging to different concepts or methodologies[2], only one of which maybe a software-related skill. This simple methodology is in line with the one used in Baruffaldi et al. (2020[1]) and in Nakazato and Squicciarini (2020[14]) and has the advantage of being relatively easy to implement and to revise. In addition, the accuracy of the proposed method has been validated on the basis of a number of sensitiveness text and random checks aimed at minimising false positives, i.e. job postings wrongly identified as being AI-related, and false negatives, i.e. AI-related jobs that would not be detected otherwise.

Identifying AI-related job postings allows investigating the demand for AI-related jobs across occupations and industries in three OECD countries, namely Canada, the United Kingdom and the United States, and one non-OECD economy, i.e. Singapore, for the period 2012-18[3].

Operationally defining and mapping the skills needed to work with AI is key to connect the discussion on labour market supply and demand, and to provide evidence in support of policymaking. The demand for skills related to Artificial Intelligence may call for adjustments in a wide array of policies, including those related to higher and vocational education, workforce development and labour market participation. Without suitable policies for human capital development, technological progress, productivity and economic performance may be hindered by skill shortages. This may potentially coexist with unemployment amongst individuals lacking the skills to transition into AI-related jobs.

3. The data used in the analysis: Online job postings data

Online job postings are a new promising source of data. They may help shed light on jobs and skills demand patterns, offer new insights on labour market dynamics, and complement traditional sources of information. Job postings provide almost real-time information and may help understanding how new technologies such as AI may shape skill requirements. They may also provide an indication of the extent to which Artificial Intelligence is penetrating firms and sectors.

Burning Glass Technologies (BGT), a Boston-based analytics software company, collects and analyses job posting data from thousands of online sources on a daily basis. It uses text mining to extract information such as job title, skills, sector and occupational group from the free text job descriptions, and claims to capture the near-universe of online job vacancies. The advantage of using BGT data for the present analysis is their large sample size and their provision of almost real-time information on skill requirements. Their broad coverage also represents an advantage, as compared to datasets based on individual online vacancy sources.

BGT data have been used in a number of studies analysing skill requirements across firms and labour markets.

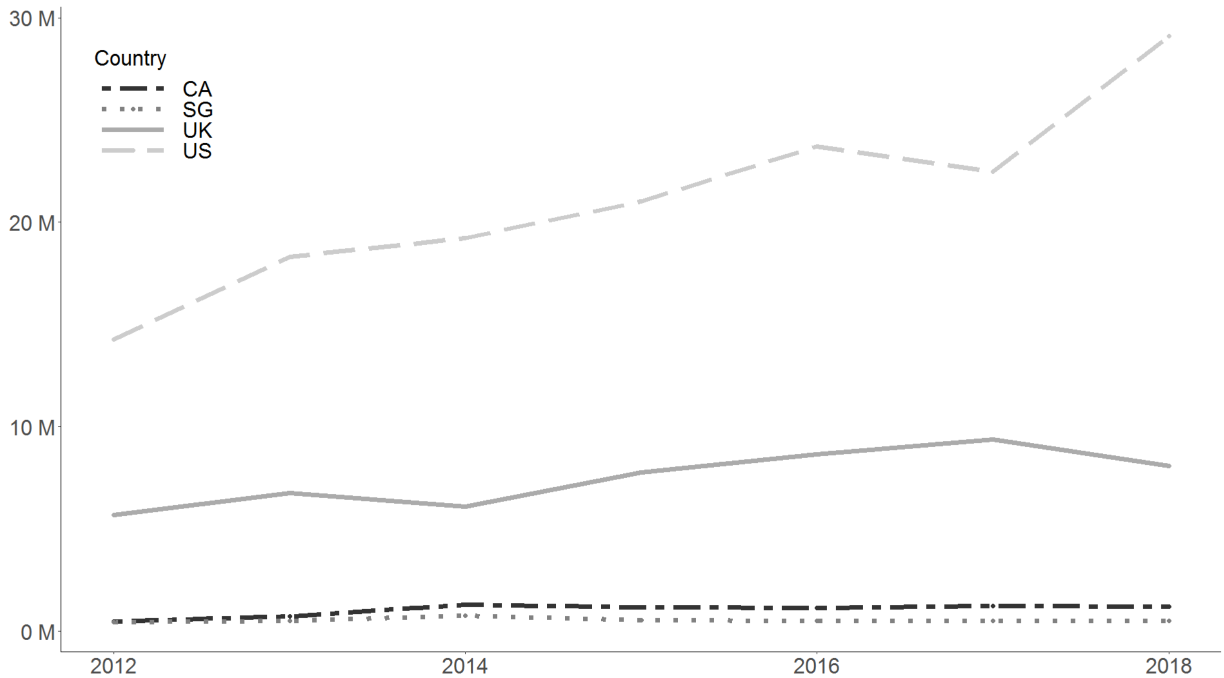
Rothwell (2014[15]) analyses skill requirements and the duration of the posting, with a particular focus on job postings in Science, Technology, Engineering and Mathematics (STEM). Beblavý et al. (2016[16]) study IT-skill requirements across occupations. Modestino, Shoag and Ballance (2016[17]) show that employer skill requirements fell during the post-recession period, between 2010 -14. Grinis (2017[18]) applies machine learning techniques to classify UK job postings into STEM and non-STEM jobs and analyses the relevant skillsets. Börner et al. (2018[19]) study the dynamic skill alignment between academic push, industry pull, and educational offerings, with a particular focus on data science and data engineering. Deming and Kahn (2018[20]) develop a skill classification based on BGT data and show that job skills have explanatory power in pay and firm performance. Sleeman and Djumalieva (2018[21]) develop a data-driven taxonomy of skills based on the BGT data from the UK using Natural Language Processing methods, such as document clustering and distributed word representations. Hershbein and Kahn (2018[22]) as well as Modestino, Shoag and Ballance (2019[23]) use BGT data to provide evidence of upskilling in times of an economic depression. Deming and Noray (2018[24]) elaborate on skill requirements in STEM jobs, highlighting the importance of technology skills in explaining life-cycle returns to education. Dillender, Marcus, Eliza C. Forsythe (2019[25]) focus on changing skill requirements due to the computerisation of white-collar jobs. Goldfarb, Bledi and Teodoridis (2019[26]) use BGT data to compare machine learning to other emerging technologies in terms of breadth of industries and research roles as well as the costs of innovation in organisational practices.

Carnevale, Jayasundera and Repnikov (2014[27]) estimate that in the US, in 2013, online job adverts captured roughly 60 to 70 percent of total job openings in the labour market. Hershbein and Kahn (2018[22]) as well as Carnevale, Jayasundera and Repnikov (2014[27]) conclude that the overall BGT data are representative of the US job market and underline the existence of an overrepresentation of those jobs requiring relatively greater skills than the average job. Hershbein and Kahn (2018[22]) find that with respect to the number of job openings, the aggregate and industry trends in BGT data are consistent with other data sources related to job vacancies in the US.[4]

Cammeraat and Squicciarini (2021, forthcoming[2]) assess the representativeness of BGT data at the 1 digit occupational level of the International Standard Classification of Occupations (ISCO 08), to inform the use of such data for policy-relevant purposes. They identify the subset of countries, years and occupational groups for which such data exhibit good statistical properties and propose a set of weights aimed to make BGT data representative of the reference population. In line with Cammeraat and Squicciarini (2021, forthcoming[2]), Figure 1 sees the United States featuring the highest number of job postings in BGT data, followed by the United Kingdom[5].

Figure 1. Total number of job openings in BGT data, by country and year

Millions of job postings

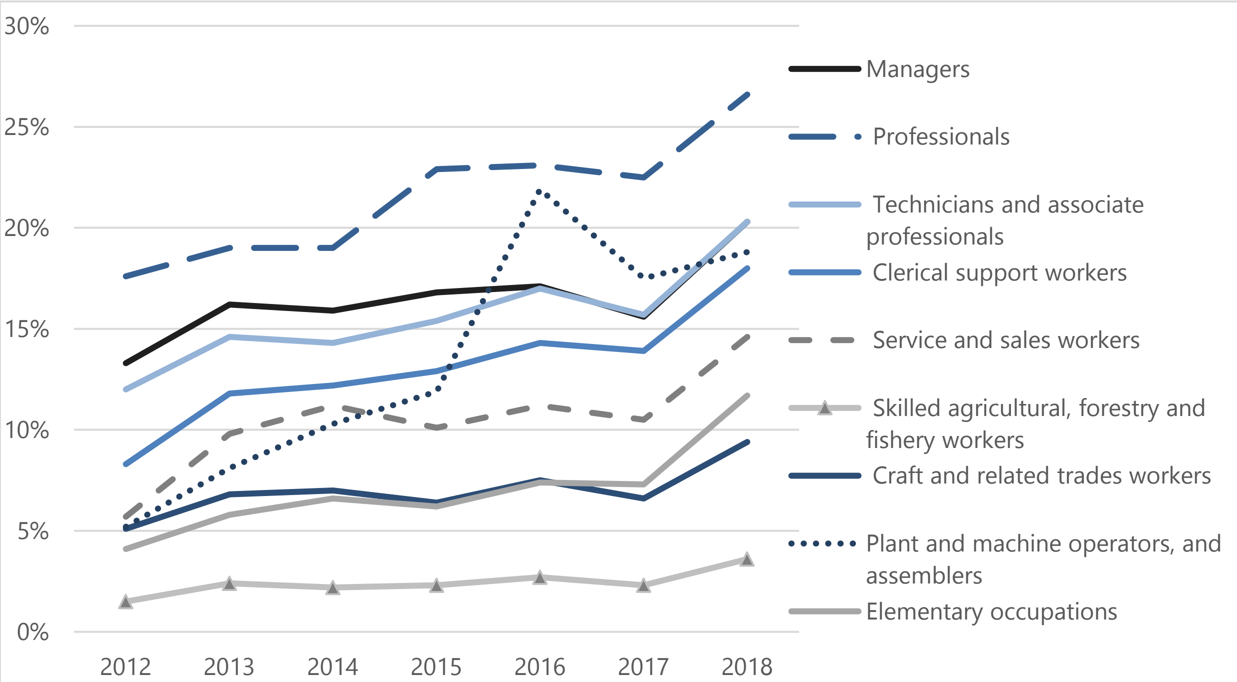


Note: Data related to December 2018 are missing for the United Kingdom.
Source: Authors' own calculations on Burning Glass Technologies data (February 2019).

It should be noticed that the vacancies appearing in BGT are likely to over represent growing firms and industries[6] as well as higher-skilled jobs, which are more likely to be posted online. Lastly, some firms may publish only one job advert but actually recruit several applicants. Also, analysis in Cammeraat and Squicciarini (2021, forthcoming[2]) shows different occupational groups to be represented to a different extent in BGT data, with low skill job openings being relatively less well represented in general.

As an example, Figure 2 shows the representativeness of BGT data for the United States for the period 2012-18, at the one-digit occupational group level. In this respect it must be noticed that assessing BGT data representativeness against official job opening figures is not possible, as these, among others, differ in the definition of what constitutes a job opening at a certain time and whether or not jobs were posted online. Cammeraat and Squicciarini (2021, forthcoming[2]) thus compare BGT data with official employment by occupation figures to assess BGT data's representativeness and quality, to inform use in policy-relevant analysis (see Cammeraat and Squicciarini (2021, forthcoming[2]) for a thorough discussion).

Figure 2. Share of Total number of job openings in the BGT data, by country and year



Note: Data related to December 2018 are missing for the United Kingdom.
Source: Authors' own compilation based on Table 2 in Cammeraat and Squicciarini (2021, forthcoming[2]).

As Cammeraat and Squicciarini (2021, forthcoming[2]) conclude in their study, BGT data appear of sufficient quality to enable cross-country comparative analysis for the economies and years included in the present study. Moreover, representativeness seems to be good especially in the case of skilled workers, which are those our study likely concentrates mostly upon, given the type of skills required in AI-related jobs.

Moreover, as AI-related jobs are by their very nature part of the digital transformation, it would be reasonable to expect the "norm" to be that they are posted online.[7] This being the case, BGT data should constitute a good source of info for the present study and we have no a-priori reason to fear that the stylised facts presented in what follows may not correspond to reality.

As a last caveat, it must be noticed that we here take data as face value, in the sense that no weighting scheme is applied to make BGT data more representative at the occupational group level (as conversely envisaged in Cammeraat and Squicciarini (2021, forthcoming[2]) for more general purposes). We do so aware that the digital transformation unfolds at a different pace and in different ways across firms and industries (see Calvino et al., 2019, for details), and that the development and adoption of AI-related technologies is a heterogeneous phenomenon (Dernis et al., 2019; Baruffaldi et al, 2020). The implicit assumption made here is therefore a direct consequence of what said above, i.e. that most if not all AI-related job openings are likely to be posted online and that this happens to a different extent across different firms, sectors and countries.

3.1. BGT variables used and coverage

In BGT data, variable names and the information provided vary across countries, as does the share of non-missing observations. In the present work, we mainly use BGT data related to skills, sector of activity, location, and occupation. The discussion that follows thus centres on these pieces of information.

3.1.1. Skills

From the full job posting text, BGT extracts and standardises skills-related information. The BGT "skill" variable contains information, in the form of keywords and multi-word expressions, about cognitive and non-cognitive skills, the way these skills are understood in existing literature, socio-emotional characteristics, as well as e.g. costumer-, management-, financial-, and computer-related skills (see also Deming and Kahn (2018[20]) about this). The latter may not strictly qualify as skills, but rather as sets of tools, features or knowledge that prospect candidates need to be endowed with or be able to deal with, if they want to succeed getting the advertised job.

Among the locutions that can be found in the skill variable there are specialised professional expertise related to a specific topic, e.g. "Throat Cancer knowledge", or industry (e.g. "Semiconductor Industry Knowledge"); broad keywords, e.g. "Firewalls"; and terms expressing a professional title rather than a skill in itself, e.g. "Birth Assistant". The data further include a considerable amount of abbreviations and acronyms and differences in spelling emerge when comparing data related to different countries, partly due to the use of British versus American English.

BGT claims to have created a skills taxonomy featuring over 17,000 unique skills[8], which they augment by means of searching the job posting text for synonyms or locutions and expressions having the same meaning. For example, in the case of "team work", BGT not only searches for the keyword "team work" but also for variations such as "ability to work as a team" (See Hershbein and Kahn (2018[22]) for details). However, such standardisation is not implemented throughout, and there are cases that are relevant to the present work where it has not.

First, the very same skill may happen to be expressed differently across and even within countries. This may happen for a number of reasons, e.g. because similar positions may be advertised differently in different countries or by different companies, or because some tools or skills may be sought in some cases in relation to AI, but not in others. For example, the software "Torch" can be found as "Torch (Machine Learning)" in some job ID's and simply as "Torch" in others.[9] The skill "Weka (machine learning)" exists only in Singapore, where it is always paired with its stand-alone expression "WEKA" as an additional skill. In Canada, the UK and the US, only the skill "WEKA" exists. Based on these data features, one may be led to believe that e.g. Weka is used for machine learning in Singapore, but not in the other countries and, similarly, that Torch is only exclusively used for machine learning in Canada and the US. Moreover, in Singapore, the software "Caffe Deep Learning Framework" is sometimes paired with "Caffe (software)" as an additional skill, in other job posting, the latter only exists on its own.

In this work, and based on first-hand information about the data gathering process itself, we consider such heterogeneity to be due to data gathering and database management issues, rather than reflecting real differences in software use by workers in different economies. We thus assume that software is used in a similar fashion across countries and harmonise data accordingly[10]. Also, we acknowledge that different behaviours and/or cultural norms may exist and that these may be reflected in the drafting and text of online job adverts. Such differences, coupled with the possible limitations and/or style constraints imposed by the online job-posting platform itself (e.g. max length of characters or words; number of sections in which the text is subdivided; the need to choose from a menu of options as compared to the possibility of including free text, etc.) may further complicate the exercise. All these difference, which we may only hypothesise but have insufficient data about, may impinge upon the comparability of skills requirements within and across countries.

Secondly, and importantly for the present work, a question arises about the criteria used by BGT to add the skill "Machine Learning" in parentheses at the end of a skill expression, even though this may not be explicitly mentioned in the job advert. For example, BGT skill "Supervised Learning (Machine Learning)" is sometimes, but not always, accompanied by the additional expression "Machine Learning" in the context of a given job posting ID. The same applies to "Boosting (Machine Learning)". Checking data we see that in the case of BGT skills such as "Supervised Learning (Machine Learning)", the BGT text-mining algorithm does not (or not consistently) separately extract the skill "Supervised Learning" and the skill "Machine Learning", calling for the need for a (lengthy and costly) granular data inspection. We assume that the extra information in parentheses has been added by BGT in order to clarify the meaning of the terms. Hence, we do not account for the term "Machine Learning" in parentheses as an additional skill[11].

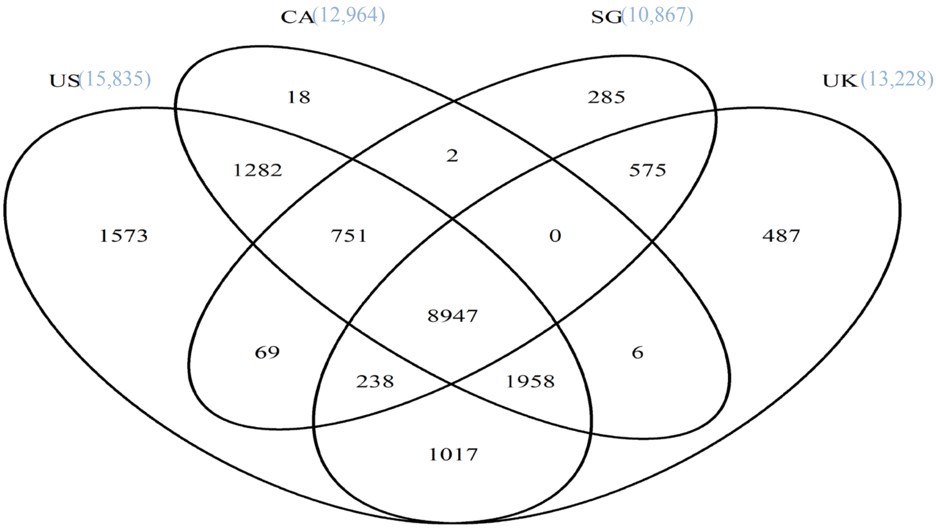
Thirdly, while BGT standardisation aims to enhance comparability and facilitate analysis, it is important to recognise that not all skills actually required for a given job may be explicitly listed in an advert. For instance, by requiring a certain university degree from candidates, employers may want to implicitly signal the need for candidate to display (certain types of) cognitive and non-cognitive abilities.

For the present analysis, data have been harmonised by means of e.g. spelling abbreviations and removing any punctuation, special characters and white spaces that may lead to mistakenly identifying as different two expressions having the same meaning (e.g. "Audio / Visual Knowledge" and "Audio/Visual Knowledge"). Also, manual corrections have been implemented when removing special characters would change the identification or meaning of some skills (e.g. C versus C++). Finally, skill duplicates have been removed (e.g. "Cascading Style Sheets (CSS)" and "CSS" or "Recurrent Neural Network (RNN)" and "Recurrent Neural Network")[12].

A first look at the clean skills data[13] for the years 2012-18 shows that 52% of skills can be found in all the four economies considered in the present analysis. 17% of skills in the database can be found in three out of 4 countries and an additional 17% in the data of two out of the 4 countries considered. Notably, 14% of skill-related data are uniquely referred to in one country only, namely the United States.

In Figure 2 a Venn Diagram shows the numbers of skills that appear in job postings in different countries, as well as the number of those found in one country only or in a subset of the countries considered in the present analysis. For instance, Figure 2 shows that there exist 1573 skills that can be uniquely found in US job postings; 18 that can be found only in Canadian job adverts, 285 that are found only in online job posted in Singapore and 487 skills only appearing in UK job postings. Also, the Venn diagram furthers shows that 1282 skills can be found in both US and Canadian job postings; 69 skills are found only in job postings appearing in the US and Singapore, and 751 skills are found in online job postings appearing in the US, Canada and Singapore. The rest of the diagram can be read in a similar way. This aspect would deserve further investigation in work to be performed on full text BGT data and on other countries' data, as it may stem from real differences in the task and skills required from workers as well as different ways of wording similar skills in different countries.

Figure 2. Venn Diagram: Number of skills that are demanded in different countries



Source: Authors' own compilation based on Burning Glass Technologies data (February 2019).
Note: Number of total skills by country in the data: CA (12,964), UK (13,228), US (15,835), SG (10,867).

3.1.2. Sector of activity

For Canada and the United States, information about the sector to which the job posting relates follows the North American Industry Classification System (NAICS) codes, at a level varying between 2 to 6 digits. For the United Kingdom and Singapore, data related to the sector of activity of the employer follow the UK Standard Industrial Classification (SIC) and the Singapore Standard Industrial Classification (SSIC) codes, respectively, in both cases at levels varying between 1 to 5 digits.

A first exploration of sector-related information shows that, for instance, for the US in 2018, the largest share of employers, i.e. over 85%, operate in one sector only (based on the 2 digit NAICS), while about 8% of employers operated in two sectors and only about 7% of employers are active in more than two sectors.

While compiling statistics of this type may be very informative, this effort is somewhat hindered by the fact that sector-related information is often missing, especially at more disaggregated levels of NAICS or SIC/SSIC. Moreover, at times, some job openings indicate the sector of activity, but others from the very same hirer do not. This would be perfectly plausible if a hirer has several branches operating in more than one sectors or locations, but checks made to assess the item-specific quality of the data show that such piece of information may be missing even if the employer has only one establishment.

To (at least partially) address such a shortcomings, in case the employer is only and always associated to one sector in the data (in a given year), we assume that this sector is the same that applies to all other job postings from the same employer for which such information is missing, and impute it accordingly. In case for a given year, several sectors are attributed to the same employer, we proceed as follows. We check whether exact pairs location / sector can be identified, i.e. if different branches / establishments for which address-related information exist always display the same sectoral code. In such a case, we assign the sector information to the missing observations, accordingly. 14 This imputation entails implicitly assuming that in each location operations pertain to one sector only[15].

The share of missing observations remaining after this imputation procedure are displayed in Table 3.1. In the case of Canada, the imputation procedure manages to substantially reduce missing values, i.e. by 7.5 percentage points at the 2-digits NAICS level (8 percentage points at 3-digits NAICS). For the US, the share of missing observations at the 2-digits NAICS decreases by almost 4 percentage points (3 percentage points at 3-digits NAICS). In the case of the UK and Singapore, sector-related missing observations decrease only slightly upon imputation (by less than 3 percentage).

In order to compare the sector distributions across countries, we convert the sector-related information into their corresponding International Standard Industrial Classification (ISIC) codes, at the 3-digit level[16].

3.1.3. Occupational information

With respect to occupational information, we use ONET Codes for Canada and SOC/SSOC codes for the United Kingdom, the United States and Singapore. Table 3.1 presents information on the share of missing observations. This is highest for Singapore, with slightly over 8% missing observations. In the other countries, shares fall below 5% (further information about the representativeness of BGT data at 1-digit occupational level can be found in Cammeraat and Squicciarini, (2021, forthcoming[2]).

For Canada, the UK and the US, we reclassify occupations following the 2008 International Standard Classification of Occupations (ISCO) system. When 1 to 1 mapping are not possible, we assign ISCO values proportionally. In the case of the UK, this only applies to less than 2% of the observations, in the US, the share amounts to 3.9%. In the Canadian data, this share is slightly higher, i.e. 5.8%. Singapore data follow the SSOC, rather than ISCO, as SSOC is the only occupational variable in the data and a 1 to 1 mapping with ISCO08 is not straightforward. It should be noticed, however, at the 1 digit level ISCO and SSOC are broadly comparable.

Table 3.1. Share of missing values, by variable, for 2018

US		UK	
Variable	NA %	Variable	NA %
JobID	-	JobID	-
Employer	22.12	Employer	62.89
State	0.00	County	13.87
City	1.83	City	26.42
NAICS 2 digits	23.07 (19.22)	SIC 1 digit	46.71 (45.16)
NAICS 3 digits	38.31 (35.21)	SIC 2 digits	51.61 (50.30)
		SIC 3 digits	63.92 (62.93)
		SIC 4 digits	65.81 (64.91)
SOC	3.94	SOC	0.49
Canada		**Singapore**	
Variable	NA %	Variable	NA %
JobID	-	JobID	-
Employer	22.12	Employer	55.28
State	0.00		
City	0.00		
NAICS 2 digits	33.02 (25.56)	SSIC 1 digit	65.14 (62.59)
NAICS 3 digits	41.21 (33.25)	SSIC 2 digits	65.68 (63.33)
		SSIC 3 digits	67.37 (65.62)
ONET	4.68	SSOC	8.17

Note: Values in parentheses in column 2 and 4 are those obtained after the imputation procedure.
Source: Authors' own calculations on Burning Glass Technologies data (February 2019).

4. Identifying AI-related skills in BGT data

Due to its popularity, the locution AI is at times overused or misused, and this makes it hard for analysts to differentiate between what is AI and what is not AI. Also, in the absence of a detailed definition of what AI is or does, we mainly rely on the operational definition proposed by Baruffaldi et al. (2020[1]) and the keywords proposed therein, as they have been validated by a wide range of constituencies and experts.[17]

Additional information and keywords about AI-related software and repositories playing a central role in AI-related developments have been kindly supplied by experts at UK BEIS. AI-related software skills need to be taken into account as such software knowledge or use represents a necessary condition for those working in the development, implementation and adoption of AI-related advances and applications.[18]

Broadly speaking, four types of keywords are considered here for the identification of AI-related skills in BGT data.

- Generic AI keywords: E.g. "artificial intelligence" and "machine learning".
- AI approaches: E.g. "Bayes", "decision trees", "deep learning", "evolutionary computation", "neural network", "random forest" and "supervised learning".
- AI applications: E.g. "autonomous systems", "computer vision", "image recognition", "intelligent agent", "natural language processing", "robotics" and "text mining".
- AI software and libraries: E.g. Keras, ND4J, Spark and TensorFlow.

Keywords have been lemmatised[19] and all possible abbreviations as well as spelling possibilities (e.g. British versus American English) considered when building the searching algorithm. After matching the data, all skills have been "translated" into British English, for consistency.

The use of keywords for the identification of AI-related skills presents a number of operational and conceptual challenges. We discuss some of the most important below.

First, "artificial intelligence" is a kind of an umbrella term, of which machine learning is part. Moreover, many keywords can be considered as being sub-categories of others. For example, k-means can be considered as a sub-group of clustering, while long short-term memory is a neural network architecture (Sak, Senior and Beaufays, 2014[28]) often used in deep learning.

Second, we cannot rule out that (at least some of) the keywords and software- and libraries-related terms in our list can be used for distinct purposes, within and across countries. This is the case e.g. for Python, which is often used for machine learning but can be also used for a wide array of purposes; and for Bayesian approaches, which may be implemented in completely different types of analysis and developments. Including these words therefore may lead to identify false positive in the data.

Third, we acknowledge that some skills that are not included in the list of keywords may also be strongly related to AI if combined with (a subset of) the identified AI-skills. Examples are linear and logistic regressions, which can be used as ML techniques, and predictive analytics, which is a field of ML applications. Leaving them out may lead to type II errors, i.e. to false negatives and thus to underestimating the phenomenon. However, we adopt a conservative approach with the aim to produce an analysis that gets at the lower bound of the phenomenon.

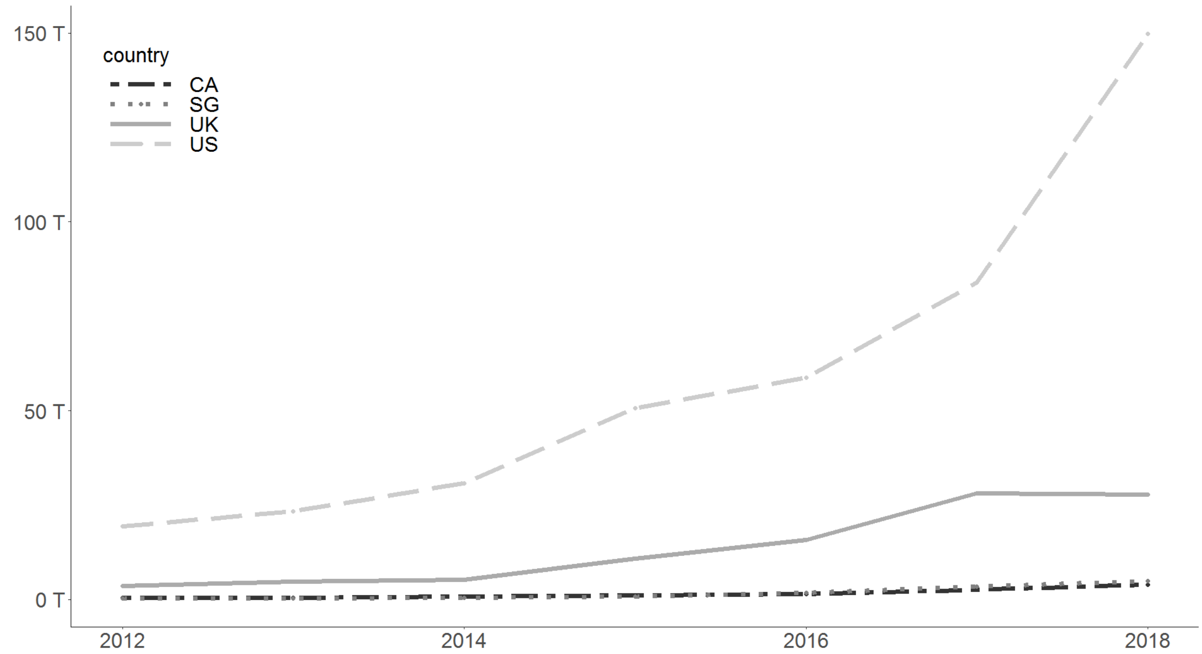
Fourth, difficulties arise as some words or concepts evoke AI, as is the case of e.g. robotics, but not always rely on AI or include AI. For example, in an “autonomous system”, AI can be characterised as the “intelligent” or cognitive component while robotics refers to its motor functions. However, the distinction between cognitive and motor functions becomes fluid in the field of mobility, such as self-driving cars, where the ability to both sense and analyse the environment is required (OECD, 2017[13]).

To address the challenges above, keywords that are similar as a concept or that strictly relate to each other have been grouped based on expert opinion. This is the case, for instance of “fuzzy c” and “fuzzy logic”. Also, to avoid over-identification, an “AI-related job” is defined as a job advert containing at least two keywords, belonging to two different groups, with one of them that may or may not be software-related. This is an approach similar to the one pursued in Baruffaldi (2020[1]) and in Nakazato and Squicciarini (2020[14]), and has been validated by experts.

Figure 3 shows the total number of AI-related jobs identified in the data based on two keywords, between 2012-18, for the countries in the analysis. As BGT claims to have increased coverage over time and we observe important increases in the overall number of job adverts captured in the dataset, Figure 4 shows the share of AI-related jobs in overall BGT job postings over time. Between 2012-18, a clear upward trend can be observed across countries, especially Singapore, where we observe a sharp increase in the relative growth rate from 2015 onwards.

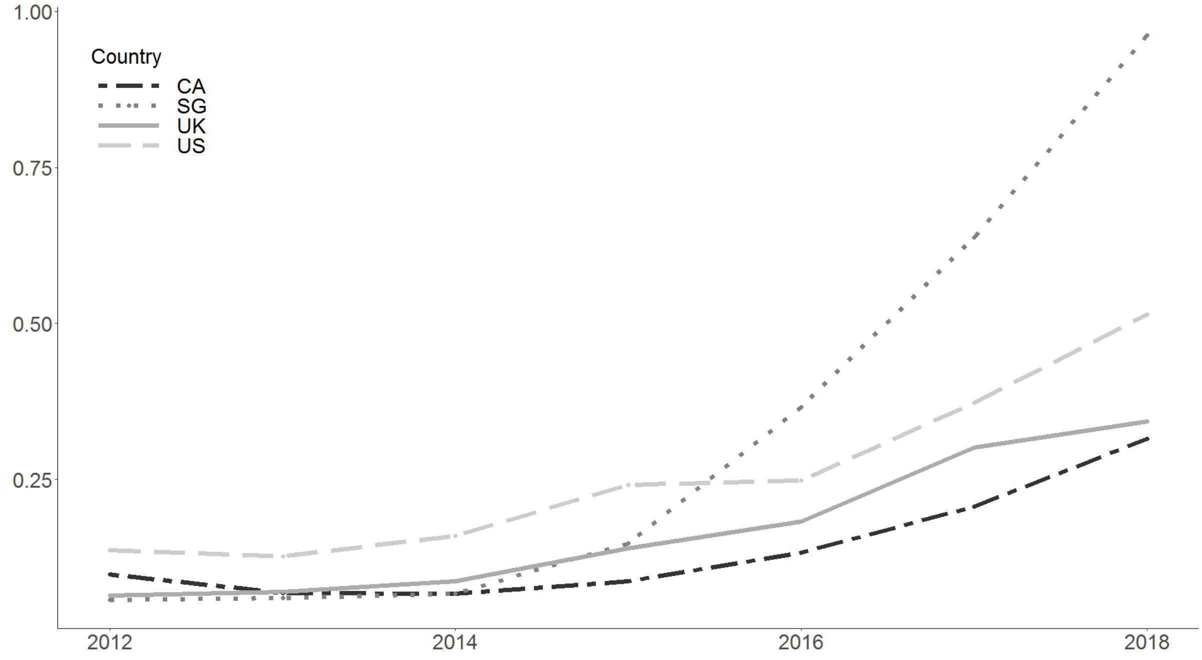
Figure 3. Number of AI-related jobs in the data, by country and year

Thousands of job postings



Note: The database lacks job postings from the United Kingdom for December 2018.
Source: Authors’ own compilation based on Burning Glass Technologies data (February 2019).

Figure 4. Share of AI-related jobs in the data, by country and year



Note: Job postings for December 2018 for the United Kingdom are missing in the BGT dataset.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

4.1. Identifying AI-related jobs: testing the sensitivity of the approach implemented

If we were to base our identification strategy on one keyword only, the number of AI-related jobs identified would increase considerably, particularly in the first years of the period under investigation. Table A.2 shows the number of jobs identified upon using one or two keywords, respectively, to identify them. It further shows the factor by which the number of AI-related jobs identified increases when using one keyword only. We see that in earlier years, the number of jobs identified as being AI-related would increase more than 10-fold, in all countries. However, over the years, such a factor would decrease to 5 in Canada, the UK and the US, and to 3 in Singapore. The highest number of additional AI-related jobs identified using only one keywords would be observed for the United States, followed by the United Kingdom. In these two countries, a clear upward trend would emerge, most notably in the US, where the number of AI-related jobs would increase by almost 80% between 2017 and 2018.

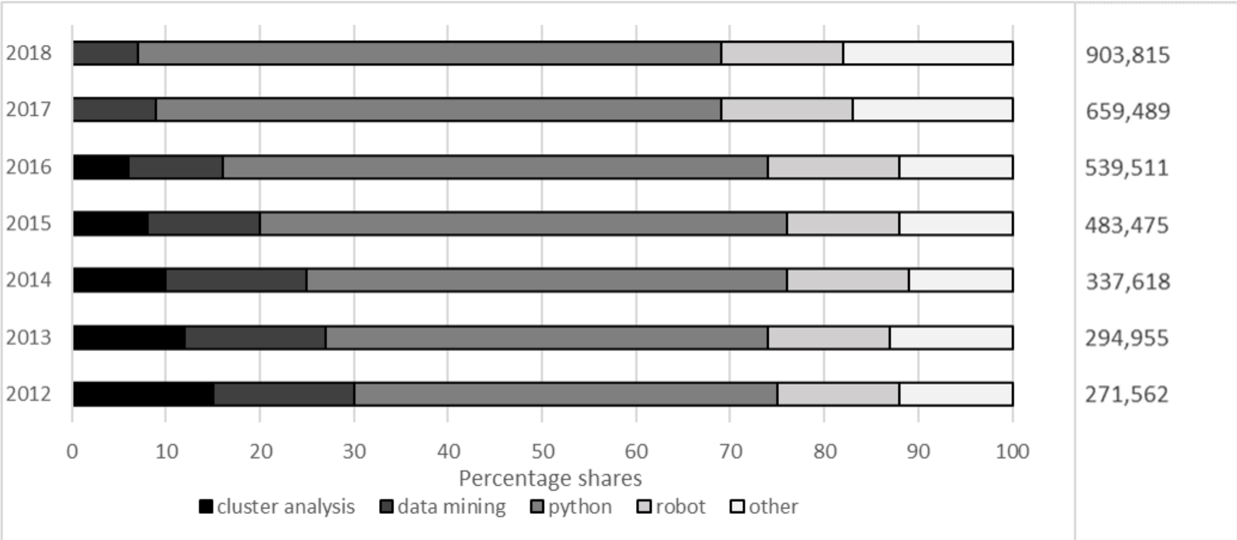
Looking at those skills that trigger the identification of the extra jobs identified as being AI-related when only one keyword is used for the purpose, similar patterns emerge across all countries. Figure 5 shows which skill keywords mostly drive the sharp increase in the number of jobs identified as being AI-related when using one only keyword. Statistics refer to pooled data from all countries considered in the study, and are aimed at giving a general idea about the drivers of such "overestimation".

Across all years, it is the software-related skill "Python" that leads to identifying the greatest share of the jobs that get additionally identified on the basis of using one keyword only, with its quantitative importance that grows over the years. "Cluster analysis" conversely leads to identifying a significant share of these additional jobs in the first years of the period considered, yet its share falls below 5% in 2017 and 2018.

The results shown in Figure 5 imply that by using two keywords for the identification of AI-jobs, we mainly exclude from our samples jobs requiring software skills related to the use or development of Python. As we know, this is a software that is progressively been used in many domains worldwide, and not only for AI-related purposes.[20]

Figure 5. BGT skills identifying additional AI-related jobs based on one keyword only

In percentage, pooled data from United States, United Kingdom, Canada and Singapore and overall number of job postings (right hand side)



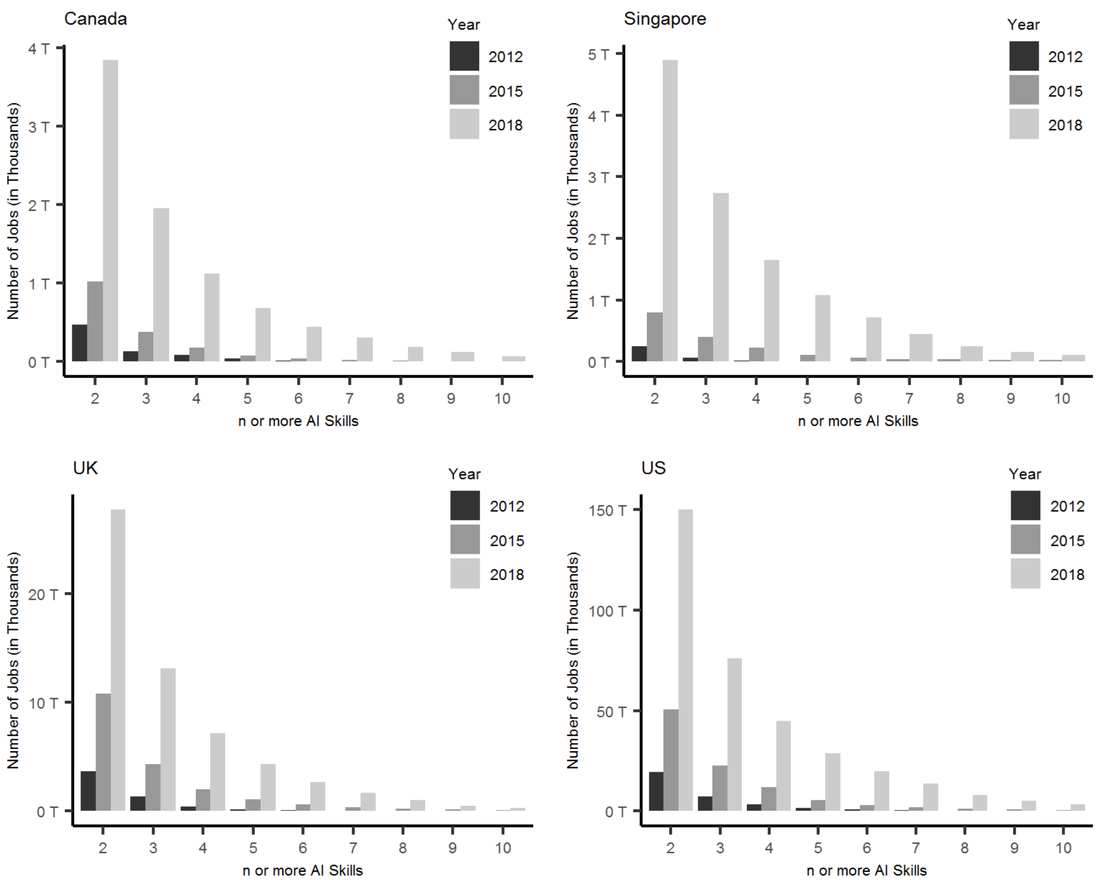
Note: Numbers on the right hand side of the chart show the absolute number of jobs the annual shares refer to. Only those skills that account for the identification of at least 5% of the additional jobs are displayed. The remaining skills are grouped and represented in the category "other".
Source: Authors' own compilation based on Burning Glass Technologies data (February 2019).

5. Identifying AI-related jobs and the set of skills they require

Figure 6 shows the frequency with which AI-related keywords appear in what we identify to be AI-related jobs, i.e. jobs containing at least 2 AI-related keywords in their description, for the years 2012, 2015 and 2018. The height of the bars mirrors the frequency with which keywords appear, with the number of keywords that vary between 2 and 10 or more (i.e. n = 2, 3, […], n ≥ 10). For this figure, skills are individually counted, irrespective of the cluster of keywords they belong to (i.e. "fuzzy c" and "fuzzy logic" count as different AI skills, but also "neural network" and "convolutional neural network") - with the exception of the vertical bars corresponding to n = 2, which shows the absolute number of AI-related jobs in the country and year.[21]

Figure 6. Number of jobs with n or more AI skills

Thousands of job postings



Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

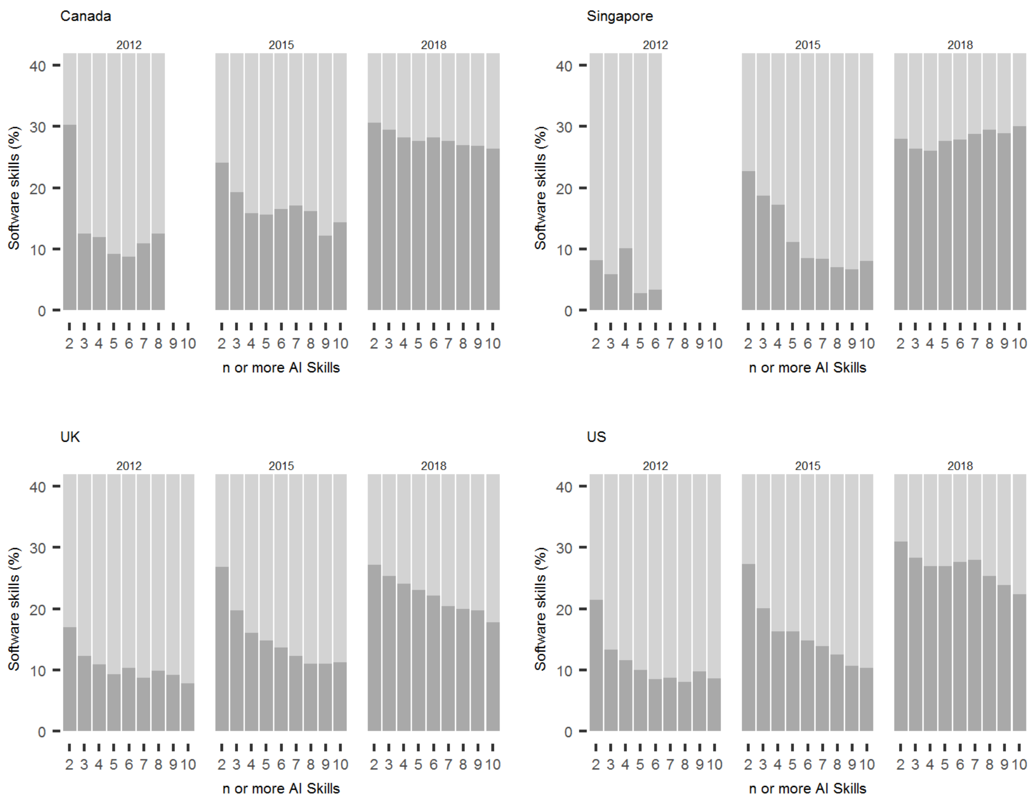
From Figure 6 it clearly emerges that the total number of AI-related jobs increases over time, but also a growing number of jobs requiring multiple AI skills emerge. In 2012, no AI-job required more than 7 AI-related skills in Canada and Singapore, or more that 9 AI skills in the UK and the US. In 2015 and 2018, we find jobs requiring 10 or more AI skills in all countries.

Looking at the last year for which data are available, i.e. the 2018, we can see that the total number of AI-related jobs would be halved if we were to require the presence of three of more AI-related skills in the advert for jobs to qualify as being AI-related.

Moreover, we observe a general trend, whereby the number of jobs requiring relatively larger numbers of AI-related skills (i.e. especially up to n=6) has been increasing over time.

Figure 7 shows the share of AI-related software listed among the AI-related skills encountered in job ads. From Figure 7, one can see that e.g. in Canada in 2012, AI-related software accounted for about 30% of all AI-related skills sought in candidates. More generally, in Canada, the UK and the US, we observe a decreasing share of AI-related software skills out of the total AI-related skills. In Singapore, this is the case only in 2015. Moreover, in all countries considered in the analysis, the overall average share of AI software-related skills increases between 2012 and 2018. .[22] In 2018, the share of AI-related software skills stabilises at about 30% of all AI-related skills

Figure 7. Share of AI software in skillsets, by number of AI-related skills in job adverts



Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure 8, Figure 9 and Figure 10 show, respectively, the top 30 non AI-related skills demanded across countries, the top 30 skills (both AI-related and not), and the top AI-related skills in both 2012 and 2018. In Figure 10, AI-related skills are denoted in grey, to distinguish them from the rest. As "artificial intelligence" is an umbrella term, we exclude it from the list of skills in these figures.

The size of the skill-related keywords in the word cloud represents the relative (i.e. quantitative) importance among the top 30 skills in the given year. The scale of the size relation between the most and least frequent skill plotted, is the same across all word clouds. The absolute values of word sizes on the other hand do not provide a mean to compare frequencies across word clouds or years. The largest word in each word cloud indicates the most frequent skill, relative to all other skills in the given top 30 distribution.

In line with what has been observed so far, the proportion of AI-related software among AI skills increases over time. On the other hand, the frequency distribution of AI-related skills in the pooled data, particularly when looking at the top 50 AI skills, shows that AI-related approaches slightly lose quantitative importance between 2012 and 2018, relative to software skills and AI applications.

The word clouds also suggest that in 2012, a considerable part of the skillset of AI jobs was related to software engineering and development - including specific programming languages such as Perl scripting language or Hypertext Preprocessor (PHP) -, and operating systems such as Unix and Linux. In 2018 however, software engineering and development seem to have lost relative importance, while AI-related skills such as Natural Language Processing (NLP) and deep learning emerge more prominently.

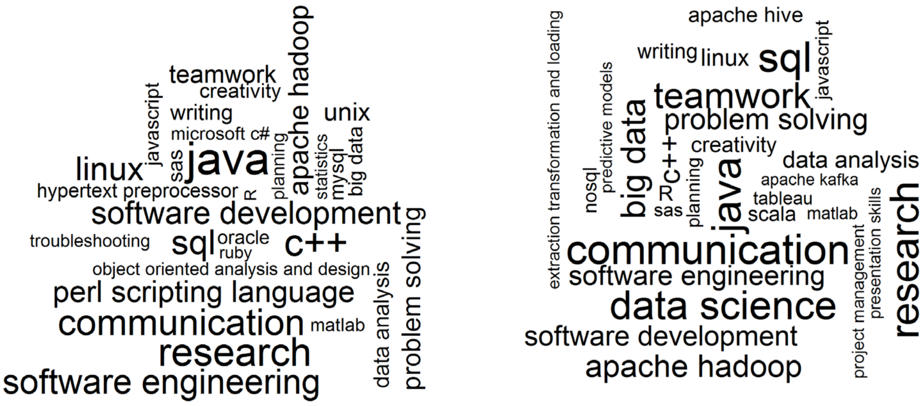
As can be observed from Figure 10 as well as from Figure A.11 to Figure A.14, when it comes to AI-specific skills deep learning and related software skills dominate the 2018 scenario. Big data, Apache Hadoop[23] and MapReduce nevertheless appear important in both 2012 and 2018, thus indicating that skills related to big data constitute a considerable part of the skills profiles of AI-related jobs, throughout the period, as can be seen in Figure 9. This should not be surprising, given that the availability of big data (and cloud computing) have enabled breakthroughs in machine learning (Chen, 2012[29]). Python, machine learning and data science also visibly increase in relative importance over time. It is worth noting that we do not consider data science as an AI-related skill. A job requiring e.g. data science and Python and no further AI keyword is not counted as an AI-related job, but is simply assumed to refer to a data science job.

Moreover, Figure 8 shows that skills related to communication, problem solving, creativity and teamwork gain relative importance over time and complement software-related skills as well as AI-specific competencies, although to different extents in different countries (see Figure A.3 - Figure A.6).

Overall, a trend towards requiring a set of generic skills in AI-related jobs emerges. This is very much in line with earlier OECD work finding that self-organisation, management and communication skills seem to be particularly important, especially in digital-intensive industries, and that workers may increasingly need to be able to quickly adapt to changes (Grundke et al., 2018[30]) (OECD, 2017[31]).

Figure 8. ALL COUNTRIES, Top 30 non-AI-related skills demanded in AI-related jobs

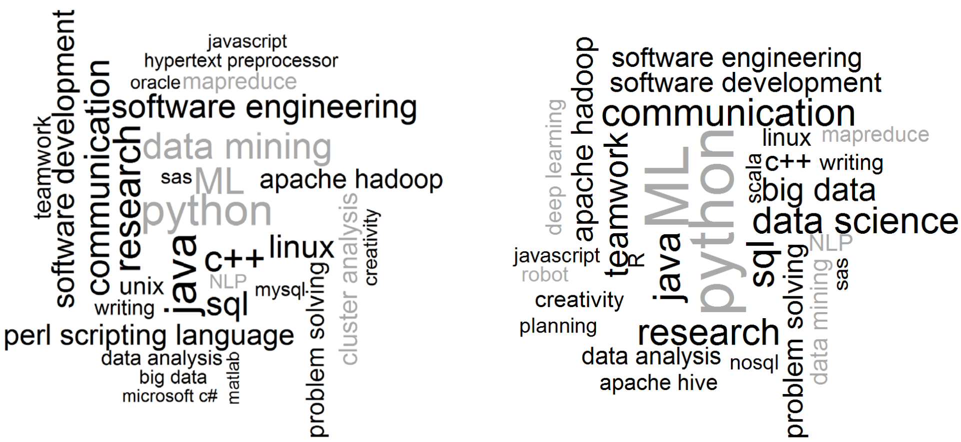
2012 **2018**



Note: In both years, the frequency of the top 30 non-AI skills accounts for around 31% of the frequency of all non-AI skills.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

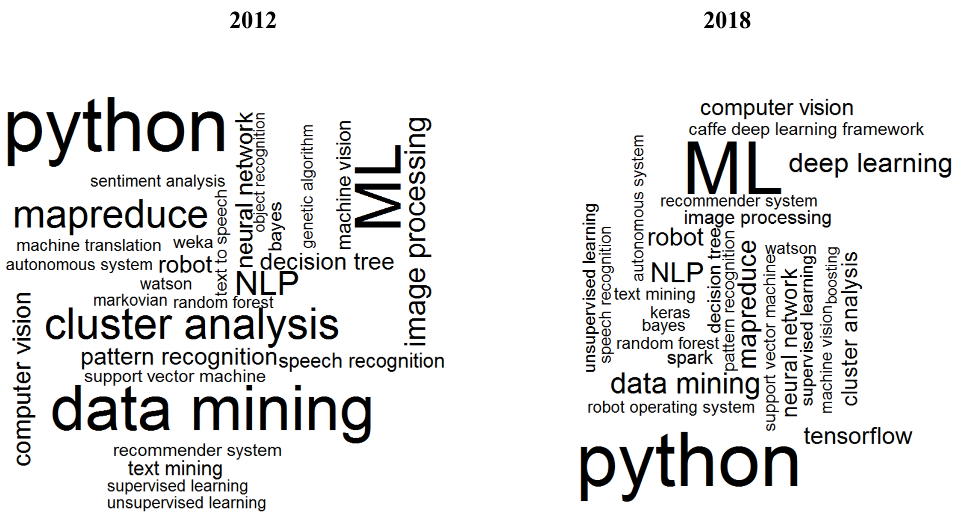
Figure 9. ALL COUNTRIES, Top 30 skills (all skills) demanded in AI-related jobs

2012 **2018**[24]



Note: Keywords in grey present AI skills. In 2012 and 2018, the frequency of the top 30 skills accounts for around 32% and 34%, respectively, of the frequency of all skills.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure 10. ALL COUNTRIES, Top 30 AI-related skills demanded in AI-related jobs



Note: In 2012 and 2018, the frequency of the top 30 AI-related skills accounts for around 98% and 96%, respectively, of the frequency of all AI-related skills
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

5.1. Skills for which demand has accelerated: a "burst" analysis

Understanding the skills that companies demand in AI-related jobs is important to inform policy making, as it sheds light on the extent to which demand patterns have changed over time. Also, this may be important to identify those skills experiencing a marked increase in demand, as compared to previous trends, as this may help inform training policies and to prioritise skill endowment-related efforts.

To this end, we implement the "DETECTS" text mining approach of Dernis, Squicciarini and de Pinho (2015[32])). It allows identifying those AI skills for which demand increased sharply (i.e. "bursts") at a certain point in time, as compared to previous levels and to the development of other skills demanded in AI-related jobs, and to see how long such accelerated demand lasts. The DETECTS approach builds on a data mining methodology devised by Kleinberg (2003[33]) and is applied on all AI-related keywords used in the analysis, including software[25]. For the moment, each keyword is counted only once per job posting, irrespective of the number of times it appears in the job advert. This should help identify the demand for a particular skills in AI-related jobs in the labour market. Including information about the frequency with which keywords appear in the same job openings would give information on how intensive jobs may be with respect to that skill(s), and how centred they may be around certain sets of skills.[26]

Figure 11 below shows the result of the burst analysis done on pooled data for Canada, the United Kingdom, the United States and Singapore for the period 2012-18, whereas Figure A.15 to Figure A.18 show the results of the burst analysis on each of the countries, individually considered.

To give an idea of the extent to which the demand for certain skills accelerated at the international level, Figure 12 displays those keywords for which demand burst in more than one country during the period considered and indicate the countries where this happens. The different shades of grey denote the weight of the burst, which can be understood as the intensity of the acceleration in the skills demanded. The darker the shade of grey, the stronger the acceleration of the AI-related skill demanded. The black and blue colour scheme in Figure 12 is exclusively aimed at distinguishing the skills that burst, to facilitate their identification.

The vertical axis of the figure displays the skills experiencing the burst, with software-related skills in green in Figure 11 and in Figure A.15 to Figure A.18 to facilitate their identification[27].

As a word of caution, it should be noted that the figure also includes tokens with low frequencies (e.g. for the US, google cloud machine learning platform (N=10), lexalytics (N=29) or mlpy (N=21)).[28]

The results are broadly comparable across Canada, the UK and the US given that overall, similar keywords burst at similar points in time. For Singapore, patterns are slightly less aligned with those of the other countries, yet similarities remain.

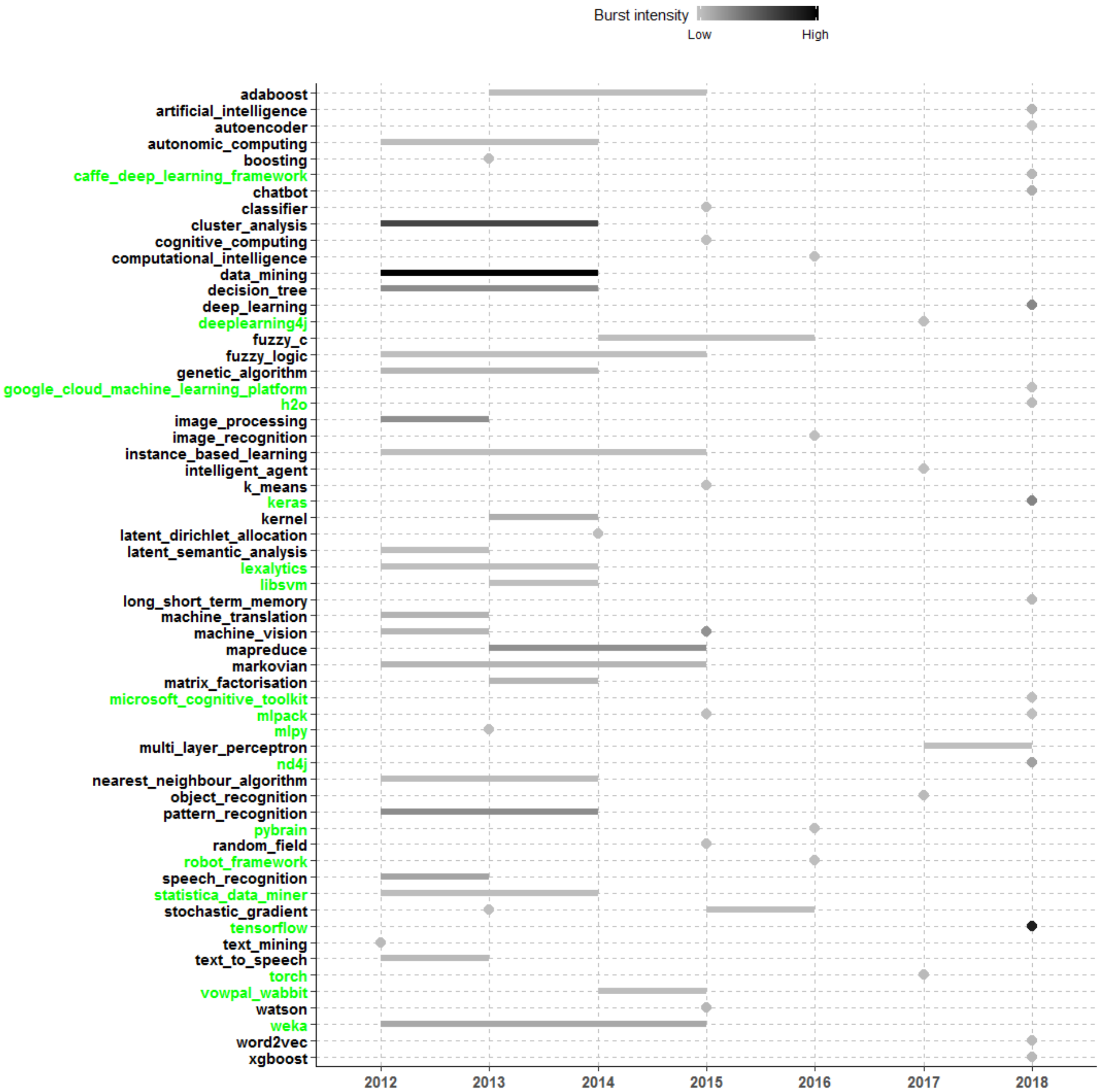
Across countries, the majority of bursts do not exceed two consecutive periods, and most burst in one year only. Overall, around 2015-16 several keywords terminate their bursting period. In 2018 however, we observe a number of "open bursts", especially in Canada, the US and, to a lesser extent, in Singapore and the UK. These bursts, depicted on the right hand side of Figure A.15 to Figure A.18, show acceleration in the demand for certain skills, and are likely to continue in following years.

Between 2012-16, we find a particularly strong bursting demand for "cluster analysis" skills across all countries, with only slightly different starting and ending periods. Moreover, particularly in Canada, the UK and the US, many of the other skills that burst in this period relate to data mining and classification, as well as to NLP and computational linguistics.

More precisely, we find bursts in skills such as "data mining", "decision tree", "statistica data miner" (software), "text mining" and "weka", as well as "lexalytics", "machine translation", "opennlp", "speech recognition" and "text to speech". In the same 2012-16 period, across all countries we also observe bursting behaviours of skills related to machine vision, including image recognition and -processing, pattern recognition as well as motion planning.

The burst behaviours observed in Canada and the US, and to a lesser extent in the UK and Singapore, confirm the more recent trend in demand for deep learning-related skills displayed in the 2018 word clouds (see. Figure 10). The burst analysis reveals that most of the acceleration in the demand for AI-related software skills concerns "deep learning", especially the caffe deep learning framework, "deeplearning4j", "h2o", "keras", "nd4j", "tensorflow" and "torch", as well as deep learning itself more generally (all burst in 2017 or 2018).[29] [30]

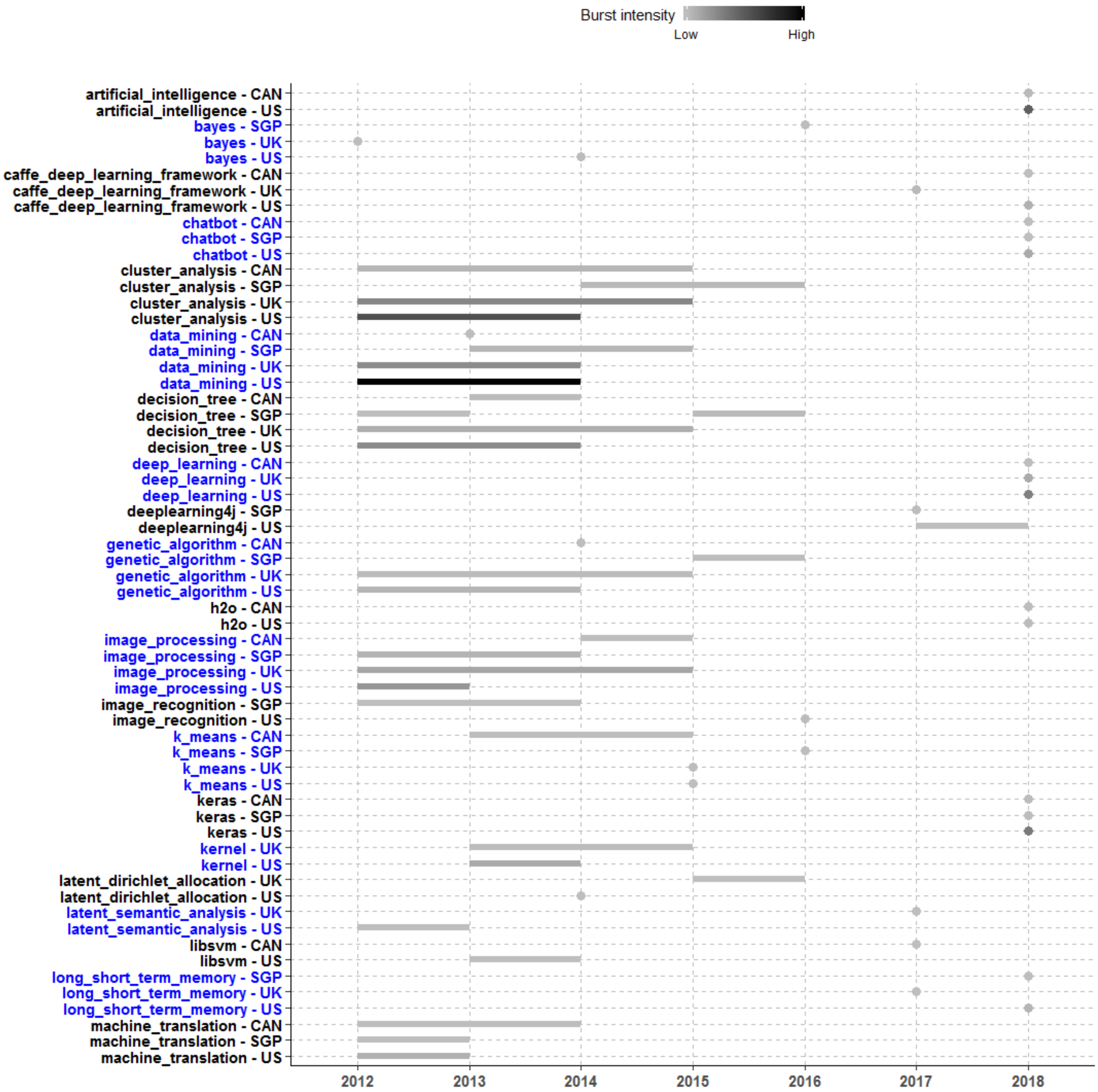
Figure 11. Bursting AI-related skills, pooled country data, 2012-18



Note: Items are listed in alphabetical order. Items in green denote AI-related software skills.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019) following Dernis et al. (2016).

Figure 12. Bursting AI-related skills, cross-country comparison, in alphabetical order

(Panel A)

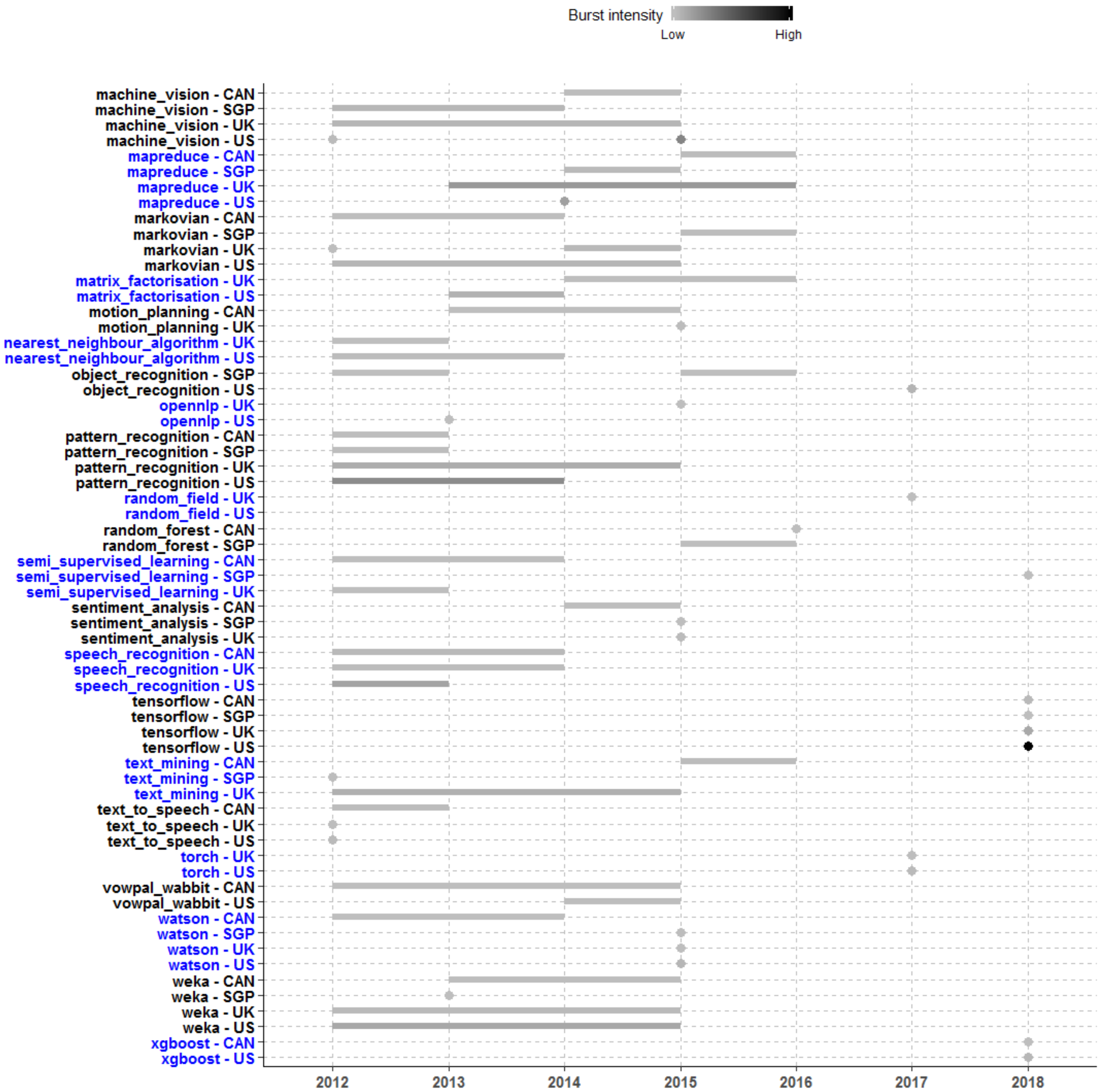


Note: The black and blue colour scheme is only meant to enhance the readability of the chart. Only items bursting in more than one country are displayed

Source: Authors' own calculations on Burning Glass Technologies data (February 2019).

Figure 12. Bursting AI-related skills, cross-country comparison, in alphabetical order

(Panel B)



Note: The black and blue colour scheme is only meant to enhance the readability of the chart. Only items bursting in more than one country are displayed.
Source: Authors' own calculations on Burning Glass Technologies data (February 2019).

6. Working with AI: jobs requiring AI-related skills

Shedding light on the human capital needed to work with AI not only means identifying the AI-related skills that are sought for on the labour market, but also identifying which type of jobs are currently requiring applicants to display AI-related skills.

To this end, we propose some simple statistics about the occupational groups under which AI-related jobs are advertised. Table 6.1 - Table 6.4 display the distribution of AI-related jobs by ISCO08 occupational group, for all countries and years considered in the present study, with the exception of Singapore, where jobs are classified using SSOC.

A first important takeaway of Table 6.1 – Table 6.4 is that, as expected, many AI-related jobs belong to occupational groups 2 and 3, i.e. "Professionals" and "Technicians and associated professionals", respectively. However, and perhaps somewhat surprisingly, with the exception of group 6, "Skilled agricultural, forestry and fishery workers" (which in addition are insufficiently represented in BGT data – see Cammeraat and Squicciarini (2021, forthcoming[2]) all occupational groups feature a growing number of AI-related jobs demanded over time. The growing demand for AI-related workers in elementary occupations in the United States certainly deserves attention and further investigation.

Also, and with the caveat that overall BGT data coverage increases over time, the biggest jump in the demand for AI-related jobs in terms of overall numbers seemingly happens between 2017 and 2018 in the United States.

Table 6.1. Number of AI-related jobs posted in Canada, by ISCO 08 Occupation

ISCO	ISCO Name	2012	2013	2014	2015	2016	2017	2018
0	Armed Forces Occupations	0	0	0	0	0	1	1
1	Managers	15	27	30	51	95	200	351
2	Professionals	380	400	699	851	1,249	2,096	2,990
3	Technicians and associated professionals	47	49	67	78	83	128	224
4	Clerical support workers	12	1	2	0	1	6	31
5	Service and sales workers	4	6	9	4	11	20	21
6	Skilled agricultural, forestry and fishery workers	0	0	0	1	0	1	1
7	Craft and related trade workers	4	2	1	5	5	7	15
8	Plant machine operators, and assemblers	0	0	0	0	1	1	5
9	Elementary occupations	0	2	0	0	3	7	17
	Total (non-missing occupation)	462	487	808	990	1,448	2,467	3,656
	Total (missing observation)	13	14	47	32	55	112	188
	Total (AI-related jobs)	475	501	855	1,022	1,503	2,579	3,844
	Total (all jobs)	487,251	733,790	1,286,119	1,175,424	1,131,653	1,248,337	1,219,683

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Table 6.2. Number of AI-related jobs posted in the United Kingdom, by ISCO 08 Occupation

ISCO	ISCO Name	2012	2013	2014	2015	2016	2017	2018
0	Armed Forces Occupations	0	0	0	0	0	0	0
1	Managers	112	92	124	359	417	1,118	1,317
2	Professionals	3,163	4,150	4,530	9,406	13,554	23,751	22,982
3	Technicians and associated professionals	251	358	361	657	1,068	1,987	2,221
4	Clerical support workers	33	33	61	65	139	146	151
5	Service and sales workers	25	30	45	67	158	311	324
6	Skilled agricultural, forestry and fishery workers	0	0	0	0	0	5	4
7	Craft and related trade workers	13	20	60	103	191	331	439
8	Plant machine operators, and assemblers	1	6	8	7	20	44	122
9	Elementary occupations	1	2	11	14	17	27	74
	Total (non-missing occupation)	3,599	4,691	5,200	10,678	15,564	27,720	27,634
	Total (missing observation)	48	54	100	161	230	461	70
	Total (AI-related jobs)	3,647	4,745	5,300	10,839	15,794	28,181	27,704
	Total (all jobs)	5,700,177	6,744,285	6,090,821	7,772,632	8,639,924	9,372,975	8,072,268

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Table 6.3. Number of AI-related jobs posted in the United States, by ISCO 08 Occupation

ISCO	ISCO Name	2012	2013	2014	2015	2016	2017	2018
0	Armed Forces Occupations	0	2	0	10	9	24	31
1	Managers	1,056	1,273	2,113	2,621	3,403	5,909	10,794
2	Professionals	16,712	19,692	25,749	42,506	50,002	69,830	122,047
3	Technicians and associated professionals	707	912	1,178	3,167	2,295	3,342	6098
4	Clerical support workers	27	114	83	126	119	149	411
5	Service and sales workers	71	163	82	153	186	284	647
6	Skilled agricultural, forestry and fishery workers	0	0	1	0	1	4	25
7	Craft and related trade workers	36	35	54	94	103	228	481
8	Plant machine operators, and assemblers	13	12	21	72	80	135	209
9	Elementary occupations	13	33	33	61	73	141	256
	Total (non-missing occupation)	18,635	22,236	29,314	48,810	56,271	80,046	140,999
	Total (missing observation)	827	1,035	1,422	1,897	2,519	3,858	8,810
	Total (AI-related jobs)	19,462	23,271	30,736	50,707	58,790	83,904	149,809
	Total (all jobs)	14,260,844	18,300,288	19,240,620	21,032,278	23,710,576	22,470,978	29,102,073

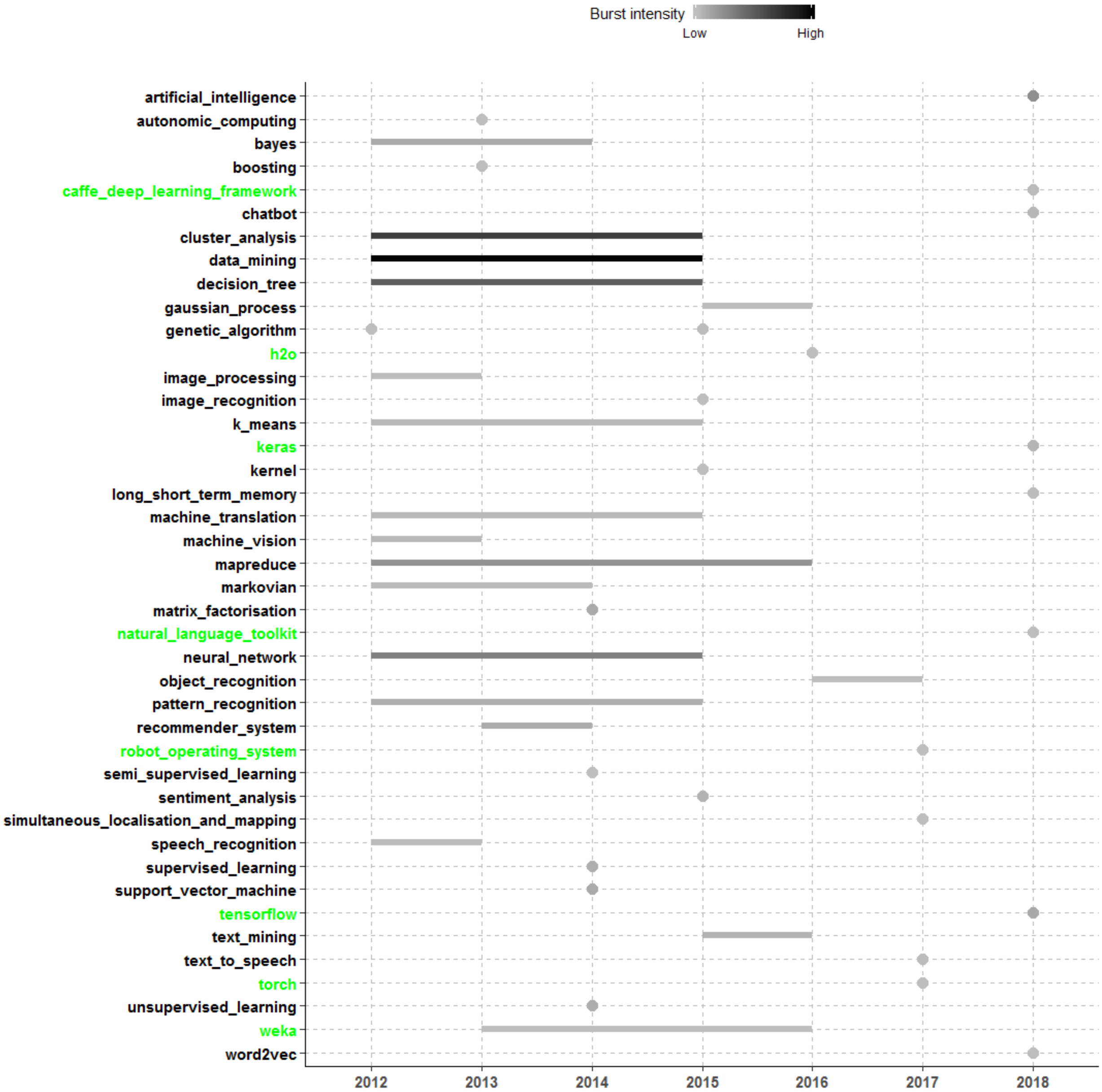
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Table 6.4. Number of AI-related jobs posted in Singapore, by SSOC Occupation

SSOC	SSOC Name	2012	2013	2014	2015	2016	2017	2018
1	Legislators, Senior Officials and Managers	3	14	27	29	75	144	211
2	Professionals	223	264	431	639	1,533	2,787	3,933
3	Associate Professionals and Technicians	1	4	7	26	64	104	165
4	Clerical support workers	1	4	4	4	13	34	113
5	Service and sales workers	7	5	3	17	13	24	35
6	Agricultural and Fishery Workers	0	0	0	0	0	0	1
7	Craftsmen and Related Trades Workers	5	0	0	2	12	1	10
8	Plant and Machine Operators and Assemblers	1	0	0	1	2	4	9
9	Cleaners, Labourers and Related Workers	0	0	0	1	4	4	5
	Total (non-missing occupation)	241	291	472	719	1,716	3,102	4,482
	Total (missing observation)	10	17	43	79	101	228	406
	Total (AI-related jobs)	251	308	515	798	1,817	3,330	4,,888
	Total (all jobs)	441,902	516,937	768,505	539,461	496,879	521,657	508,187

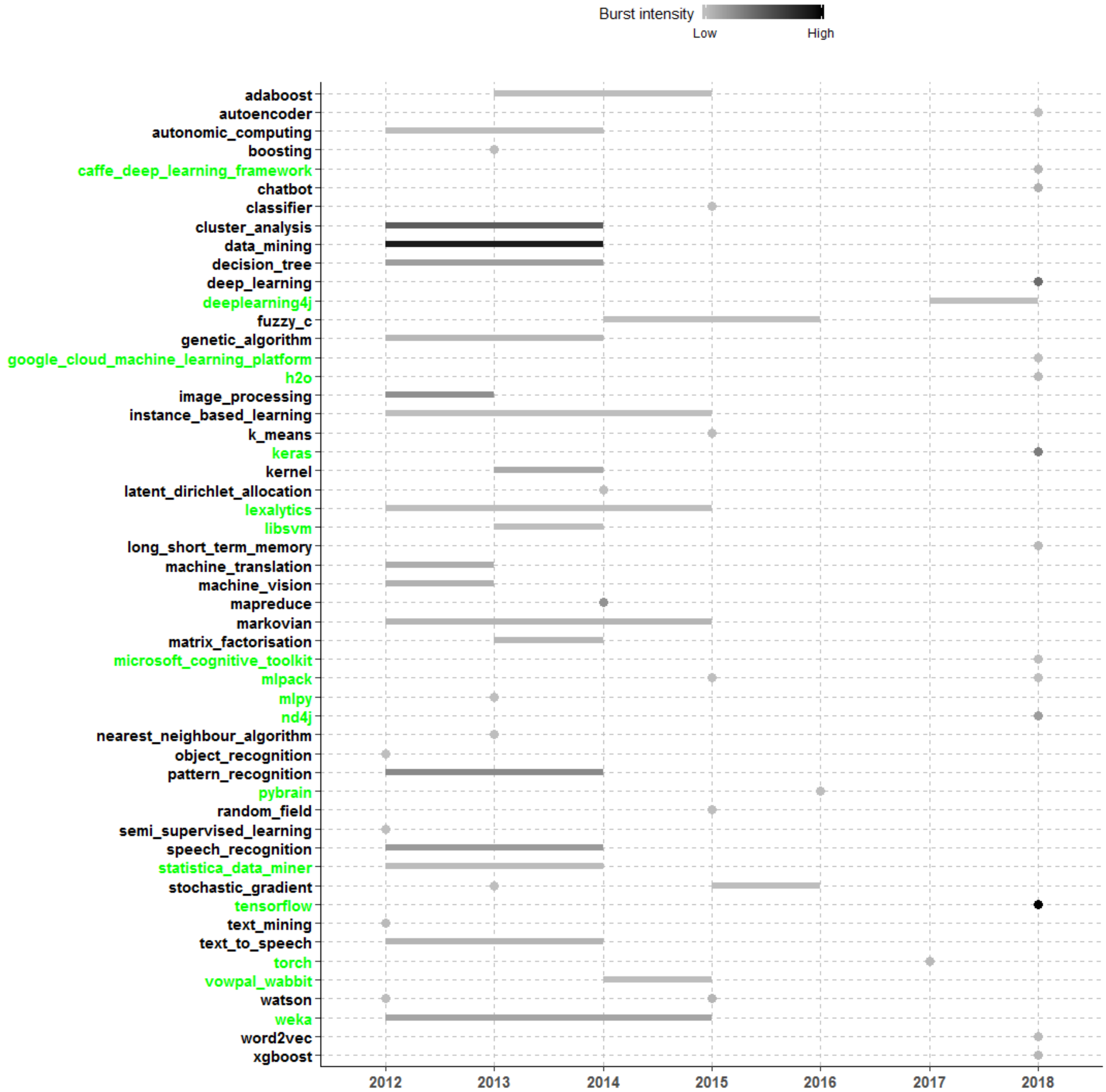
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure 13. Acceleration in the demand for AI-related skills, pooled data, Canada, UK and US – ISCO Group 1, Managers



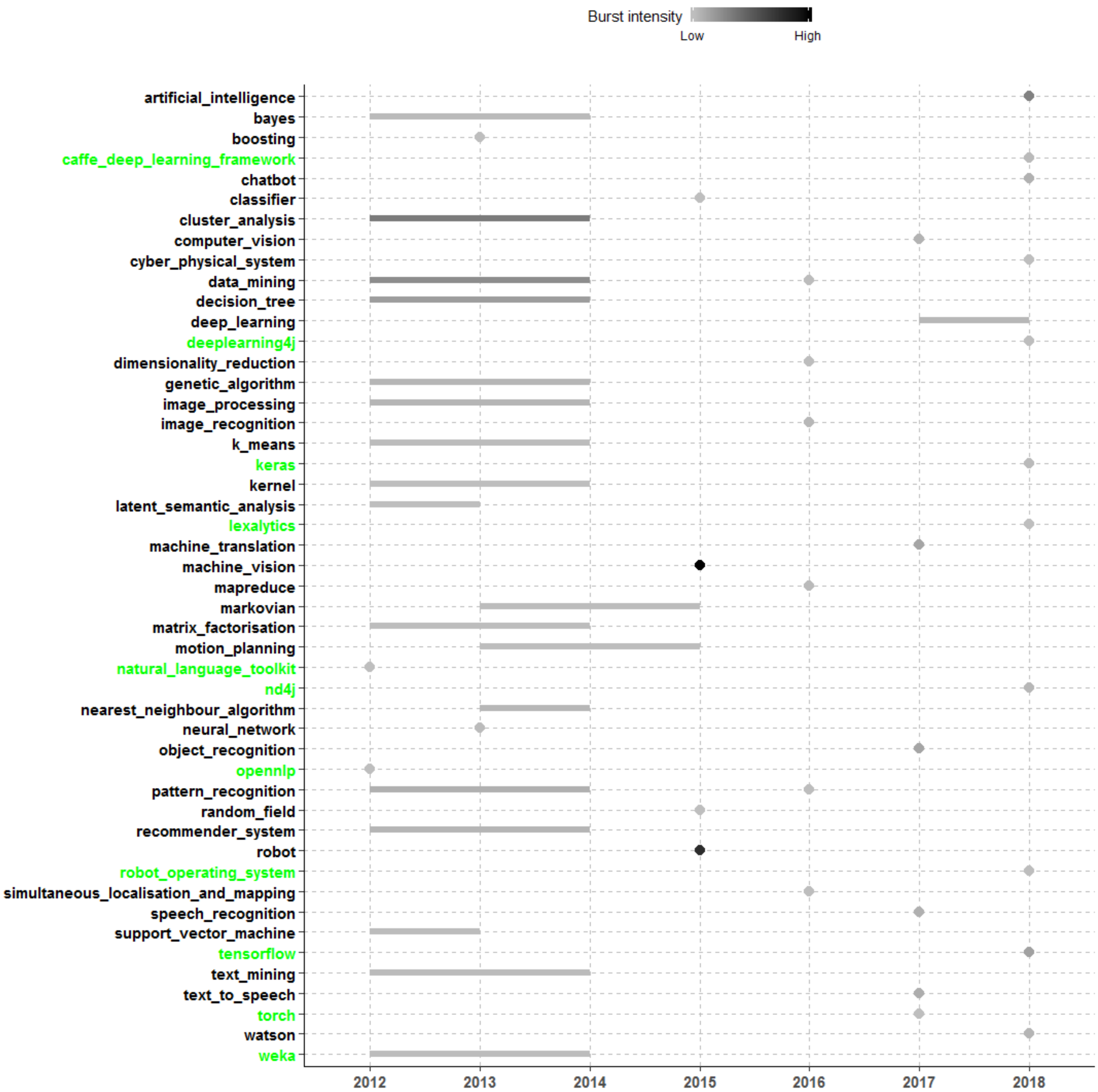
Note: Items are listed in alphabetical order. Items in green denote AI-related software.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019) following Dernis et al. (2016).

Figure 14. Acceleration in the demand for AI-related skills, pooled data, Canada, UK and US – ISCO Group 2, Professionals



Note: Items are listed in alphabetical order. Items in green denote AI-related software skills.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019) following Dernis et al. (2016).

Figure 15. Acceleration in the demand for AI-related skills, pooled data, Canada, UK and US – ISCO Group 3, Technicians and associated professionals



Note: Items are listed in alphabetical order. Items in green denote AI-related software.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019) following Dernis et al. (2016).

Figure 13 to Figure 15 try to give an idea of the extent to which skills demand has accelerated in different occupational groups, in terms of AI-related skills. Here, the burst analysis was performed on pooled data for Canada, the UK and the US. Due to the differences in occupational classification, we refrain from including Singapore in this part of the analysis. In what follows the most important results will be briefly highlighted.

In the first part of the period, we observe similar patterns in all of the three occupational groups. Figure 13 to Figure 15 display a general burst in demand related to "data mining", "decision tree" and "cluster analysis". In the case of Managers, a burst can be observed also with respect to “MapReduce”, a model for processing and generating big data on a cluster. For the first part of the period, and for all three occupational groups, we further find that skills demand accelerate in relation to machine vision, especially “image processing” and “pattern recognition”.

In the case of “Associate Professionals and Technicians”, we see strong one-year long bursts of the terms “machine vision” and “robot”, as well as a lighter burst in “random field”[31] in 2015. These are followed/accompanied by bursts in keywords such as “classifier”, “computer vision”, “dimensionality reduction”[32], “image-“, “object-“ and “pattern recognition”, “simultaneous localisation” and “mapping”[33], “cyber-physical system” and “robot operating system” in the period 2016-18. This pattern points to a pronounced trend demand for machine vision-related skills in the field of robotics (robot coordination) and, more generally, Industry 4.0 type of technologies.

For “Professionals”, most of the bursts related to “Natural Language Processing”, such as “latent dirichlet allocation”, “lexalytics”, “machine translation”, “speech recognition” and “text to speech”, take place in the first part of the period. Bursts in deep learning and related software in 2017-18 is visible in all three occupational groups considered, yet it is most pronounced for “Professionals”.[34]

7. AI Jobs by Sector

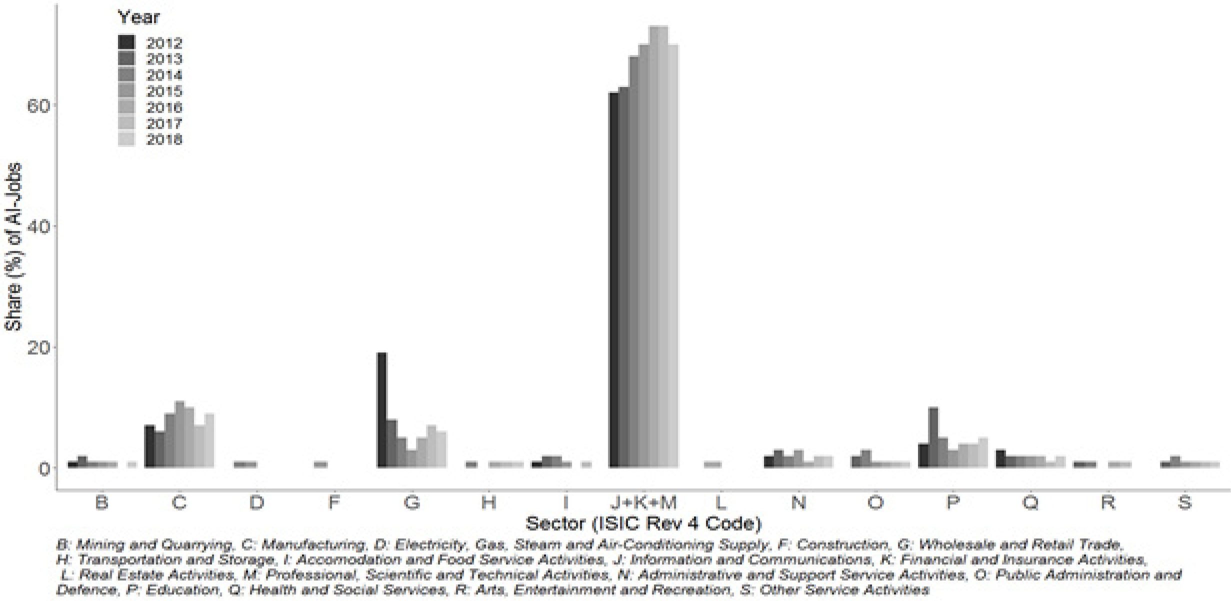
To understand the way AI is penetrating economies and labour markets it may be interesting to look at demand for AI-related jobs by sector. To this end, Figure 16 to Figure 19 show the distribution of AI-related job postings in BGT by sector, for all countries and years considered.

The distribution of AI-related jobs by sector[35] indicates that skills related to artificial intelligence are in demand across almost all sectors of the economy, though to varying degrees. Figure 16 to Figure 19 reveal that the group of sectors "Information and Communication" (J), "Financial and Insurance Activities" (K) and "Professional, Scientific and Technical Activities" (M) ranks at the top in terms of AI-job intensive sectors, in all countries considered.

In the case of the UK and Singapore, where these sectors can be looked at individually, all three sectors show to account for high shares of AI-related jobs (see Figure A.19 and Figure A.20).

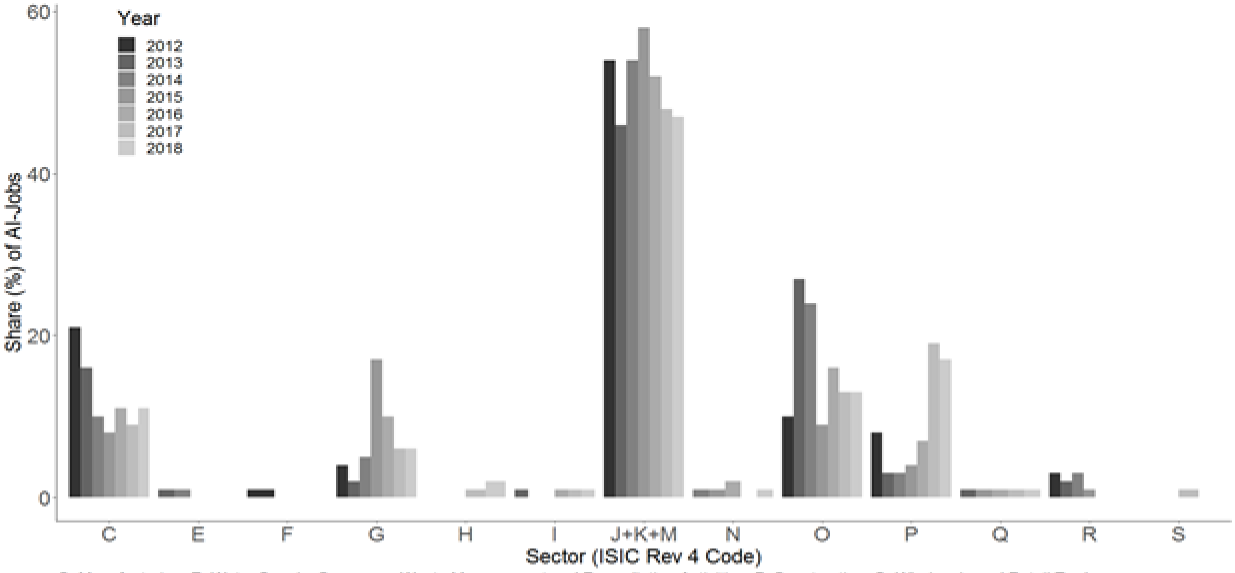
Moreover, considerable shares of AI-related jobs adverts appear to be posted by firms in "Manufacturing", "Wholesale and Retail Trade" as well as in "Education", in all countries. Figure A.20 further shows that in Singapore, a relatively high share of AI-related jobs are in "Public Administration and Defence", a sector that does not rank particularly high in any of the other countries considered.[36]

Figure 16. Canada: Distribution of AI-related jobs across Sectors



Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

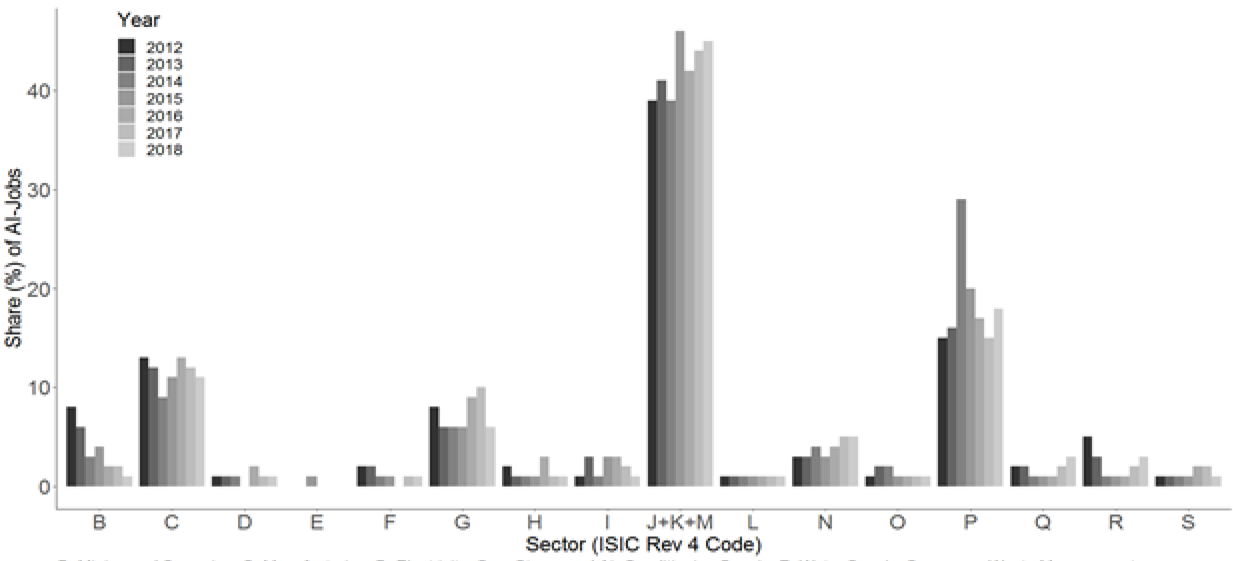
Figure 17. Singapore: Distribution of AI-related jobs across Sectors



C: Manufacturing, E: Water Supply; Sewerage, Waste Management and Remediation Activities, F: Construction, G: Wholesale and Retail Trade, H: Transportation and Storage, I: Accomodation and Food Service Activities, J: Information and Communications, K: Financial and Insurance Activities, M: Professional, Scientific and Technical Activities, N: Administrative and Support Service Activities, O: Public Administration and Defence, P: Education, Q: Health and Social Services, R: Arts, Entertainment and Recreation, S: Other Service Activities

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

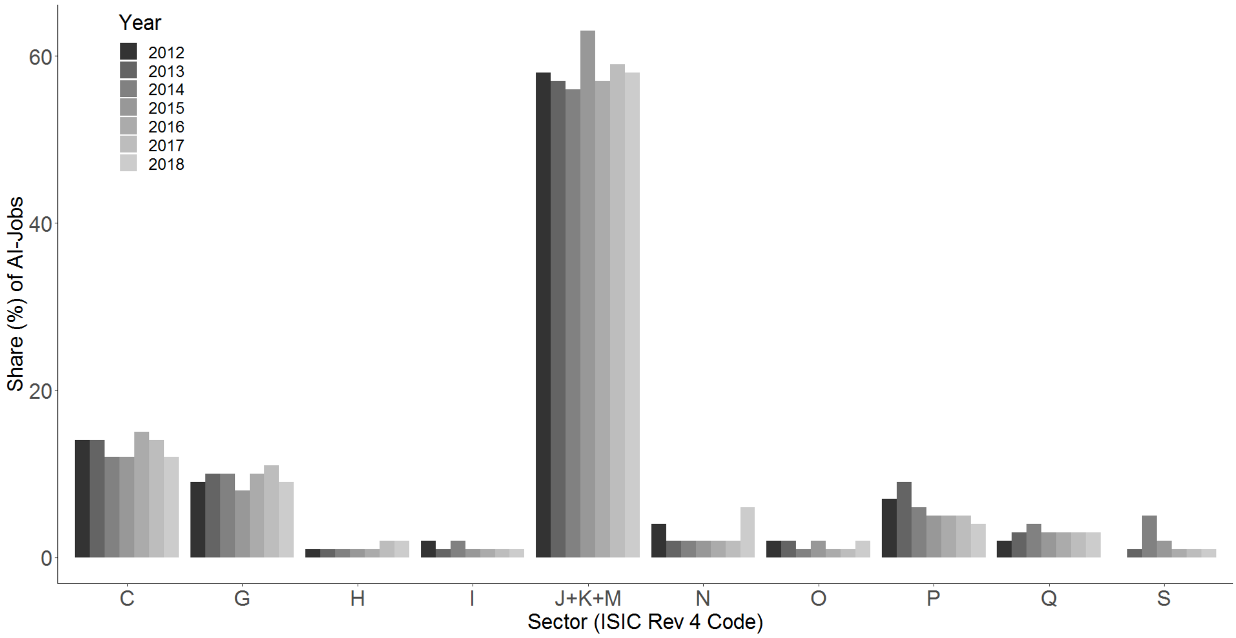
Figure 18. UK: Distribution of AI-related jobs across Sectors



B: Mining and Quarrying, C: Manufacturing, D: Electricity, Gas, Steam and Air-Conditioning Supply, E: Water Supply; Sewerage, Waste Management and Remediation Activities, F: Construction, G: Wholesale and Retail Trade, H: Transportation and Storage, I: Accomodation and Food Service Activities, J: Information and Communications, K: Financial and Insurance Activities, L: Real Estate Activities, M: Professional, Scientific and Technical Activities, N: Administrative and Support Service Activities, O: Public Administration and Defence, P: Education, Q: Health and Social Services, R: Arts, Entertainment and Recreation, S: Other Service Activities

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure 19. US: Distribution of AI-related jobs across Sectors



C: Manufacturing, G: Wholesale and Retail Trade, H: Transportation and Storage, I: Accomodation and Food Service Activities, J: Information and Communications, K: Financial and Insurance Activities, M: Professional, Scientific and Technical Activities, N: Administrative and Support Service Activities, O: Public Administration and Defence, P: Education, Q: Health and Social Services, S: Other Service Activities

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

8. Some first conclusions

This work offers first-time evidence about the occupations requiring Artificial Intelligence-related competences, which we call AI-related jobs, and the type of AI-related competences and skills demanded from workers. It aims to inform the discussion on skills demand and the role that human capital may play in enabling the digital transformation of firms and industries - especially the diffusion of AI-related technologies -, to provide evidence in support of policies addressing technology adoption and development, economic performance and skills needs.

The analysis relies on information from online job platforms and companies' websites collected by Burning Glass Technologies (BGT) for Canada, Singapore, the United Kingdom and the United States for the period 2012-18. It further relies on the findings and AI-related keywords identified in WPIA work assessing AI-related developments in science and technology (Baruffaldi et al. (2020[1])). The analysis has further benefitted from expert advice from the UK Department for Business, Energy and Industrial Strategy (BEIS) about software packages and software repositories used in AI-related developments.

We find that the total number of AI-related jobs has increased over time, and has reached almost 150 thousand AI-related job postings in the US in 2018. We also see that, in all countries, a growing number of jobs requires multiple AI-related skills. In 2012, no AI--related job required more than 7 AI-related skills in Canada and Singapore, or more that 9 AI skills in the UK and the US. In 2015 and 2018, we find jobs requiring 10 or more AI skills in all countries.

In all countries considered in the analysis, the overall average share of AI software-related skills increases between 2012 and 2018. In 2018, the share of AI-related software skills stabilises at about 30% of all AI-related skills sought from workers.

In 2012, a considerable part of the skillset of AI jobs was related to software engineering and development as well as operating systems. In 2018 however, software engineering and development seem to have lost relative importance, while AI-related skills such as Natural Language Processing (NLP) and deep learning emerge more prominently. Skills related to big data constitute a considerable part of the skills profiles of AI-related jobs, throughout the period considered, in all countries.

Skills related to communication, problem solving, creativity and teamwork gain relative importance over time and complement software-related skills as well as AI-specific competencies, although to different extents in different countries. Overall, a trend towards requiring a set of generic skills in AI-related jobs emerges. This is very much in line with earlier OECD work finding that self-organisation, management and communication skills seem to be particularly important, especially in digital-intensive industries, and that workers may increasingly need to be able to quickly adapt to changes (Grundke et al., 2018[30]) (OECD, 2017[31]).

The analysis related to the extent to which demand for some skills experience sudden and marked increases shows that between 2012-16, demand for "cluster analysis" skills bursts across all countries Moreover, particularly in Canada, the UK and the US, many of the other skills that burst in this period relate to data mining and classification, NLP and computational linguistics.. In the same period, across all countries we also observe bursting behaviours of skills related to machine vision, including image recognition and processing, pattern recognition as well as motion planning. The burst behaviours observed in Canada and the US, and to a lesser extent in the UK and Singapore, further confirm a growing trend in demand for deep learning-related skills in 2018.

In terms of occupational groups under which AI-related jobs are advertised, we find that, in line with expectations, many AI-related jobs belong to the "Professionals" and "Technicians and associated professionals" occupational groups. Moreover, with the exception of "Skilled agricultural, forestry and fishery workers" (which nevertheless are insufficiently represented in BGT data – see Cammeraat and Squicciarini (2021, forthcoming[2])) all occupational groups feature a growing number of AI-related jobs demanded over time.

To understand the way AI is penetrating economies and labour markets we further look at the distribution of AI-related job postings in BGT by sector, for all countries and years considered. This confirms that skills related to artificial intelligence are in demand across almost all sectors of the economy, though to varying degrees. The group of sectors "Information and Communication" (J), "Financial and Insurance Activities" (K) and "Professional, Scientific and Technical Activities" (M) are the most intensive in terms of AI-jobs in all countries considered.

This work is currently being complemented by analysis performed on full text data recently received from Burning Glass Technologies. This is aimed at refining both the methodology and the results of the analysis. In addition, we will perform a similar analysis on data from job adverts posted in European countries, which we are awaiting from BGT. Finally, an analysis of skills bundles in AI-related jobs will be performed to understand the set of skill required to work and thrive in the digital era and to work with AI.

Delegates are kindly asked to:

- Advise on the methodology implemented and comment on the results;
- Share information about similar work performed in countries and about data that could be used to refine the present exploration;
- Advise on the work planned.

Endnotes

[1] No universally accepted definition of AI exists. The OECD's AI Experts Group (AIGO) defines an AI system as it 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; abstracts such perceptions into models (in an automated manner e.g. with machine learning or manually); and uses model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy." (OECD, 2019, p. 15[35]).

[2] This in practice means that, if a vacancy contains the words "neural networks" and "convolutional neural networks", this counts for one only keyword, and the vacancy will not be considered as being AI-related unless we identify a second and different one (e.g. "computer vision"). We do so to remain conservative and avoid that the repetition of similar locutions may lead to over identifying AI-related jobs.

[3] BGT data at present only contains info about 6 countries. Data representativeness concerns detailed in Cammeraat and Squicciarini (2021, forthcoming[2]) motivate the exclusion from the present analysis of Australia and New Zealand.

[4] The data sources used are the Current Population Survey (CPS), the Occupational Employment Statistics (OES) and Job Openings and Labor Turnover Survey (JOLTS). See https://www.census.gov/programs-surveys/cps.html, https://www.bls.gov/oes/home.htm, and https://www.bls.gov/jlt/jltwhat.htm, respectively, for more details. It has to be noticed that most BGT-based analysis have focused on the United States.

[5] The exact number of observations per country and year can be found in table in Table A.1.

[6] Davis, Faberman and Haltiwanger (2013[37]) demonstrate this to be true for the JOLTS database.

[7] Evidently, direct hiring by companies and other institutions of e.g. professors met at a conference or other AI-related workers would escape BGT statistics, as well as any official statistics.

[8] BGT's skill taxonomy development technique is described in Burning Glass Technologies (2019[36])

[9] "Torch (Machine Learning)" exists in Canada and the US, where "Torch" as stand-alone expression does not exist at all. Yet, Torch as stand-alone keyword exists in Singapore and the UK (while the whole expression does not). Due to this consistency, we assume that "Torch" also always refers to the software of that name.

[10] In the case of Singapore this, for instance, means that we drop the resulting double entries related to WEKA or Caffe Deep Learning Framework from data.

[11] These issues will be checked in analysis on the full text of job vacancies recently received from BGT. The assumptions thus far made will be revised, if needed.

[12] A list of abbreviations cleaned in this process can be found in Table A.3. The Annex further contains a more detailed description of the cleaning process.

[13] Without accounting for variations in British/American English.

[14] For Singapore, no geographical information is available. We thus impute missing observations if employers are always and only associated to one sector in the data. For the other countries, we use the available information on the city and state/county, to ensure that the location is indeed unique, e.g. "Cambridgeshire Cambridge".

[15] We acknowledge that, while improving coverage, such an imputation strategy may have the possible drawback of "favouring" employers posting a relatively larger number of jobs online, thus

making their sectors likely more represented than those of firms posting relatively less jobs online (e.g. relatively smaller firms).

16 As the share of missing observations increases from 2-digits NAICS to 3-digits NAICS, we impute the 3-digits NAICS proportionally to their 2-digits distribution before converting to ISIC. The Annex provides more details on the sector imputation and the distributional characteristics of the NAICS variables.

17 See Baruffaldi et al. (2020[1]) for details about the keywords and the validation process.

18 The expert list of keywords is augmented based on insights gained during the matching process in the data. These are: “Weka” (see the discussion in the main text related to this), “autonomous system”, based on fuzzy matching the original keywords “autonomous vehicle” and “autonomous weapon”; “robot framework”, “robot operating system”, “statistica data miner”, “caffe deep learning framework” and “core ml”.

19 Lemmatising entails grouping together different forms of a word so they can be analysed as a single item, identified by the word's lemma, also known as dictionary form.

20 See e.g. https://towardsdatascience.com/top-programming-languages-for-ai-engineers-in-2020-33a9f16a80b0 for a discussion (last visited 30 March 2020).

21 The figure gives an idea of the sensitiveness of the definition to the number of words considered to identify AI-related jobs. The more restrictive the AI-identification approach, the lower the number of AI-related jobs identified.

22 Over time, a number of AI-related software packages appeared, and some of them became very popular, almost a “must” for workers in the AI field. This may in part contribute to explain why the demand for AI-related software packages increased over time, to then stabilise in later years. We observe that, e.g. some AI-related software packages in high demand in 2018 had not yet been released or had not reached maturity until 2015. This is the case, for instance, for Caffe Deep Learning Framework and Deeplearning4j. TensorFlow was also released at the end of 2015.

23 Apache Hadoop is a software framework for distributed storage and big data processing using the MapReduce programming model.

24 The standard deviation of the top30 words frequencies is larger in 2018. In 2018, python and ML have frequencies of over 130,000 and over 120,000, respectively, while the top3 to top10 words have frequencies of 45,000 to 65,000 and the least frequent word in the top30 has a frequency of around 20,000. In 2012, the range between the most and least frequent top30 word is between 11,000 and 2,800. Hence, in 2018, relative to the size of ML and Python, all other words are considerably smaller, taking up less space, resulting in an original overall smaller plot than 2012. The word cloud has been here cropped to enhance visibility.

25 The parameter γ in Kleinberg’s model has been set to 1.0 for the entire analysis here. See Dernis, Squicciarini and de Pinho (2015[32])) for details about the implication of such a choice.

26 We may embark on such an analysis in the future. It may be interesting to note that particularly the keyword “robot” in the US is highly sensitive to the way the frequencies are calculated. When allowing for multiple counts per job, “robot” bursts with a considerable weight in the US.

27 The software release life cycle (release date, maturity etc.) may affect the burst behaviour of a given software, in addition to its popularity in use.

28 Most keywords exhibit relatively high frequencies in the US, whereas low frequencies can be mostly observed for Singapore and Canada and, to a lesser extent, in the UK data.

29 We acknowledge that these softwares are not uniquely used for deep learning. However, they serve as an indication of the overall trend.

30 Caffe deep learning framework, deeplearning4j, h2o, keras, nd4j, tensorflow and torch are computing frameworks and/or libraries that provide or support different functionalities, such as algorithms, for deep learning.

[31] Gaussian Markov Random Fields (GMRF) can be used to model robot coordination in 3D environments (Wang et al., 2018[40]).

[32] Dimensionality reduction is used in approaches to derive planning algorithms producing robot coordination, e.g. hand grasps (Ferrari and Canny, n.d.[39]).

[33] Simultaneous Localisation and Mapping (SLAM) deals with exploring the structure of an unknown environment and is used in the field of robotics.

[34] The burst analysis has also been performed by country and occupational groups. Results can be obtained upon request from the authors. As could be expected the burst analysis for the US drives the results of the burst analysis performed on the pooled country data. In the case of “Managers”, the pronounced bursts in “data mining” and “cluster analysis” in the first part of the period are visible across countries. The bursting behaviour for skills related to deep learning however, are almost exclusively driven by the US, with a few bursts being also visible in the UK data. For “Professionals”, the burst behaviour in the field of deep learning in 2017-18 can also be observed when countries are considered individually. Finally, in the case of “Associate Professionals and Technicians”, demand for skills related to deep learning burst across countries, yet to different extents. The bursting behaviour for “machine vision” and robotics emerging in the second part of the period, as described above, is almost exclusively driven by the US.

[35] The figures only show bars for those sectors accounting for at least 1% of the AI-related jobs postings identified in the analysis.

[36] Interestingly, in the UK, in 2012 and 2013, more than 5% of the demand for AI-related jobs posted online seemingly comes from the Mining and Quarrying sector.

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Annex A. Complementary Tables and Figures

Table A.1. Number of total jobs, AI-related jobs and relative shares across countries and years

Year	Country	Total Jobs	AI Jobs	
2012	**CAN**	487,251	475	
2013		733,790	501	
2014		1,286,119	855	
2015		1,175,424	1,022	
2016		1,131,653	1,503	
2017		1,248,337	2,579	
2018		1,219,683	3,844	
2012	**UK**	5,700,177	3,647	
2013		6,744,285	4,745	
2014		6,090,821	5,300	
2015		7,772,632	10,839	
2016		8,639,924	15,794	
2017		9,372,975	28,181	
2018		8,072,268	27,704	
2012	**US**	14,260,844	19,462	
2013		18,300,288	23,271	
2014		19,240,620	30,736	
2015		21,032,278	50,707	
2016		23,710,576	58,790	
2017		22,470,978	83,904	
2018		29,102,073	149,809	
2012	**SGP**	441,902	251	
2013		516,937	308	
2014		768,505	515	
2015		539,461	798	
2016		496,879	1,817	
2017		521,657	3,330	
2018		508,187	4,888	

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Table A.2. Number AI-related jobs depending on number of keywords, across countries and years

Year	Country	AI Jobs (2 Keywords)	AI Jobs (1 Keyword)	Factor			
2012	**CAN**	475	6,425	14			
2013		501	8,087	16			
2014		855	13,291	16			
2015		1,022	11,874	12			
2016		1,503	13,332	9			
2017		2,579	18,158	7			
2018		3,844	19,996	5			
2012	**UK**	3,647	50,943	14			
2013		4,745	64,361	14			
2014		5,300	62,432	12			
2015		10,839	106,124	10			
2016		15,794	125,246	8			
2017		28,181	164,647	6			
2018		27,704	137,273	5			
2012	**US**	19,462	211,508	11			
2013		23,271	219,565	9			
2014		30,736	257,687	8			
2015		50,707	360,307	7			
2016		58,790	389,676	7			
2017		83,904	464,230	6			
2018		149,809	731,009	5			
2012	**SGP**	251	2,686	11			
2013		308	2,942	10			
2014		515	4,208	8			
2015		798	5,170	6			
2016		1,817	11,257	6			
2017		3,330	12,454	4			
2018		4,888	15,537	3			

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Table A.3. List of cleaned abbreviations

Abbreviation	Full expression
ADLs	Activities of daily living
AI	Artificial Intelligence
AIX	Advanced Interactive Executive
ALM	Application lifecycle management
AML	Anti Money Laundering
APC	Ambulatory Payment Classifications
API	Application Programming Interface
ASP.NET	Active Server Pages
ATM	Asynchronous Transfer Mode
AWS	Amazon Web Services
BAM	Bacteriological Analytical Manual
BDD	Behavior-Driven Development
BI	Business Intelligence
Blackboard LMS / CMS	Blackboard Learning Management System / Content Management Systems
BPM	Business Process Monitor
BW	Business Warehouse
CAD	Computer-Aided Design
CAM	Computer-Aided Manufacturing
CGI	Computer-Generated Imagery
CMS-1500 Forms	Centers for Medicare & Medicaid Services-1500 Forms
CMS/Medicare Guidelines	Centers for Medicare & Medicaid Services/Medicare Guidelines
Ektron CMS	Ektron Content Management Systems
Kentico CMS	Kentico Content Management Systems
CNC	Computer Numerical Control
CPR	Cardiopulmonary Resuscitation
CRM	Customer Relationship Management
CSS	Cascading Style Sheets
CT	Computed Tomography
DAO	Data Access Object
DBA	Database Administration
DNA	Deoxyribonucleic Acid
DOM	Document Object Model
DRG	Diagnostic Related Group
EHR	Electronic Health Record
EIGRP	Enhanced Interior Gateway Routing Protocol
EMR	Electronic Medical Records
ERP	Enterprise Resource Planning
ETL	Extraction Transformation and Loading
FAS	Financial Accounting Standard
GIS	Geographic Information System
GPS	Global Positioning System
HCM	Human Capital Management
HCPCS	Healthcare Common Procedure Coding System
HIE	Health Information Exchange
HIPAA	Health Insurance Portability and Accountability Acts
Hipaa	Health Insurance Portability and Accountability Acts
HIV	Human Immunodeficiency Virus

HPLC	High-Performance Liquid Chromatography
HR	Human Resources
HRMS	Human Resources Management Systems
HVAC	Heating, ventilation and air conditioning
I&AM	Identity and Access Management
ICD	International Classification of Diseases
ICS	Industrial Control Systems
IP	Internet Protocol
IDE	Integrated Development Environment
IDS	Intrusion Detection Systems
IP	Internet Protocol
IPS	Intrusion Prevention Systems
KNIME	Konstanz Information Miner
LAN	Local Area Network
LDAP	Lightweight Directory Access Protocol
MMR	Measles Mumps Rubella
MRI	Magnetic Resonance Imaging
MVC	Model-View-Controller
OSPF	Open Shortest Path First
OT	Operational Technology
OQ	Operational Qualification
PC	Personal Computer
PCA Pump	patient-controlled analgesia (PCA) pump
PCB	Printed Circuit Boards
PLC	Programmable Logic Controller
PLM	Product Lifecycle Management
PPM	Project portfolio management
PR	Public Relations
PV	Photovoltaic
RF	Radio Frequency
RPG	Report Program Generator
SEO	Search Engine Optimization
Siemens Plc	Siemens Programmable Logic Controller
SIP	Session Initiated Protocol
SNMP	Simple Network Management Protocol
SOA	Service-Oriented Architecture
TCL/TK	Tool Command Language/Tool Kit
TDM	Time-division multiplexing
TOGAF	The Open Group Architecture Framework
UI	User Interface
VPN	Virtual Private Networking
WAN	Wide Area Network
XML	Extensible Markup Language

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Cleaning abbreviations

We clean the data from abbreviations assuming that an abbreviation is a sequence of capital letters that may or may not stand within parentheses. We further assume that if an abbreviation in the aforementioned form stands within parentheses, it is preceded by the respective full expression. On the other hand, those observations containing sequences of capital letters that are not in parentheses (stand-alone abbreviations) are assumed not to include the full expression. Thus, we match those stand-alone abbreviations with the abbreviations in parentheses and replace them with their full expression. We subsequently drop abbreviations in parentheses from the data. In order to neatly distinguish between abbreviations, we add empty spaces to both sides of each stand-alone abbreviation before matching them with the full expressions. In addition, we also manually replace those stand-alone abbreviations that could not be matched with the full expression in the data, given that frequency share is high (n>500). The list of abbreviations cleaned in this manner can be found in Table A.3.[1] Cleaning the abbreviations in this way revealed that some pairs of a stand-alone abbreviation and the associated full expression are included as two separate skills in the job postings. For instance, "Enhanced Interior Gateway Routing Protocol (EIGRP)" and "EIGRP" are two unique skills that always appear separately in each job posting. However, this is not the case for all abbreviations found in the data. In cases such as "Cascading Style Sheets (CSS)" and "CSS", some job postings include only the former, while others only include the latter expression. Hence, matching all abbreviations with their respective full expression and subsequently removing double entries is key analysis of BGT skill data.

Distributional Analysis of NAICS

Table A.4. Frequency distribution, number of sectors (2 digit NAICS) per employer, US, 2018

Number of sectors	Frequency	Share (%)
1	634,612	85
2	62,128	8
3	23,146	3
4	11,514	1
5	6,568	1
6-20	12,535	2

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Table 3.1 shows that the share of missing observations for the 3 digits NAICS, SIC and SSIC is considerably larger than for the 2 digits values. This poses the question whether there are significant distributional deviations between the available non-missing 2 digits and 3 digits sector data, particularly as we use 3 digits values for the conversion to ISIC.

For the US 2018 data, Table A.5 provides the sector distribution based on the non-missing values of the imputed 2 digits NAICS as well as the distribution based on the non-missing values of the imputed 3 digits NAICS.

[1] Most stand-alone abbreviations identified are firm or software acronyms and programming languages, which were not changed.

Assuming that the missing observations in the 2 digits NAICS and the 3 digits NAICS are both completely random, the distributions should be similar. The bold values in Table A.5 are those indicating a difference of one or more percentage points between the two distributions. The by-far highest and likely most significant deviation is found in the sector "Health Care and Social Assistance" with a difference of about 5 percentage points. Across all other sectors, the deviations remain within an acceptable range, indicating that the loss of precision from using the 3 digits NAICS as compared to the 2 digit level is negligible.

Table A.5. Distributions of 2 digit NAICS and 3 digit NAICS

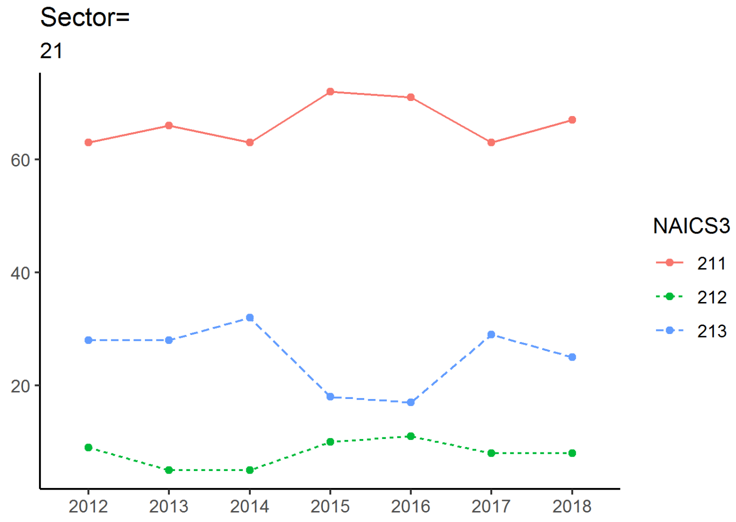
Data for the US 2018

Name 2 digit NAICS	2 digit NAICS (%)	3 digit NAICS (%)
Agriculture, Forestry, Fishing and Hunting (11)	0.1	0.1
Mining, Quarrying, and Oil and Gas Extraction (21)	0.4	0.3
Utilities (22)	0.4	0.4
Construction (23)	1.8	1.7
Manufacturing (31-33)	**8.7**	**6.4**
Wholesale Trade (42)	0.9	1.0
Retail Trade (44-45)	**11.2**	**11.8**
Transportation and Warehousing (48-49)	6.4	7.0
Information (51)	3.0	3.5
Finance and Insurance (52)	7.9	8.6
Real Estate and Rental and Leasing (53)	2.2	2.2
Professional, Scientific, and Technical Services (54)	10.2	9.3
Management of Companies and Enterprises (55)	0.2	0.2
Administrative and Support and Waste (56)	**5.1**	**6.3**
Educational Services (61)	6.0	7.0
Health Care and Social Assistance (62)	**21.0**	**16.7**
Arts, Entertainment, and Recreation (71)	1.0	1.2
Accommodation and Food Services (72)	**8.5**	**10.2**
Other Services (except Public Administration) (81)	1.9	2.4
Public Administration (92)	3.2	3.3

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

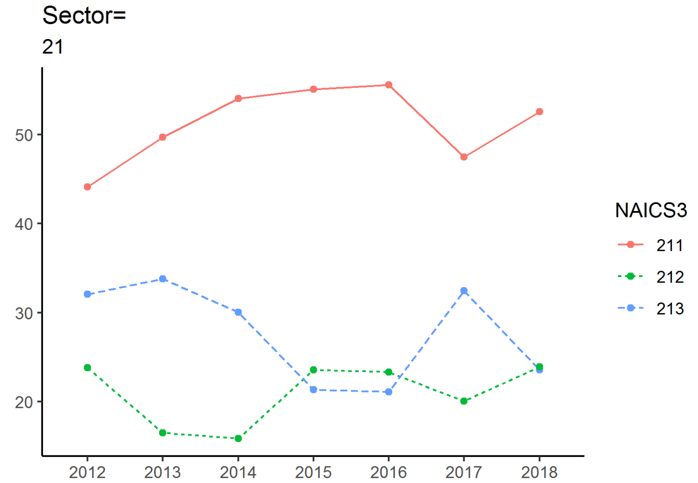
We further examine the distributions of the 3 digits sector data within its respective 2 digits levels across the years. For Mining, Quarrying, and Oil and Gas Extraction (NAICS=21), Figure A.1 shows the distribution of the 3 digit sector levels within their respective 2 digit sector over the period 2012-18, for the US in 2018. Figure A.2 shows the equivalent result for Canada. These figures are based on imputed sector data. The 3 digits sector level "Other Services, private households" (NAICS=814) is missing completely, all other 3 digits NAICS levels are represented in the data.

Figure A.1: Distribution of 3 digits NAICS within its 2 digits counterpart, US, 2018



Source: Authors' own compilation on Burning Glass Technologies data (February 2019)

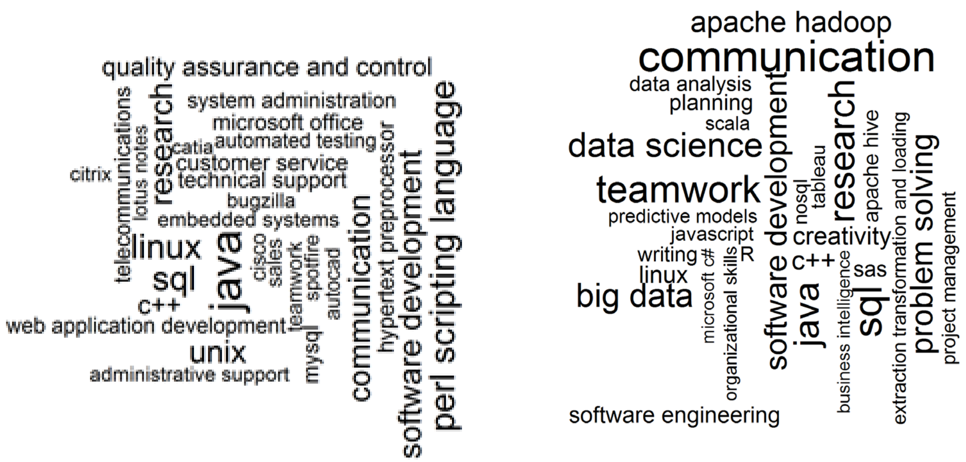
Figure A.2: Distribution of 3 digits NAICS within its 2 digits counterpart, Canada, 2018



Source: Authors' own compilation on Burning Glass Technologies data (February 2019)

Figure A.3. CANADA, Top 30 non-AI-related skills demanded in AI-related jobs

2012 2018



Note: In 2012, the frequency of the top 30 non-AI skills accounts for around 37% of the frequency of all non-AI skills, 29% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

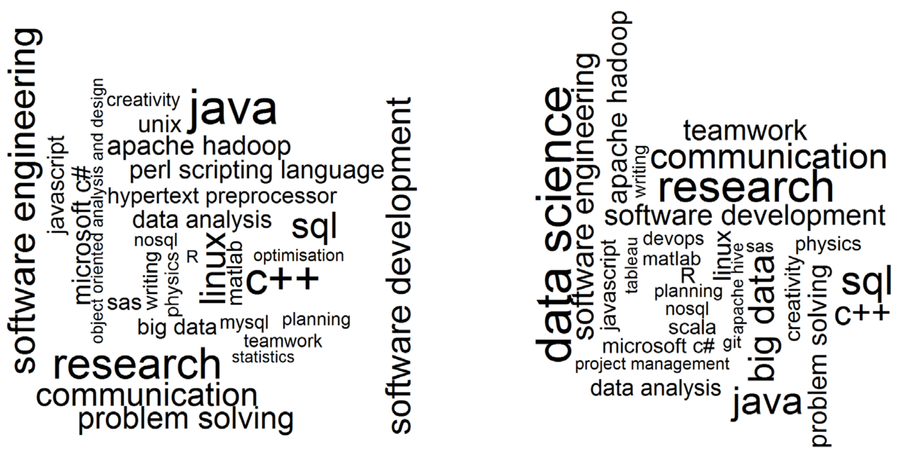
Figure A.4. SINGAPORE, Top 30 non-AI-related skills demanded in AI-related jobs

2012 **2018**

Note: In 2012, the frequency of the top 30 non-AI skills accounts for around 40% of the frequency of all non-AI skills, 36% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.5. UK, Top 30 non-AI-related skills demanded in AI-related jobs

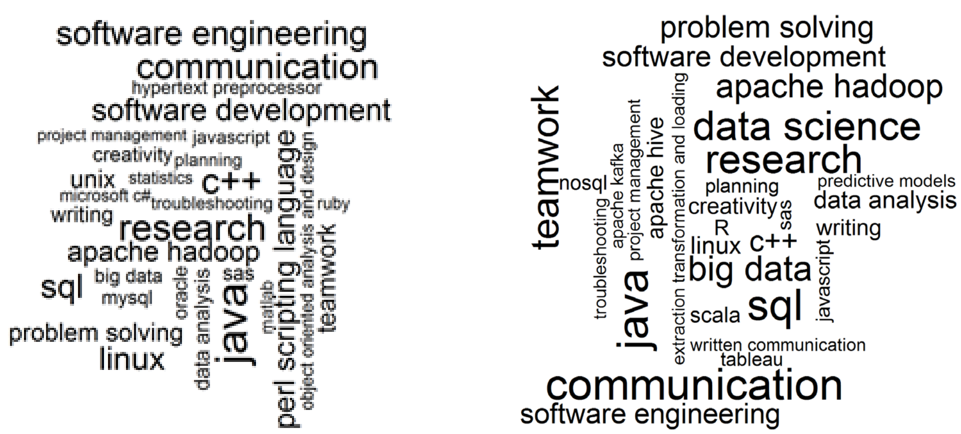
2012 **2018**



Note: In 2012, the frequency of the top 30 non-AI skills accounts for around 36% of the frequency of all non-AI skills, 35% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.6. US, Top 30 non-AI-related skills demanded in AI-related jobs

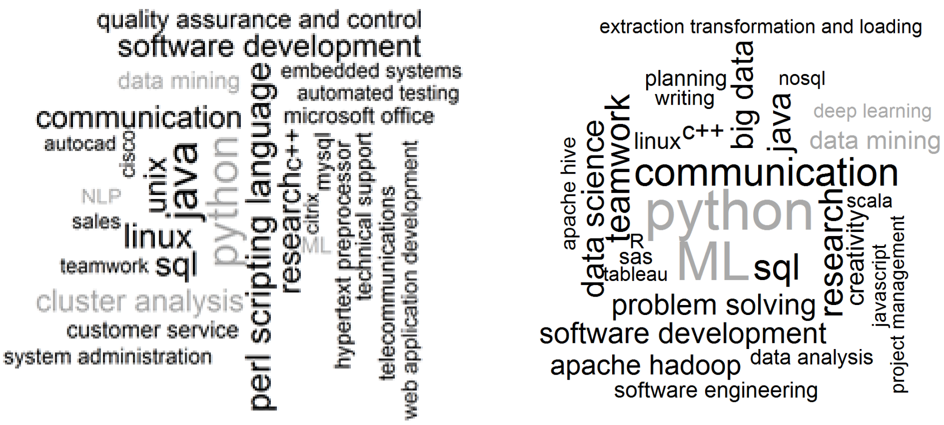
2012 2018



Note: In 2012, the frequency of the top 30 non-AI skills accounts for around 30% of the frequency of all non-AI skills, 31% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.7. CANADA, Top 30 skills (all skills) demanded in AI-related jobs

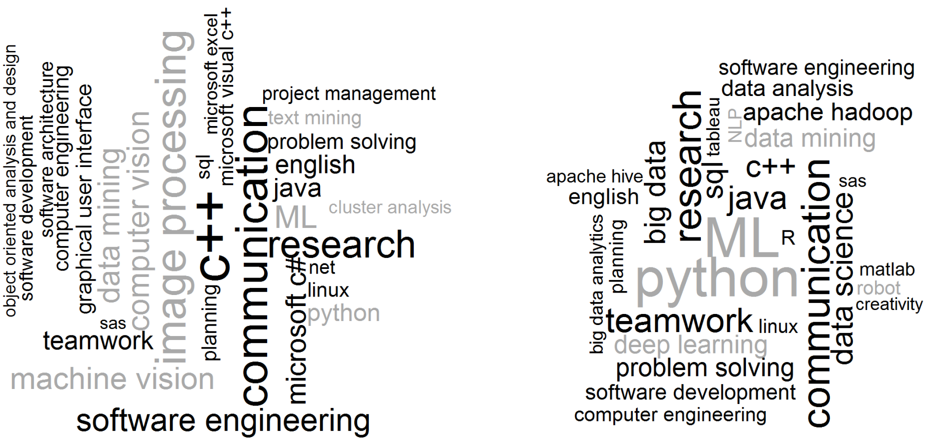
2012 2018



Note: Keywords in grey present AI skills. In 2012, the frequency of the top 30 skills accounts for around 37% of the frequency of all skills, 31% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.8. SINGAPORE, Top 30 skills (all skills) demanded in AI-related jobs

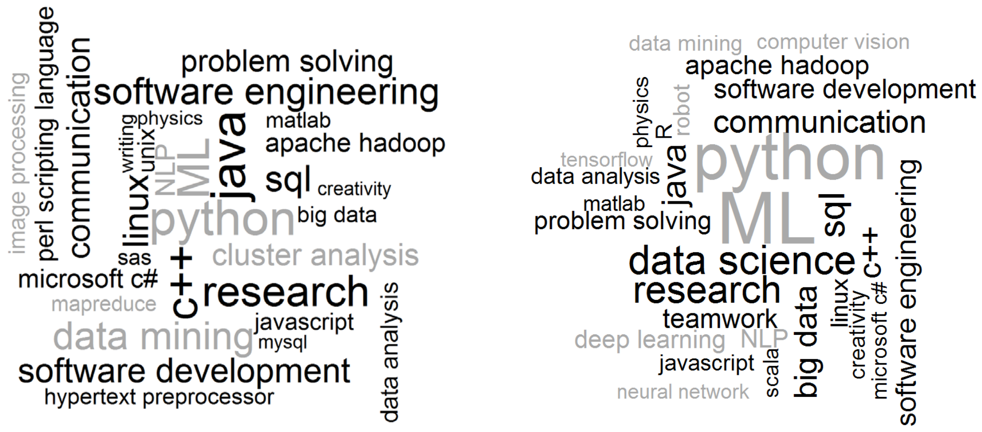
2012 **2018**



Note: Keywords in grey present AI skills. In 2012, the frequency of the top 30 skills accounts for around 43% of the frequency of all skills, for 38% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.9. UK, Top 30 skills (all skills) demanded in AI-related jobs

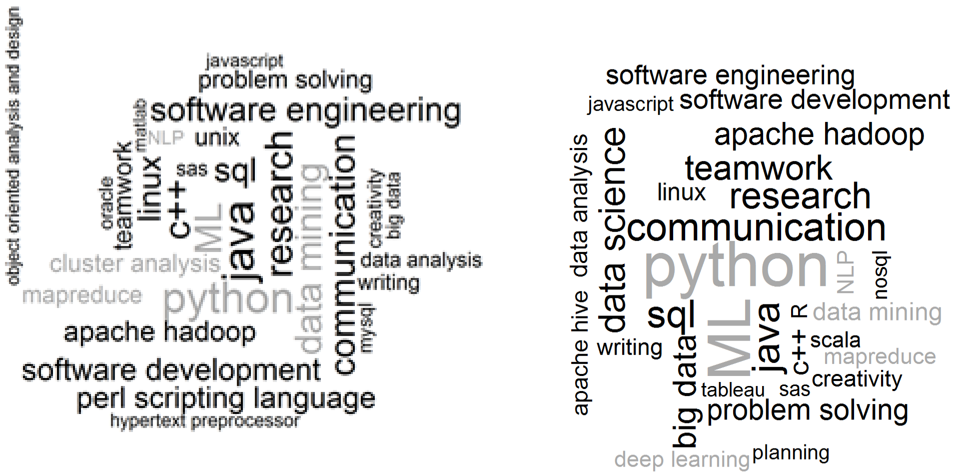
2012 **2018**



Note: Keywords in grey present AI skills. In 2012, the frequency of the top 30 skills accounts for around 38% of the frequency of all skills, 39% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.10. US, Top 30 skills (all skills) demanded in AI-related jobs

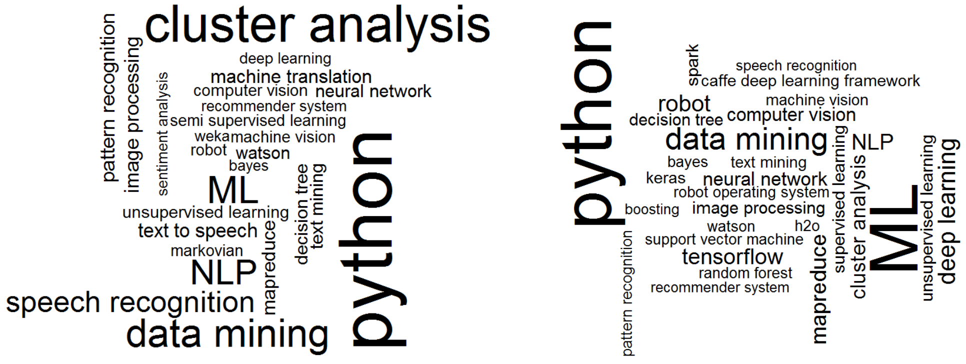
2012 2018



Note: Keywords in grey present AI skills. In 2012, the frequency of the top 30 skills accounts for around 32% of the frequency of all skills, for 33% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.11. CANADA, Top 30 AI-related skills demanded in AI-related jobs

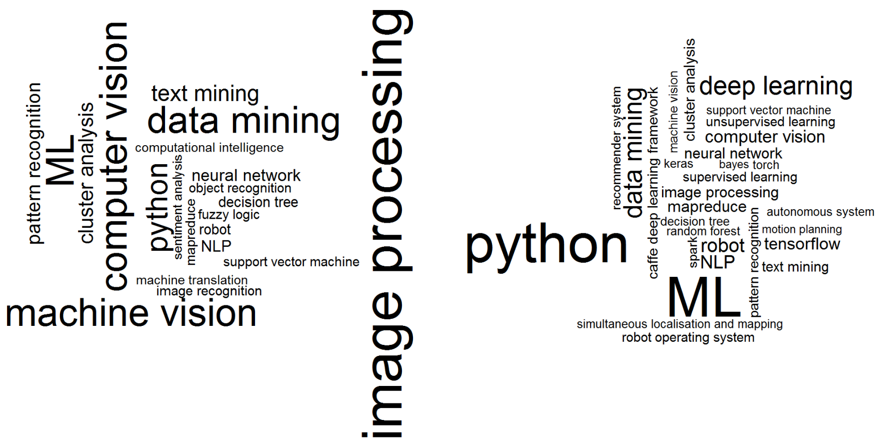
2012 **2018**



Note: In 2012, the frequency of the top 30 AI-related skills accounts for around 99% of the frequency of all AI-related skills, for 97% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.12. SINGAPORE, Top 30 AI-related skills demanded in AI-related jobs

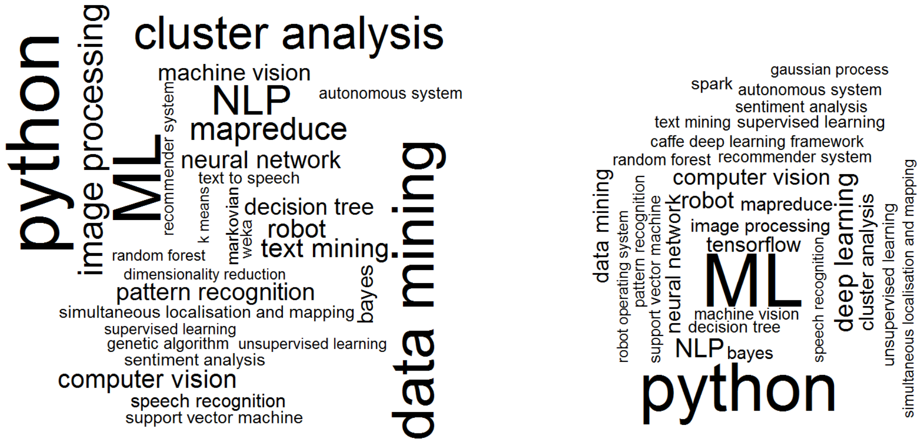
2012 **2018**



Note: In 2012, the data contains less than 30 AI-related skills. In 2018, the frequency of the top 30 AI-related skills accounts for around 96% of the frequency of all AI-related skills.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.13. UK, Top 30 AI-related skills demanded in AI-related jobs

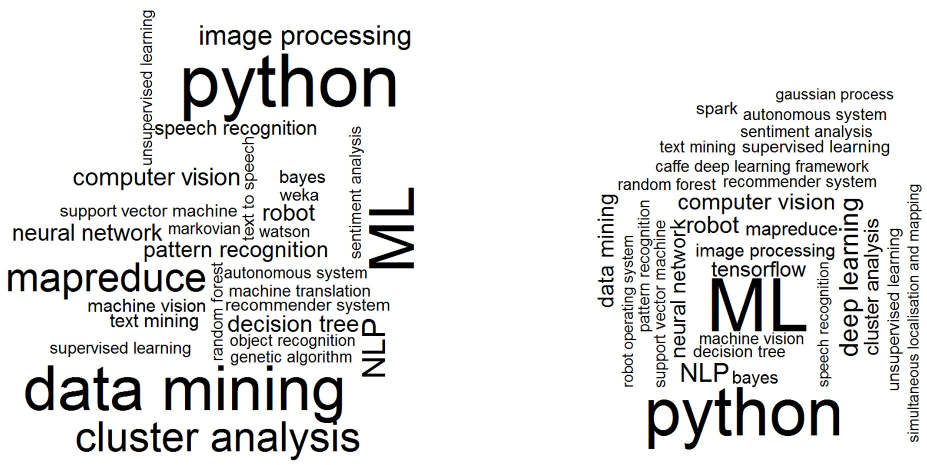
2012 | 2018



Note: In 2012, the frequency of the top 30 AI-related skills accounts for around 99% of the frequency of all AI-related skills, 98% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

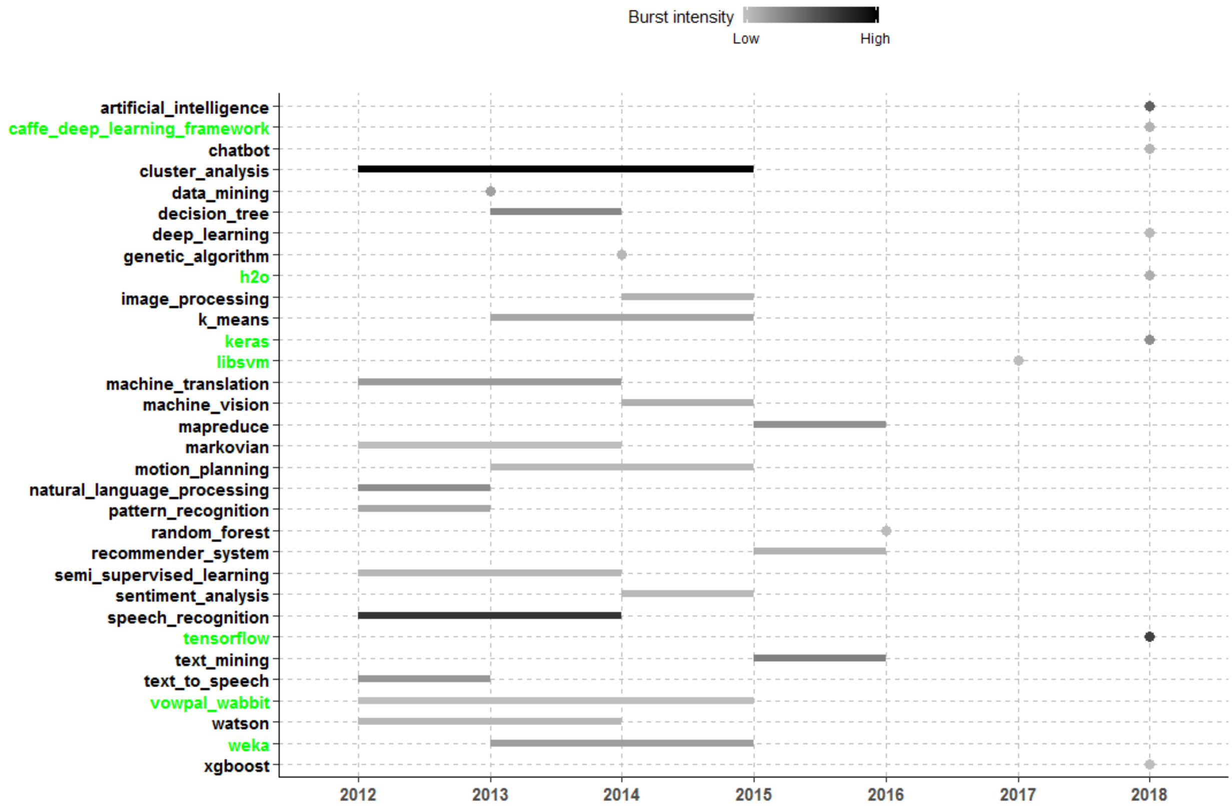
Figure A.14. US, Top 30 AI-related skills demanded in AI-related jobs

2012 | 2018



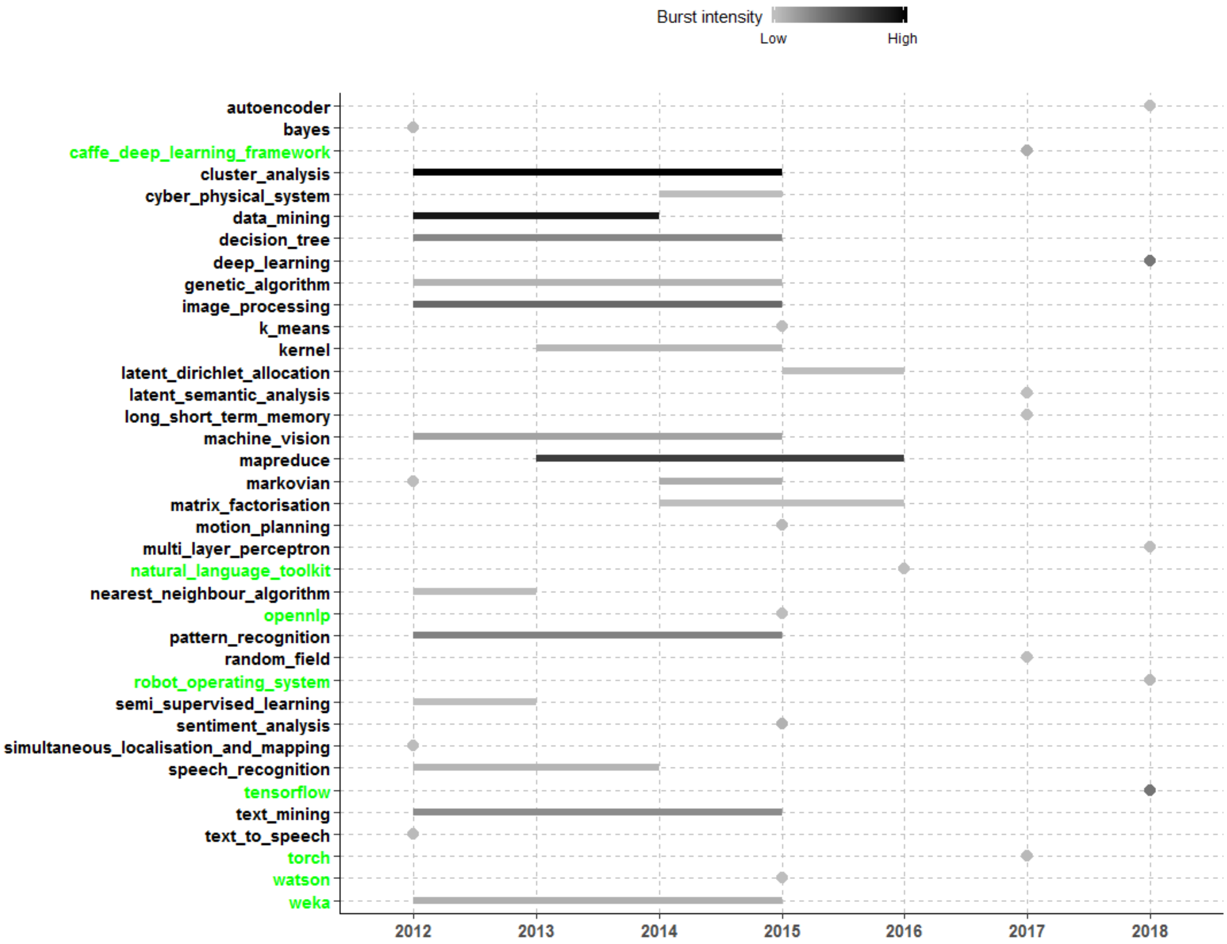
Note: In 2012, the frequency of the top 30 AI-related skills accounts for around 98% of the frequency of all AI-related skills, for 96% in 2018.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.15. Bursting AI-related skills, Canada, 2012-18



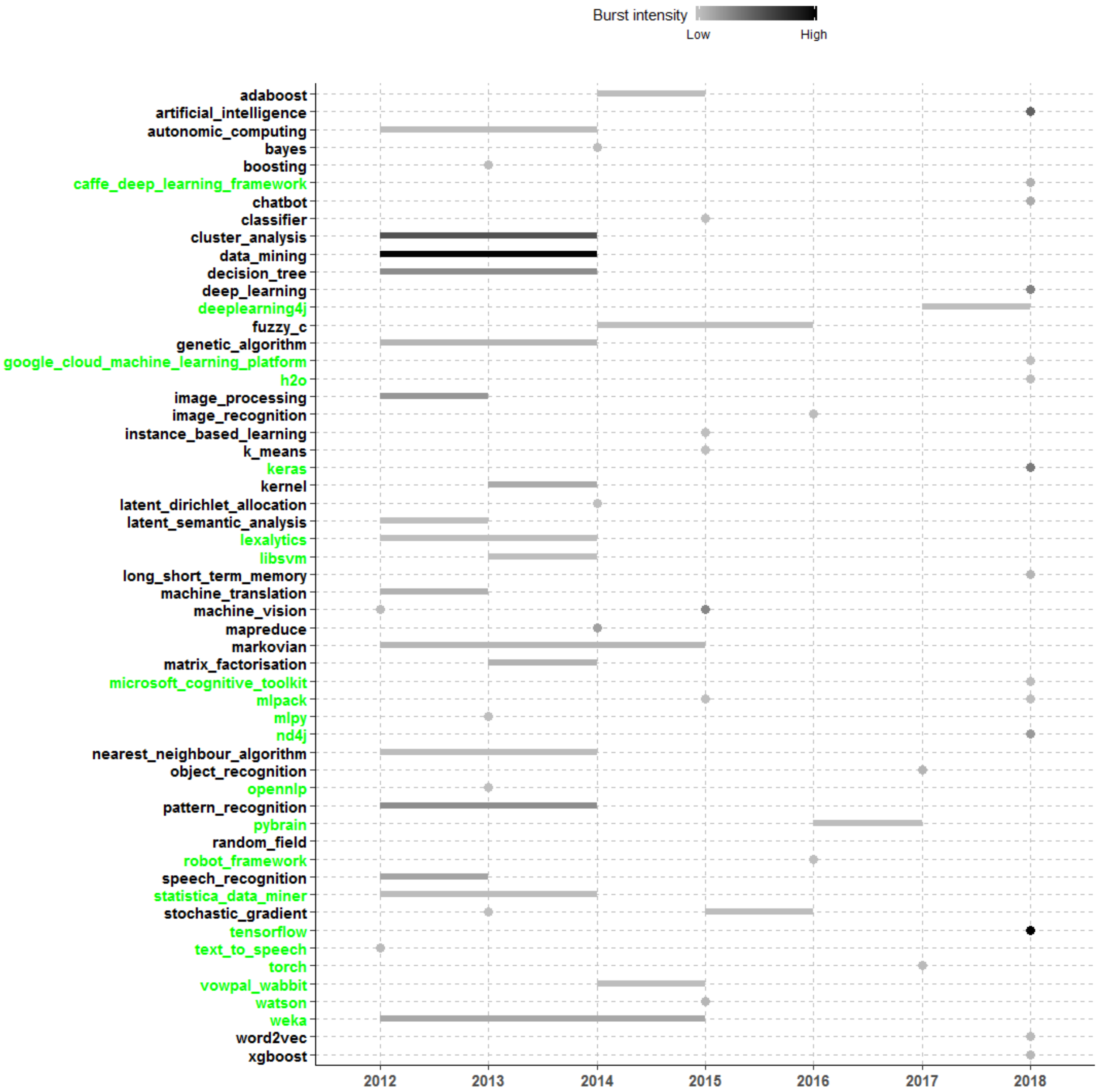
Note: Items are listed in alphabetical order. Items in green denote AI-related software.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019) following Dernis et al. (2016).

Figure A.16. Bursting AI-related skills, UK, 2012-18



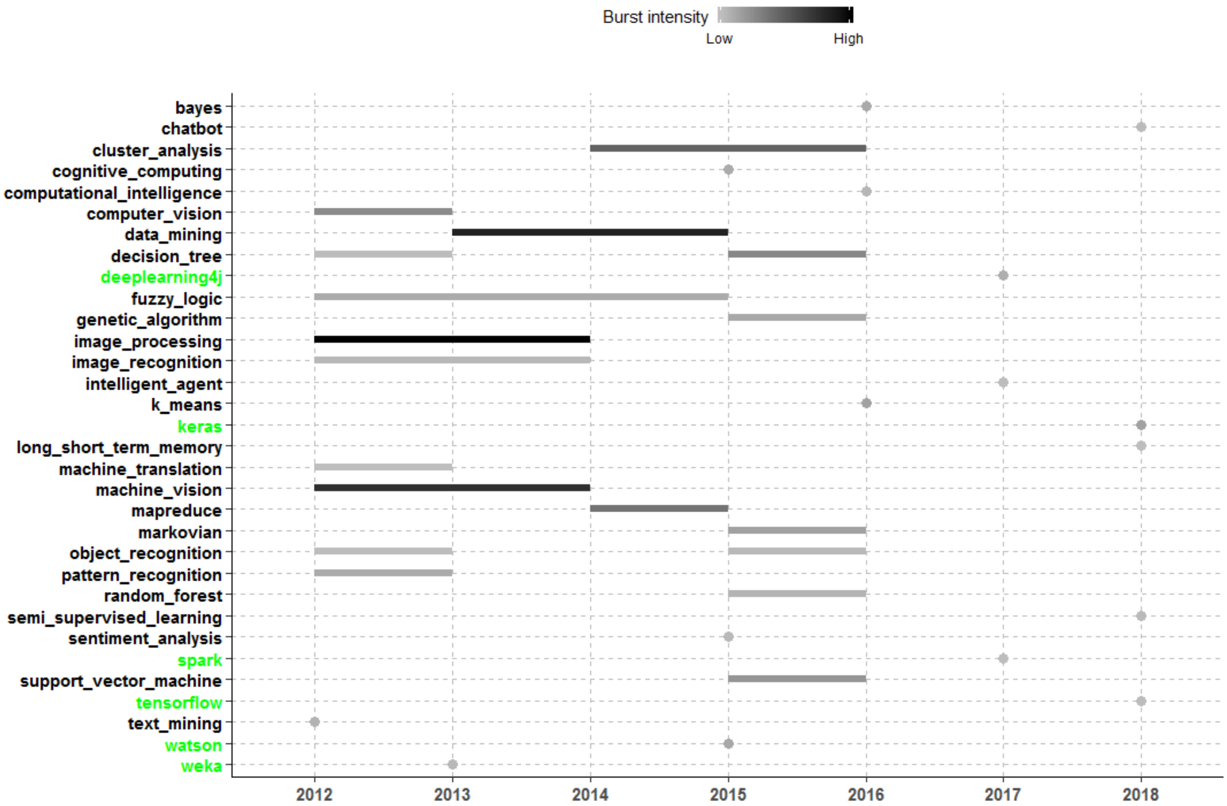
Note: Items are listed in alphabetical order. Items in green denote AI-related software.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019) following Dernis et al. (2016).

Figure A.17. Bursting AI-related skills, US, 2012-18



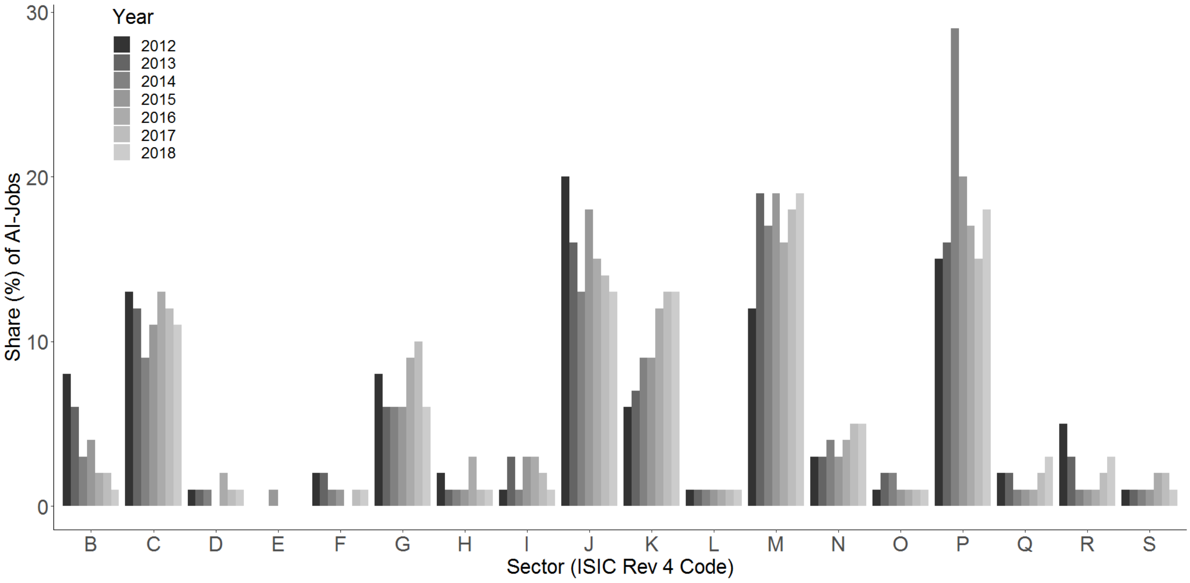
Note: Items are listed in alphabetical order. Items in green denote AI-related software.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019) following Dernis et al. (2016).

Figure A.18. Bursting AI-related skills, Singapore, 2012-18



Note: Items are listed in alphabetical order. Items in green denote AI-related software.
Source: Authors' own compilation on Burning Glass Technologies data (February 2019) following Dernis et al. (2016).

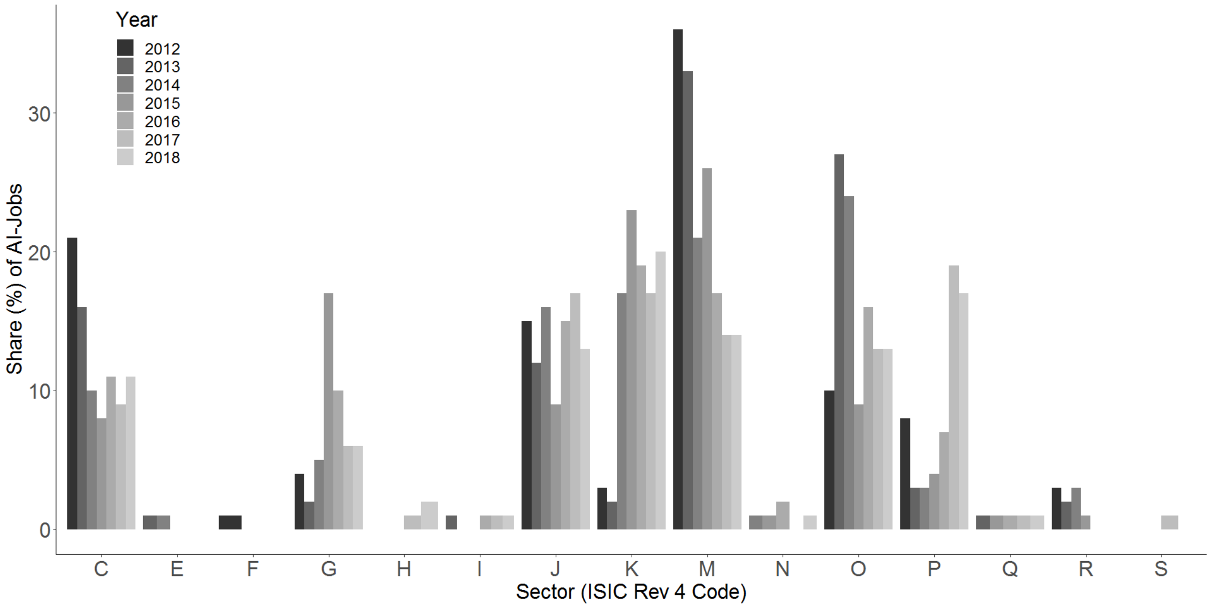
Figure A.19. UK - Distribution of AI-related jobs across sectors



B: Mining and Quarrying, C: Manufacturing, D: Electricity, Gas, Steam and Air-Conditioning Supply, E: Water Supply; Sewerage, Waste Management and Remediation Activities, F: Construction, G: Wholesale and Retail Trade, H: Transportation and Storage, I: Accomodation and Food Service Activities, J: Information and Communications, K: Financial and Insurance Activities, L: Real Estate Activities, M: Professional, Scientific and Technical Activities, N: Administrative and Support Service Activities, O: Public Administration and Defence, P: Education, Q: Health and Social Services, R: Arts, Entertainment and Recreation, S: Other Service Activities

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).

Figure A.20. Singapore - Distribution of AI-related jobs across sectors



C: Manufacturing, E: Water Supply; Sewerage, Waste Management and Remediation Activities, F: Construction, G: Wholesale and Retail Trade, H: Transportation and Storage, I: Accomodation and Food Service Activities, J: Information and Communications, K: Financial and Insurance Activities, M: Professional, Scientific and Technical Activities, N: Administrative and Support Service Activities, O: Public Administration and Defence, P: Education, Q: Health and Social Services, R: Arts, Entertainment and Recreation, S: Other Service Activities

Source: Authors' own compilation on Burning Glass Technologies data (February 2019).