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THE HUMAN CAPITAL BEHIND AI

JOBS AND SKILLS DEMAND FROM ONLINE JOB POSTINGS

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The human capital behind AI: jobs and skills demand from online job postings

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Building on recent OECD work, this paper analyses the skills sets ("skills bundles") demanded in artificial intelligence (AI)-related online job postings. The analysis uses Burning Glass Technologies' data for the United States and the United Kingdom and finds that skills related to the open source programming software Python and to machine learning represent "must-haves" for working with AI. Employers additionally value specialised skills related to robotics, AI development and applying AI. A comparison of the periods 2013-15 and 2017-19 shows that the latter two have become more interrelated over time, with "neural network" skills connecting both groups. Network analysis relating AI skills to general skills highlights the growing role of socio-emotional skills; and of skill bundles related to programming, management of big data and data analysis. Key results hold for both countries and time periods, though differences emerge across occupations and industries.

Keywords: AI, Online jobs, Skills, Skill bundles

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Synthèse

Sur la base de travaux récents de l'OCDE, ce document analyse les ensembles de compétences (« skill bundles ») exigées dans les offres d'emploi en ligne liées à l'intelligence artificielle (IA). L'analyse, qui utilise les données de Burning Glass Technologies pour les États-Unis et le Royaume-Uni, trouve que les compétences liées au logiciel de programmation open source Python et à « l'apprentissage automatique » représentent des compétences incontournables pour travailler avec l'IA. Les employeurs apprécient en outre les compétences spécialisées liées à la robotique, au développement de l'IA et à l'application de l'IA. Une comparaison des périodes 2013-15 et 2017-19 montre que les développements de l'IA et les compétences liées aux applications de l'IA sont devenus de plus en plus interdépendants au fil du temps, les compétences de « réseau de neurones » reliant ces deux groupes. L'analyse des réseaux reliant les compétences en IA aux compétences générales met en évidence le rôle croissant des compétences socio-affectives et des ensembles de compétences liées à la programmation, à la gestion du « big data » et à l'analyse des données. Les principaux résultats sont valables pour les deux pays et les deux périodes, bien que des différences apparaissent selon les professions et les industries.

Kurzfassung

Ergänzend zu aktuellen Studien der OECD werden Kompetenzbündel („skill bundles“) analysiert, die in online ausgeschriebenen Stellen im Zusammenhang mit Künstlicher Intelligenz (KI) gewünscht werden. Die Analyse verwendet Daten von Burning Glass Technologies für die Vereinigten Staaten von Amerika und das Vereinigte Königreich und zeigt, dass Kompetenzen im Zusammenhang mit der frei zugänglichen („open source“) Programmiersoftware Python und mit maschinellem Lernen "must haves" für die Arbeit mit KI darstellen. Arbeitgeber schätzen zusätzlich spezialisierte Fähigkeiten in Bezug auf Robotik, die Entwicklung von KI und deren Anwendung. Der Vergleich der Zeiträume 2013-15 und 2017-19 zeigt, dass die beiden Letzteren im Laufe der Zeit immer stärker durch "neuronale Netzwerke" miteinander verknüpft sind. Eine Netzwerkanalyse der KI-spezifischen und allgemeineren Fähigkeiten unterstreicht die wachsende Rolle von sozio-emotionalen Kompetenzen und von Kompetenzbündeln im Zusammenhang mit Programmierung, Handhabung großer Datenmengen („big data“) und der Datenanalyse. Die wichtigsten Ergebnisse gelten sowohl für beide Länder als auch für die untersuchten Zeiträume, wobei aber Unterschiede zwischen Berufs- und Sektorengruppen bestehen.

Executive Summary

This paper analyses the set of skills demanded by employers in the United States and the United Kingdom in online job postings related to Artificial Intelligence (AI). It relies on Burning Glass Technologies' (BGT) online vacancy data for the period 2012-19 to provide first-time evidence about the relationships between the different AI skills that are demanded on the job, and between AI and non-AI skills. AI skills are identified as in Squicciarini and Nachtigall (2021[1]), using a list of AI-related keywords of Baruffaldi et al. (2020[2]), whereas non-AI skills are any type of cognitive and socio-emotional skills that workers are required to be endowed with.

The evidence provided in this paper contributes to the OECD's programme on AI in Work, Innovation, Productivity and Skills (AI-WIPS), supported by the German Federal Ministry of Labour and Social Affairs (BMAS). This work aims to inform industrial, innovation, labour and education policies, by shedding light on the set of workers' skills that are demanded on the job in relation to the development and adoption of AI. It further provides evidence about those skills that are central to the deployment of AI, and the way these focal skills relate to other cognitive and socio-emotional skills. This helps prioritise interventions and informs the design of policies fostering the development of the human capital needed for AI to become the economically and societally enhancing technology countries hope for.

The main findings of the analysis and their implications for policymaking are as follows.

- Employers in the United States and the United Kingdom require relatively similar skill bundles for AI-related workers, and these remain largely the same across both periods considered (2013-15 and 2017-19). This may mean that, while AI is rapidly evolving, the skills required for AI-related workers are relatively stable and are expected to be also needed for the AI talent of the future.
- AI-related workers are technically skilled people, who need to exhibit a set of AI-related skills regardless of whether their job entails developing or adopting AI. All AI workers should be endowed with *Python* and *machine learning (ML)* skills, as they are by far the most frequently demanded skill pair, forming the foundation for AI-related workers' skill profiles. Other important AI-related skills include *data mining, cluster analysis, natural language processing* and *robotics.*
- Three main bundles of AI-related skills emerge, which relate to 'developing and advancing AI', 'AI applications' and 'robotics' but employers also often require additional specialisations.
- Skills associated with AI applications and with developing or advancing AI have become more interrelated over time, with *neural network* (i.e. algorithms processing information in a way that mimics the way the human brain operates) becoming more central, connecting both groups.
- Expanding the scope of the analysis beyond AI-related skills, by also including other technical and socio-emotional skills in AI-related jobs, allows to further separate these specialisations (i.e. the bundles) into 'programming and software related skills', 'the management of big data', 'data analysis tools and broader analytical skills' and 'socio-emotional skills'.
- Programming languages (beyond *Python*) are important in both countries, namely *Java, SQL* and *C++,* although the latter seemingly loses importance over the time

period considered. AI-related jobs further require competencies related to *big data* and, in most recent years, *data science*, which is an inter-disciplinary field using scientific methods to extract knowledge and insights from data. The demand for *data science*-related abilities points to the need of AI workers to comb through vast amounts of collected data, to help identify business opportunities and to optimise product and process development.

- In both periods, a significant number of socio-emotional skills are demanded in combination with more cognitive skills. They can broadly be denoted as *communication, teamwork* and *problem solving* skills, which appear together with *creativity* and *writing*. When considering differences between sectors, we find that socio-emotional skills are particularly important for AI-related jobs in business services and education.
- Although the composition of the socio-emotional skill bundle remains basically unchanged over time when considering the top-30 skills, looking at the top-50 skills demanded reveals that *communication* skills gained in relative importance and that there is the need for AI talent to be further endowed with *presentation* skills and for being *detail oriented*.
- *Communication*-related skills are especially key in the United States as compared to the United Kingdom, possibly because there is relatively greater demand for AI-related managers in the United States. Results reflect the need to communicate within the team involved in the development and adoption of AI, as well as communicating among the different parts of the firm or institution developing or adopting AI, for AI to be correctly deployed.
- Of AI-related jobs, 87% relate to the professionals occupation, and the networks for professionals looks very similar to the one for all occupations combined. In the case of managers, however, socio-emotional skills are much more important (12 out of the top-30 skills, as compared to the 5 socio-emotional skills found across all occupations). When it comes to these socio-emotional skills, high centrality is observed again in the case of *communication* skills, *problem solving* and *creativity*, but for managers in the AI field, also *presentation* skills, *planning*, *budgeting* and *business development* are important.
- From the different occupational groups, professionals, craft and related trade workers and plant and machine operators and assemblers stand out in terms of the relatively higher number of different AI skills sought out of total skills demanded. This may reflect the need to be more specific about AI-related skills in job postings in occupational groups where AI skills cannot be taken for granted.
- Companies looking for AI-related managers or technicians generally also try to hire AI-related professionals, that is, recruitment related to these different occupational categories often happen jointly in the same organisation. This may indicate that professionals are crucial for the development and implementation of AI (which also represent the bulk of AI-related personnel sought) and that complementarities exist between the work of professionals and those of managers and technicians.
- Demand for AI-related jobs appears very concentrated geographically. Although the number of AI-related vacancies has increased across all regions in both countries, also as a share of total vacancies, a majority of those jobs continues to be located in London in the United Kingdom and in California in the United States, with little change observed over time.

Résumé

Ce document analyse l'ensemble des compétences demandées par les employeurs aux États-Unis et au Royaume-Uni dans les offres d'emploi en ligne liées à l'intelligence artificielle (IA). Il s'appuie sur les données de postes vacants en ligne de Burning Glass Technologies (BGT) pour la période 2012-19, pour fournir pour la première fois des preuves sur les relations entre les différentes compétences en IA requises au travail, et entre les compétences en IA et non-IA. Les compétences en IA sont identifiées de la même manière que dans Squicciarini et Nachtigall (2021[1]), en utilisant une liste de mots-clés liés à l'IA d'après Baruffaldi et al. (2020[2]), alors que par compétences non-IA, nous désignons tout type de compétences cognitives et socio-affectives dont les employé s doivent être dotés.

Les preuves fournies dans ce document contribuent au programme de l'OCDE sur l'IA dans le travail, l'innovation, la productivité et les compétences (AI-WIPS), soutenu par le ministère fédéral allemand du Travail et des Affaires sociales (BMAS). Ce travail vise à éclairer les politiques industrielles, d'innovation, du travail et de l'éducation, en mettant en lumière l'ensemble des compétences exigées des travailleurs dans les emplois en relation avec le développement et l'adoption de l'IA. Il fournit en outre des preuves sur les compétences essentielles au déploiement de l'IA et sur la manière dont ces compétences essentielles sont liées à d'autres compétences cognitives et socio-affectives. Cela aide à hiérarchiser les interventions et aide à la conception de politiques favorables au développement du capital humain nécessaire pour que l'IA devienne la technologie de progrès économique et sociétal que les pays espèrent.

Les principales conclusions de l'analyse et leurs implications pour l'élaboration des politiques sont les suivantes.

- Les employeurs aux États-Unis et au Royaume-Uni exigent des ensembles de compétences relativement similaires pour les travailleurs liés à l'IA, et ceux-ci restent en grande partie les mêmes sur les deux périodes considérées (2013-15 et 2017-19). Cela peut signifier que, alors que l'IA évolue rapidement, les compétences requises pour les travailleurs liés à l'IA sont relativement stables et devraient rester nécessaires pour les futurs talents en IA.

- Les travailleurs en lien avec l'IA sont des personnes techniquement qualifiées qui doivent faire preuve d'un ensemble de compétences liées à l'IA, que leur travail implique le développement ou l'application de l'IA. Tous les travailleurs en IA doivent être dotés de compétences en *Python* et en *apprentissage automatique (AA)*, car il s'agit de loin de la paire de compétences les plus demandées, constituant la base des profils de compétences des travailleurs liés à l'IA. D'autres compétences importantes liées à l'IA incluent l'*exploration de données,* l'*analyse de clusters*, le *traitement du langage naturel* et la *robotique.*

- Trois principaux ensembles de compétences liées à l'IA émergent, qui concernent le 'développement et les avancées en IA', les 'pplications d'IA' et la 'robotique'. Toutefois, les employeurs ont également souvent besoin de personnel disposant de spécialisations supplémentaires.

- Les compétences associées aux applications de l'IA et au développement ou aux avancées en IA sont devenues plus interdépendantes au fil du temps, le *réseau neuronal* (c'est-à-dire les algorithmes traitant les informations d'une manière qui

imite le fonctionnement du cerveau humain) devenant plus central, reliant les deux groupes.

- L'élargissement de la portée de l'analyse au-delà des compétences liées à l'IA, en incluant également d'autres compétences techniques et socio-affectives dans les emplois liés à l'IA, permet de séparer davantage ces spécialisations (c'est-à-dire les ensembles) en 'compétences liées à la programmation et aux logiciels', 'la gestion du *big data*', 'les outils d'analyse des données et les compétences analytiques plus larges' et 'les compétences socio-affectives'.
- Les langages de programmation (au-delà de *Python*) sont importants dans les deux pays, à savoir *Java, SQL* et *C++*, bien que ce dernier semble perdre de son importance au cours de la période considérée. Les emplois liés à l'IA nécessitent en outre des compétences liées au *big data* et, ces dernières années, à la *data science*, qui est un domaine interdisciplinaire utilisant des méthodes scientifiques pour extraire des connaissances et idées à partir de données. La demande de compétences liées à la *data science* souligne le besoin des employés en IA de passer au peigne fin de vastes quantités de données collectées, d'aider à identifier les opportunités commerciales et d'optimiser le développement de produits et de procédés.
- Durant les deux périodes, un nombre significatif de compétences socio-affectives sont demandées, combinées à des compétences plus cognitives. Elles peuvent être globalement décrites comme des compétences en *communication, travail d'équipe* et *résolution de problèmes*, qui apparaissent simultanément avec la *créativité* et la *rédaction*. Lorsque l'on considère les différences entre secteurs, nous constatons que les compétences socio-affectives sont particulièrement importantes pour les emplois liés à l'IA dans les services aux entreprises et l'éducation.
- Bien que l'ensemble de compétences socio-affectives reste globalement inchangé au fil du temps lorsque l'on considère les 30 premières compétences, l'examen des 50 premières compétences requises révèle que les compétences en *communication* ont gagné en importance relative et qu'il est nécessaire pour les talents en IA d'être en outre dotés de compétences en *présentation* et d'être *méticuleux*.
- Les compétences liées à la *communication* sont particulièrement essentielles aux États-Unis par rapport au Royaume-Uni, peut-être parce qu'il y a une relativement plus grande demande de managers en lien avec l'IA aux États-Unis. Les résultats reflètent la nécessité de communiquer aussi bien au sein de l'équipe impliquée dans le développement et l'adoption de l'IA, qu'entre les différentes parties de l'entreprise ou de l'institution développant ou adoptant l'IA, afin que l'IA soit correctement déployée.
- Parmi les emplois liés à l'IA, 87% se rapportent à des professions intellectuelles et scientifiques, et les réseaux pour ces métiers paraissent très semblables à ceux pour l'ensemble des professions combinées. Dans le cas des managers, cependant, les compétences socio-affectives sont beaucoup plus importantes (12 des 30 premières compétences, par rapport à 5 compétences socio-affectives trouvées pour toutes les professions). En ce qui concerne les compétences socio-affectives, une centralité élevée est à nouveau observée dans le cas des compétences en *communication*, en *résolution de problèmes* et en *créativité*, mais pour les managers dans le domaine de l'IA, les compétences en *présentation,* en *planification,* en *budgétisation* et en *développement commercial* sont également importantes.

- Parmi les différents groupes de professions, les professions intellectuelles et scientifiques, les métiers qualifiés de l'industrie et de l'artisanat et les conducteurs d'installations et de machines, et ouvriers de l'assemblage se distinguent par le nombre relativement plus élevé de compétences différentes en IA recherchées par rapport aux compétences totales demandées. Cela peut refléter la nécessité d'être plus précis sur les compétences liées à l'IA dans les offres d'emploi de ces groupes de professions où ces compétences en IA ne peuvent pas être considérées comme acquises.
- Les entreprises à la recherche de managers ou de techniciens liés à l'IA essaient généralement aussi d'embaucher des professions intellectuelles et scientifiques liées à l'IA, c'est-à-dire que le recrutement lié à ces différentes catégories professionnelles se fait conjointement dans la même organisation. Cela peut indiquer que les professions intellectuelles et scientifiques sont cruciales pour le développement et la mise en œuvre de l'IA (elles représentent également la majeure partie du personnel lié à l'IA recherché) et que des complémentarités existent entre le travail des professions intellectuelles et scientifiques et celui des managers et des techniciens.
- La demande d'emplois liés à l'IA apparait très concentrée géographiquement. Bien que le nombre de postes vacants liés à l'IA ait augmenté dans toutes les régions des deux pays, la majorité de ces emplois continue d'être située à Londres au Royaume-Uni et en Californie aux États-Unis en pourcentage du nombre total de postes vacants, avec peu de changements

Zusammenfassung

Diese Studie analysiert Kompetenzen im Zusammenhang mit Künstlicher Intelligenz (KI), die von Arbeitgebern in den Vereinigten Staaten von Amerika (USA) und im Vereinigten Königreich (GB) in online ausgeschriebenen Stellen gefordert werden. Um erstmals Erkenntnisse sowohl über die Beziehungen zwischen den verschiedenen KI-Fähigkeiten, die am Arbeitsplatz erwartet werden, als auch zwischen KI- und Nicht-KI-Fähigkeiten zu gewinnen, werden online Stellenausschreibungsdaten von Burning Glass Technologies (BGT) für den Zeitraum 2012-19 untersucht. KI-Fähigkeiten werden wie in Squicciarini und Nachtigall (2021[1]) mit Hilfe einer Liste von KI-bezogenen Schlüsselwörtern von Baruffaldi et al. (2020[2]) identifiziert. Als Nicht-KI-Kompetenzen werden alle kognitiven und sozio-emotionalen Fähigkeiten bezeichnet, die ein Arbeitnehmer haben sollte.

Die in dieser Studie enthaltenen Erkenntnisse sind ein Beitrag zum OECD-Programm "AI in Work, Innovation, Productivity and Skills" (AI-WIPS), das vom deutschen Bundesministerium für Arbeit und Soziales (BMAS) unterstützt wird. Diese Studie soll Industrie-, Innovations-, Arbeits- und Bildungspolitik unterstützen, indem sie die Fähigkeiten der Arbeitnehmer beleuchtet, die im Zusammenhang mit der Entwicklung und Einführung von KI am Arbeitsplatz erforderlich sind. Ferner liefert sie Erkenntnisse über die Fähigkeiten, die für den Einsatz von KI von zentraler Bedeutung sind, und über die Art und Weise, wie diese mit anderen kognitiven und sozio-emotionalen Kompetenzen zusammenhängen. Die Studie soll helfen Prioritäten bei politischen Entscheidungen zu setzen und über die Gestaltung von Maßnahmen zu informieren, die die Entwicklung des Humankapitals fördern und die KI damit, wie von den Ländern erhofft, zu der wirtschaftlich und gesellschaftlich dienlichen Technologie machen.

Die wichtigsten Ergebnisse der Analyse und ihre Implikationen für die Politik sind:

- Die Arbeitgeber in den USA und in GB verlangen vergleichbare Kompetenzbündel für KI-bezogene Arbeitskräfte, die über beide betrachteten Zeiträume (2013-15 und 2017-19) weitgehend unverändert bleiben. Eine Erklärung könnte sein, dass trotz schneller Weiterentwicklung der KI die diesbezüglich erforderlichen Fähigkeiten relativ unverändert sind und voraussichtlich auch in Zukunft benötigt werden.
- KI-bezogene Arbeitskräfte sind technisch versierte Personen, die eine Vielzahl entsprechender Fähigkeiten aufweisen müssen, und das unabhängig davon, ob ihr Job in der Entwicklung oder Anwendung von KI besteht. Alle KI-Fachkräfte sollten über Kenntnisse in *Python* und *maschinellem Lernen (ML)* verfügen, da diese mit Abstand das am häufigsten nachgefragte Kompetenzpaar und somit die Grundlage für das Kompetenzprofil der KI-Fachkräfte bilden. Weitere wichtige KI-relevante Fähigkeiten bestehen in der *Datenextraktion (data mining), Clusteranalyse, Verarbeitung natürlicher Sprache* und der *Robotik*.
- Es zeichnen sich drei Hauptbündel von KI-relevanten Fähigkeiten ab, die sich auf "Entwicklung und Weiterentwicklung von KI", "KI-Anwendungen" und "Robotik" beziehen, wobei Arbeitgeber oft zusätzliche Spezialisierungen anfragen.
- Fähigkeiten, die mit KI-Anwendungen und mit der Entwicklung oder Weiterentwicklung von KI in Verbindung gebracht werden, sind im Laufe der Zeit immer stärker miteinander verknüpft worden. *Neuronale Netzwerke* (d. h. Algorithmen, die Informationen nach Arbeitsweise des menschlichen Gehirns verarbeiten) werden immer zentraler und verbinden beide Gruppen miteinander.

- Erweitert man den Umfang der Analyse auf andere technische und sozio-emotionale Fähigkeiten in KI-bezogene Jobs, so können die Spezialisierungen (d. h. die Bündel) weiter unterteilt werden. Diese sind "Programmier- und softwarebezogene Fähigkeiten", "Handhabung großer Datenmengen", "Datenanalysewerkzeuge und breitere analytische Fähigkeiten" und "sozio-emotionale Fähigkeiten".

- Programmiersprachen wie *Java, SQL und C++* (neben *Python*) sind in beiden Ländern wichtig, wobei letztere über den betrachteten Zeitraum an Bedeutung zu verlieren scheint. KI-bezogene Jobs erfordern darüber hinaus Kompetenzen im Zusammenhang mit *großen Datenmengen* und in den letzten Jahren *Data Science*. *Data Science* ist ein interdisziplinärer Bereich, der wissenschaftliche Methoden nutzt, um Wissen und Erkenntnisse aus Daten zu gewinnen. Die Nachfrage nach diesen Fähigkeiten deutet darauf hin, dass zum Erkennen von Geschäftsmöglichkeiten und zur Optimierung der Produkt- und Prozessentwicklung große Datenmengen zu sichten sind.

- In beiden Zeiträumen wird eine beträchtliche Anzahl von sozio-emotionalen Fähigkeiten in Kombination mit eher kognitiven Kompetenzen gefordert. Sie lassen sich in *Kommunikations-, Teamwork-* und *Problemlösungsfähigkeiten* einteilen und sind vergesellschaftet mit Kreativität und Schreiben. Bei der Betrachtung der einzelnen Industriesektoren ist festzustellen, dass bei KI-bezogenen Jobs in Unternehmensdienstleistungen und Bildung sozio-emotionale Fähigkeiten besonderes Gewicht haben.

- Bei den Top 30 nachgefragten Fähigkeiten zeigt über den Untersuchungszeitraum das sozio-emotionale Kompetenzbündel im Wesentlichen kaum Veränderungen. Betrachtet man jedoch die Top 50 Fähigkeiten, so haben in diesem Bündel *Kommunikationsfähigkeiten* an relativer Bedeutung gewonnen. Gut *präsentieren* zu können und *Detail orientiert* zu sein ist auch wichtig.

- *Kommunikationsbezogene Fähigkeiten* sind in den USA im Vergleich zu GB besonders wichtig. Das liegt möglicherweise daran, dass in den USA eine relativ größere Nachfrage nach KI-bezogenen Führungskräften besteht. Die Ergebnisse zeigen die Notwendigkeit der Kommunikation innerhalb des Teams, als auch zwischen den verschiedenen Bereichen des Unternehmens bzw. der Institution, die an der Entwicklung und Einführung von KI beteiligt sind. So kann KI richtig eingesetzt werden.

- 87% der KI-bezogenen Jobs sind akademische Berufe, weshalb sich deren Kompetenznetzwerke unwesentlich von denen aller Berufe unterscheiden. Im Fall von Führungskräften spielen jedoch sozio-emotionale Fähigkeiten eine deutlich wichtigere Rolle (12 der Top-30-Fähigkeiten bei Führungskräften im Vergleich zu den 5 sozio-emotionalen Fähigkeiten bei allen Berufen). In diesem Zusammenhang weisen *Kommunikationsfähigkeiten, Problemlösung* und *Kreativität* eine hohe Zentralität auf, wobei für Manager im KI-Bereich auch *Präsentationsfähigkeiten*, *Planung, Budgetierung* und *Geschäftsentwicklung* bedeutsam sind.

- Von den verschiedenen Berufsgruppen fallen akademische Berufe, Handwerker sowie Anlagen-/Maschinenbediener und Montageberufe durch den erhöhten Anteil der geforderten KI-Fähigkeiten im Vergleich zu den insgesamt geforderten Kompetenzen auf. Eine Erklärung könnte sein, dass in diesen Berufsgruppen verstärkt auf KI-Fähigkeiten in Stellenausschreibungen eingegangen wird, weil diese bei ihnen nicht als selbstverständlich vorausgesetzt werden.

- Unternehmen, die nach KI-bezogenen Führungskräfte oder Technikern suchen, versuchen in der Regel auch KI-bezogene Fachkräfte einzustellen, d.h. die Rekrutierung in Bezug auf diese verschiedenen Berufskategorien erfolgt oft innerhalb einer Organisation gemeinsam. Dies könnte darauf hindeuten, dass einerseits Fachkräfte für die Entwicklung und Implementierung von KI entscheidend sind (sie machen ja den Großteil des gesuchten KI-Personals aus) als auch andererseits Komplementaritäten zwischen der Arbeit von Fachkräften und der von Managern und Technikern existieren.
- Die Nachfrage nach KI-bezogenen Stellen scheint geografisch sehr konzentriert zu sein. Obwohl die Zahl der KI-bezogenen offenen Stellen in allen Regionen beider Länder absolut zugenommen hat, ist auch ihr Anteil an den gesamten offenen Stellen relativ gewachsen. Die Mehrheit dieser Stellen finden wir weiterhin in London (GB) und in Kalifornien (USA); diesbezüglich ist auch im Beobachtungszeitraum keine Veränderung eingetreten.

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1. Introduction

In recent years, Artificial Intelligence (AI) has been gaining central stage and animates the discussions of policy makers as well as citizens and scientists. While being used widely, this term may have different meanings, as no universally accepted definition of AI exists. The OECD's AI Expert Group (AIGO) defined AI[1] as a machine-based system designed to operate autonomously and to make predictions, recommendations or decisions using machine and/or human-based inputs (OECD, 2019[3]). Bringsjord and Govindarajulu (2020[4]) conversely say AI refers to the simulation of human intelligence in machines that are programmed to mimic human actions; exhibiting traits associated with human minds (e.g. learning and problem solving), and having the ability to rationalise to achieve specific goals. Many further argue AI is a general-purpose technology, e.g. Brynjolfsson, Rock and Syverson (2017[5]), having the potential to penetrate and deeply transform economies and societies.

As AI diffuses, it changes the way firms and sectors behave and produce and, with this, the type of tasks that workers need to perform on the job as well as the skills needed to work with AI. Squicciarini and Nachtigall (2021[1]) offer first-time evidence on occupations and jobs requiring AI-related competences. They show that, while some occupational profiles are seemingly more affected by this new technological paradigm, demand for AI-related skills can be found in relation to all occupational categories, thus confirming the potential of this general purpose technology to change every aspect of production and, consequently, to affect all workers.

Building on Squicciarini and Nachtigall (2021[1]), we here shed light on the set of skills needed to thrive in the digital era and to work with AI. As combinations of skills may be more valuable than the sum of the parts, we believe it is important to map and analyse the skill bundles[2], i.e. combinations of skills, demanded in AI-related jobs, to provide a more accurate picture of the human capital needed for the development and adoption of AI.

As in Squicciarini and Nachtigall (2021[1]), we use online job openings data collected from online platforms and companies' websites by Burning Glass Technologies (BGT). A number of text mining techniques are applied to BGT information related to the skills sought by the employers to identify the sets of skills demanded in AI-related jobs posted online. We analyse the differences in skill bundles that emerge over time, and across occupations and industries, and shed light on the distribution of AI jobs across economic agents, as well as how AI jobs are distributed across geographical areas.

This first-time exploratory analysis focuses on the United States and the United Kingdom, as both are among the countries leading the development of AI in the world (Savage, 2020[6]), and BGT data exhibit good statistical representativeness for them (Cammeraat and Squicciarini, 2021[7]). The analysis compares the periods 2013-15 and 2017-19[3], to contribute evidence in support of the discussion on the changes triggered by the evolution of this technological paradigm.

It should be noted that while technically skills can be defined as proficiencies obtained through training and experience (OECD, 2019[8]), the present work follows BGT's broad definition, whereby the term skills encompasses a wide array of competencies, knowledge areas, software-related knowledge and industry-specific knowledge.

The results confirm that skills related to the open source Python programming language and to machine learning (ML, i.e. AI systems able to learn from data and to identify patterns to make decisions with minimal human intervention) are the most frequently demanded skills, as already found by Squicciarini and Nachtigall (2021[1]).

The analysis performed in order to uncover the skills that are most frequently demanded together, in the same job posting (i.e. the so called "co-occurrences"), clearly shows that Python and ML are also the skills that are most frequently demanded together. They can thus be considered the "key" competences demanded from AI-related workers, in relation to both the development and the adoption of AI.

A network analysis is undertaken to shed light on the way different AI-skills relate to each other. Doing so allows three main skill bundles to emerge, namely those related to robotics, to developing AI itself and to AI applications. Comparing the network structures characterising skills demand in the period 2013-15 and in 2017-19, we see skills related to AI development and to applications of AI in different domains become more intertwined over time. Skills related to neural networks emerge as the node, i.e. the central point, connecting these two clusters of skills. An explanation for this may be that *deep neural networks* and *deep learning* were typically associated with *supervised learning* models, and that *clustering*, *natural language processing* and other *unsupervised machine learning* models also started to use *neural networks* more recently. The driver of this interconnectedness may be related to the emergence of *deep learning*, driven by AlphaGo[4], DeepMind, and the acquisition of DeepMind by Google. While people skilled in *deep learning* are relevant to advancing the state of AI, many companies also started to look into applications for these *deep learning* classifiers, i.e. algorithms using training data to understand how given input variables relate to a class or group.

Moving beyond an analysis of AI skills only to include non-AI skills, i.e. any type of cognitive and socio-emotional skills that are demanded in online job postings, points to the growing importance of mixes of cognitive and socio-emotional skills over time. In particular, in AI-related job postings clusters of skills related to computer programming, to the management of big data and to data analysis more broadly emerge.

The main results hold for both countries, time-periods and when using community detection models[5] to test for the stability of the network using hierarchical clustering, i.e. using a different way of aggregating skills. Different skill bundles are nevertheless demanded across occupations and industries, in particular with respect to socio-emotional skills, where we find socio-emotional skills to be more important for managerial occupations and for the business services and education sectors.

From a geographical point of view, we see the demand for AI workers to be spatially concentrated, in London for the United Kingdom and in California for the United States. This confirms AI-related development and adoption tends to happen in an uneven fashion, also geographically, in line with the findings of Daiko et al. (2017[9]), Dernis et al. (2019[10]) and Baruffaldi et al. (2020[2])

The evidence provided in this paper contributes to the OECD's programme on AI in Work, Innovation, Productivity and Skills (AI-WIPS), supported by the German Federal Ministry of Labour and Social Affairs (BMAS) and aims to inform a wide array of policies. It further aims to foster a human-centric approach to AI, by analysing the human capital behind AI.

Analysing online job postings demanding AI-related skills helps inform innovation and industry policies, as AI-related hiring patterns can be helpful in assessing the extent to which firms or sectors develop and adopt AI (as well as other technologies), and the type of human capital needed to foster diffusion. If paired with skill supply-related information, the analysis may further shed light on the existence of possible skill mismatches or skill shortages. This would help policymakers prioritise interventions in specific domains, allowing human capital supply to meet existing and future demand and avoiding human capital shortages that may jeopardise the deployment of AI and, more generally, of the next production revolution (OECD, 2017[11]).

Our analysis also informs labour market policies, by shedding light on the way in which AI-related requirements are penetrating labour markets and the AI-related tasks to be performed on the job as well as the skills needed to do so. Studying skills demand is important to build better labour markets through policies that direct people into the jobs of the post-COVID world (OECD, 2020[12]).

Finally, by characterising the demand for AI-related skills and the skills needed to work with AI, this work informs training and education policies about the skill endowment-related actions to prioritise in order to meet the demand for AI-related workers and about the sets of cognitive and socio-emotional skills needed for this new technological paradigm. Traditional measures of human capital have focused on workers' training, years of experience or education. Although more recent work acknowledges the importance of cognitive and socio-emotional skills to characterise human capital (Grundke et al., 2018[13]; Cammeraat, Samek and Squicciarini, 2021[14]; 2021[14]), this remains a non-trivial endeavour.

As a caveat, it should be noted that, while the analysis relies on a large sample size[6] of almost real-time information on skill requirements for the UK and the US, BGT data only allows a demand side picture of AI-related skills, i.e. what employers demand. Informing policies related to AI development and adoption also requires information about the supply side, i.e. the skills (bundles) that individuals are endowed with, in particular in relation to the workers that applied to the online vacancies considered here and who joined the recruiting agent. This would, among others, help get a sense of the possible mismatch that may exist on the labour market and that may hinder the deployment of AI, if the relevant (sets of) skills cannot be found in the population. Undersupply of the relevant skills is known to have first order effects over innovation and economic performance (OECD, 2017[15]) and shapes the competitiveness of firms, industries and countries alike.

Second, without any follow up information on filled positions, we cannot know if the vacancy is filled at all or, conversely, if employers recruit several applicants using the same job advert. In such cases, we may be over- or underestimating the demand for workers with particular skill sets and, hence, may not be able to well capture the true extent of AI development and adoption. Third, while BGT provides information on the skills that sought workers should be endowed with[7], we do not observe the skill distribution of the existing workforce. The skills demanded from new hires can well be complementary and specific to the existing workforce's skill mix, or be related to changes in the organisation of the recruiting agent, or to expansions and branching out to new areas of production.

Finally, the analysis focuses on two countries only, i.e. the UK and the US. Despite the fact that these countries are among the leading economies when it comes to AI development and adoption, care needs to be applied when generalising results.

Despite these caveats, analyses like the present one represent a much needed source of hard evidence in support of policy making fostering the deployment of AI and allowing this technological paradigm to deliver its promises of enhanced economic and societal welfare and wellbeing.

The remainder of this paper is as follows. Section 2 provides a brief summary of the existing literature on skill bundles and AI diffusion. Section 3 introduces Burning Glass Technologies' data. A general introduction to the skills demanded in AI-related jobs is proposed in section 4, whereas an analysis of individual AI-related skills and AI skill bundles is presented in section 5. Section 6 looks beyond specialist AI-related skills by analysing also other types of cognitive as well as socio-emotional skills required from AI workers. Finally, we show where AI talent is hired, in terms of geographical location, and discuss skill profile differences across occupations and industries, as well as the occupational distribution of AI jobs across AI-related organisations, before concluding.

2. Skill bundles and AI diffusion

This work contributes to shed light on the diffusion of AI (Dernis et al., 2019[10]; Baruffaldi et al., 2020[2]; Squicciarini et al., 2021, forthcoming[16]). Recent OECD work (Nakazato and Squicciarini (2021[17]) proposes an experimental methodology for the identification of AI-related trademarks and contributes to shed light on the extent to which AI-related goods and services penetrate markets. Results show that AI diffusion has increased from 2016 onwards and that AI has pervaded computer related products and services in particular. The authors also find (un)supervised learning and natural language generation technologies to be frequently used, developed or implemented together with statistical learning.

As the adoption of AI technologies relies on a workforce that needs to be endowed with the necessary skills to put e.g. ML algorithms into practical commercial use, analysing the demand for workers performing AI-related tasks helps shed light on AI diffusion. By studying how different types of AI-related competencies are demanded across AI-related jobs and across occupations and industries, we help inform the policy discussion on AI diffusion through the lens of skills. We not only contribute first time evidence in this respect but also add to the ongoing discussion about the importance of skills for technology development and adoption, as well as for economic performance.

The importance of cognitive (e.g. literacy, numeracy and problem solving) and socio-emotional skills for thriving in a digital and interconnected global economy has been widely acknowledged (OECD, 2016[18]; OECD, 2017[15]). Existing studies also point to the need to distinguish and analyse the role played by cognitive, socio-emotional and tasks-based skills, given that human capital is highly specific to the tasks carried out by workers (Gibbons and Waldman, 2004[19]; Gathmann and Schönberg, 2010[20]; Grundke et al., 2017[21]; 2018[13]; Cammeraat, Samek and Squicciarini, 2021[14]; 2021[22]).

For instance, Grundke et al. (2017[21]) and OECD (2017[15]) use data from the Survey of Adult Skills (PIAAC) and find empirical evidence about bundles of cognitive skills and of competencies related to managing and communication, marketing and accounting as well as self-organisation, to be highly rewarded on the labour market, because of their contribution to economic performance. Muller and Safir (2019[23]) use online job vacancies data scraped from the Ukrainian website HeadHunter and find that employers require their workers to be endowed with a mix of cognitive, socio-emotional and technical skills, in line with Grundke et al. (2017[21]).

Anderson (2017[24]) employs a network-based approach to explore workers' skill bundles in more detail, using data from online freelance websites. She finds that diverse skill sets are associated with higher wage premia than specialised skills and that workers with synergistic skill diversity, i.e. skill combinations filling a gap in the market, earn more than workers whose diverse skills can be applied independently on numerous jobs.

This is also confirmed by Stephany (2020[25]), who finds skills related to programming languages (*C++, JavaScript* and *Python*) to be particularly rewarded, when studying the same data source containing freelancers' job profiles. Furthermore, when investigating skill profiles containing AI, his endogenous clustering approach reveals that competencies tend to be grouped around software and technology as well as admin and support. Although smaller skill groups also emerge around the areas of product design, translation and editing, marketing, and law, the most frequently mentioned skills, besides programming languages, relate to *ML, data science, natural language processing, neural networks* and *data analysis/mining/visualisation*.

In a semi-automated analytical process, based on web scraping, expert judgment, text mining and topic modelling techniques, De Mauro et al. (2018[26]) analyse *big data* related online vacancies and confirm Miller's (2014[27]) findings that skill requirements for data scientists go beyond their expertise on analytical methods. In fact, their natural clustering distinguishes between technology-enablers (technical role with focus on systems and applications) and business-impacting professionals (business-oriented role with focus on data analysis and economic impact). These can be further disaggregated into four different job families, namely business analysts, data scientists, big data developers and big data engineers.

With a heterogeneous phenomenon like AI unfolding at different levels across different industries and countries (Calvino and Criscuolo, 2019[28]), the composition of existing skill mixes is likely to change over time, to enable workers to succeed in these new technology-rich work environments. Therefore, it is not surprising that Squicciarini and Nachtigall (2021[1]) find the total number of AI-related jobs to have increased in both, the United Kingdom and the United States over time, and that these jobs also require a growing number of different AI-related skills. In addition, they find jobs that software skills and competencies related to communication, problem solving, creativity and teamwork gained relative importance over time.

Lane and Saint-Martin (2021[29]) also observe a rise in the demand for AI-related skills and argue that, despite all developments, a workforce needs to be endowed with competencies beyond specialised AI skills. Based on research carried out by the venture capital fund MMC Ventures (2019[30]), Lane and Saint-Martin conclude that, in addition to a doctoral degree in mathematics, statistics or programming, AI jobs at the top end of the market also require increasingly sector-specific, engineering and commercial competencies, reaffirming the need to also examine non-AI skills in AI-related jobs.

In line with this, using BGT's data to study demand in core AI and AI-adjacent jobs, Toney and Flagg (2020[31]) find that roughly 80 percent of all AI jobs require a bachelor degree with a declining share requiring qualifications beyond that. This could provide evidence for some catching-up effect by AI adopters relative to developers as AI enters the phase in which it starts being adopted more widely.

Independently of the country considered or the data source used, existing studies all point to the need to shed light on both specialist as well as non-specialist skills and competences when characterising the human capital needed to work with AI.

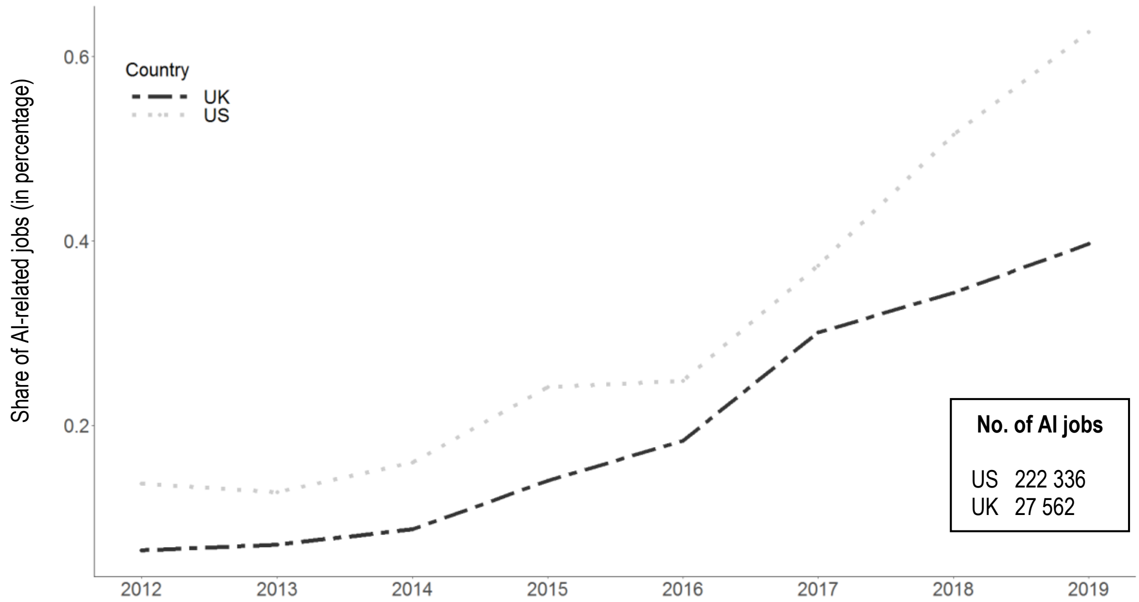
3. Burning Glass Technologies' online vacancy data

This analysis relies on Burning Glass Technologies' (BGT) online vacancy data, which is collected by web-scraping over 40 000 distinct job boards and company websites. BGT claims to cover the near-universe of all online job postings and provides detailed and timely information on labour and skill demand posted online.

In addition to collecting the data, BGT also cleans and structures the data, by de-duplicating vacancies appearing on multiple websites, by categorising online job postings and by structuring them according to variables, such as geographical location, occupation, industry, required skills, and education and experience levels. Some of the variables are standardised according to official classifications, e.g. occupation and location, which makes it possible to link these data to other datasets. While the skills variable is the most important for this study on skill bundles, we also use the geographic, occupation and industry information to better understand differences that emerge in demand for AI-related human capital for different areas, job types or sectors.

The total number of job openings in BGT data is large, for the United States, varying from more than 11 million job openings in 2010 to more than 35 million job openings in 2019. A similar picture emerges for the United Kingdom, in which the total number of job postings in the BGT dataset increases from 5.7 million in 2012 to more than 9 million in 2017, after which it falls to around 7 million in 2019. As shown in Figure 3.1, AI-related jobs in 2019 account for around 0.6% and 0.4% in the United States and the United Kingdom, respectively, with a clear upward trend since 2012. These equal around 222 000 AI-related jobs in the United States and almost 28 000 AI-related jobs in the United Kingdom.

Figure 3.1. Share of AI-related jobs in the data, by country and year



Source: Based on Squicciarini and Nachtigall (2021[1]) and updated by authors to include 2019

As for all data, BGT data also have some limitations. First, not all vacancies are published online, and therefore BGT data cannot be representative of "offline" job openings. This may potentially raise concerns about representativeness, as different types of occupations, characterised by e.g. different educational levels, have a different likelihood to be posted online. Another characteristic to take into account in policy-relevant analysis is that the number of vacancies also dependents on turnover rates and is therefore not automatically a good measure of underlying employment. However, Cammeraat and Squicciarini (2021[7]) address these representativeness questions and find that BGT data exhibit good statistical representativeness for a number of countries, including the United Kingdom and the United States. This is in line with Hershbein and Kahn (2018[32]) as well as Carnevale, Jayasundera and Repnikov (2014[33]) who argue that, overall, BGT data are representative of the United States' job market but that jobs requiring relatively higher skills than the average job are overrepresented.

Cammeraat and Squicciarini (2021[7]) further construct weights helping to obtain a balanced representation of all occupational categories, to be used in analyses aiming to generalise results for the entire population of workers, to inform policy. This work nevertheless refrains from using weights, due to the nature of AI-related jobs. As AI is arguably about algorithms and "lives" in the digital space, we are confident that the vast majority of AI-related job openings are very likely to be posted online. Moreover, more than 80 percent of AI vacancies appear to occur in the occupational group "professionals", which is well represented in BGT data, thus making it less relevant to correct for possible differences in representativeness between different occupational groups.

4. Which skills to work with AI? A general overview

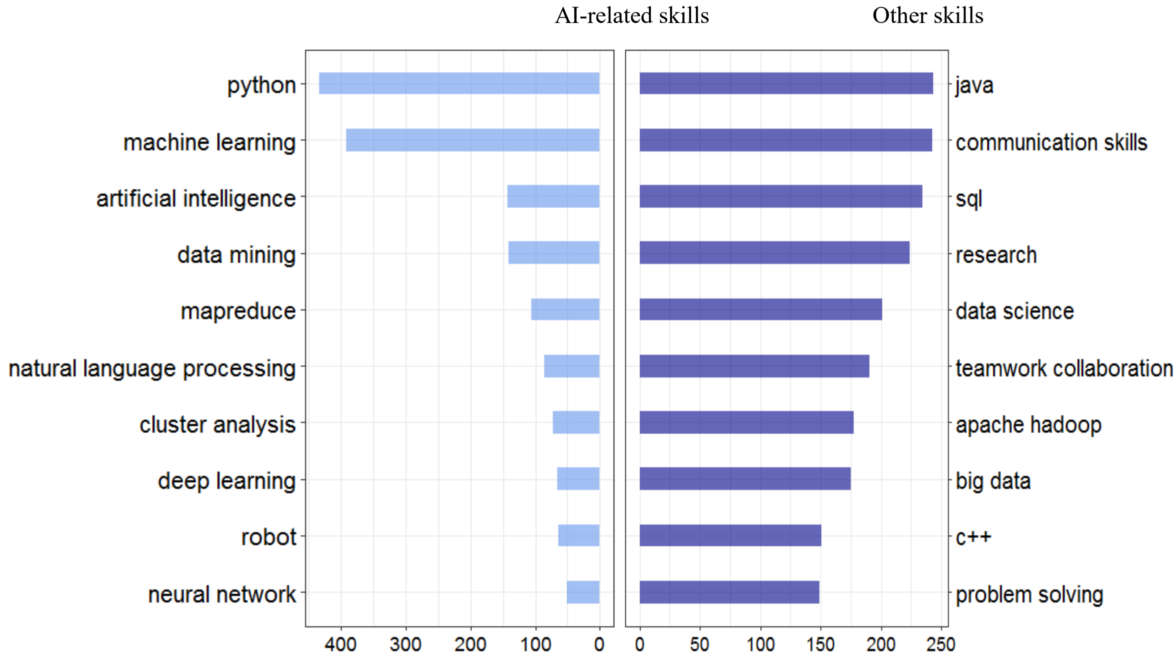
Figure 4.1 shows the top 10 most common individually considered skills mentioned in AI-related job postings for the United States over the period 2012-19. These skills can be divided into specialist AI-related skills, presented in the left panel, and other types of cognitive as well as socio-emotional skills, shown in the right panel. At first glance, it becomes apparent that *Python* and *ML* are by far the two most demanded AI-related skills, while the most frequently mentioned non-AI related skills in AI-related jobs are a more balanced mix of software and programming-related skills as well as socio-emotional skills, with competencies related to *Java, communication* and *SQL* being at the top.

A similar picture emerges with regards to the AI-related skills in Figure 4.2, which presents the list of top 10 skills for the United Kingdom across the same period. While non-AI related skills constituting the list are very similar across both countries (eight out of ten), British AI-related employers seemingly require competencies such as *data science, research* and *SQL* and generally put less emphasis on socio-emotional skills.

The broad evidence gathered raises the question about whether demand patterns by AI-agents are persistent or change over time. With AI being a rapidly evolving technological paradigm penetrating industries and countries to different extents (Calvino and Criscuolo, 2019[28]), skill mixes are likely to change alongside over time. This potentially creates challenges for policy makers if they want to enable workers with the necessary skills to succeed in these new technology-rich work environments. Such a task may be complicated by the fact that skills are known to be “sticky” and human capital adjusts relatively slowly to changes – i.e. what we find today might not be relevant tomorrow. Therefore, the remainder of this paper investigates which skills are demanded individually as well as in bundles in AI-related jobs over time.

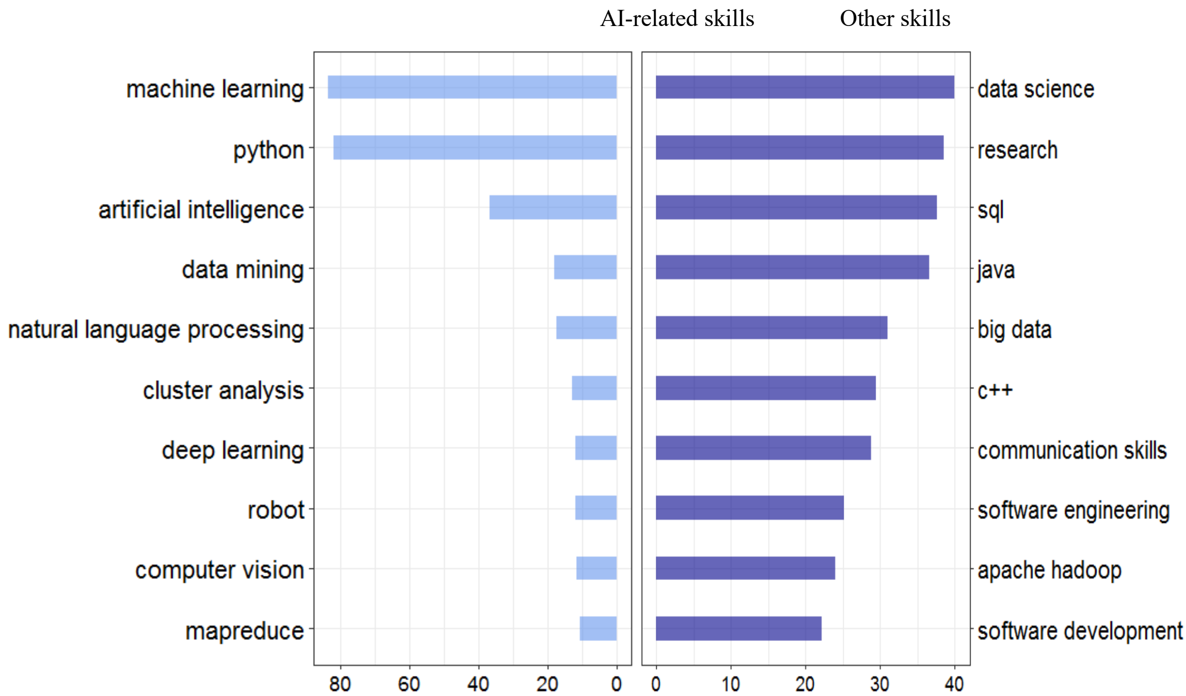
To obtain as a clear picture as possible of the evolution of AI skills over time, and contribute to the discussion on whether and to what extent AI is evolving, we subdivide the period 2012-19 into two sub-periods of three years each. We also drop an interval of one year, i.e. the year 2016, between the two periods considered, namely 2012-15 and 2017-19, to make sure that the two periods do not overlap nor are continuous. This should allow us to uncover real long-term trends as well as differences over time. Despite having data for 2020, we leave this year aside in the present analysis, as the COVID-19 pandemic has impacted importantly on vacancies and including the year 2020 may actually introduce biases in the analysis, rather than making it more timely. We leave to future work an analysis of demand for AI skills in the COVID-19 pandemic time.

Figure 4.1. Top 10 skills demanded in AI-related jobs, United States, 2012-19



Note: The x-axis shows are the frequencies (in thousands) with which each of the top 10 most common individually considered skills are mentioned in AI-related jobs over the period 2012-19
Source: Authors' own compilation based on BGT data

Figure 4.2. Top 10 skills demanded in AI-related jobs, United Kingdom, 2012-19



Note: The x-axis shows are the frequencies (in thousands) with which each of the top 10 most common individually considered skills are mentioned in AI-related jobs over the period 2012-19
Source: Authors' own compilation based on BGT data

5. What AI-specific skills should AI talent be endowed with?

5.1. Top 10 AI-skills demanded

Identifying the most frequently demanded AI-related skills helps getting a better understanding of the skills that AI-related human capital is expected to be endowed with.

Table 5.1 lists the top 10 most common individually considered AI-related skills mentioned in AI-related job postings for the United States and the United Kingdom in both the earlier period 2013-15 and the later period 2017-19. Skills that are common across both time-periods and both countries, which encompass the majority of (six out of ten) skills, are highlighted in pale blue.

Table 5.1. Top 10 occurring AI-related Skills in AI-related Jobs

United States				United Kingdom			
2013 - 2015		2017 - 2019		2013 - 2015		2017 - 2019	
1. Python	61,171	1. Python	321,958	1. Python	11,989	1. ML	63,542
2. ML	49,124	2. ML	302,190	2. ML	9,695	2. Python	58,022
3. Data mining	36,144	3. AI	129,376	3. Data mining	5,069	3. AI	30,689
4. MapReduce	26,294	4. Data mining	81,385	4. Cluster analysis	3,980	4. Natural language processing	11,798
5. Cluster analysis	18,256	5. Natural language processing	64,241	5. MapReduce	3,396	5. Deep learning	11,094
6. Natural language processing	12,515	6. MapReduce	62,617	6. Natural language processing	2,914	6. Robot	9,175
7. Neural network	12,515	7. Deep learning	61,119	7. AI	2,684	7. Cluster analysis	8,927
8. Decision tree	7,634	8. Robot	50,880	8. Image processing	2,330	8. Data mining	8,142
9. Robot	7,521	9. Tensorflow	42,749	9. Computer vision	1,720	9. Computer vision	6,607
10. Image processing	7,410	10. Cluster analysis	42,292	10. Robot	1,491	10. Neural network	6,515

Note: Skills, which are common across all years and both countries are highlighted in pale blue.
Source: Authors' own compilation based on BGT data

This simple ranking exercise shows very clearly that AI-related agents in both countries require similar AI-related skills and that the most important AI-related skills in 2013-15 remain important in 2017-19. These include *Python, ML, data mining, cluster analysis, natural language processing* and *robot.*

At the top of the list, for both countries and across all years, there are the programming language *Python* and *ML*, which is considered as a part of AI and refers to computer algorithms that rely on data and experience to improve automatically. Their importance becomes apparent when focussing attention on the frequency distribution of the different AI skills also shown in Table 5.1. *Python* and *ML* are each about twice as often demanded as the third most often-required AI-skill, which is general *AI* itself. To put that into perspective, it may be interesting to notice that the AI-related skill that ranks at the bottom of the table is demanded only a little more than a tenth of the times that *Python* and *ML* are, in both countries and time-periods.

When comparing the frequency rankings of the different AI-related skills over time, it becomes apparent that *AI* and *deep learning* - a subfield of *ML* working iteratively, by layers, to progressively extract higher-level features from raw inputs -, gained importance.

This happened at the expense of *MapReduce*, *data mining* and *cluster analysis*. *MapReduce* is a programming and implementation approach used to process and generate big data sets with parallel distributed algorithms on a cluster, while both data mining and cluster analysis[8] are processes which help turning raw data into useful information by looking for patterns or clusters in large data.

When comparing the United States and the United Kingdom over the period 2017-19, data mining and *MapReduce* have higher frequency rankings in the United States while the United Kingdom requires their AI talent to be more often endowed with *natural language processing*, which enables machines to read, decipher and derive meaning from human languages, and deep learning.

5.2. What are the most demanded AI-related skill pairs?

Analysing whether and to what extent different skills are demanded together is important to shed light on possible skill complementarities. To this end, we first offer a network representation of the counts of common pairs of skills that can be found in the same online job posting, and then propose a network representation of the pairwise correlations[9] calculated among the different skills relative to how often skills appear separately. The first representation provides insights about the most frequently demanded skill pairs, and shows the importance of AI-related skill combinations in absolute terms. The latter has the advantage of showing how often skills appear together relative to how often they appear separately in job adverts, thus allowing to see the relative importance of different skills within different skill bundles.

Representations of networks feature links, which are referred to as *edges* in the literature, between the skills, which are called *nodes*. The thickness of the edges represents how strong the relationship between two skills is. That is to say, the more frequently two skills are listed together in an AI-related job posting, either in absolute terms (presented in the co-occurrences) or in relative terms (presented in the correlations), the thicker the edge is.

Figure 5.1 shows the co-occurrences of skills in the United States for the periods 2013-15 and 2017-19 in the upper and lower panel, respectively. To aid presentation, only links, i.e. edges, with more than 1 000 co-occurrences (i.e. that are observed together) are shown for the earlier period and with more than 5 000 co-occurrences for the later period. Using a threshold, which is five times higher in the later period, reflects the fact that the number of AI-related jobs in the observed countries increased continuously over time with about five times as many AI-skills demanded in the period 2017-19 compared to 2013-15. As a result, also the pairwise counts of skills multiply.

In line with observations in Table 5.1, the most frequent skill pair appearing in both periods is made of *Python* and *ML*. This is also the case for AI-related jobs in the United Kingdom, as shown in Figure 5.2. In the United States, *Python* and *ML* also appear often with the keywords *data mining* and *MapReduce* throughout the years, and with *AI, deep learning* and *natural language processing* in more recent years. The same can be observed for AI-related jobs in the United Kingdom, although here *AI* was already frequently required together with *Python* and *ML* in the earlier period and continued to gain importance over time.

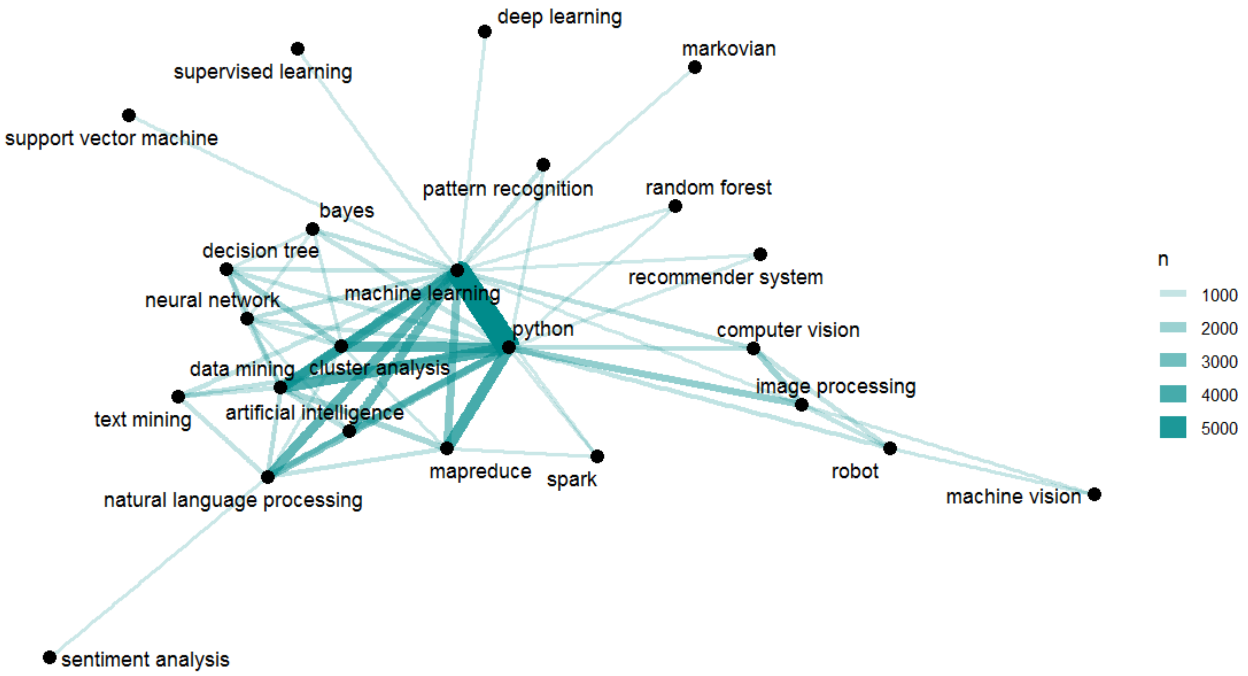
Co-occurrences mirror the broader set of AI-related skill pairs demanded in AI-related jobs and may help uncover the foundational skills AI-related workers should be endowed with, as they are the most frequently demanded skill pairs. The following correlation networks, in comparison, provide more insight into the skills required in more "specialised" roles of AI-related work, as these correlations no longer reflect the frequency of being demanded together, but rather shows how often two skill pairs are demanded together relative to being demanded in a separate fashion. Therefore, findings from the co-occurrence networks are likely to inform educational and training policies with regards to the design of AI-related foundation courses, while the correlation analysis highlights areas more relevant for AI specialisations.

Figure 5.1. Co-occurring AI-related skills in AI-related jobs, United States

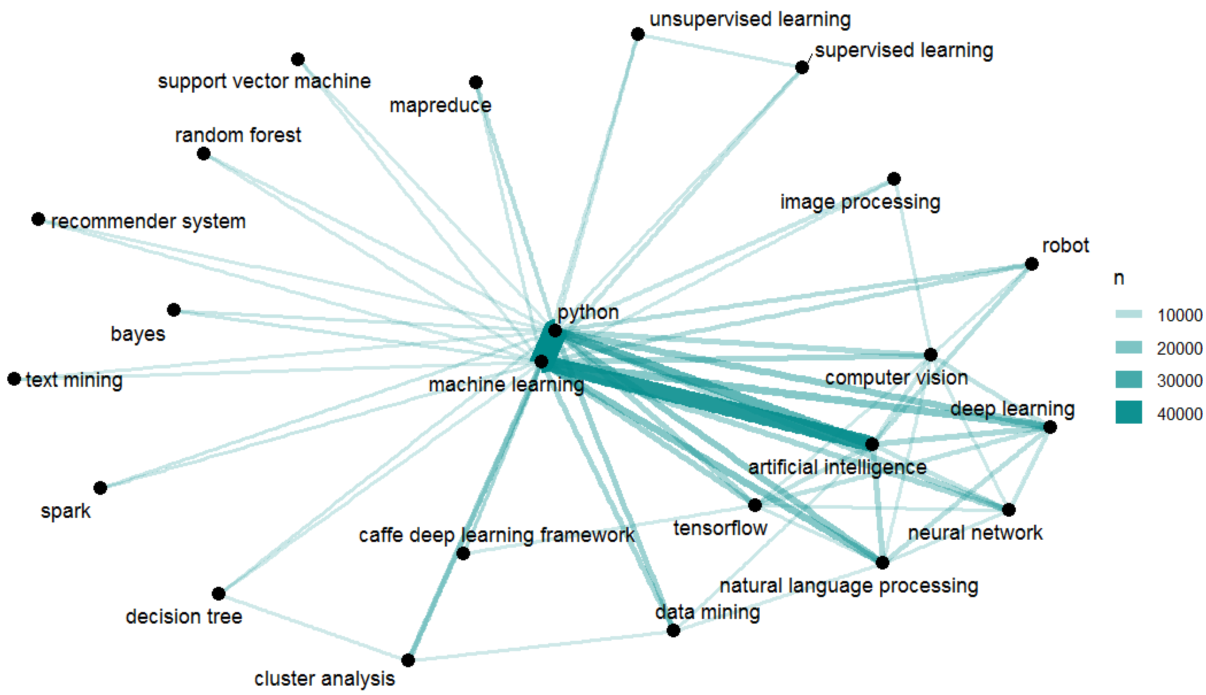
Note: Co-occurrences refer to the simultaneous presence of two distinct terms in the same job posting.
Source: Authors' own compilation based on BGT data

Figure 5.2. Co-occurring AI-related skills in AI-related jobs, United Kingdom

Network of skills for the period 2013-15 (co-occurrences > 200)



Network of skills for the period 2017-19 (co-occurrences > 1,000)



Note: Co-occurrences refer to the simultaneous presence of two distinct terms in the same job posting.
Source: Authors' own compilation based on BGT data

5.3. Most important AI skills within different AI skill bundles

We here show the pairwise correlations among skills to highlight how often they appear together relative to how often they appear separately, to provide additional insights about the different skill bundles required by different types of AI-related jobs.

In Figure 5.3 and Figure 5.4, we show show the correlation networks of AI-related skills for the United States over the periods 2013-15 and 2017-19, respectively to allow changes over time to emerge. The thickness of the edges here mirrors the pairwise correlations, rather than the pairwise counts, between the nodes. Therefore, the more frequently two skills are listed together in an AI-related job posting relative to being mentioned separately, the thicker the edge is. To aid presentation, only edges with a correlation exceeding 0.1 are shown here. Moreover, the size of the nodes in Figure 5.3 and Figure 5.4 represents the centrality of the skill. The bigger the node, the more central that particular skill is to the network and, hence, the more the skills it is highly correlated with. In other words, the centrality here gives the importance of a skill within a skill bundle. Relatively higher centrality implies that the skill is correlated (with a correlation of at least 0.1) with more skills.

Centrality in these correlation networks, however, should not be confused with the frequency with which the two skills co-occur (the latter is presented above, in the co-occurrence figures). For example, frequently demanded skills, such as *Python* and *ML* have a lower centrality in Figure 5.3 and Figure 5.4 compared to many other, less frequently demanded skills. An explanation is that some of the most frequently demanded skills are related to many different skill bundles and thereby show a relatively low correlation with more specific skills or skill bundles. At the same time, less frequently occurring skills can still be highly correlated with a number of other skills if they are central to a specific skill bundle.

In the earlier period 2013-15 in the United States, shown in Figure 5.3, the AI-related skills most frequently highly correlated with other AI skills are subfields of *ML*. The most central node is the machine-learning algorithm *support vector machine*. This is followed by *deep learning* and the supervised *ML* algorithm *decision tree*, which classifies subjects into known groups. Three main clusters emerge.

First, a methodological part of the network can be identified (highlighted in blue) that encompasses numerous groups of skills surrounding the three most central nodes (*support vector machine*, *deep learning* and *decision tree*) and that is related to 'developing and advancing AI' itself. One of the groups contains the *ML* tasks *un-, semi-* and *supervised learning* and *kernel*, which encompasses algorithms for pattern analysis, including the highly central skill *support vector machine*. Furthermore, the bundle includes *deep learning* frameworks, such as *caffe, torch,* or *keras*, and *Pybrain*, a modular *ML* library for *Python*; all useful in building *deep learning* models.

Also correlated with *deep learning* as well as with *support vector machine* is the statistical modelling method *Markov Random field* often applied in pattern recognition and *ML* and used for structured prediction. In the data it is portrayed by the keywords *Markovian* and *random fields*. In addition, employers tend to also demand skills related to the supervised learning procedure classification shown by the frequently mentioned *classifier.* Finally, a larger group emerges in this bundle of skills, which advance AI, that is associated with both, *support vector machine* and *decision tree*. This includes *neural networks*, the probabilistic graphical network model (e.g. between diseases and symptoms) *Bayes*[10]*,* and the powerful variants of decision trees like *random forests* and gradient/adaptive *boosting* (which are essentially simplified versions of *neural networks*). Along with those, AI-related employers also often demand the unsupervised learning process *cluster analysis*, which finds logical relationships and patterns from the structure of the data (the corresponding supervised procedure is the previously introduced concept of classification) and the unsupervised clustering algorithm *k means* (commonly used in medical imaging, biometrics and related fields).

Given the demand for competencies around *un-, semi-* and *supervised learning*, it is not surprising that the skill bundle related to AI developments also contains the supervised learning algorithm *XGBoost*.[11] However, it is part of a smaller, more distinct group within the bundle, which further encompasses the online interactive *ML* system library *Vowpal Wabbit*[12], the *ML* platform *H2O* and *stochastic gradient.*

Second, the analysis reveals two smaller skill bundles that can both be classified as 'AI applications' (see orange circles). Contrasting the large methodological skill bundle described earlier, skills related to AI applications can be divided into two groups, one clustered around *computer vision* and the other one around *natural language processing*. The fact, that these two groups are linked through the AI development bundle, suggests that employers tend to require their AI-related workers to be endowed with more specialised AI applications focussing on either of the two areas. It is not surprising that *computer vision* tends to be demanded together with *image processing* as well as *pattern*, *object* and *image recognition*. When AI-related job postings ask for *natural language processing* skills, they often want their potential workers to be also endowed with competencies related to *speech recognition*, *machine translation*, *text mining* or *sentiment analysis*. Along with those, the presentation program *OpenLP*, IBM's *Watson* and the *Natural Language Toolkit*, which is a suite of libraries and programs for *natural language processing* written in *Python*, are also frequently requested.

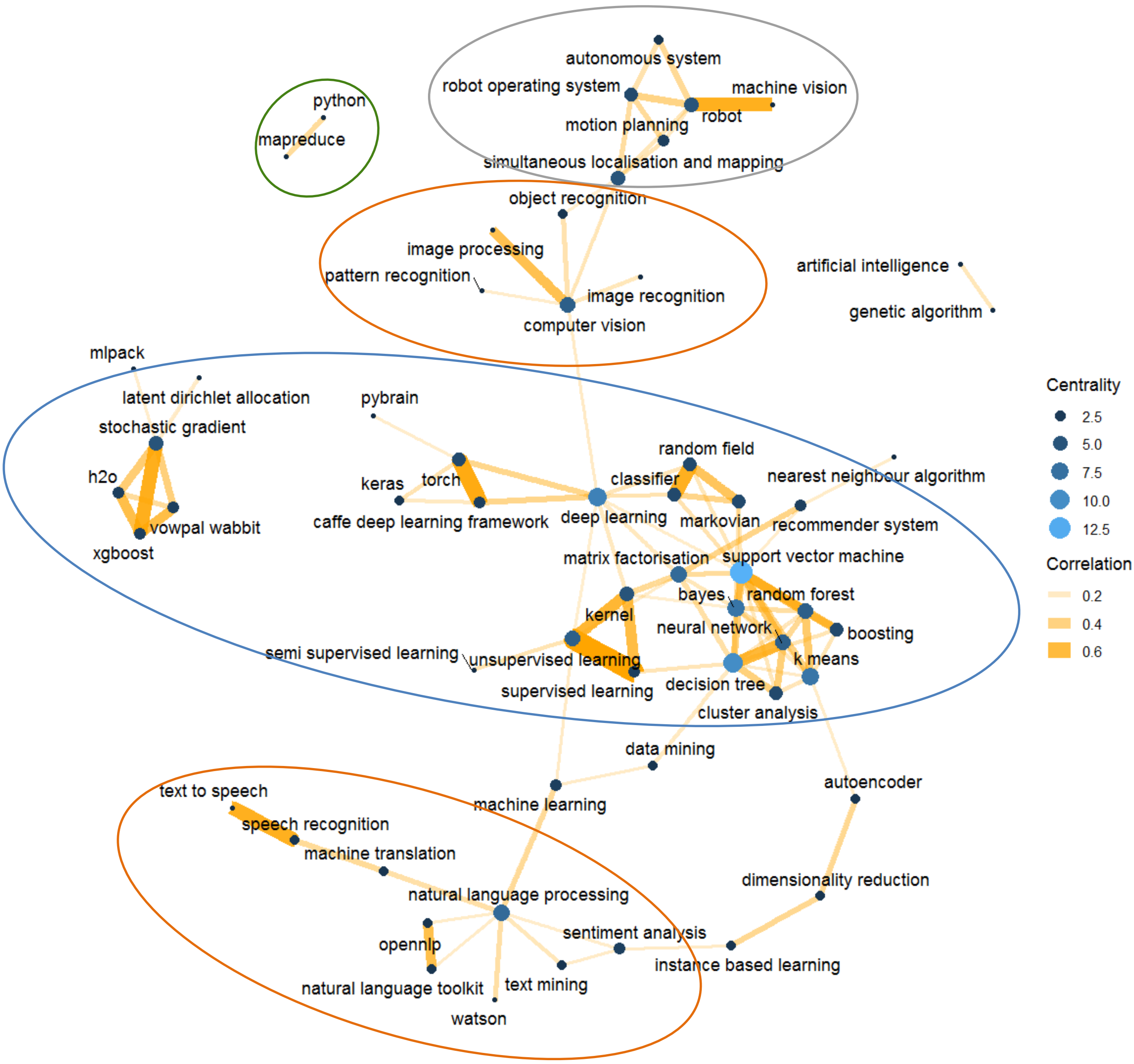
The network further reveals that skills related to *ML* and *big data* link the AI application to the AI adoption bundle. For instance, *instance based learning*, a family of *ML* algorithms, often appears together with the *neural network autoencoder*, which is used to learn efficient data representations in an unsupervised manner, and *dimensionality reduction*. The latter is common in fields that deal with large data, e.g. in *natural language processing*, which we consider to be an AI application, but also in *cluster analysis*, which is part of the AI development bundle. Given that *big data* and *cloud computing* allowed breakthroughs in *ML*, it is to be expected that the "connecting" nodes *ML* and *data mining* themselves are frequently demanded together.

Third, a skill bundle broadly related to 'robotics' (highlighted in grey) appears, which amongst others encompasses *robots*, *machine vision*, *autonomous* and *robot operating systems*, *motion planning* and *simultaneous localisation and mapping*. Given the frequent application of vision systems in robotics, e.g. in the automotive industry, pharmacy, military and police equipment, it is not surprising to find this robotics related skill bundle linked to *computer vision*, an AI application. Therefore, robotics is an example of a field that evokes but does not necessarily rely on AI as such (Baruffaldi et al., 2020[2]).

Finally, the data reveal a rather small skill bundle consisting of 'AI IT basics' (highlighted in green), such as *Python* and *MapReduce*.

Figure 5.3. AI-related skills in AI-related jobs, United States, 2013-15

Network of skills with correlation > 0.1



Note: The identified skill bundles are colour coded as follows: 1) Skills related to developing and advancing AI are blue; 2) AI applications are orange; 3) robotics are grey; and 4) AI IT basics are green.
Source: Authors' own compilation based on BGT data

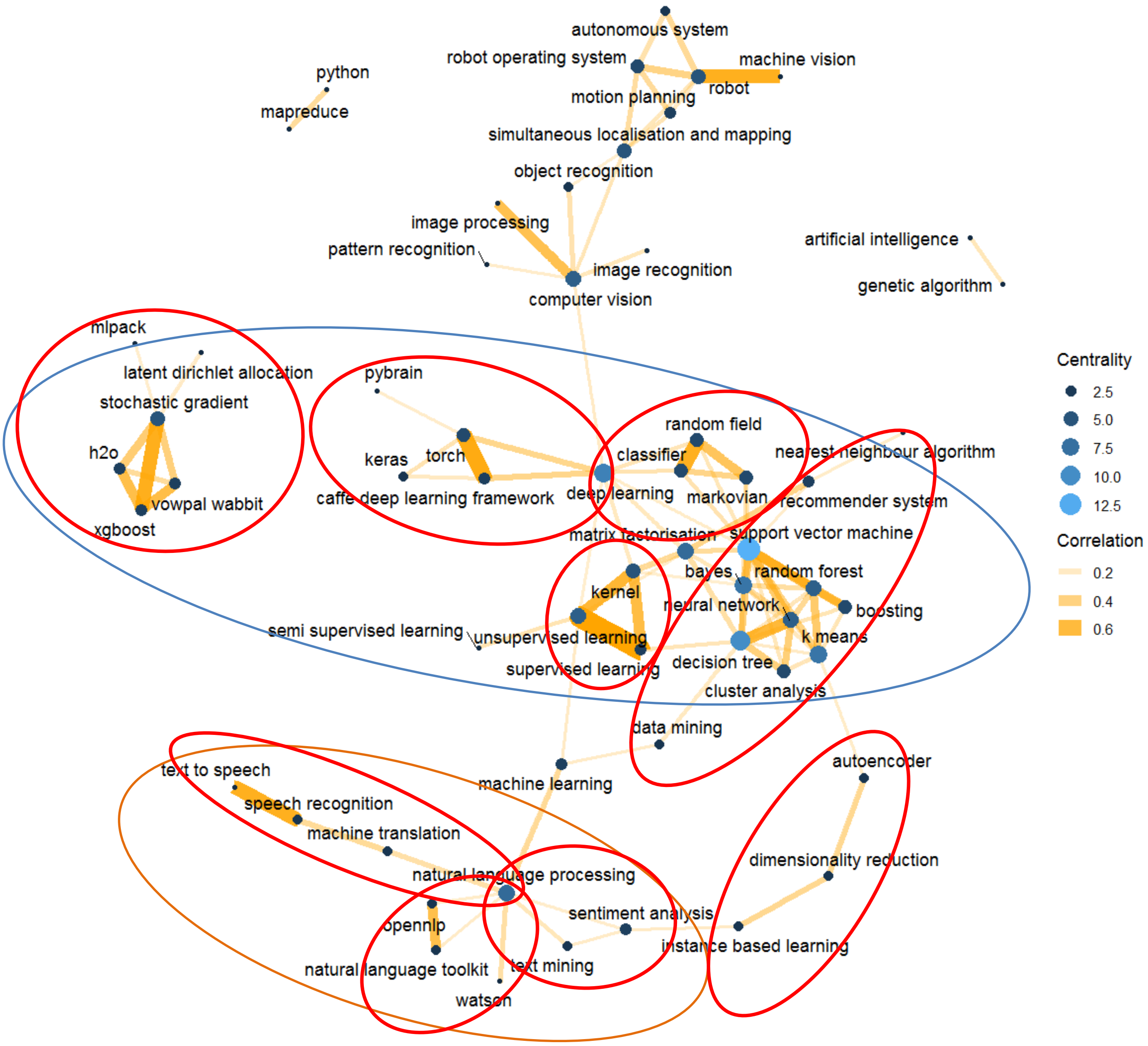
Figure 5.4 shows the same network graph for the United States over the period 2015-19, but now divides the broader AI skill bundles defined above into smaller sub-bundles, marked by red circles. Central in the skills bundle related to “developing and advancing AI” (in blue) is *deep learning,* with sub-bundles emerging in the neighbourhood of IT skills such as *deep learning frameworks* and *coding* (in red). In addition, several *computer vision* skills are based on *deep learning* algorithms, and are developed on *deep learning frameworks* (such as *torch* and *keras)*, fact that explains the proximity of these items in the main bundle.

Furthermore, we observe *deep learning* and *support vector machine* linked to ‘learning’ skills, i.e. *supervised* or *unsupervised learning*, which refers to a collective form of relevant skills on how AI is developed and applied. A final sub-bundle in the broader developing and advancing AI bundle is one of skills associated with optimisation, such as *stochastic gradient descent*. These are found adjacent to libraries or relevant methods such as *h2o* or *xgboost.*

When we look deeper into the broader AI applications bundle (in green), we observe that *natural language processing* is a skill that has 4 adjacent sub-bundles: (i) natural language processing applications such as *speech recognition* and *text to speech*; (ii) software skills such as the *natural language toolkit* library; (iii) the collective term of AI skills i.e. *text mining*, *sentiment analysis*; and (iv) the *dimensionality reduction* skills usually required for natural language processing.

Figure 5.4. Sub-bundles of AI-related skills in AI-related jobs, United States, 2013-15

Network of skills with correlation > 0.1



Note: This figure decomposes the broader skill bundles for skills related to developing and advancing AI (in blue) and AI applications (in orange) into smaller sub-bundles coloured in red.
Source: Authors' own compilation based on BGT data

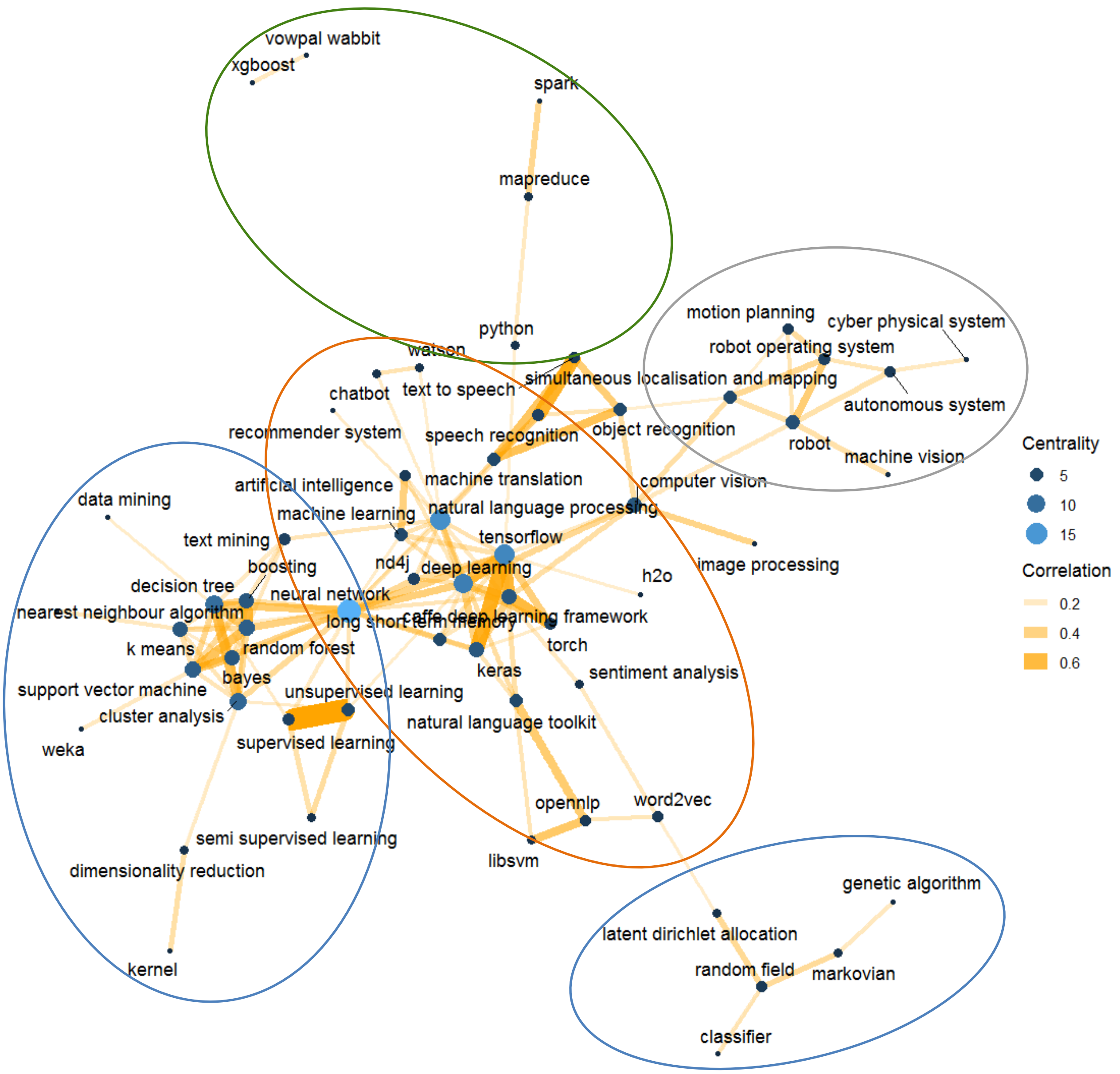
By comparing the network structure for the period 2017-19 (Figure 5.5) with the network for 2013-2015 (Figure 5.3), we can shed light on the evolution of skill demand over time in AI-related jobs. We observe that skills related to AI development and to applications of AI in different domains become more intertwined, with several skill categories collapsing into three central node skills: *neural network*, *deep learning*, and *natural language processing*. N*eural networks* emerge as the central node connecting the developing and applications clusters of skills. This may be explained by the fact that that *deep neural networks* and *deep learning* are typically associated with *supervised learning* models, but that *clustering*, *natural language processing* and other *unsupervised machine learning* models also started using *neural networks*. The driving force behind this interconnectedness may thus be related to the emergence of *deep learning*, driven by AlphaGo, DeepMind, and Google's acquisition of DeepMind. While the people skilled in *deep learning* advance the state of AI, others are looking for applications for these *deep learning* classifiers.

Another related reason for the increasing interconnectedness observed between the different skill bundles may be the emergence of hybrid AI. These are software systems employing a combination of AI-related methods and techniques in parallel, for example combining *neural networks* and *fuzzy logic* in *neuro-fuzzy systems*. This indicates greater complementarity between AI skills, but may also be interpreted as organisations demanding more workers endowed with both method and software skills. These workers are also known as software developers with AI skills and are more recently named as "machine learning engineers". At the same time, however, some organisations, such as Ocado and Uber, may look for human capital that is very specialised in a particular field, e.g. natural language processing or computer vision, and look for "computer vision engineers".

Finally, by taking a closer look at the skill bundles in Figure 5.5, we identify, adjacent to the *neural network* skills, AI skills such as *decision tree*, *support vector machine*, *cluster analysis*, and the 'learning' skills. *Deep learning* is highly correlated with *neural network* and *tensorflow*. This is expected because *deep learning* skills are based on *neural network* skills and more recently on software libraries for *deep learning* coding. A skill sub-bundle concentrated around the extensive use of *deep learning* skills are the *natural language processing* skills, including *speech recognition* skills[13].

Figure 5.5. AI-related skills in AI-related jobs, United States, 2017-19

Network of skills with correlation > 0.1



Note: The identified skill bundles are colour coded as follows: 1) Skills related to developing and advancing AI are blue; 2) AI applications are orange; 3) robotics are grey; and 4) AI IT basics are green.
Source: Authors' own compilation based on BGT data.

Figure A.1 and Figure A.2 show the equivalent network graphs of AI-related skills for the United Kingdom over the periods 2013-15 and 2017-19, respectively. While the findings across the United States and the United Kingdom are relatively comparable in recent years, the skill profile that British employers require their AI talent to be endowed with appears more nuanced in the earlier observation period compared to the United States. For instance, in the United States only very few nodes stood out as having high centrality, with *support vector machine* being the most central one. When looking at the same period in the United Kingdom in Figure A.1, it becomes apparent that more nodes depict high centrality, i.e. skills are (highly) correlated with many skills in job postings. Although *support vector machine* is one of those skills, British employers seemingly demand more frequently also skills related to probabilistic graphical network models in the same skill bundle, namely *Bayesian* and *Markovian* networks, and the decision tree variant *random forest*; to a lesser extent also *decision tree* and *genetic algorithm*. Therefore, a more diverse set of skills materialised at the centre of the skill network in the earlier period relative to the picture that emerged in the United States.

However, when comparing the skill profiles of AI-related workers in the United Kingdom (Figure A.2) with the ones observed in the United States (Figure 5.5) in more recent years, a much more homogenous picture emerges. Again, the different skill bundles related to AI applications and AI development become much more interrelated. *Neural network* moves to the centre of the skill network observed in the United Kingdom connecting both, the AI application and the AI adoption skill bundles. Similarities with regards to the composition of the skill bundles also arise.

For instance, the skill bundle related to ‘advancing AI’ in the United Kingdom in 2013-15 also encompasses skills around *un-, semi-* and *supervised learning*, algorithms for *pattern analysis, deep learning* frameworks and *graphical network* models, to name just a few. These skills remain largely the same over time[14].

Similarly, the skill bundle(s) around ‘AI applications’ in the United Kingdom reflect the ones already identified in the United States and can be summarised broadly by the overarching terms *computer vision, natural language processing* and *object recognition*. However, the latter portrays a much higher centrality, compared to the network for the United States, and is correlated with the *deep learning* frameworks’ *caffe* and *torch* in earlier years.

The skill composition of the previously identified bundle related to ‘robotics’ (highlighted in grey) does not only remain virtually unchanged over time in the United Kingdom, but it is also almost identical to the pattern observed in the United States. It consists of *robots, machine vision, autonomous* as well as *robot operating systems* and *motion planning*. Between 2017 and 2019 it also encompasses *simultaneous localisation and mapping* in the United Kingdom, as it is the case in both periods for the United States. Due to weak links with *robots* and *motion planning* in the earlier period, *image processing* appears to be part of the robotics cluster but it is highly correlated with *computer vision*, as it usually is, and hence, it is rather classified as a competence related to AI applications.

In both time periods, the skill bundle related to ‘AI IT basics’ is much smaller in the United Kingdom consisting of only *Python*, *MapReduce* and *Spark* between 2013 and 2015 and the latter two from 2017 to 2019. Given that *Spark* is a faster alternative to *MapReduce* and is often considered to signal a new era of *big data*, it is interesting to see that it is not sufficiently correlated and, hence, not evident in the skill networks of AI-related workers in the United States in either of the two periods.

Finally, in the United States, a strong focus was also on *deep learning*, which plays a less central role in the United Kingdom.

6. Does it suffice to be a geek to work with AI? An analysis of the overall skill set sought in AI human capital

6.1. What are the top 10 skills demanded?

Shedding light on the full set of skills needed to work and thrive in the digital era and to perform AI-related jobs requires looking beyond specialist AI-related skills, and analyse the extent to which other types of cognitive and socio-emotional skills are required from AI workers. It is also important to see how different skills relate to one another to better understand the set of skills that the human capital behind AI needs to be endowed with, to inform education and (vocational) training policies. In a similar fashion to Table 5.1, Table 6.1 shows the 10 skills most frequently mentioned in AI-related job postings for the United States and the United Kingdom, independently of whether they are AI-related or not (i.e. all skills considered together).

Table 6.1. Top 10 occurring Skills in AI-related Jobs

United States				United Kingdom			
2013 - 2015		2017 - 2019		2013 - 2015		2017 - 2019	
1. Python	61,171	1. Python	321,958	1. Python	11,989	1. ML	63,542
2. ML	49,124	2. ML	302,190	2. ML	9,695	2. Python	58,022
3. Java	46,755	3. Communication	174,423	3. Java	7,703	3. AI	30,689
4. Communication	40,106	4. SQL	167,886	4. SQL	6,870	4. Data science	30,397
5. Research	38,687	5. Java	161,474	5. Research	6,320	5. Research	26,494
6. SQL	38,170	6. Data science	158,499	6. C++	6,092	6. SQL	24,714
7. Apache Hadoop	37,574	7. Research	155,654	7. Big data	5,900	7. Java	21,815
8. Data mining	36,144	8. Teamwork collaboration	145,506	8. Apache Hadoop	5,401	8. Big data	19,856
9. Big data	30,434	9. AI	129,376	9. Communication	5,398	9. Communication	19,200
10. C++	29,083	10. Big data	122,691	10. Data mining	5,069	10. C++	17,860

Note: Skills, which are common across all years and both countries are highlighted in pale blue.
Source: Authors' own compilation based on BGT data

Country- and time-consistent skill profiles of AI talent observed earlier emerge also when including in the analysis other cognitive skills as well as socio-emotional skills. Employers in both the United States and the United Kingdom exhibit very similar requirements, and these have not changed very much over time. In fact, seven out of the top 10 skills remain the same in both countries and periods. Also, *Python* and *ML* continue to be the two most demanded skills.

This may mean that, first and foremost, AI-related workers remain technically skilled people, who need to exhibit a set of AI-related skills in the first place, regardless of whether their job entails developing, adapting or adopting AI. Such a consideration is reinforced by the fact that the top 10 list above also includes other programming languages (i.e. beyond *Python*) in both countries, namely *Java, SQL* and *C++,* although the latter seemingly loses importance over time.

AI-related jobs further require their workforce to be endowed with competencies related to *big data* and, in most recent years, *data science*. *Data science* is an inter-disciplinary field, which uses scientific methods, processes, algorithms and systems in a view to extract knowledge and insights from structured and unstructured data, and applies knowledge and actionable insights from data across a broad range of application domains. The demand for *data science*-related abilities point to the need of AI agents to comb through the vast amount of data collected by businesses and other agents of organisations, users or markets, to help identify business opportunities, optimise product/process development, and so on.

When it comes to socio-emotional skills, data clearly point to *communication*-related skills to be key, especially so in the United States as compared to the United Kingdom. In more recent years, employers in the United States also require their AI talent to be endowed with *teamwork collaboration* skills, while this competency only ranks 12th in the United Kingdom. Taken together, these results reflect the need to communicate within the team involved in the development and adoption of AI, as well as communicating among the different parts of the very firm or institution penetrated by AI, for AI to be correctly deployed. It may also refer to the need to communicate also with outside agents, for AI to permeate the value chain in a suitable way.

6.2. What skill are more frequently demanded together?

Analysis assessing the returns to skills clearly shows that human capital is all the more valuable the more it possesses certain sets of skills, and that this is especially true in digital intensive sectors (Grundke et al., 2018[13]). As AI represents one of the key technological trajectories of the digital era, informing policies about the skills needed to work with AI calls for an analysis of skill bundles, i.e. about which skills are demanded together.

Figure 5.1 and Figure 5.2 showed above represented graphically the pairwise counts of common AI-related skills appearing jointly in the same online vacancy posted in the United States and the United Kingdom, respectively. Here Figure 6.1 and Figure 6.2 depict the equivalent but the focus is broadened to show the co-occurrences of the top 30 most demanded skills, regardless of whether they are AI-related or not.

To aid presentation, for the United States only edges with more than 15 000 co-occurrences are shown for the earlier period and with more than 60 000 co-occurrences for the later period. For the United Kingdom, we use 2 000 and 8 000 as thresholds, respectively. To reiterate, using a fourfold threshold in the later period reflects the vast increase in the number of AI-related jobs posted and collected by BGT.

As the previous co-occurrence networks already alluded to, the most frequently appearing skill pair in more recent years in both countries is *Python* and *ML*. Interestingly, in the earlier period 2013-15 *Java* played an equally important role in both countries, being frequently demanded together with *Apache Hadoop, Python* and *ML*. Also *Apache Hadoop* was, in relative terms, more frequently co-occurring with *Python, big data* and *MapReduce* in the earlier period. *MapReduce* is used to build big datasets within the hadoop library framework for which *Python* can be used. The link between *Apache Hadoop, big data* and *MapReduce* may not come as a surprise as *Apache Hadoop* is an open source cloud/distributor (as opposed to *Amazon Web Services*, Microsoft Azure and Google Cloud Platform) used for large data sets while *MapReduce* is a library/functionality that enables the set-up. Prior to the era of the "Big 3" Cloud Service Providers (*Amazon Web Services*, Microsoft Azure and Google Cloud Platform), *Apache Hadoop* was frequently used with *MapReduce* to build distributed datasets of large sizes. With computational developments and free versions of Cloud Service Providers, this is no longer necessary.

Again, we find evidence of a small set of IT skills that are a necessary (but seemingly not sufficient) condition to work with AI.

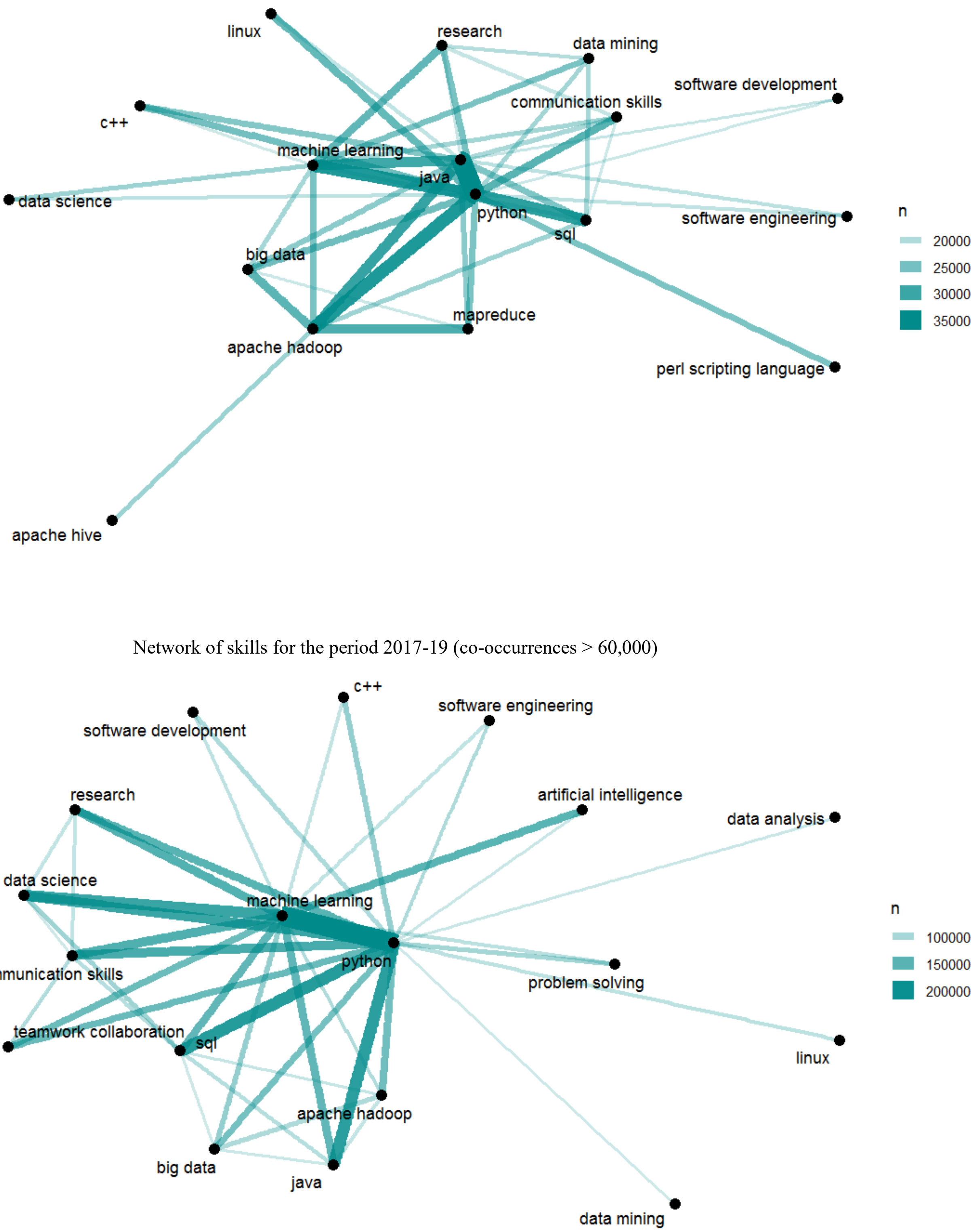
The co-occurrence figures for the period 2017-19 have a star shape for both the United States and the United Kingdom, with *Python* and *ML* at the centre connecting the other skills, confirming that these two AI-related skills are key for AI-related workers. While most skills in the later period are related to both *Python* and *ML*, e.g. *data science* and *research,* some differences emerge in the extent to which skills are demanded in pair with either of them. AI itself is more frequently demanded jointly with *ML* and the programming language *Java; SQL* and *Linux* are more frequently demanded together with the core programming language *Python*. This suggests that some specialisation is taking place in either programming or *ML*, and that skill demand is changing accordingly.

When zooming in on the differences between the United States and United Kingdom in the period 2017-19, we find that *Python* and *ML* are even more dominant compared to the other skills in the United Kingdom. While in the United States, *Java, SQL* and *communication* skills are still often co-occurring with other skills, this is less the case in the United Kingdom, where only *AI* is relatively more frequently demanded with *ML*. In line with this, soft skills such as *teamwork collaboration*, *research* and *communication* skills are more frequently demanded together with *ML* and *Python* in the United States compared to the United Kingdom. Consequently, the need to communicate within the team of AI workers but also with different parts of the institution or with outside agents penetrated by AI is evident, particularly in the United States.

Figure 6.1. Top 30 skills demanded jointly in AI-related jobs, United States

Network of skills for the period 2013-15 (co-occurrences > 15,000)

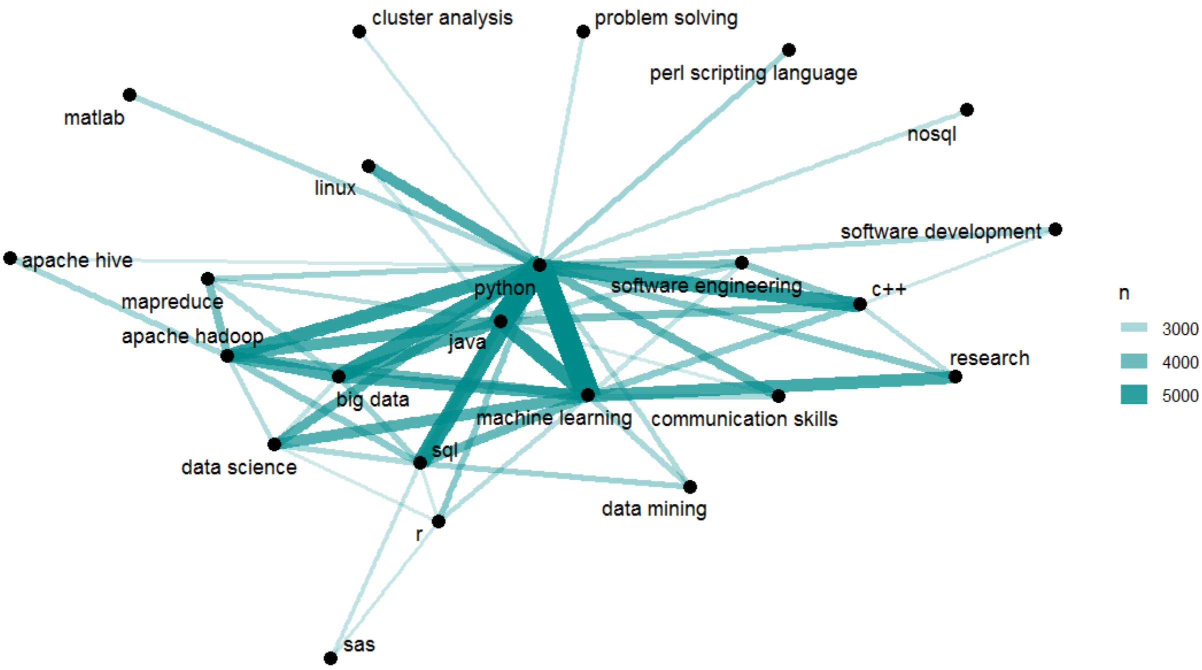
Network of skills for the period 2017-19 (co-occurrences > 60,000)



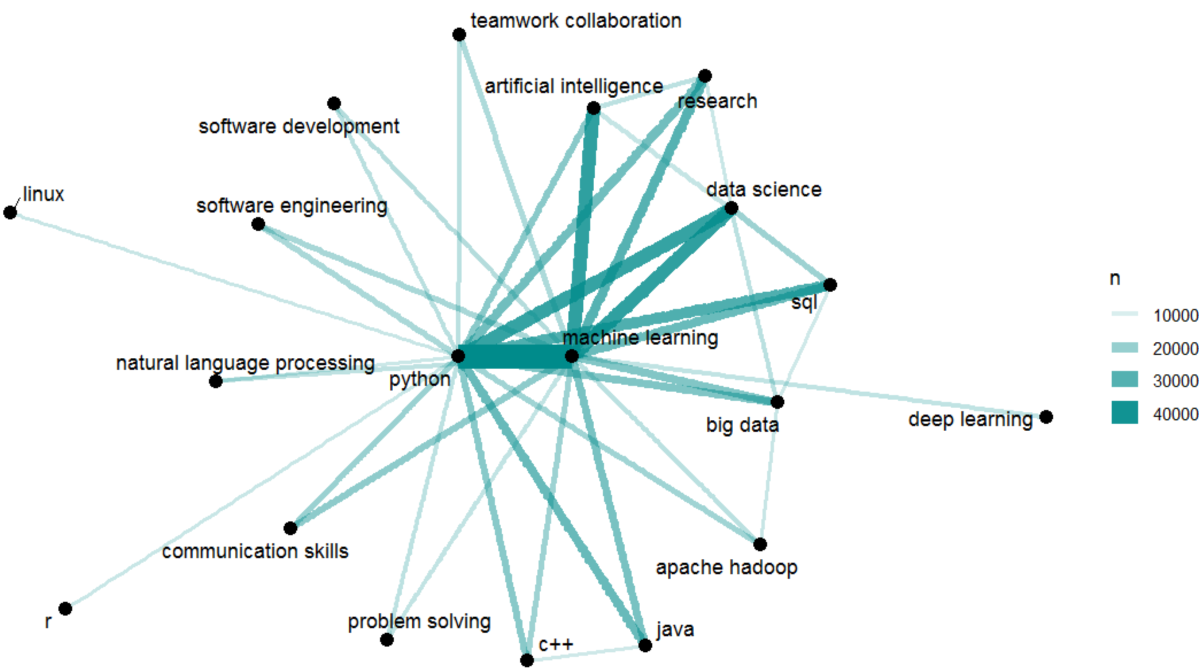
Note: Co-occurrences refer to the simultaneous presence of two distinct terms in the same job posting.
Source: Authors' own compilation based on BGT data

Figure 6.2. Top 30 skills demanded jointly in AI-related jobs, United Kingdom

Network of skills for the period 2013-15 (co-occurrences > 2,000)



Network of skills for the period 2017-19 (co-occurrences > 8,000)



Note: Co-occurrences refer to the simultaneous presence of two distinct terms in the same job posting.
Source: Authors' own compilation based on BGT data

6.3. Key skills of different skill bundles

Figure 6.3 and Figure 6.4 depict the correlation networks of the 30 overall most frequently demanded skills in AI-related jobs in the United States over the periods 2013 to 2015 and 2017 to 2019, respectively. These networks need to be looked at in comparison with Figure 5.3 and Figure 5.4, as they take into account the full set of skills, i.e. both AI and non-AI skills. In a way, by applying the top 30 most frequently occurring skill selection criteria to the correlation figure, a picture emerges reflecting both the co-occurrence and correlation networks presented before. Thereby, it strikes the right balance by visualising skill bundles through correlations, but now for the most commonly demanded skills[15].

In both Figure 6.3 and Figure 6.4 skills appear to be rather "general" and often relate to "tools of the job". This is also confirmed by the fact that the programming languages *Java*, followed by *SQL* and *Python*, are at the centre of the network and remain there in the later observation period.

Figure 6.3 also shows that three technical skill bundles emerge consisting of both AI and non-AI skills. The bundle highlighted in red mostly contains 'programming and software-related skills', including *Java, Python, Linux* and *software development*. This programming-related skill bundle is linked through *Python* and *Java* to a second skill bundle for the 'management of big data' (highlighted in green), which includes *big data*, *MapReduce* and *Apache Hadoop*. It is not surprising that *Python* and *Java* are connecting the programming and big data skill bundles, as they are both programming languages that are often used to work with *big data*. The big data skill bundle is also linked, through *SQL* and *data science*, to the third technical skill bundle, which contains 'data analysis tools' and rather broader analytical skills (highlighted in blue), including the programming language *R, ML, data analysis* and *research*. It is plausible that the big data and data analysis skill bundles are linked through *data science* and *SQL*. *Data science* is about using scientific methods to extract knowledge and insights from data, while SQL is useful for handling structured data.

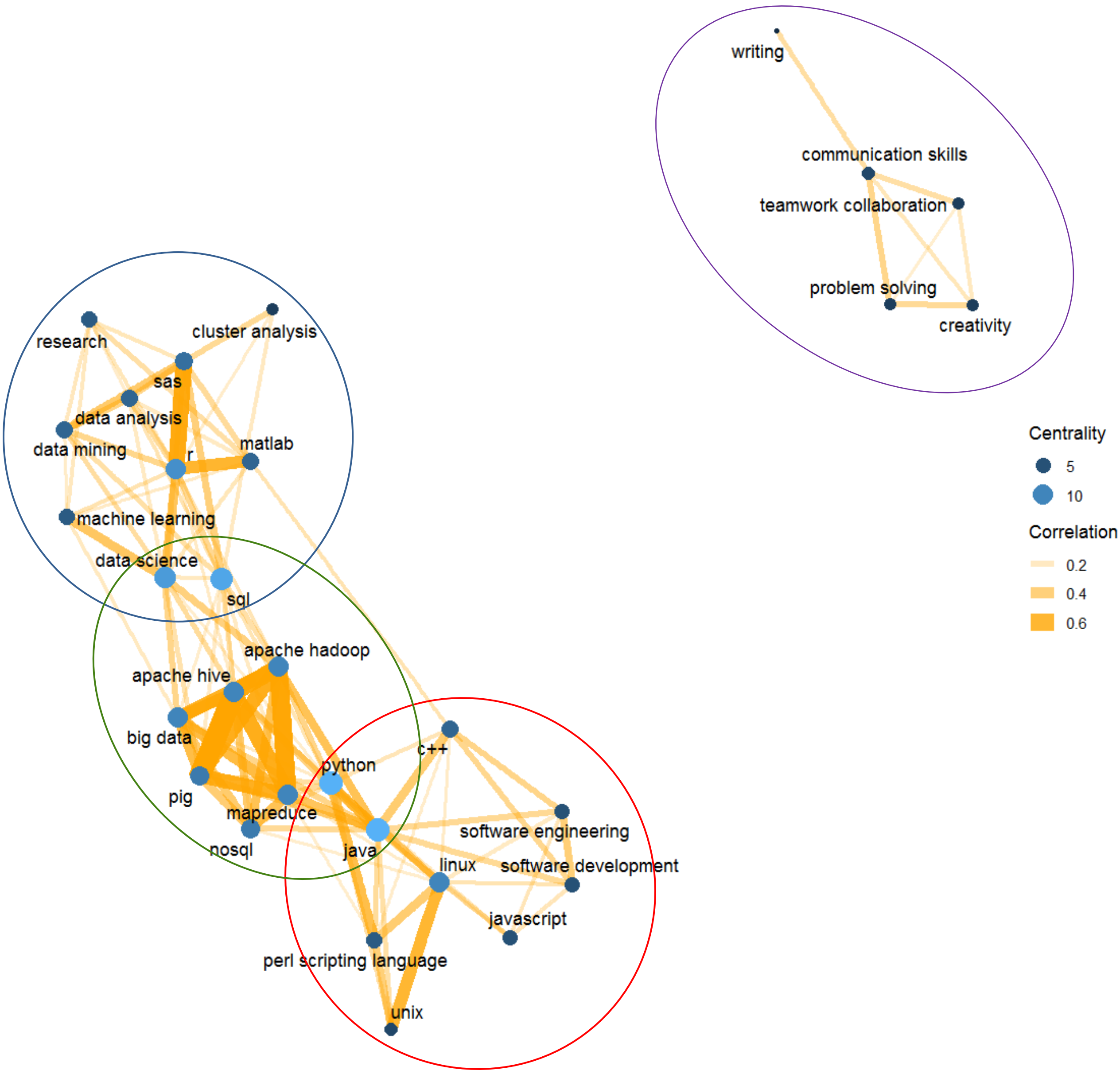
Similar technical skill bundles are found in the period 2017-19, presented in Figure 6.4, but now the skill bundle on data analysis is split. A new bundle (highlighted in black) emerges which includes *ML, deep learning, natural language processing* and *AI* itself. The emergence of this new skill bundle points to a progressive specialisation of the human capital needed to work with AI. Interestingly, *Python* is part of all three technical skill bundles in the latter period, a fact that highlights the importance as such a programming language for most AI jobs.

Furthermore, the network in both periods reveals that a significant number of 'socio-emotional skills' (highlighted in purple) are demanded in combination with more cognitive skills. They can broadly be denoted as *communication*, *teamwork* and *problem solving* skills, which appear together with *creativity* and *writing*. Although the composition of the socio-emotional skill bundle remains basically unchanged over time when considering the top 30 skills, looking at the top 50 skills demanded reveals that *communication* skills gained in relative importance and that there is the need for AI talent to be further endowed with *presentation* skills and for being *detail oriented*.

Another interesting result is that socio-emotional skills are very much correlated among each other, but much less with AI-related skills. This could indicate that they are required together in many different types of AI jobs, and thus show a relatively lower correlations with AI skills individually considered. We examine this in more detail by analysing individual correlation networks for managers, professionals and technicians in section 7.1.

Figure 6.3. Top 30 skills in AI-related jobs, United States, 2013-15

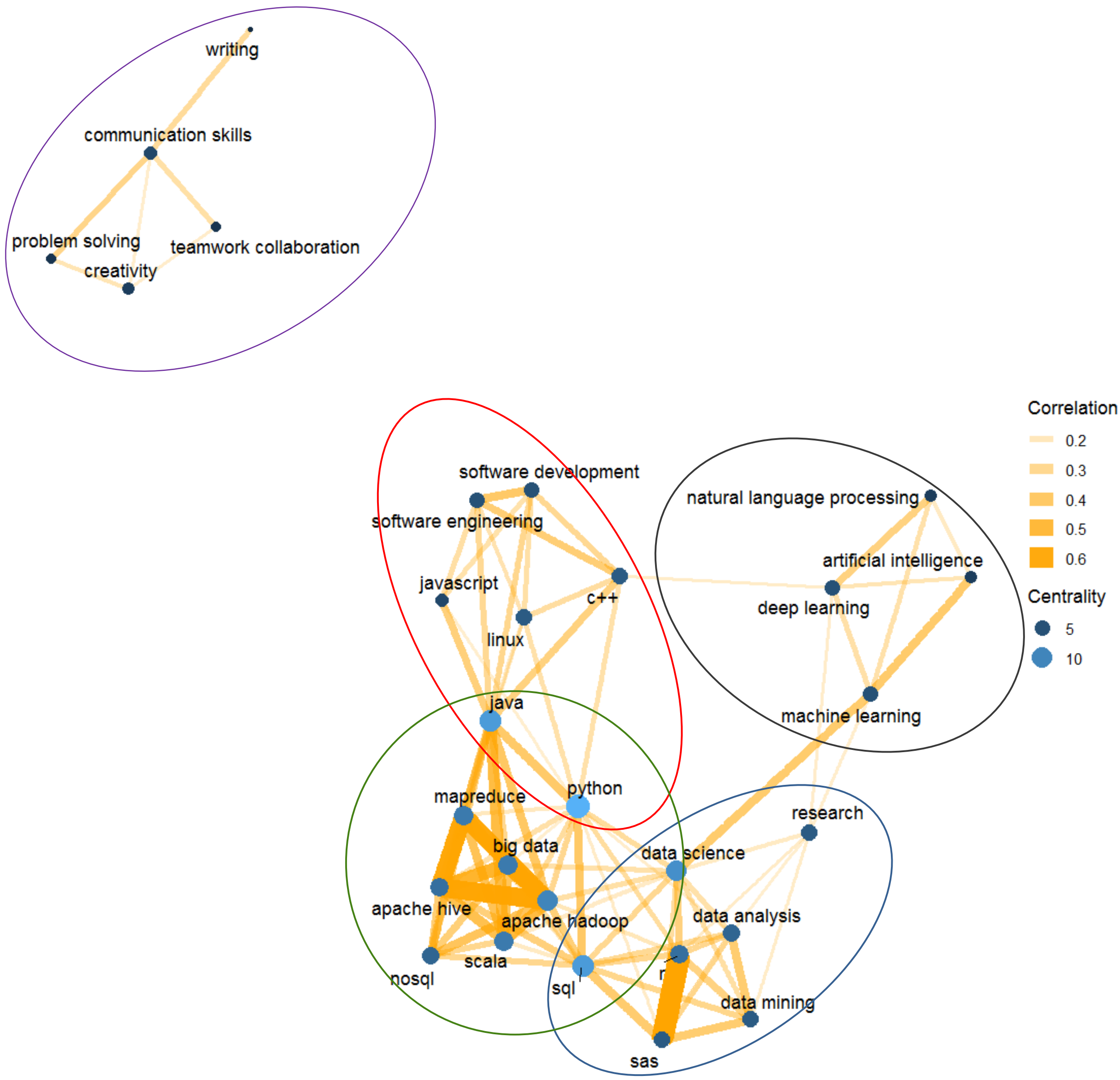
Network of skills with correlation > 0.1



Note: The identified skill bundles are colour coded as follows: 1) programming and software-related skills are red; 2) management of big data is green; 3) data analysis tools and broader analytical skills are blue; and 4) socio-emotional skills are purple.
Source: Authors' own compilation based on BGT data

Figure 6.4. Top 30 skills in AI-related jobs, United States, 2017-19

Network of skills with correlation > 0.1



Note: The identified skill bundles are colour coded as follows: 1) programming and software-related skills are red; 2) management of big data is green; 3) data analysis tools and broader analytical skills are blue; and 4) socio-emotional skills are purple. An additional black circled bundle emerges with different subsets of AI technologies.
Source: Authors' own compilation based on BGT data

As shown by the network graphs in the Annex A , these general observations remain the same when looking at the overall skill set employers of AI-related jobs search for in the United Kingdom. Figure A.1 shows the network of the top 30 skills demanded in AI-related jobs for the period 2013 to 2015 while Figure A.2 shows the equivalent for the period 2017 to 2019. The most central and, hence, the skills, which are highly correlated with most other skills, are programming languages, namely *Java* and *Python* in both periods and *SQL* and *C++* but also *data science* in the period 2017 to 2019. However, similar to the United States, competencies in those programming languages are often demanded in combination with others, such as *R* or *Apache Hive/Hadoop*, which remains the case over time.

Also the main skill bundles denoted as 'programming' (in red), 'big data' (in green), 'data analysis' (in blue) and 'socio-emotional skills' (in purple) are observed again in 2013-15. In the latter period, however, the big data and data analysis bundles merge into one bundle, while at the same time, an additional black circled bundle emerges with different subsets of AI technologies.

While also the socio-emotional skills identified in the United Kingdom generally mirror the ones observed in the United States, *creativity* only joins the list of top 30 skills in the later period, while writing skills remain absent throughout both periods. Considering the top 50 skills allows to see that *project management* and *planning* gain importance in the United Kingdom only in the later period.

Furthermore, given that both countries are *English*-speaking ones, it may be somewhat surprising that it is a requirement frequently enough mentioned to be among the top 50 skills stated in British online job adverts. This may stem from (specialist) skills' shortage (which is often reported by AI actors, see e.g. Peltarion (2019[34]), Ammanath, Jarvis and Hupfer (2020[35])), and recruiters trying to tap into the repository of skills of other countries, i.e. outside the United Kingdom, in more recent years.

Concluding, AI talent seemingly needs to be more and more endowed with a relatively wide range of skills, i.e. both competencies related to programming languages, data analysis and the management, analysis and visualisation of *big data*, as well as socio-economic skills.

To check whether these findings are sensitive to the analytical tool at hand, a different network feature that relies on hierarchical clustering is also employed and results are presented in Annex B. In that analysis, we group nodes together if there is a higher density of edges within groups than between those groups. In other words, skills form a bundle if they are more frequently demanded together than with any of the skills outside of that bundle. The community detection model generally confirms the skill composition of the skill bundles previously identified through the correlation analysis. At the same time, it reveals that the partitioning is relatively weak supporting the argument that some skill specialisation seems to be evident in online job postings but that AI talent needs to be endowed with a skill set beyond core AI-related competencies.

7. Where is AI talent hired and do skill bundles vary across occupations or industries?

7.1. Occupation-specific skill bundles in AI-related jobs

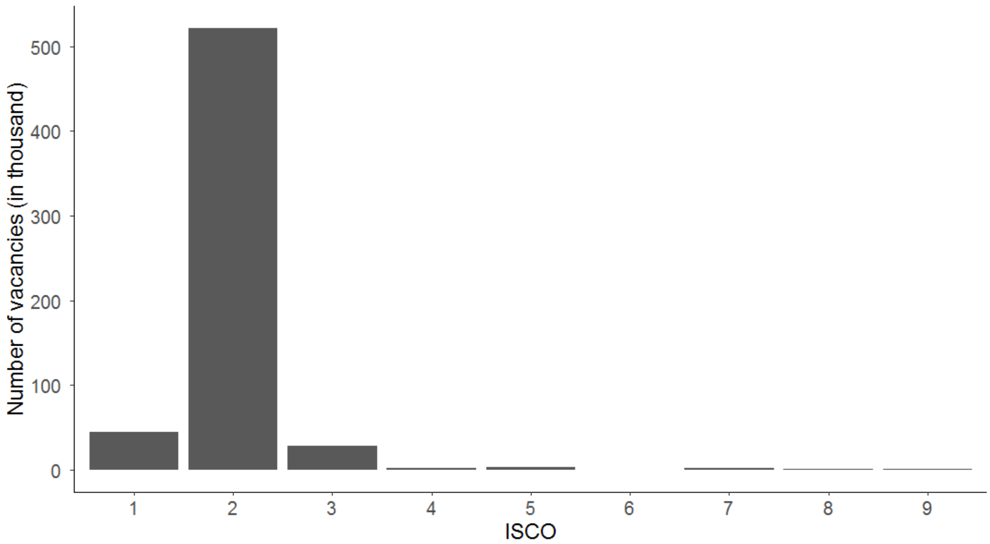
While the sections above have provided an in-depth overview of how different AI skills relate to each other, this section aims to take into account how AI skill bundles differ across occupations. For instance, recent evidence suggests that high skilled occupations involving non-routine cognitive tasks, such as lab technicians, engineers and actuaries, are most exposed to AI (Lane and Saint-Martin, 2021[29]). A reorganisation of tasks within these occupations is expected to take place, making it important to know which skills are needed to both develop and adopt AI. This section aims to contribute to this debate, by characterising the skill bundles demanded for the first three occupations classified by the 1-digit International Standard Classification of Occupations (ISCO), representing managers (ISCO 1), professionals (ISCO 2) and technicians and associate professionals (ISCO 3).

Before looking at the skill bundles, Figure 7.1 presents the number of AI-related vacancies by 1-digit ISCO for the United States, to show the relative importance of the different occupations for the development and adoption of AI. The first three ISCO occupations account for 99% of the AI-related vacancies over the period 2012-19, with more than half a million AI-related jobs for professional occupations (87%), 45 000 for managers (7%) and 28 000 for technicians and associate professionals (5%). For the United Kingdom, however, we find a somewhat different occupational distribution of AI-related jobs in Figure 7.2. While professionals still make up 85% of all AI-related jobs, the share of managers decreases to about 4% whereas technicians and associate professionals account for about 8% of all AI-related jobs. Together they represent 97% of the jobs now, leaving slightly larger shares for clerical support workers (ISCO 4), service and sales workers (ISCO 5) and craft and related trade workers (ISCO 7) compared to the United States.

However, not all occupational groups can be taken at face value. When looking into the job titles of elementary occupations (ISCO 9), we find that these jobs may not necessarily align with the general idea of elementary occupations e.g. in terms of educational background required. Caution should also be used when interpreting results for skilled agricultural forestry and fishery workers (ISCO 6) for the United Kingdom, as this group relies on only 12 AI-related jobs openings.

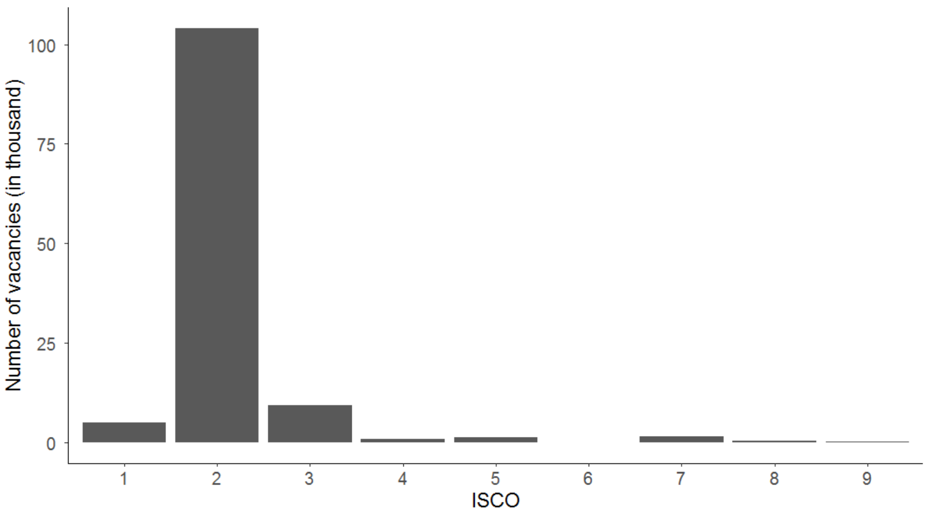
In what follows, we study the different skill bundles demanded for managers, professionals and technicians for the United States in 2017-19. Breaking down the aggregate network graphs by occupation is likely to be especially important in terms of socio-emotional skills, which are most likely different for managers as compared to professionals and technicians.

Figure 7.1. Number of AI-related vacancies demanded for different occupations, United States, 2012-19



Note: Occupations defined by 1-digit International Standard Classification of Occupations (ISCO) code. Frequencies for different occupations are: 1) 44,886 Managers; 2) 522,126 Professionals; 3) 27,618 Technicians and associate professionals; 4) 1,805 Clerical support workers; 5) 3,087 Service and sales workers; 6) 61 Skilled agricultural forestry and fishery workers; 7) 1,565 Craft and related trades workers; 8) 755 Plant and machine operators, and assemblers; 9) 887 Elementary occupations.
Source: Authors' own compilation based on BGT data.

Figure 7.2. Number of AI-related vacancies demanded for different occupations, United Kingdom, 2012-19



Note: Occupations defined by 1-digit International Standard Classification of Occupations (ISCO) code. Frequencies for different occupations are: 1) 5,008 Managers; 2) 104,157 Professionals; 3) 9,274 Technicians and associate professionals; 4) 774 Clerical support workers; 5) 1,319 Service and sales workers; 6) 12 Skilled agricultural forestry and fishery workers; 7) 1,560 Craft and related trades workers; 8) 317 Plant and machine operators, and assemblers; 9) 218 Elementary occupations. As occupation 6 only has 12 AI-related jobs, we suggest to not further consider any results for this occupational group for the United Kingdom.
Source: Authors' own compilation based on BGT data.

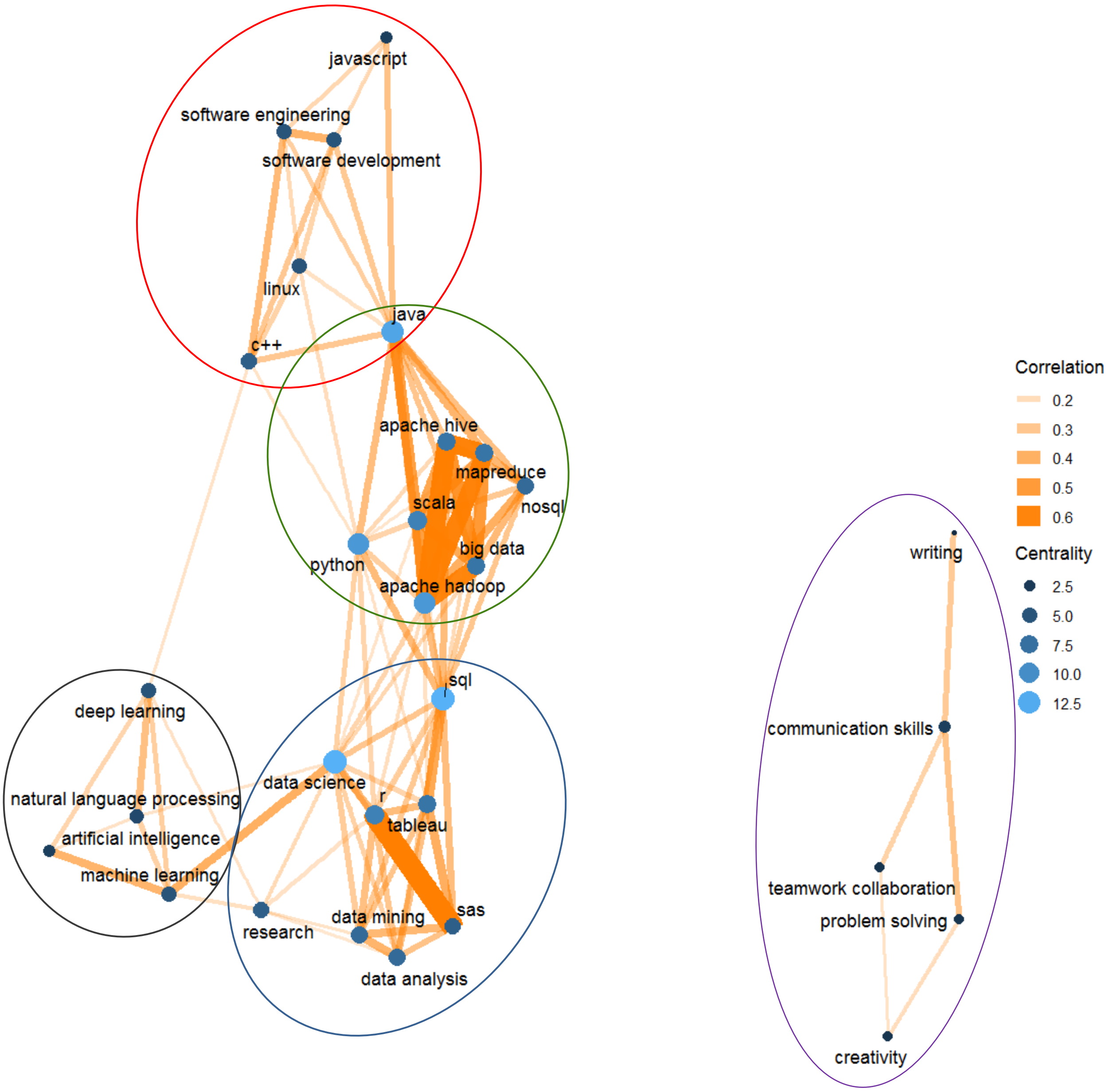
Figure 7.3 presents the correlation network for the top 30 most demanded skills in AI-related jobs but now only for professionals, defined by the 1-digit ISCO code, which is the 1-digit ISCO occupation that contains 87% of all AI jobs. This explains why the network looks very similar to the network of all occupations combined in Figure 6.4. We find again skill bundles for programming (in red), big data (in green), data analysis (in blue), and the fourth skill bundle - including *deep learning, natural language processing*, *AI* and *ML* - in black.

Figure 7.4 gives the equivalent correlation network shown in Figure 7.3 but now for managers only. The purple circles represent again the less technical socio-emotional skills, which contain 12 of the top 30 skills now and, thus many more than the 5 socio-emotional skills found across all occupations in Figure 6.4. When it comes to socio-emotional skills, high centrality is observed again for *communication* skills, *problem solving* and *creativity*, but for managers in the AI field, also *presentation* skills*, planning*, *budgeting* and *business development* appear to be important.

The more technical skill bundles observed before in Figure 6.4 are merged into one big technical skill bundle now in Figure 7.4, containing skills from the programming, big data and data analysis skill bundles previously identified. Only *AI* and *ML* remain rather separately, which is plausible given that they were part of the new skill bundle (highlighted in black) that emerged in the later period. However, both are linked to *product management/development*. At the same time, *AI* is linked to the socio-emotional skill bundle through *business development* skills, and *ML* is connected to the technical skill bundle through *data science*. Furthermore, *robotics* is the only other technical skill that is outside of the technical skill bundle and rather central to the socio-emotional skill bundle instead. This confirms again that competencies related to robotics are somewhat separate from the usual skill profile common to AI-jobs.

Figure 7.3. Top 30 skills in AI-related jobs, United States, Professionals, 2017-19

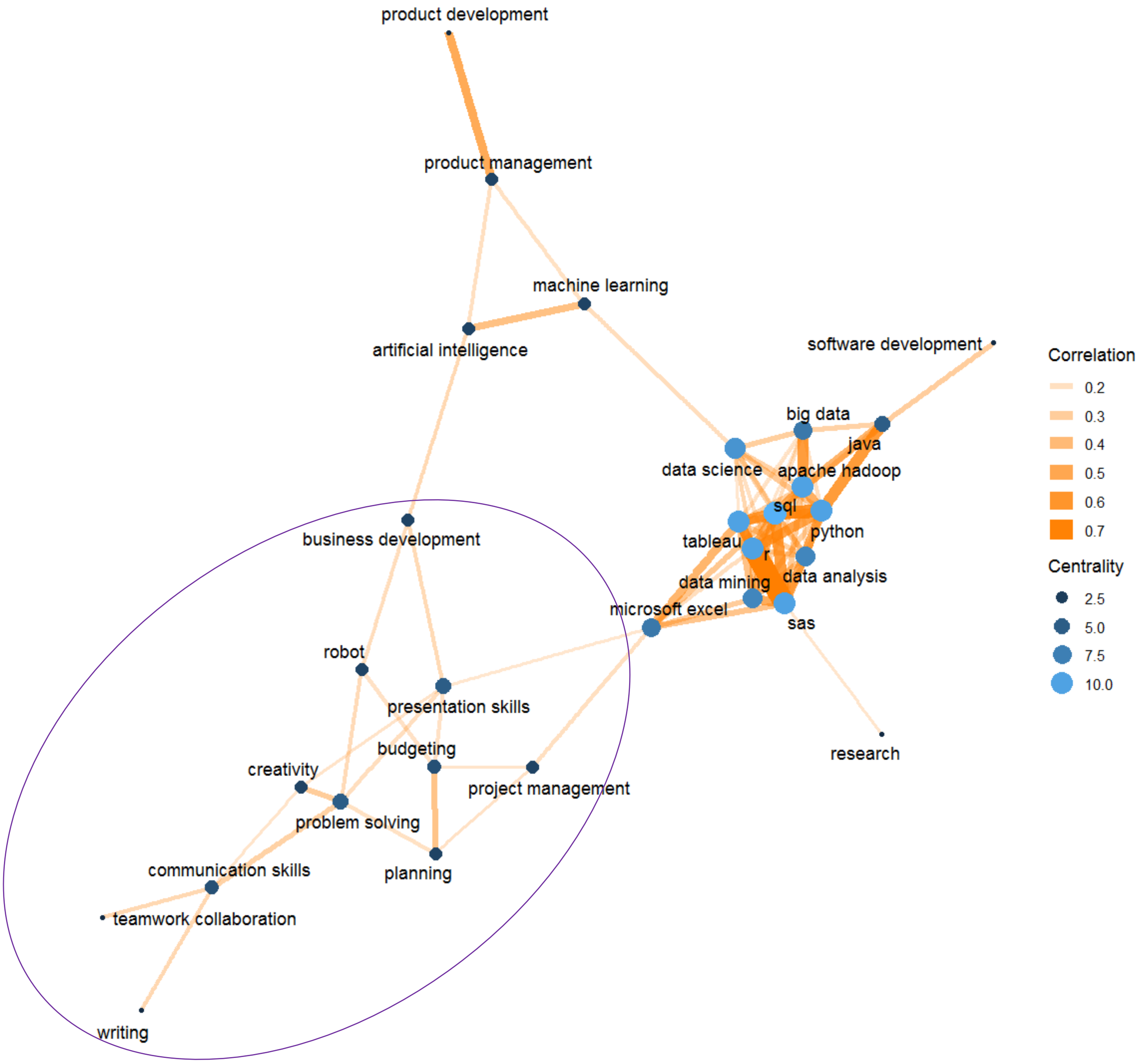
Network of skills with correlation > 0.1



Note: Professionals, defined by 1-digit International Standard Classification of Occupations (ISCO) code. The identified skill bundles are colour coded as follows: 1) programming and software-related skills are red; 2) management of big data is green; 3) data analysis tools and broader analytical skills are blue; and 4) socio-emotional skills are purple. An additional black circled bundle emerges with different subsets of AI technologies.
Source: Authors' own compilation based on BGT data.

Figure 7.4. Top 30 skills in AI-related jobs, United States, Managers, 2017-19

Network of skills with correlation > 0.1



Note: Managers, defined by 1-digit International Standard Classification of Occupations (ISCO) code. The identified socio-emotional skill bundles is colour coded purple.
Source: Authors' own compilation based on BGT data.

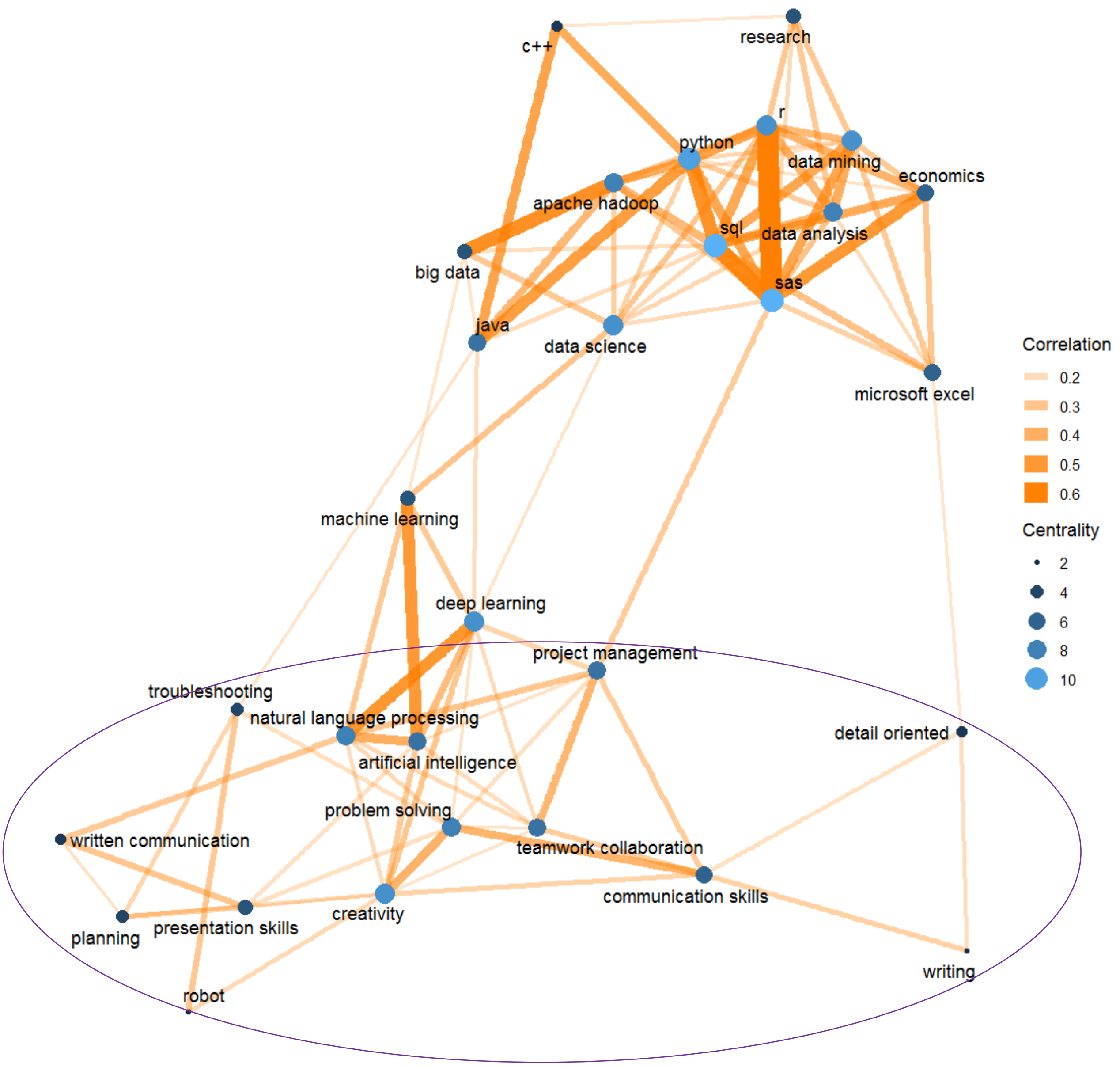
The third occupation group with relatively many AI jobs is technicians and associate professionals, for which we show the top 30 correlation network in Figure 7.5. For technicians and associate professionals a picture emerges that is somewhat in between the graph for managers and the graph for professionals, with relatively many socio-emotional skills, and with the technical skills more bundled together in one group.

For the United Kingdom, the top 30 correlation graphs for managers, professionals and technicians are presented in the appendix in Figure A.1, Figure A.6 and Figure A.7, respectively. Again, we find most socio-emotional skills demanded for managerial occupations, which are largely the same socio-emotional skills presented in the United States case, but now also include *mentoring* and *stakeholder management*. While in the United States, *Microsoft Excel* was connecting the socio-emotional with the technical skill bundle, in the United Kingdom, *Microsoft Excel* becomes even more central by being connected to many of the socio-emotional skills. For professional occupations, again fewer socio-emotional skills are required compared to the other occupations and they are again forming a separate cluster, suggesting that they are often demanded together. For technicians, less of these socio-emotional skills are demanded in the United Kingdom compared to the United States. Overall, similar technical skills are demanded for the different occupations in the United Kingdom as compared to the United States, but these technical skill bundles for technicians are much more connected in the United Kingdom's case, forming one big technical skill bundle.

While skills required for AI-related workers are sufficiently stable over time, skill bundles nonetheless vary across occupations. Therefore, it would be important to take occupation-specific needs into account when designing or prioritising policy interventions aimed to meet future demand.

Figure 7.5. Top 30 skills in AI-related jobs, United States, Technicians, 2017-19

Network of skills with correlation > 0.1



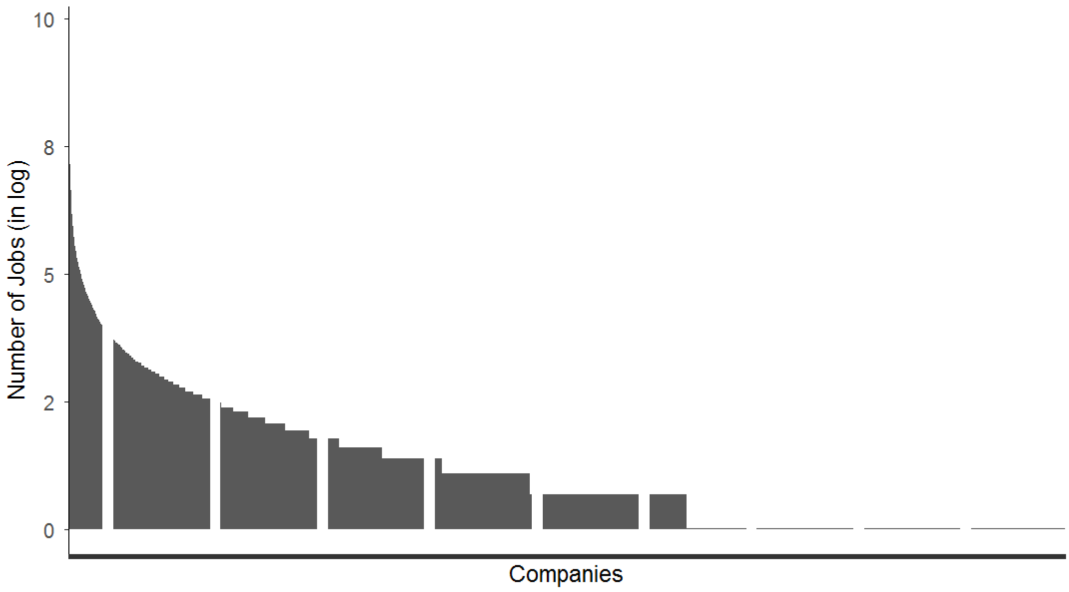
Note: Technicians, defined by 1-digit International Standard Classification of Occupations (ISCO) code. The identified socio-emotional skill bundles is colour coded purple.
Source: Authors' own compilation based on BGT data.

7.2. Interplay between different occupations in AI-related companies

This section goes a step further and studies the occupational distribution of AI-related jobs to gain insights in the interplay between occupations related to management, development and implementation of AI. This is done to shed light on the occupations that emerge as being essential for the development and adoption of AI and the occupations that are complementary to core AI jobs.

Figure 7.6 shows the distribution of the number of AI-related jobs (in log) over the around 30 000 companies that posted at least one AI-related vacancy in the United States. It shows that, while most companies posted only one or two AI-related vacancies over the period 2012-19, the company that demanded most AI related jobs in the United States, Amazon, posted more than 17 000 AI-related vacancies during this period. Figure A.8 shows a similar distribution for the United Kingdom.

Figure 7.6. Number of AI-related jobs (in log) by company, United States, 2012-19



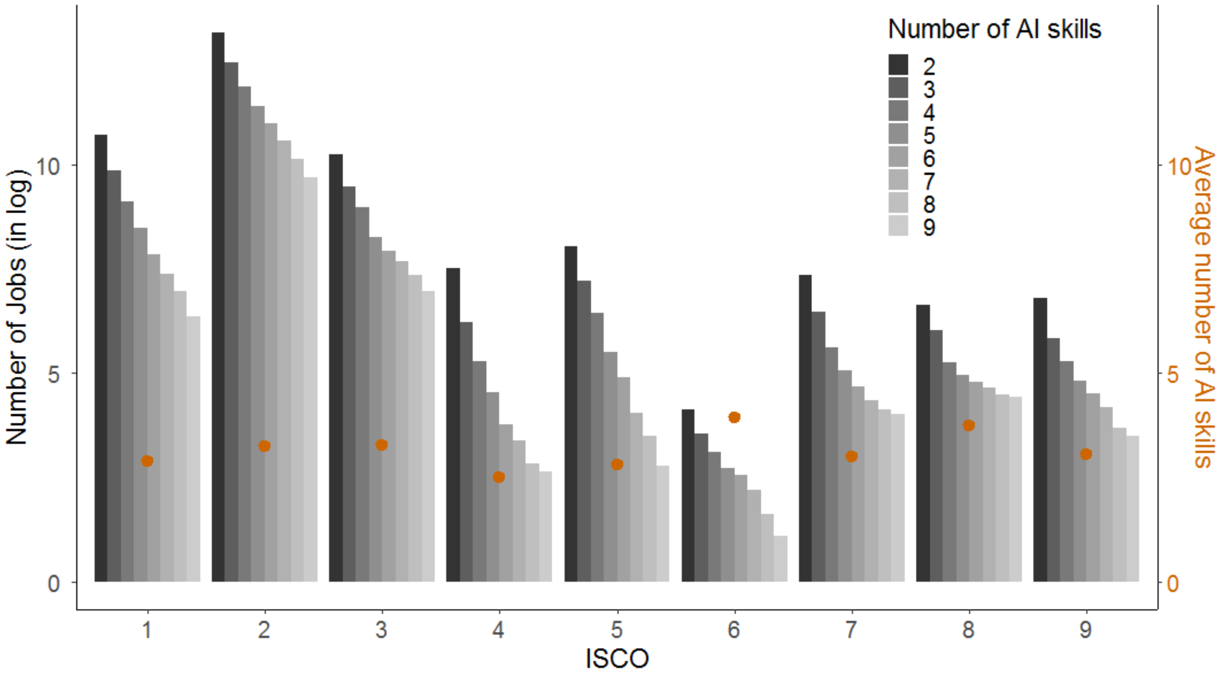
Note: Based on 29,929 companies demanding AI-related workers in the period 2012-19.
Source: Authors' own compilation based on BGT data.

Figure 7.7 shows the number of jobs (in log) demanding different numbers of AI skills for the different occupational groups. Moving from dark to light grey along the bars in each panel reflects an increase in the number of AI-related skills demanded in the respective occupation group. Most AI-related job postings in all different occupations list only two AI-related skills and the distribution of the number of jobs with different numbers of AI skills is relatively similar for the different occupational groups, with a similar downward slope representing fewer and fewer vacancies where higher numbers of AI skills are demanded. For plant and machine operators and assemblers (ISCO 8) we observe a less steep slope, suggesting that these jobs require more often a larger bundle of AI skills compared to the other occupational groups.

In line with this, the average number of AI skills in AI related jobs, shown by the orange diamonds in the same Figure 7.7, is also the largest for plant and machine operators and assemblers (ISCO 8). This may reflect greater specificity about the AI skills required as

AI-related skills are do not represent a typical feature of these occupational types and thus, companies need to be more explicit about what they are looking for.

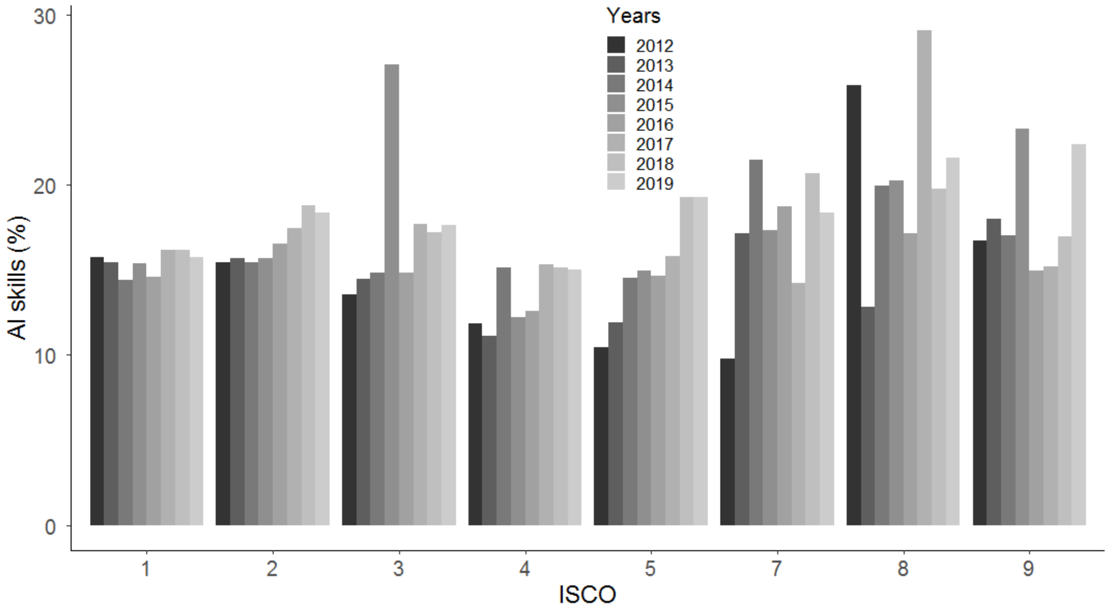
Figure 7.7. Number of jobs (in log) and average number of AI skills within jobs for different occupations, United States, 2012-19



Note: Occupations are defined by 1-digit International Standard Classification of Occupations (ISCO) code. Codes represent: 1) Managers; 2) Professionals; 3) Technicians and associate professionals; 4) Clerical support workers; 5) Service and sales workers; 6) Skilled agricultural forestry and fishery workers; 7) Craft and related trades workers; 8) Plant and machine operators, and assemblers; 9) Elementary occupations.
Source: Authors' own compilation based on BGT data.

Another possible way of shedding light on 'core' AI occupations may be to look at share of AI skills demanded over the total of skills listed as sought in a job posting. For the United States, the share of AI skills out of the total number of skills is presented in Figure 7.8. The highest share is found again for machine operators (ISCO 8), but also professionals (ISCO 2) and craft and related trade workers (ISCO 7) are reaching a share of about 20% or higher in some of the years. Another interesting result from this figure is that the share of AI skills is increasing over time for most occupations, suggesting that the AI intensity of AI-related jobs is increasing.

Figure 7.8. Share of AI skills out of total skills by occupation, United States, 2012-19



Note: The share of AI skills is calculated by dividing the number of AI skills by the total number of skills. Occupations are defined by 1-digit International Standard Classification of Occupations (ISCO) code. Codes represent: 1) Managers; 2) Professionals; 3) Technicians and associate professionals; 4) Clerical support workers; 5) Service and sales workers; 7) Craft and related trades workers; 8) Plant and machine operators, and assemblers; 9) Elementary occupations. ISCO 6, representing Skilled agricultural forestry and fishery workers, is not displayed in this figure because of the small number of AI jobs related to this occupation group.
Source: Authors' own compilation based on BGT data.

Figure A.9 and Figure A.10 show the same figures for the number of AI jobs and the share of AI skills for the United Kingdom. While in line with the results for the United States, differences across occupations and over time are more pronounced. The results show that AI-related jobs for professionals (ISCO 2), Craft and related trades workers (ISCO 7) and Plant and machine operators and assemblers (ISCO 8) require on average more AI-related skills, while AI-related jobs for technicians and associate professionals (ISCO 3) require on average less AI-related skills. These findings follow from the different distributions observed in terms of the number jobs requiring different numbers of AI skills by occupation in Figure A.9 and the shares of AI skills displayed in Figure A.10. Hence, it seems that the majority of AI jobs for managers and technicians are rather general, while plant/machine operators and craft and trade workers demand seem to be more specific. Another interesting finding is that the share of AI-related skills demanded in AI-related jobs has increased much more over time relative to the United States, suggesting that AI intensity in AI-related jobs increased even more in the United Kingdom.

Table 7.1 gives the results of a simple regression model showing that the differences between occupations are statistically significant for both the number of AI skills and the share of AI skills. Professional occupations are chosen as the reference category as they represent the vast majority of AI jobs and they are the occupational group typically associated with AI. As the occupational dummies are the only variables in this model, the constant shows the average number of skills (columns 1 and 3) and the average share of AI skills (columns 2 and 4) for the professional occupation group. The coefficients for the other occupational groups show how the number of skills or the percentage share compares to the professional occupation group, meaning that the number of skills or the percentage can be simply calculated by taking the sum of the constant and the coefficient of the respective occupation group.

The constants in the first and third columns of Table 7.1 show that AI-related vacancies for professionals demand on average 3.24 AI skills in the United States and 3.03 in the United Kingdom. The share of AI skills, however, is higher in the United Kingdom (24.85%) compared to the United States (17.6%). This shows that employers in the United States demand on average more skills in a vacancy than employers in the United Kingdom, which is most likely also the reason why slightly more AI skills are demanded in AI-related jobs in the United States.

Table 7.1. Regression results showing number of AI skills and share of AI skills out of total skills for different occupations

	United States		United Kingdom	
	(1)	(2)	(3)	(4)
	Number of AI skills	Share of AI skills	Number of AI skills	Share of AI skills
Constant	3.24***	17.6***	3.03***	24.84***
	(0.00)	(0.02)	(0.01)	(0.05)
1. Managers	-0.37***	-1.87***	-0.16***	-3.51***
	(0.01)	(0.06)	(0.02)	(0.23)
3. Technicians and associate professionals	0.02	0.45***	-0.37***	-6.1***
	(0.01)	(0.07)	(0.02)	(0.17)
4. Clerical support workers	-0.75***	-3.19***	-0.41***	-2.84***
	(0.05)	(0.28)	(0.06)	(0.57)
5. Service and sales workers	-0.44***	0.12	-0.22***	1.43***
	(0.04)	(0.22)	(0.04)	(0.43)
6. Skilled agricultural forestry and fishery workers	0.69***	7.35***	0.89*	-1.53
	(0.25)	(1.54)	(0.47)	(4.52)
7. Craft and related trades workers	-0.26***	0.72**	0.39***	8.95***
	(0.05)	(0.30)	(0.04)	(0.40)
8. Plant and machine operators and assemblers	0.48***	4.11***	0.83***	5.78***
	(0.07)	(0.44)	(0.09)	(0.88)
9. Elementary occupations	-0.21***	1.02**	-0.24**	1.36
	(0.07)	(0.44)	(0.11)	(1.06)
Number of observations	602,790	602,790	122,639	122,639

Note: Regression models showing the average number of AI skills and share of AI skills for the different occupation groups defined by the 1-digit International Standard Classification of Occupations (ISCO) code. Professional occupations (ISCO 2) are chosen as the reference category as they represent the vast majority of AI jobs.
Source: Authors' own compilation based on BGT data.

Vacancies for AI-related managers demand on average fewer AI skills and exhibit a lower AI share in both countries; the same is true for technicians in the United Kingdom. Technicians in the United States, however, demand a higher share of AI skills than professionals. We already found in Figure 7.1 and Figure 7.2 that AI-related technicians are relatively less demanded in the United States compared to the United Kingdom. This, in combination with finding a higher share of AI skills, may suggest that technicians in the United States are more 'core' AI workers, compared to technicians in the United Kingdom.

As pointed out before, the other occupational groups account for much less job demand, and occupations 7 and 9 could for this reason be overlooked. Nevertheless, online vacancies related to plant and machine operators (ISCO 8) are sufficiently represented and stand out for their large number of AI skills and high share of AI skills. As stated before, this could be interpreted as occupation group 8 being relatively more specialised, and / or reflect the need to be more specific when describing the job requirements of occupational group where AI skills cannot be taken for granted.

While the number of AI skills and the share of AI skills help in better understanding the extent to which different occupational groups may feature 'core' AI occupations, another way to look at the issue can be to consider the occupational distribution of AI-related jobs by company. This is shown in Figure 7.9 for the United States. This figure shows the number of companies posting AI-related job openings in different 1-digit ISCO occupations. The horizontal axis shows the number of unique occupations demanded by the companies represented in the bar. It shows that a large majority of AI-related companies post AI-related jobs in only one ISCO occupational group, which is almost always professionals (ISCO 2). Moreover, companies looking for AI-related managers (ISCO 1) or technicians (ISCO 2) mostly also search for AI-related professionals (ISCO 2) at the same time. This indicates that professionals can indeed be considered as being more core, i.e. AI workers needed in all companies developing or implementing AI, while managers and technicians seemingly complement AI-related professional workers, as they are rarely demanded separately.

The diamond in the figure shows that most companies posted only a few AI-related vacancies, but that the number of unique ISCO occupations demanded by a company grows importantly as the average number of posted vacancies increases. Very few companies search for AI-related workers across all different 1-digit occupational groups, but the companies that do, on average, posted more than 3 000 AI-related vacancies online.

Figure 7.9. Number of companies demanding different numbers of unique ISCO occupations, United States, 2012-19

Note: Left axis shows the number of companies demanding x number of unique 1-digit ISCO occupations. The orange diamonds denote the average number of AI-related jobs demanded by companies posting vacancies related to x number of unique 1-digit ISCO occupations. The colours of the bars denote the occupational group that is demanded which are defined by 1-digit International Standard Classification of Occupations (ISCO) code representing: 1) Managers; 2) Professionals; 3) Technicians and associate professionals; 4) Clerical support workers; 5) Service and sales workers; 6) Skilled agricultural forestry and fishery workers; 7) Craft and related trades workers; 8) Plant and machine operators, and assemblers; 9) Elementary occupations. The diamonds for 6-9 unique occupations are outside the figure to allow better visibility of the first 5 diamonds. The average number of jobs by company (the diamonds) varies from 3.4 for companies demanding one unique occupation to 12,577 jobs for companies demanding AI related jobs for all 9 unique occupations. Companies demanding 6, 7 or 8 unique occupations posted on average 708, 1627, and 2995 AI-related vacancies online.
Source: Authors' own compilation based on BGT data.

For the United Kingdom, the same information about the number of companies demanding different numbers of unique ISCO occupations is shown in Figure A.11. While the distribution of the total number of companies demanding different numbers of unique occupations is similar to the one of the United States, some differences emerge for the composition of the bars across occupations. We have shown for the United States that managers and technicians are typically demanded together with AI-related professional occupations. This is less the case for the United Kingdom, where slightly more companies post only jobs for AI-related managers or technicians compared to companies posting jobs for these occupations along with jobs for AI-related professionals. This difference may indicate some companies are specialising in AI management or AI-related work for technicians, while these different tasks generally take place in the same company in the United States. Another difference that stands out between these two countries is that there are relatively more companies posting AI-related vacancies for technicians in the United Kingdom.

7.3. Sectoral skill bundles in AI-related jobs

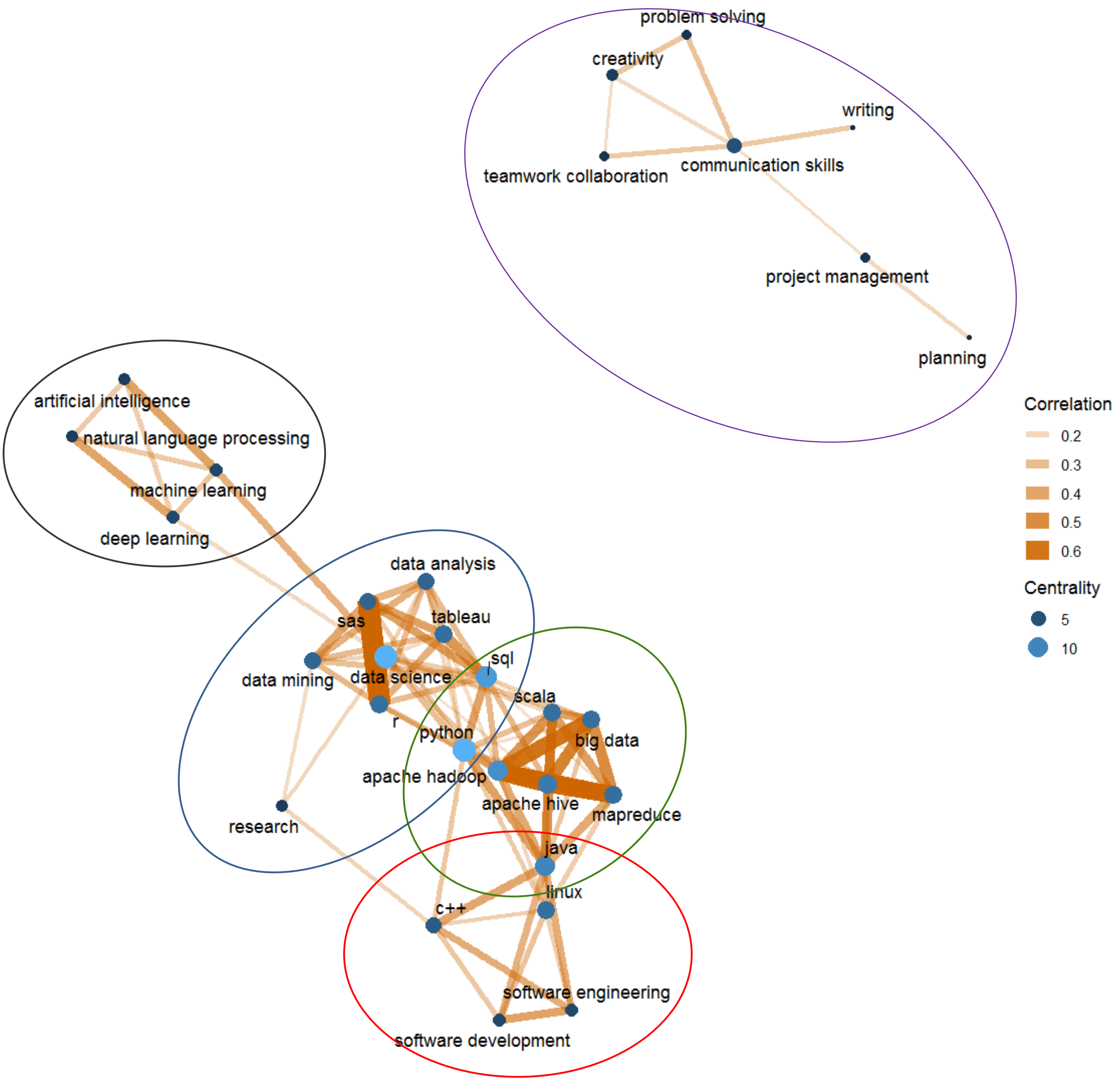
Previous studies have shown that AI is particularly penetrating sectors such as information and communication (International Standard Industrial Classification, ISIC code J), financial and insurance activities (K) and professional, scientific and technical activities (M), and that a considerable share of AI-related vacancies also being posted by firms in manufacturing (C) as well as wholesale and retail (G) (LinkedIn, 2019[36]; Alekseeva et al., 2020[37]; Toney and Flagg, 2020[31]; Squicciarini and Nachtigall, 2021[1]). While of less prominence in the United States, education (P) is the second biggest recruiter of AI talent (ranking just after M) in the United Kingdom (Squicciarini and Nachtigall, 2021[1])[16].

The successful deployment of AI requires expertise to design, adapt, monitor, and maintain sector and business-specific AI applications (LinkedIn, 2019[36]), although not all AI talent working in a given sector is necessarily carrying out AI related tasks specific to that sector alone. AI-related skills can be used in any area that generates large amounts of data. As AI permeates sectors differently, as do all digital technologies (Calvino et al., 2018[38]), it is safe to assume that sectoral specific skill profiles are likely to vary, too. For instance, a report published by the World Economic Forum (2016[39]; 2020[40]) finds that *big data* allows for increased sophistication in inventory management or product personalisation in wholesale and retail while finance or information and communication sectors increasingly face consumers' concerns related to labour standards and privacy.

This section focuses on the aforementioned sectors to shed light on sectoral specific skill profiles. Figure 7.10 shows the correlation network of the business service sector (including information and communication (J), financial and insurance activities (K) and professional, scientific and technical activities (M)) for the latest period 2017-19 for the United States. Although approximately a quarter of AI-related jobs cannot be allocated to any sector due to lacking information in BGT, almost 60% of the remaining jobs are found in this sector group. Therefore, the skill profile observed here mirrors the one already presented in Figure 6.4. Nevertheless, it is noteworthy that *data science* not only gains importance when focussing on skill requirements demanded in AI-related jobs in the business service sector, but it is in fact the most central skill in the network. The socio-emotional skill bundle now also includes *project management* and *planning*.

Figure 7.10. Top 30 skills in AI-related jobs, United States, Business Services, 2017-19

Network of skills with correlation > 0.1



Note: This group of sectors encompasses information and communication (ISIC Rev 4 code J), financial and insurance activities (ISIC Rev 4 code K) and professional, scientific and technical activities (ISIC Rev 4 code M). The identified skill bundles are colour coded as follows: 1) programming and software-related skills are red; 2) management of big data is green; 3) data analysis tools and broader analytical skills are blue; and 4) socio-emotional skills are purple. An additional black circled bundle emerges with different subsets of AI technologies.
Source: Authors' own compilation based on BGT data.

Compared to the United States, a larger proportion of AI-related vacancies (six in ten) has missing industry information in the United Kingdom. However, among the jobs, for which sectoral information can be retrieved, 45% are found in the group of business services (sectors J, K and M). Furthermore, the data allows examining each of the three sectors individually[17] (see Figure A.12), which reveals differences in the composition of the socio-emotional skill bundle as well as in the importance of more technical and cognitive skills.

For instance, recruiting firms in the information and communication sector look for socio-emotional skills beyond *teamwork* and (*written*) *communication* skills and often also mention *mentoring*. AI workers in financial and insurance activities are asked to be further endowed with competencies related to *stakeholder* and *risk management* as well as *presentation* skills. While *problem solving* is demanded in the majority of online job postings, it is particularly important in vacancies advertised in professional, scientific and technical activities, as indicated by the high centrality. In fact, it is more correlated with technical skills, such as *cluster* or *data analysis* and programming languages, than with other socio-emotional skills. Business development and, to a lesser extent, project management are also important.

The networks also suggest that research is an integral part of the tasks carried out in the information and communication sector and, to some extent, in finance. Interestingly, finance is correlated with *physics* in the financial sector, which might indicate that analytical skills innate to *physics* are transferrable and useful in that industry. *Product development* is also important in the information and communication sector.

All three sectors in the United Kingdom have in common that they require their AI talent to be endowed with programming language skills and competencies related to *data science/big data* and *software engineering* or *development*.

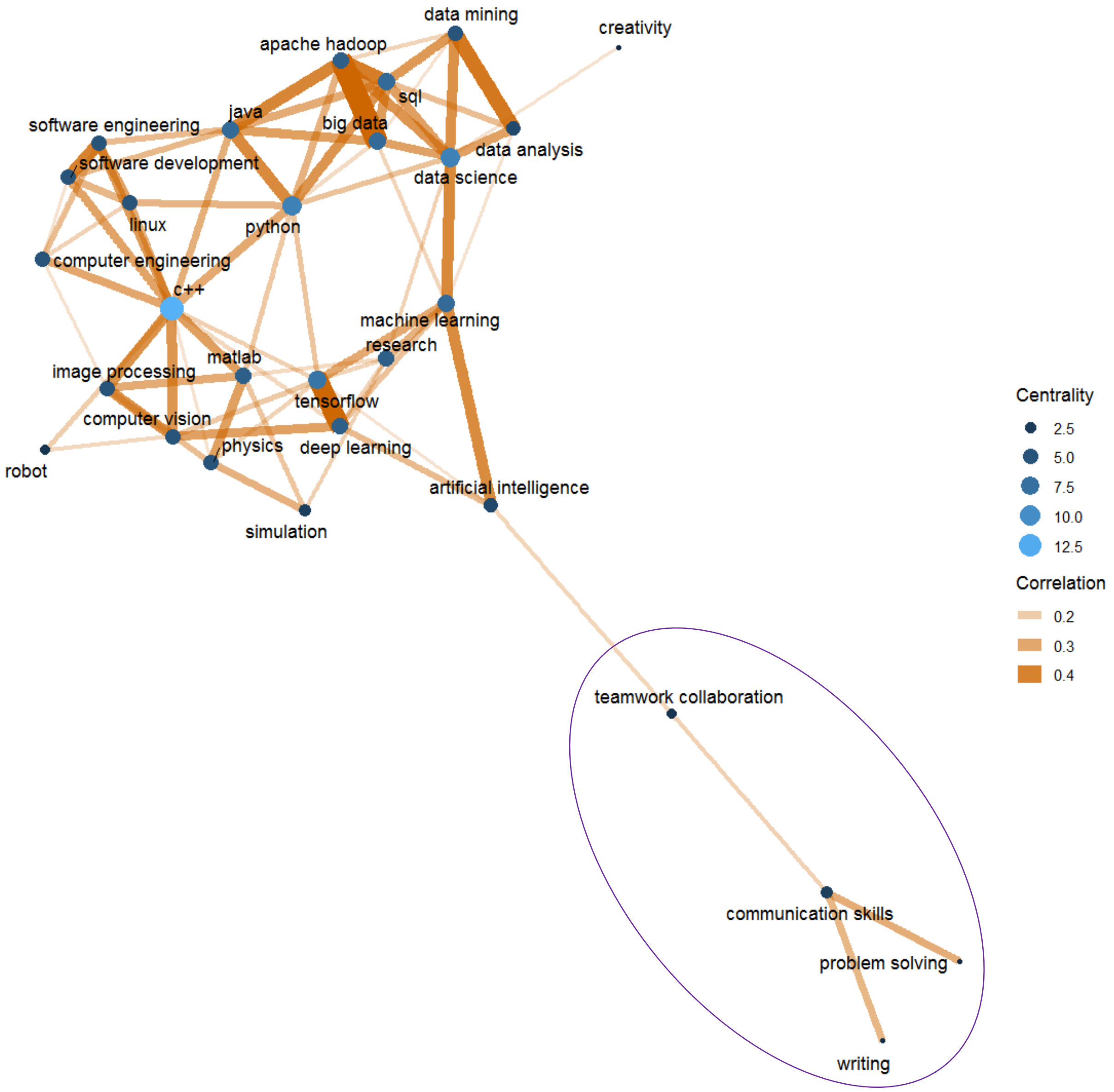
With more than one in ten (14%) AI-related jobs being advertised in manufacturing in the United States, it is the second most AI-intensive sector (following business services). Figure 7.11 shows the skills demanded in the United States for AI-related jobs in the manufacturing sector. Compared to business services, more emphasis is put on competencies related to *robotics* and *computer/software engineering*. The programming language *C++,* which connects these two skills bundles, is also more central to the network.

A similar picture emerges when looking at the manufacturing sector in the United Kingdom (see Figure A.13), where 11% of all identified AI-related job vacancies are posted. However, here jobs related to *robotics* or *software engineering* and *development* predominantly require *C++* skills while the other programming languages (*Python*, *SQL* and *R*) are primarily associated with vacancies related to *data science/big data* and *Java* acts as a connector between the two groups.

While the network for the business services sector mirrors the network for all sectors combined, with more or less the same skill bundles, the different skill bundles are more interrelated in the manufacturing and wholesale and retail sectors. In both countries, the socio-emotional skills among the top 30 skills identified encompass *teamwork*, (*written*) *communication* and *problem solving* skills; *creativity* is associated with data management/analysis. The socio-emotional skills are, however, more important for jobs in business services and the education sector compared to the manufacturing or wholesale and retail sectors. Overall, while there are some skills that are very central in all sectors, such as *data science*, important differences emerge in the AI skill bundles demanded in the different sectors, which are important to consider when designing industrial policy.

Figure 7.11. Top 30 skills in AI-related jobs, United States, Manufacturing, 2017-19

Network of skills with correlation > 0.1



Note: Manufacturing is defined by ISIC Rev 4 code C. The identified socio-emotional skill bundle is colour coded purple.
Source: Authors' own compilation based on BGT data.

The wholesale and retail sector encompasses around 8% and 7% of all AI-related jobs in the United States and the United Kingdom between 2017 and 2019, respectively.

Given the amount of data that is collected and used in the wholesale and retail sector, it is of no surprise that employers in the United States want their AI talent to be endowed with competencies related to the management and analysis of *big data*, as shown in Figure 7.12. This is also reflected in the high centrality of the *data science*, *SQL, Python* and *Java* nodes and the fact that knowledge of data structure is one of the top 30 demanded competencies in the United States' wholesale and retail sector; so are *Amazon web services*. This image is mirrored in the United Kingdom (see Figure A.14), although here software development seems to constitute to the skill profile of AI talent almost as much as *data science* does. At the same time, *predictive models* rather than data mining move to the forefront when focusing on the analytical skill bundle. *E-commerce* also emerges.

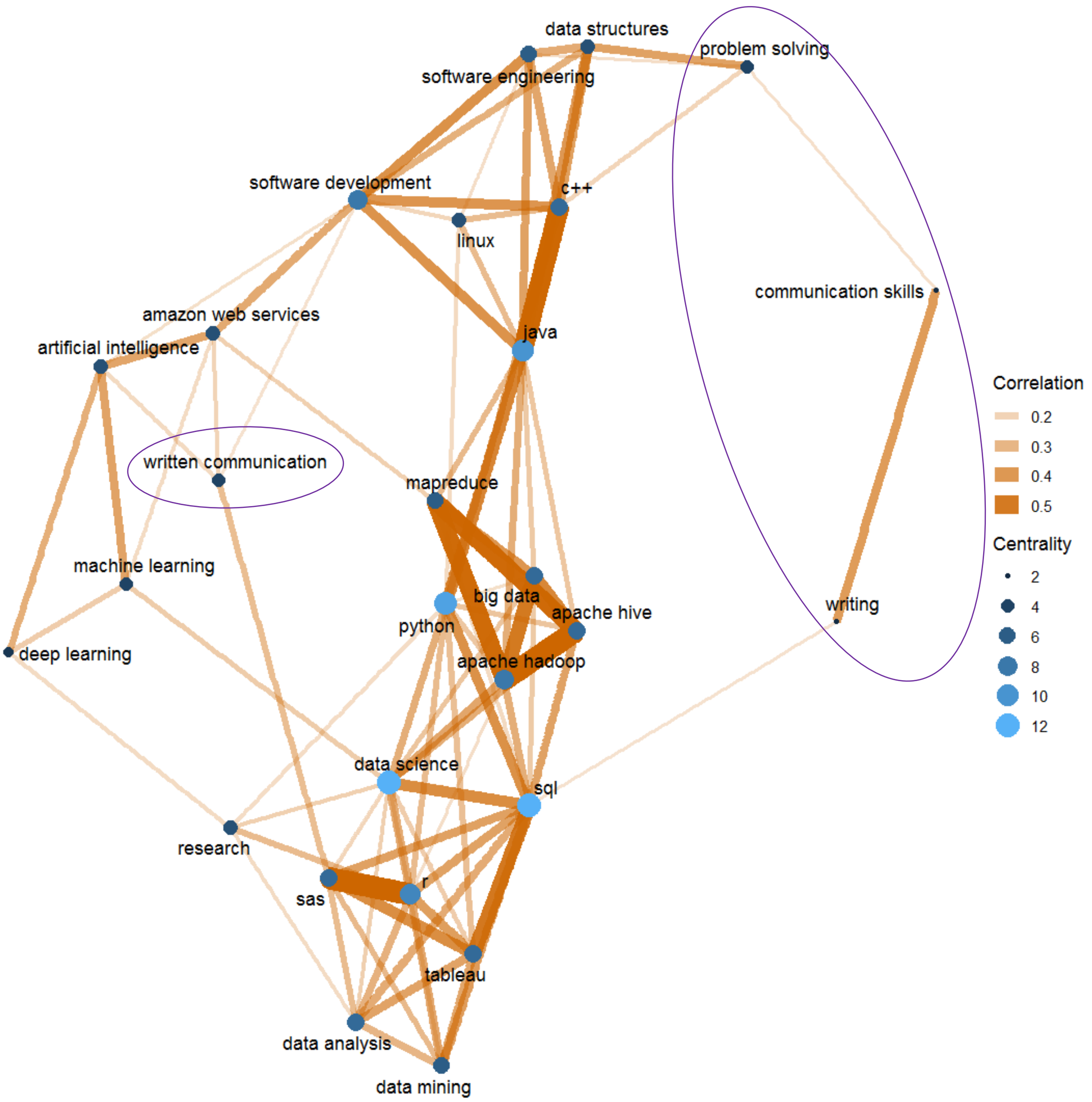
With regards to socio-emotional skills, *written communication* and *problem solving* skills appear to be most important in the United States while the firms in the United Kingdom more often also require *teamwork* skills and *creativity*.

As almost one in five (18%) AI-related jobs in the United Kingdom are found in the education sector (in the United States it only accounts for 4% of jobs), we finally look into the skill profiles demanded there. In Figure 7.13, two skill bundles emerge. One features keywords such as "teaching" and "lecturer" whereas the second bundle centres around programming language skills, in particular *Python, C++, Java* and *Matlab*.

While the usual socio-emotional skills are also common in the education sector, they gain relative importance compared to other sectors. Given the tasks of academics, which encompass teaching as well as regular interactions with students beyond *teaching*, (*written*) *communication* skills, *planning, teamwork* and *problem solving* appear also as being important. Finally, we find that English is not necessarily a frequently mentioned job requirement in all AI-related jobs (as initially highlighted in chapter 6.3) but that it is in academia. Following the previous argument, this suggests that AI talent is also searched for, and potentially recruited from, outside the United Kingdom in more recent years.

Figure 7.12. Top 30 skills in AI-related jobs, United States, Wholesale and Retail, 2017-19

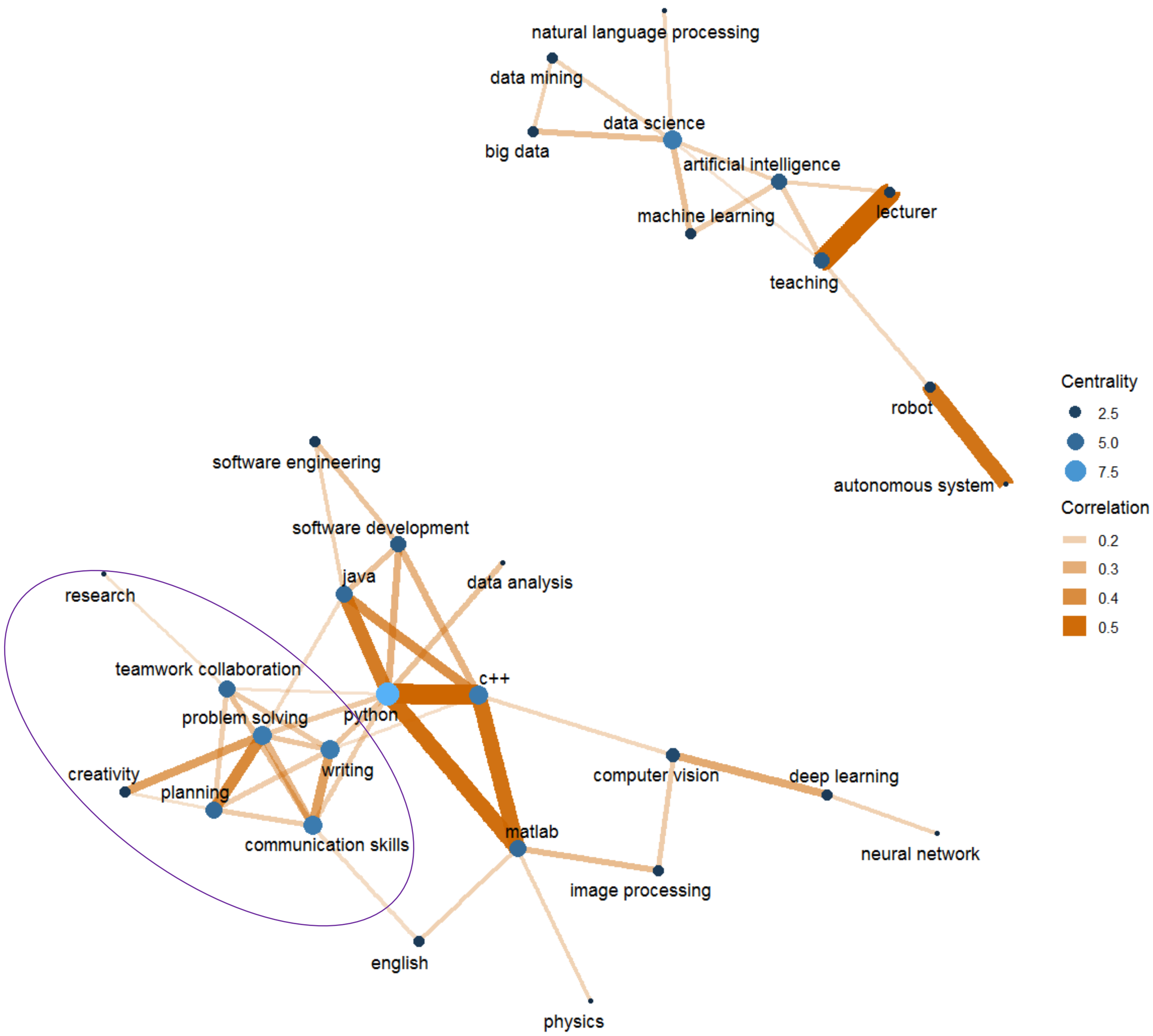
Network of skills with correlation > 0.1



Note: Wholesale and Retail is defined by ISIC Rev 4 code G. The identified socio-emotional skill bundle is colour coded purple.
Source: Authors' own compilation based on BGT data.

Figure 7.13. Top 30 skills in AI-related jobs, United Kingdom, Education, 2017-19

Network of skills with correlation > 0.1



Note: Education is defined by ISIC Rev 4 code P. The identified socio-emotional skill bundle is colour coded purple.
Source: Authors' own compilation based on BGT data.

7.4. Where is AI talent hired?

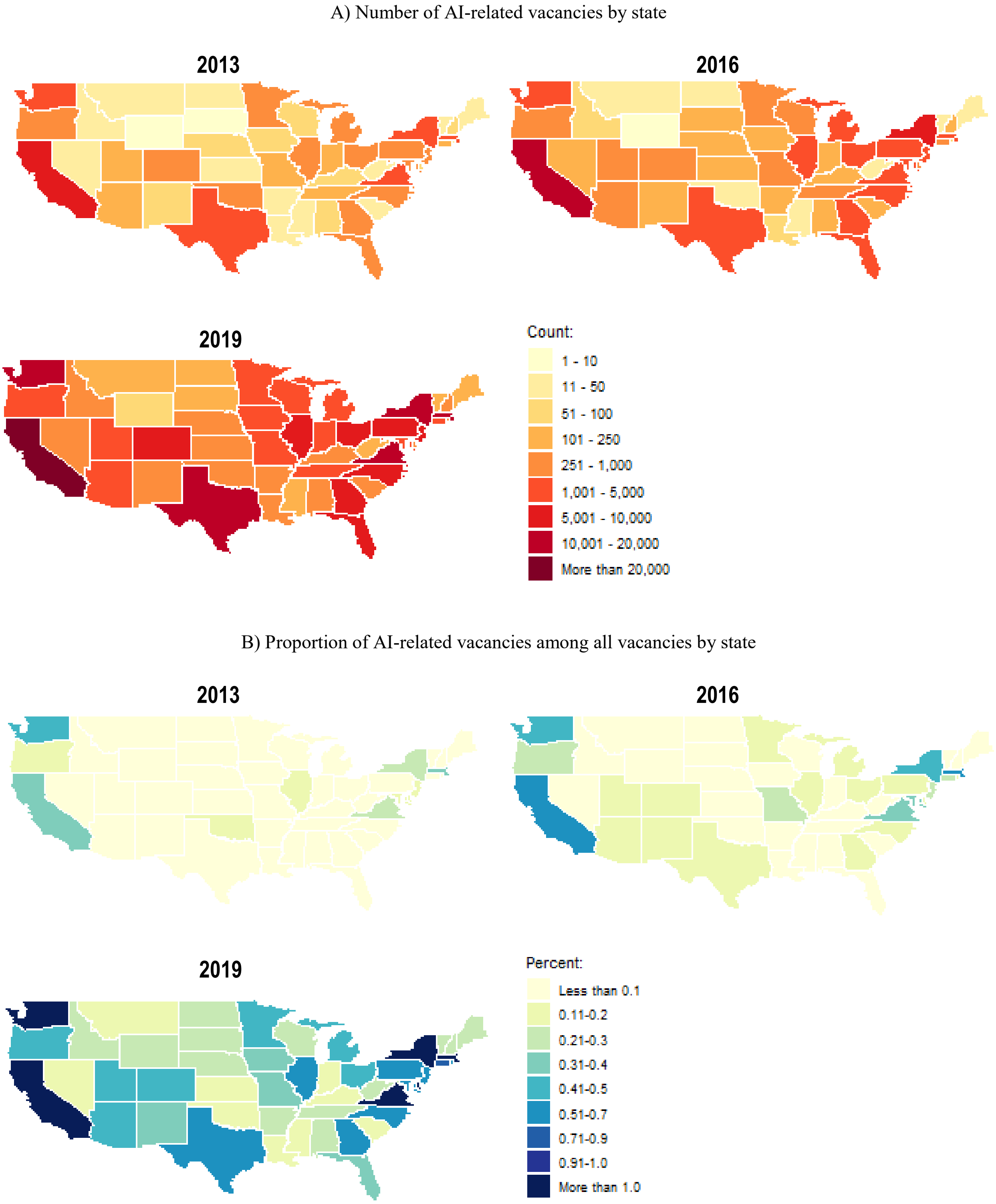
This work also sheds light on the extent AI diffuses geographically. This is possible since BGT collects information on (most of) its vacancies' location and, hence, allows us to pinpoint where and to what degree AI development and adoption take place. Figure 7.14 shows three different heat maps of the conterminous United States (hereafter referred to as United States) for the years 2013, 2016 and 2019. Panel A shows the number of AI-related vacancies in each state, panel B portrays the share of AI-related vacancies of all job postings found in BGT by state and, finally panel C shows how AI-related jobs are distributed across states. The intensity of the colour of the area in each map reflects the density of AI-related vacancies, whereby progressively darker tones characterise a larger number of AI-related vacancies. For instance, moving from pale yellow (the smallest band) to dark red (the highest band) in panel A reflects an increase in the number of AI-related jobs from between one to ten jobs to more than 20 000 jobs in the area considered. Therefore, the maps in panel A show that at least one AI-related vacancy was posted in each of the states during these three years.

The maps in all three panels show that, across the three years observed, AI-related jobs tend to be clustered in only relatively few areas, with more than one in four (26% in 2019) being posted in California (see panel C). More specifically, AI talent in California tends to be hired in and around San Francisco and San José, followed by Los Angeles and San Diego. Other states portraying high counts of AI-related jobs, as shown in panel A, include Virginia, mainly in McLean, Arlington and Reston, as well as Texas, especially in Austin, Dallas and Houston. There are also a number of places, which stand out as AI-intensive states but these jobs tend to be concentrated in only one city. These include New York City, Seattle in Washington, Boston in Massachusetts and, in more recent years, also Chicago in Illinois[18].

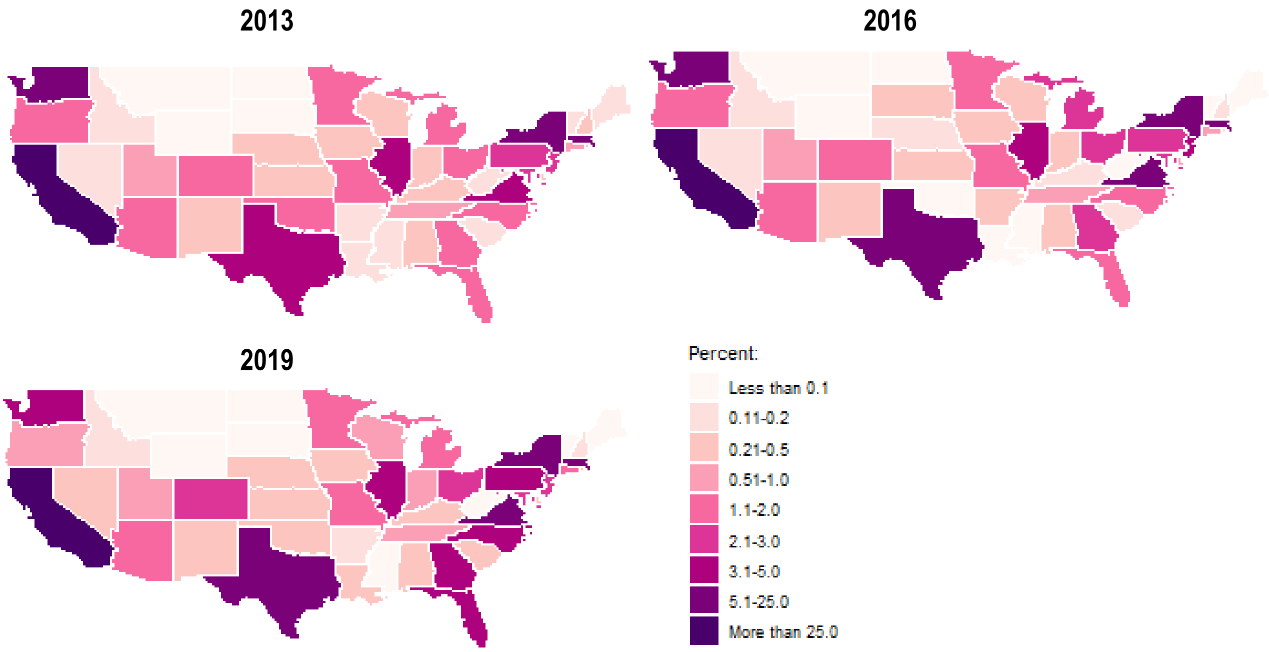
The maps in panel A also show that the number of AI-related vacancies, especially in these aforementioned states, increased over time. Although this is not surprising given that the overall number of vacancies in BGT also increased, the rising share of those jobs (as a percentage of overall jobs posted) presented in panel B shows that these trends are indeed driven by more demand for AI-related talent rather than by an overall increase in vacancies over time. That is to say, these states become more AI-intensive with a higher proportion of vacancies requiring their workers to be endowed with AI-related competencies, in more recent years. At the same time, also the proportion of AI-related vacancies in surrounding areas is increasing, thus signalling the existence of possible knowledge spillovers and knowledge clustering type of effects (which would deserve further investigation). Furthermore, the heat maps in both panel A and panel B show clusters also emerging along the east and west coast and between Utah, Colorado, Arizona and New Mexico.

The regional concentration of those vacancies in relative terms in panel C shows that this distribution of AI-related jobs across states is relatively constant over time. In other words, while the number of AI-related vacancies and those jobs as a share of all jobs have increased since 2012, there has not been a lot of movement across states over the observation period. However, while Washington and, especially, California remain so to speak “AI-intensive” states over the years, they have seen a “re-allocation” of AI-jobs to other states. In 2012, around 37% and 7% of all AI-related jobs in the United States were in California and Washington. In 2019, that proportion was 26%[19] and less than 5%, respectively. As a result, we can observe an increase of AI-related jobs in other states such as Texas, where the proportion more than doubled; in 2019 more than 7% of all AI-related jobs are located in Texas compared to only 3% in 2012. The concentration also doubled along the east coast, especially in Florida, Georgia and North Carolina, each reaching more than 3% in 2019. Albeit still being relatively less AI-intensive in 2019 than other states, Iowa, Louisiana, Maine, Ohio, Oregon, South Carolina and West Virginia all have attracted more and more AI-related jobs over time.

Figure 7.14. Location of AI talent demanded in the conterminous United States



C) Regional (state) proportions of all AI-related vacancies



Source: Authors' own compilation based on BGT data

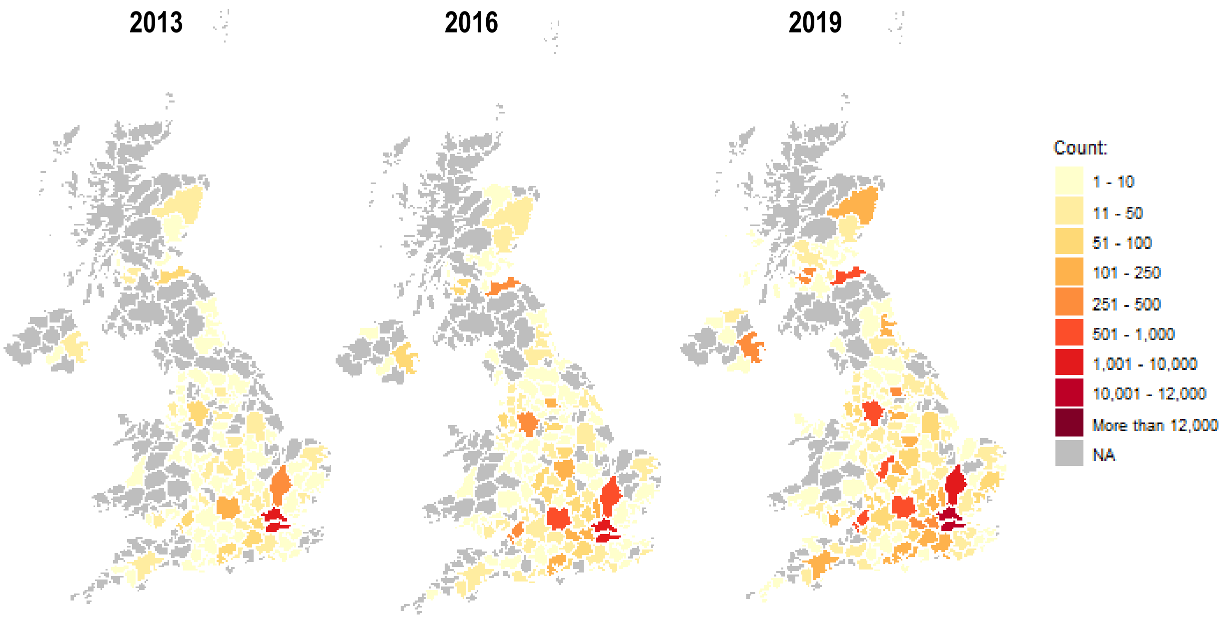
A very similar image of AI-related vacancy hubs and clusters emerges in the United Kingdom, shown in Figure 7.15. Here, panel A shows the number of AI-related vacancies by United Kingdom's travel to work areas (TTWAs[20]) for the years 2013, 2016 and 2019. Panel B portrays the share of AI-related vacancies of all job postings found in BGT by TTWA and, finally panel C shows how AI-related jobs are distributed across TTWAs. Similar to the heat maps shown for the United States in Figure 7.14, the intensity of the colour of the area in each map reflects the density of AI-related vacancies. In contrast to the United States, there are some areas in the United Kingdom, highlighted in grey, where no AI-related jobs are observed. However, as approximately one in six AI-related job postings in BGT does not have a TTWA allocated, these vacancies are not portrayed here but could potentially populate some of those grey areas[21].

Similar to what was found for the United States, AI-related jobs in the United Kingdom tend to be clustered in relatively few areas, with the majority of AI-related vacancies being in London and its surrounding area. In fact, more than one in every two (52% in 2019) AI-related vacancies comes from London (see panel C). Even though London hosts the largest number of AI-related jobs throughout the years (see panel A), it generally offers most job opportunities and, hence, is attractive for anyone, not only AI talent. When taking that into account and looking at the proportion of jobs requiring AI-related skills, compared to all jobs, Cambridge stands out in all three years (see panel B).

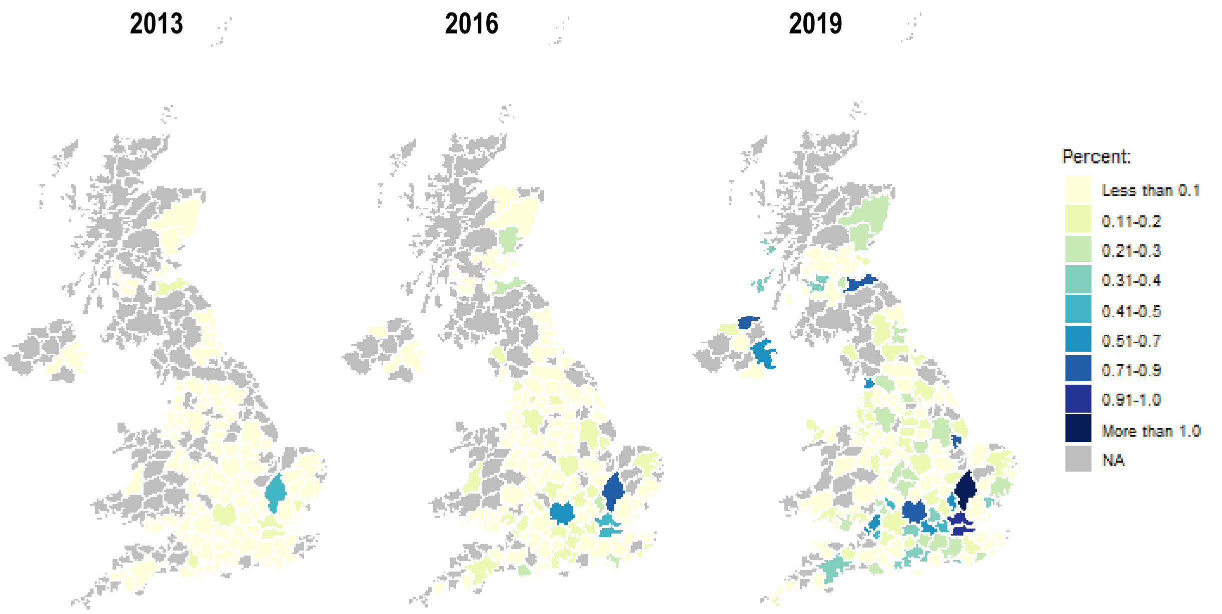
Nonetheless, new areas are emerging and existing clusters are growing. Examples include Coleraine and Belfast in Northern Ireland, Glasgow and Edinburgh in Scotland, and Manchester, Birmingham as well as Oxford in England, to name just a few. Proportionally more of those jobs are now also found in the South like Reading, Heathrow, or Southampton, as well as the South East. At the same time, also the proportion of AI-related vacancies surrounding those areas is increasing.

Figure 7.15. Location of AI talent demanded in the United Kingdom

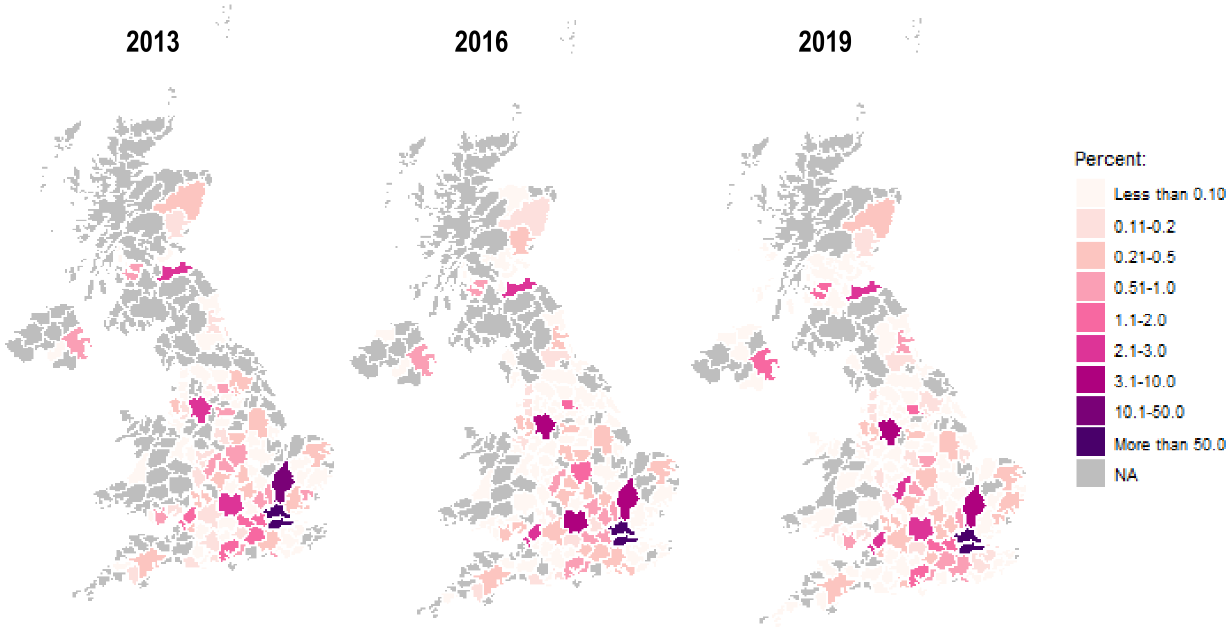
A) Number of AI-related vacancies by travel to work area



B) Proportion of AI-related vacancies among all vacancies by travel to work area



C) Regional (travel to work area) proportions of all AI-related vacancies



Note: 1/6 of AI-related jobs could not be exactly located and are not displayed in the map.
Source: Authors' own compilation based on BGT data

The emergence of hubs and the growth of clusters become especially apparent when comparing the shares in panel B and panel C to the absolute numbers in panel A. Panel B shows that these trends are driven by more demand for AI-related talent rather than by an overall increase in vacancies over time. Areas important for the development and adoption of AI, like London, Cambridge or Oxford become even more AI-intensive with a higher proportion of vacancies requiring their workers to be endowed with AI-related competencies in more recent years.

However, when looking at the regional concentration of those vacancies in relative terms in panel C, a stagnant picture of jobs similar to the United States emerges. At its peak in 2017, London attracted more than 60% of all AI-related jobs identified in BGT, which fell to just over 50% in 2019. While some clusters also develop and grow over time because some of those vacancies emerge from other areas, no significant changes over time become evident. These changes do not seem to be sufficient to create hubs of AI talent comparable in size to the existing ones.

8. Conclusion

This paper sheds light on the skill profiles that employers in the United States and the United Kingdom require AI talent to be endowed with, using the online vacancy data collected by BGT. We examine the relationships between different skills, i.e. skill bundles, for the period 2013-15 and 2017-19, building on the work of Squicciarini and Nachtigall (2021[1]), who provided a first analysis on AI skills demand using the same data.

Importantly, to better understand the set of skills required to thrive in the digital era and to work with AI, this study goes beyond individual skills by looking into skill bundles, including non-AI related competencies such as socio-emotional skills. With the help of various network graphs, showing co-occurrences, pairwise correlations with centrality measures and community clusters, we uncover the composition of skill bundles required for various types of AI-related jobs, to inform industrial, labour and education policies.

The results show that the majority of AI-related jobs is located in London in the United Kingdom and in California in the United States. At the same time, the number of AI-related vacancies has increased across all regions in both countries, also as a share of total vacancies, while the distribution of AI-related jobs across regions remained largely the same.

When studying AI skills in more detail, it becomes apparent that *Python* and *ML* are not only the most frequently demanded skills, as already found by Squicciarini and Nachtigall (2021[1]), but they are also most frequently demanded together, forming the foundation for AI-related workers. When going beyond the most frequently co-occurring skills to look at correlations, three main skill bundles emerge, namely for developing and advancing AI itself, for AI applications and for robotics.

When also including non-AI skills in the analysis, and by focussing on the top 30 most frequently demanded skills in AI-related jobs, we find that these can be separated further in four skill bundles: ‘programming and software related skills’, ‘the management of big data’, ‘data analysis tools and broader analytical skills’ and finally ‘socio-emotional skills’. While these main results are consistent across both countries, both periods and when using community detection algorithms, differences emerge across occupations and industries. In particular, socio-emotional skills are found to be more demanded for managers as compared to professionals and vary in their composition across various industries.

By looking at the occupational distribution of AI-related jobs within companies, it appears that professionals are the most sought after AI-related workers, while managers and technicians are generally only demanded together with professionals. This finding, together with observing a relatively large number of AI skills for professionals, indicates that professionals may be more crucial for the development and adoption of AI, while managers and technicians may typically complement these AI-related professional.

When taking a closer look at the differences emerging over time, we see the skills *AI* and *neural networks* becoming more important at the expense of *MapReduce*, *data mining* and *cluster analysis*. In addition, we observe that the skills for developing and advancing AI have become more interrelated with AI applications, with *neural network* becoming more central connecting both groups. Among the non-AI related skills, *Java* was most important in the earlier period 2013-15, but lost significance in the later period 2017-19, while socio-emotional skills, especially *communication* skills, have gained importance.

One of the main takeaways from this study is that there is no one size fits all answer, because different skill profiles emerge for different types of AI-related jobs. Furthermore, also non-AI skills, such as socio-emotional skills, make up a fundamental part of the skill profile of AI talent and, thus, need to be taught and trained jointly with AI-related skills.

While the most (co-)occurring demanded skills, like *Python* and *ML*, can be a good starting point when investing in the foundation of AI-related human capital, additional specialisation is often valued by employers. Different specialisations are demanded for those developing and for those adopting AI, but also for specialisations in ‘programming and software related skills’, ‘the management of big data’ and ‘data analysis tools and broader analytical skills’. The socio-emotional skills, however, are often demanded together with other socio-emotional skills, and are of similar importance for the various AI specialisations mentioned above.

Our results call for the need to know more about how the demanded skill profiles for AI-related workers relate to the skill profiles of the existing workforce, both at an aggregate level and at the firm or sectoral level. Matching skill demand and supply of AI talent at the aggregate level can help detect skill shortages, to inform industrial and education policies aimed to re-skill and up-skill the workforce. Taking a closer look at the workforce at the firm or institution level could provide insights in the extent to which new hires complement or substitute the skill profiles of the hiring organisation’s existing workforce. A firm level analysis could also show if companies and institutions tend to hire AI workers themselves or if they rather rely on buying AI services from organisations specialised in AI.

While we do not know how the skills of new hires complement the already available skill sets of the workforce, a strength of this study is that AI-related vacancies are observed over a sufficiently long period to get a broad impression of how new hires’ AI skills complement the skills of AI-related workers hired in the earlier period (2013-15). While challenging, it should be possible to get even deeper insights by going a step further, taking all vacancies (including non-AI) over an earlier period (e.g. 2010-17) as a proxy of the skills of the current workers and study how skills in a later period (e.g. 2018-19) complement or substitute these skills, at the company level.

More also needs to be known, given the different skill bundles observed across occupations and industries, about how skill profiles of AI-related workers vary across different types of firms or their characteristic, e.g. small start-ups versus well-established multinationals. This would further contribute to shed light on how different skill profiles correspond to AI development and adoption in the US and the UK. In addition, it would be important to extend this analysis to other countries, to identify country specificieties, enabling or hindering factors, as well as common AI-related features.

Another relevant contribution for future work would be to look deeper into the economic value of the different AI skills and AI skill bundles by relating them to salaries. Again, this would provide insights on skill shortages and thereby help to inform policies to endow workers with the skill combinations in demand.

Endotes

1 For a detailed discussion on the statistical definitions of AI and the AI questions in official ICT use surveys in selected OECD countries, please refer to Montagnier and Ek (2021[48]).

2 An AI skill bundle refers to the combination of skills demanded in relation to the development, application or use of AI.

3 In fact, data are available for earlier years as well as for 2020, but given this rapidly developing field and the disruption caused by the COVID-19 pandemic in 2020, we focus on the period 2013-19 and omit the latest year from the analysis.

4 DeepMind Technologies' "AlphaGo" was the first computer program to defeat a professional human Go player and a Go world champion. DeepMind was later acquired by Google. See https://deepmind.com/research/case-studies/alphago-the-story-so-far.

5 Community detection problems in network analysis have the goal to find groups of nodes that are more similar to each other than to the other nodes. See Li et al. (2019[49]) for more details

6 BGT claims to capture the near-universe of online job vacancies.

7 Online job posting data likely encompass staff sought to be recruited in addition to the one already in the firm, or supposed to replace (part of) staff leaving for different reasons (e.g. retirement, dismissal, voluntary separation).

8 The terms *clustering* and *cluster analysis* are sometimes used in the AI-field as a synonym for *unsupervised learning*. These two concepts, however, should not be confused as *cluster analysis* can also be used more generally, referring to the broader class of techniques that are used to classify objects into relative groups called clusters.

9 We use phi coefficients for the binary correlation analysis, which measures which measures how often both skills appear together relative to appearing separately.

10 The keyword "*Bayes*" provided in BGT could also refer to the algorithm "naïve Bayes" used for classification but the node's position in the network suggests it rather refers to the term "Bayes network".

11 *XGBoost* is an open-source software library which provides a framework for gradient boosting (which is a *ML* technique for regression and classification problems), for programming software such as *C++, Java, Python* and *R*.

12 *Vowpal Wabbit* is an open-source, fast, parallel *ML* system with features, such as continuous learning or dimensionality reduction, and hence allows fast learning on *big data*.

13 Basically deep learning is entirely based on artificial neural networks. One cannot be there without the other. The software libraries are needed to code the neural networks models in a way that they are treated as deep learning. Any neural network with 2 or more layers is considered a deep neural network. From a skills point of view, it seems that deep learning is kind of absorbing all the sub-bundles, which aligns with what is discussed in the AI technical literature, where deep learning is mentioned adjacent to e.g. Artificial Neural Networks or tensorflow.

[14]In the earlier period *speech recognition*, which is otherwise associated with AI applications, was frequently required with keywords usually associated with advancing AI, i.e. the stochastic processes *Gaussian process*, *Kernel* and *Markovian* (from probability theory).

[15] While the co-occurrence networks are largely driven by occurrences of skills, the correlation figures are useful for visualising skill bundles, but underestimate the importance of some of the most commonly demanded skills.

[16] This is not to say that AI talent is not demanded in academia in the United States but recruitment may happen in different ways or collaborations between industry and academia be more frequent.

[17] Due to a different industry classification system applied in the United State (Statistical classification of economic activities in the European Community, NACE), this disaggregation can only be done using BGT data for the United Kingdom. Over the period 2017-19, 12% of AI-related jobs are in information and communication (J), 13% in financial and insurance activities (K) and 19% in professional, scientific and technical activities (M).

[18] When comparing the number of AI-related online job postings relative to the working age population of a state, Toney and Flagg (2020[31]) find the District of Columbia followed by Colorado, Washington state and Minnesota to have the largest market demand in AI skills.

[19] This stark reduction is particularly concentrated in the early period when the share fell from 36.9% in 2012 to 29.6% in 2013.

[20] Due to diffuse commuting patterns, it is not possible to divide the United Kingdom into entirely self-contained labour market areas (where all commuting occurs within the boundary of that area). Therefore, travel to work areas (TTWAs) have been constructed, so that of the resident economically active population, “at least 75% of an area's resident workforce work in the area and at least 75% of the people who work in the area also live in the area" (ONS, 2016[44]). In other words, it is developed so that relatively few commuters cross a TTWA boundary on their way to work.

[21] There is no way of knowing whether they contribute to existing clusters or, in the extreme case, form their own hub of AI-related jobs in the United Kingdom.

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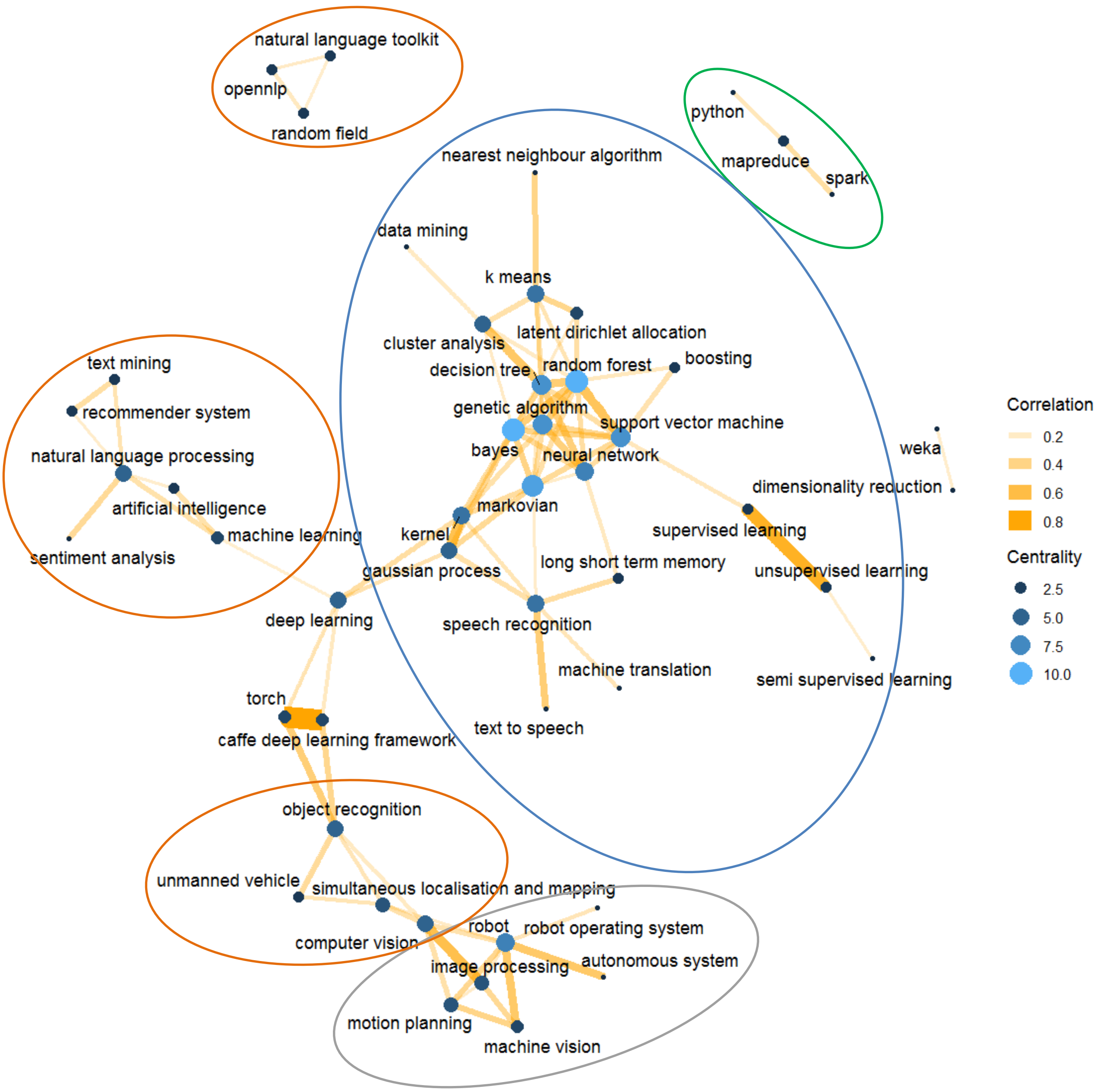
Annex A. Additional Tables and Figures

Figure A.1. AI-related skills in AI-related jobs, United Kingdom, 2013-15

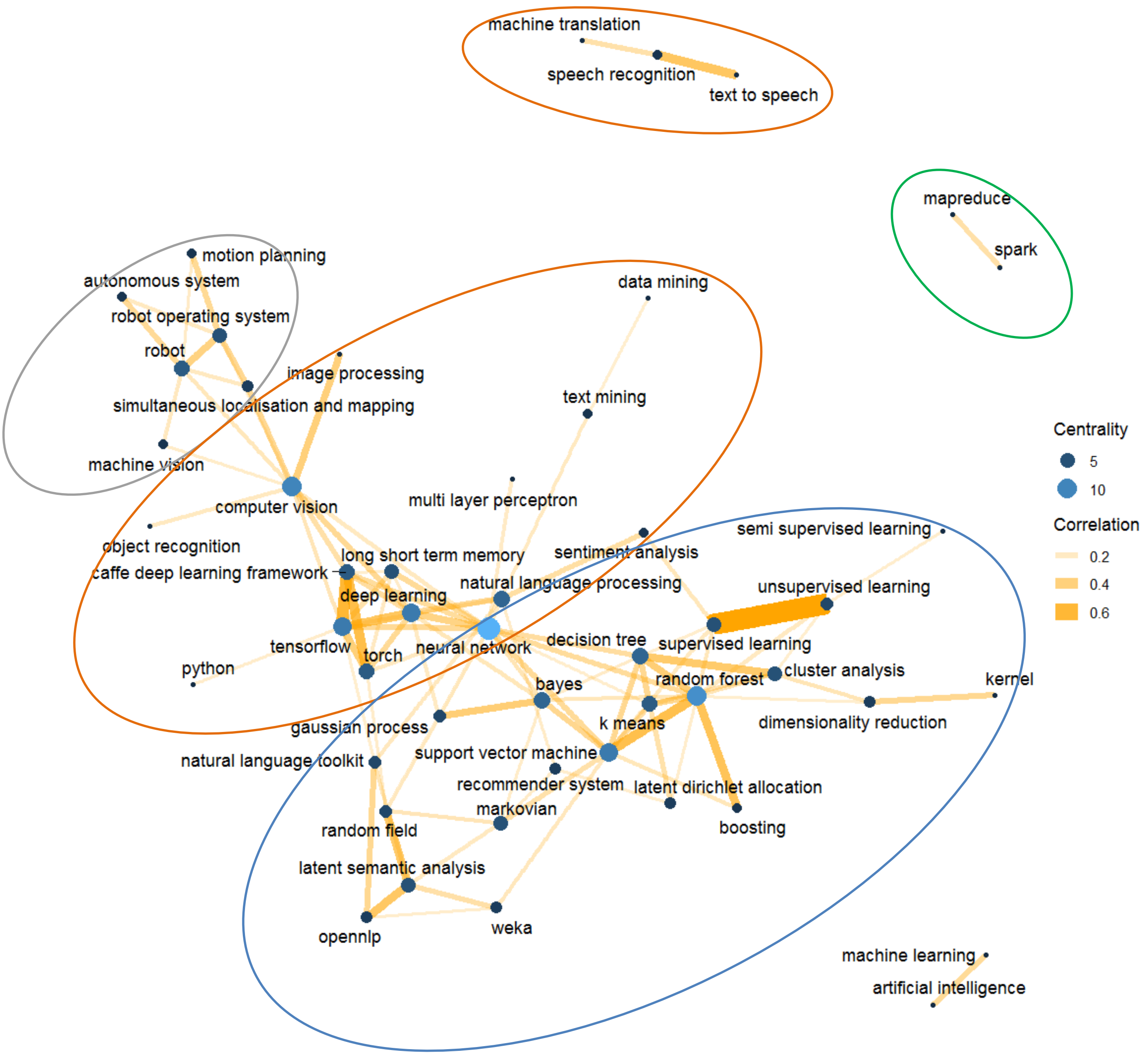
Network of skills with correlation > 0.1



Note: The identified skill bundles are colour coded as follows: 1) Skills related to developing and advancing AI are blue; 2) AI applications are orange; 3) robotics are grey; and 4) AI IT basics are green.
Source: Authors' own compilation based on BGT data

Figure A.2. AI-related skills in AI-related jobs, United Kingdom, 2013-15

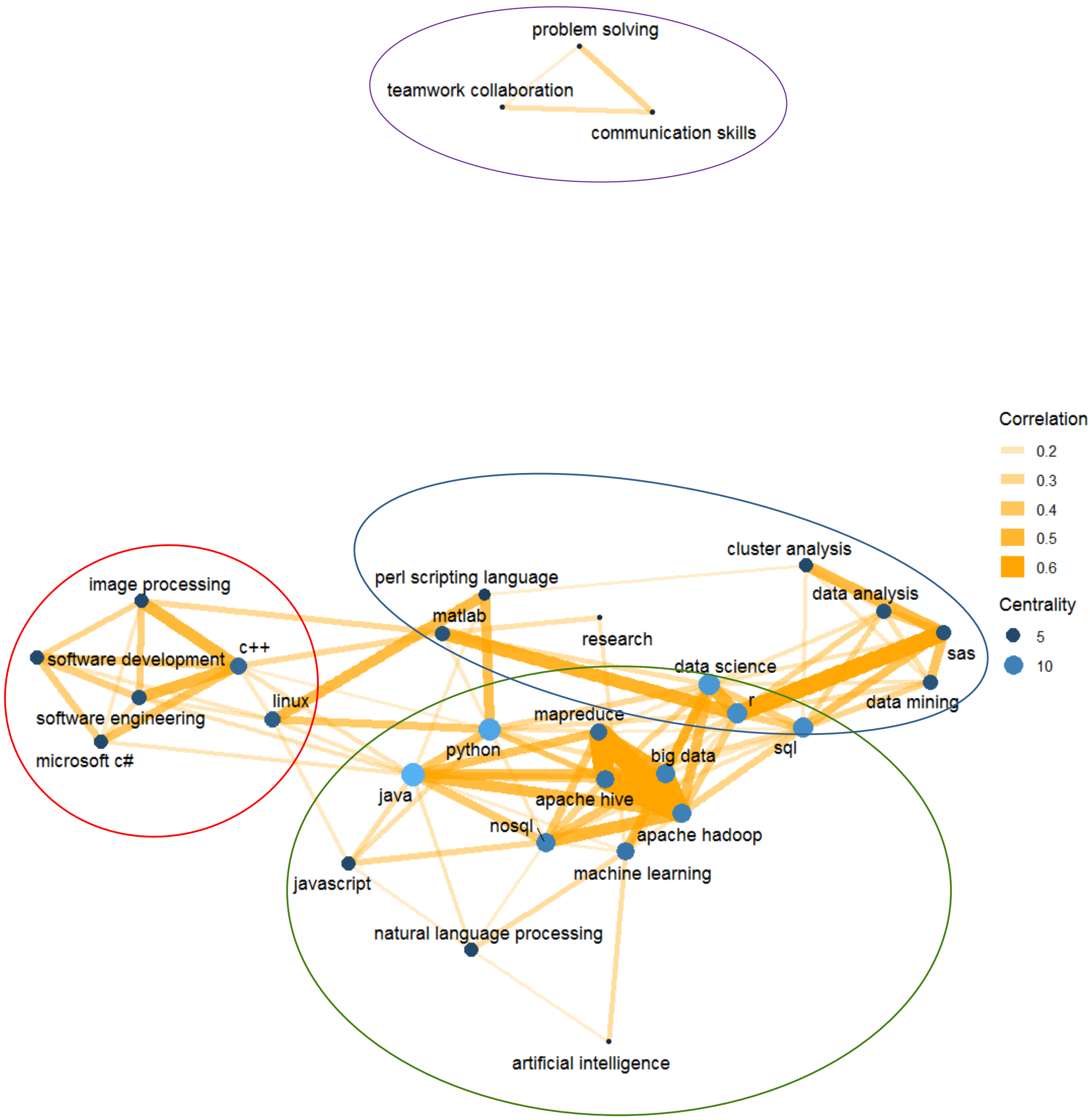
Network of skills with correlation > 0.1



Note: The identified skill bundles are colour coded as follows: 1) Skills related to developing and advancing AI are blue; 2) AI applications are orange; 3) robotics are grey; and 4) AI IT basics are green.
Source: Authors' own compilation based on BGT data

Figure A.3. Top 30 skills in AI-related jobs, United Kingdom, 2013-15

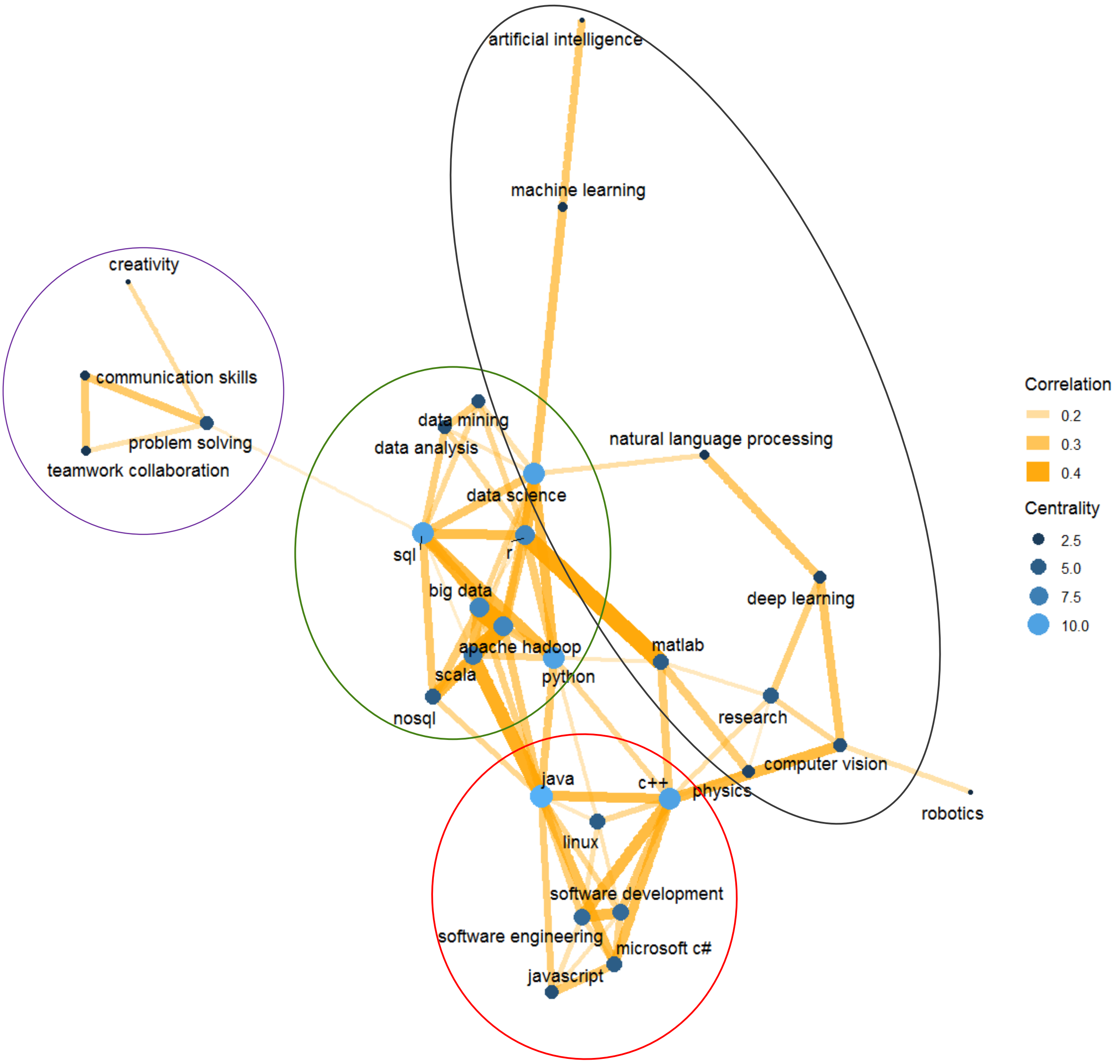
Network of skills with correlation > 0.1



Note: The identified skill bundles are colour coded as follows: 1) programming and software-related skills are red; 2) management of big data is green; 3) data analysis tools and broader analytical skills are blue; and 4) socio-emotional skills are purple.
Source: Authors' own compilation based on BGT data

Figure A.4. Top 30 skills in AI-related jobs, United Kingdom, 2017-19

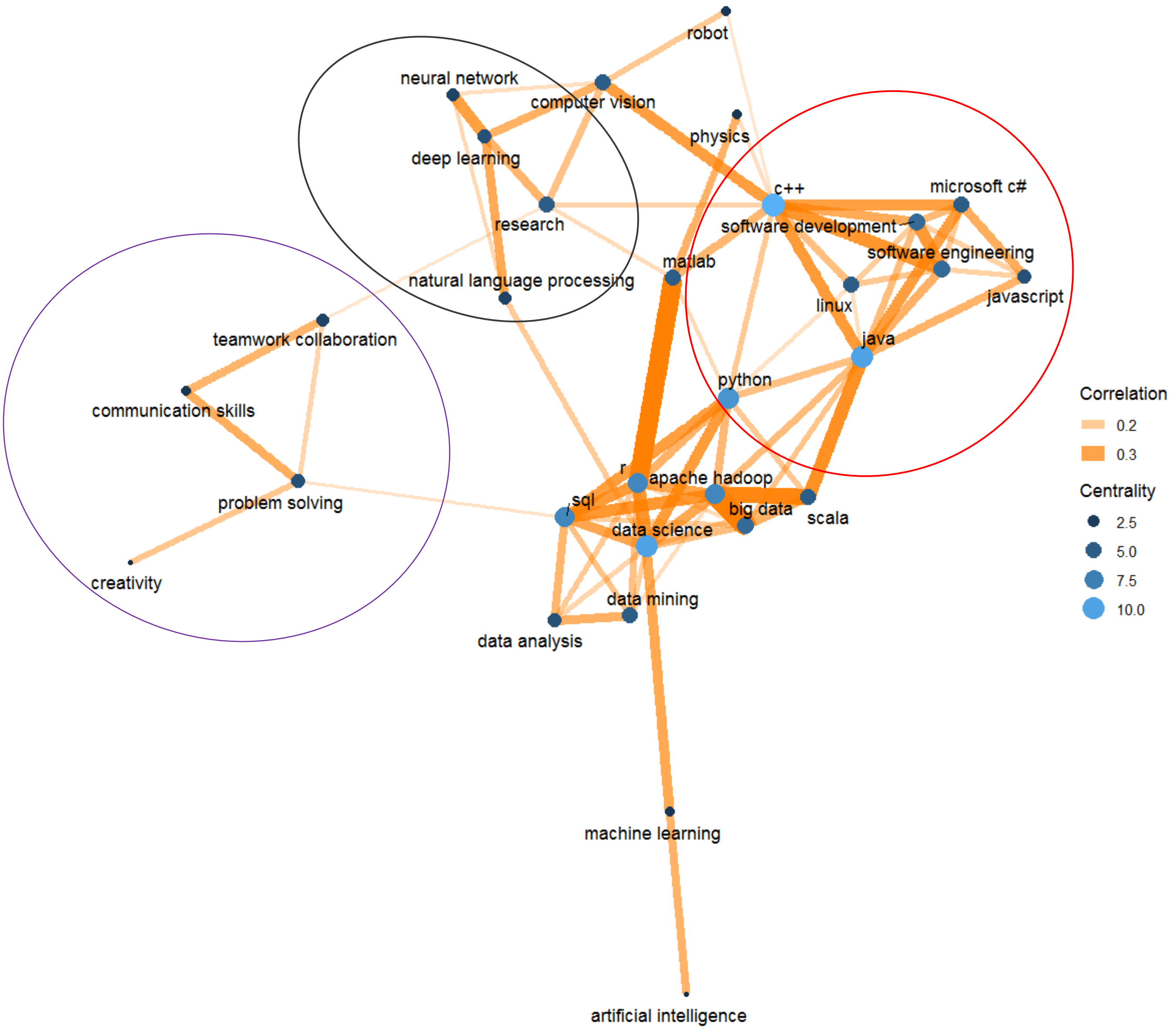
Network of skills with correlation > 0.1



Note: The identified skill bundles are colour coded as follows: 1) programming and software-related skills are red; 2) management of big data is green; 3) data analysis tools and broader analytical skills are blue; and 4) socio-emotional skills are purple. However, instead of a blue circled bundle, a black circled bundle emerges with different subsets of AI technologies.
Source: Authors' own compilation based on BGT data

Figure A.5. Top 30 skills in AI-related jobs, United Kingdom, Professionals, 2017-19

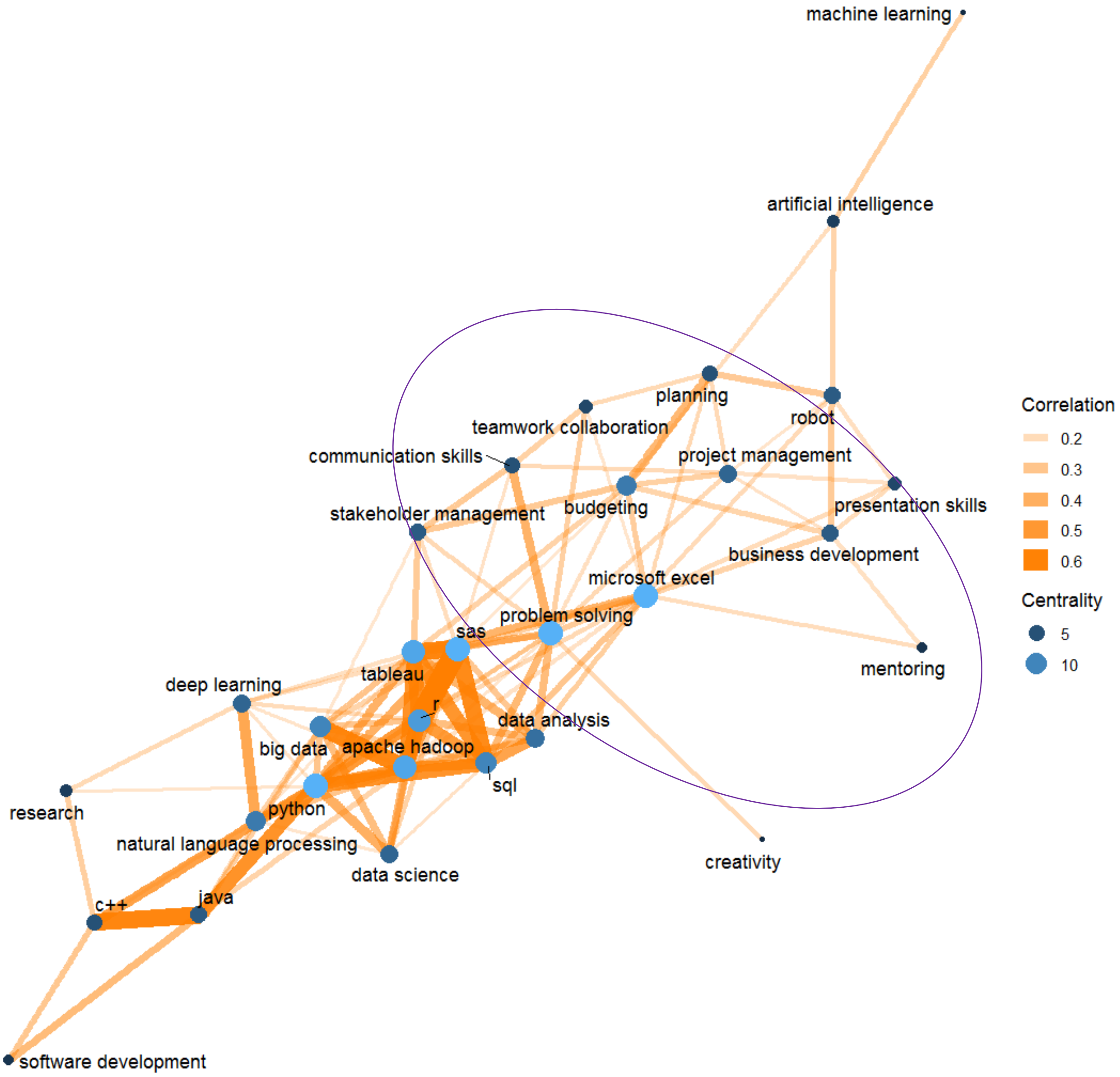
Network of skills with correlation > 0.1



Note: Professionals, defined by 1-digit International Standard Classification of Occupations (ISCO) code. The identified skill bundles are colour coded as follows: 1) programming and software-related skills are red; 2) socio-emotional skills are purple. An additional black circled bundle emerges with different subsets of AI technologies.
Source: Authors' own compilation based on BGT data.

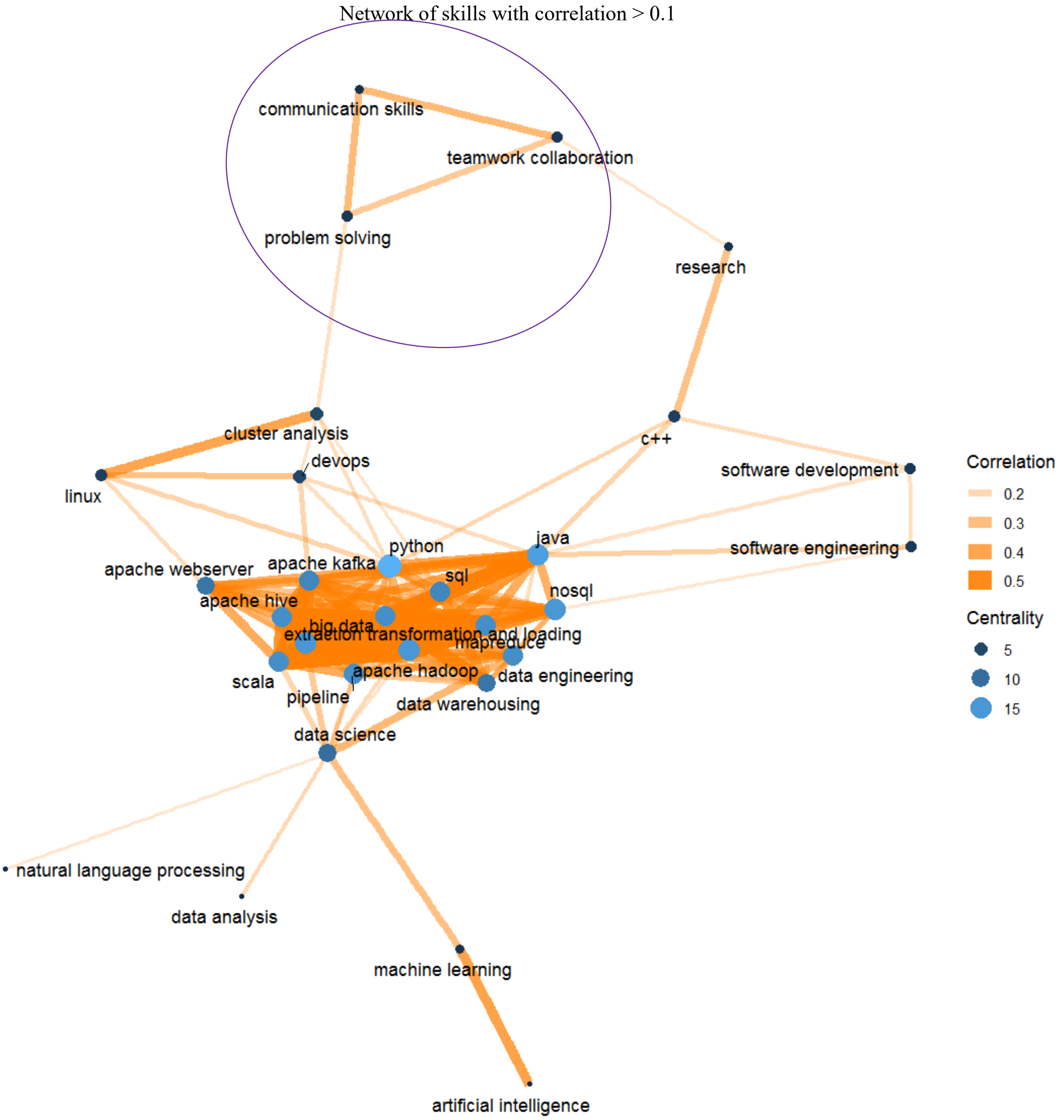
Figure A.6. Top 30 skills in AI-related jobs, United Kingdom, Managers, 2017-19

Network of skills with correlation > 0.1



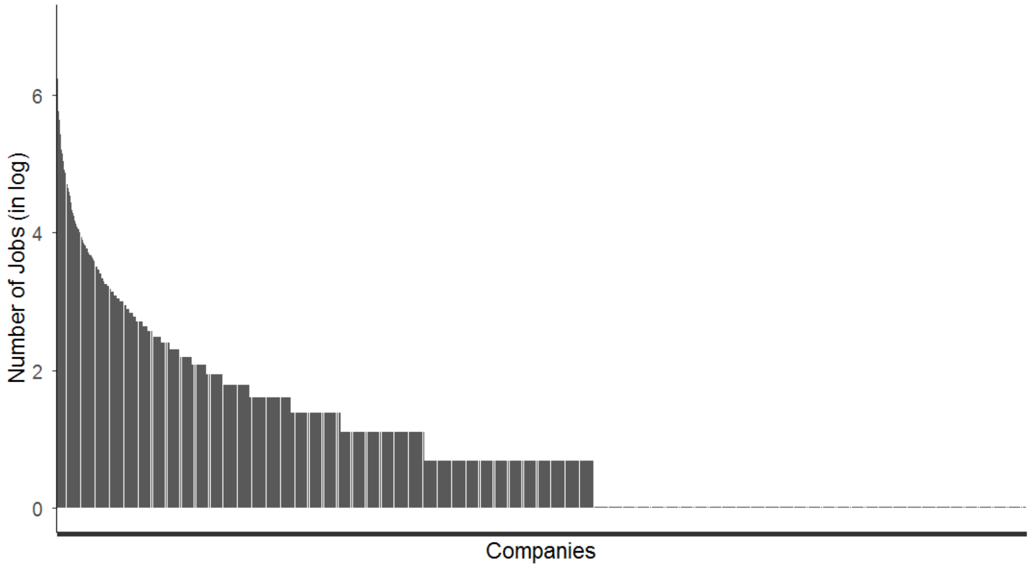
Note: Managers, defined by 1-digit International Standard Classification of Occupations (ISCO) code. The identified socio-emotional skill bundle is colour coded purple.
Source: Authors' own compilation based on BGT data.

Figure A.7. Top 30 skills in AI-related jobs, United Kingdom, Technicians, 2017-19



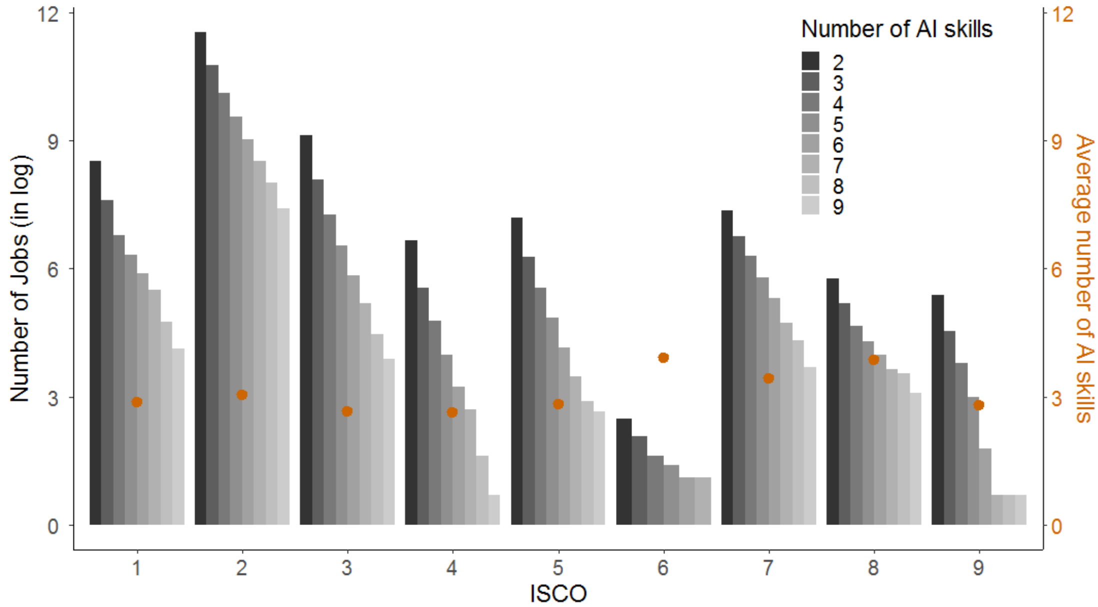
Note: Technicians, defined by 1-digit International Standard Classification of Occupations (ISCO) code. The identified socio-emotional skill bundle is colour coded purple.
Source: Authors' own compilation based on BGT data.

Figure A.8. Number of AI-related jobs (in log) by company, United Kingdom, 2012-19



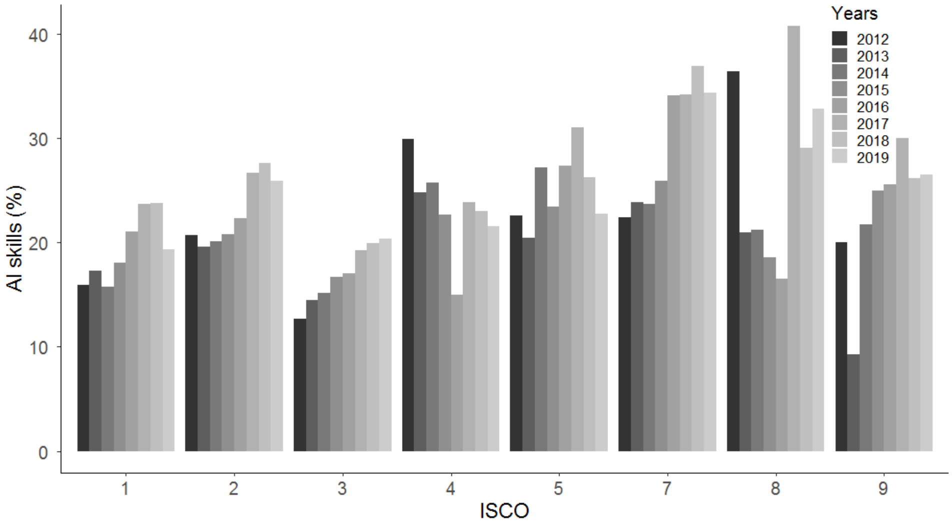
Note: Based on 5,515 companies demanding AI-related workers in the period 2012-2019.
Source: Authors' own compilation based on BGT data.

Figure A.9. Number of jobs (in log) and average number of AI skills within jobs for different occupations, United Kingdom, 2012-19



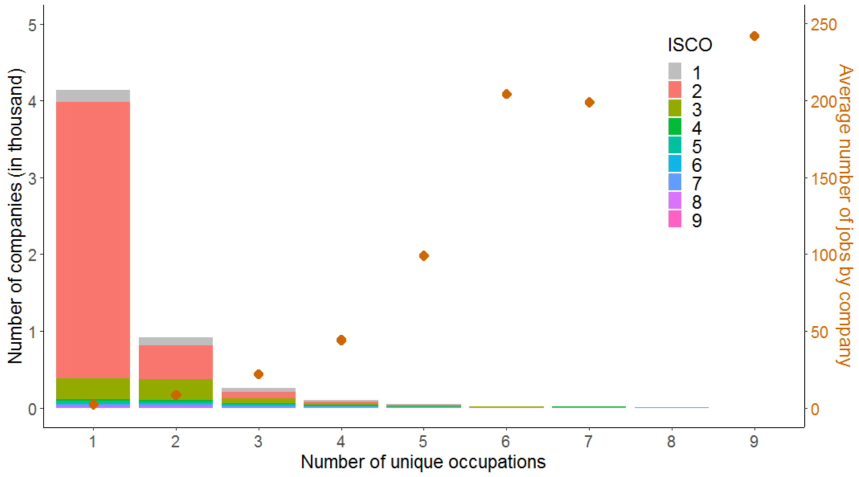
Note: Occupations are defined by 1-digit International Standard Classification of Occupations (ISCO) code. Codes represent: 1) Managers; 2) Professionals; 3) Technicians and associate professionals; 4) Clerical support workers; 5) Service and sales workers; 6) Skilled agricultural forestry and fishery workers; 7) Craft and related trades workers; 8) Plant and machine operators, and assemblers; 9) Elementary occupations.
Source: Authors' own compilation based on BGT data.

Figure A.10. Share of AI skills out of total skills by occupation, United Kingdom, 2012-19



Note: The share of AI skills is calculated by dividing the number of AI skills by the total number of skills. Occupations are defined by 1-digit International Standard Classification of Occupations (ISCO) code. Codes represent: 1) Managers; 2) Professionals; 3) Technicians and associate professionals; 4) Clerical support workers; 5) Service and sales workers; 7) Craft and related trades workers; 8) Plant and machine operators, and assemblers; 9) Elementary occupations. ISCO 6, representing Skilled agricultural forestry and fishery workers, is not displayed in this figure because of the small number of AI jobs related to this occupation group.
Source: Authors' own compilation based on BGT data.

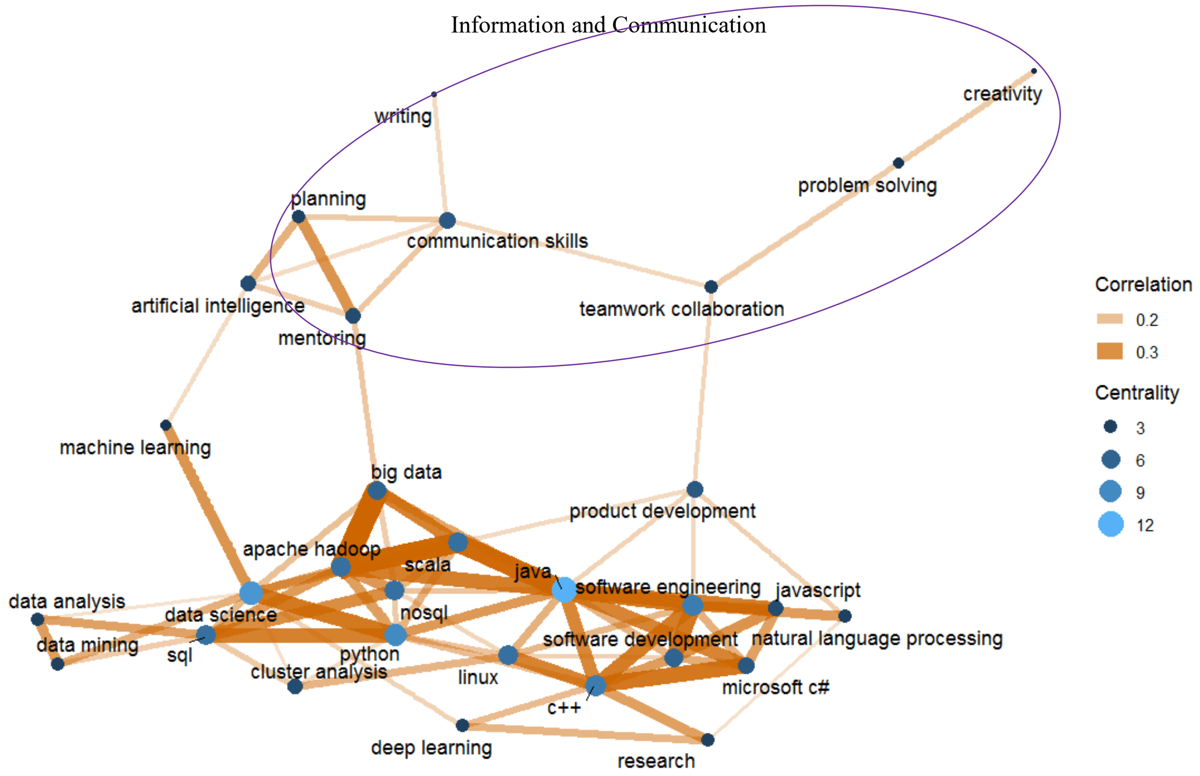
Figure A.11. Number of companies demanding different number of unique ISCO occupations, United Kingdom, 2012-19



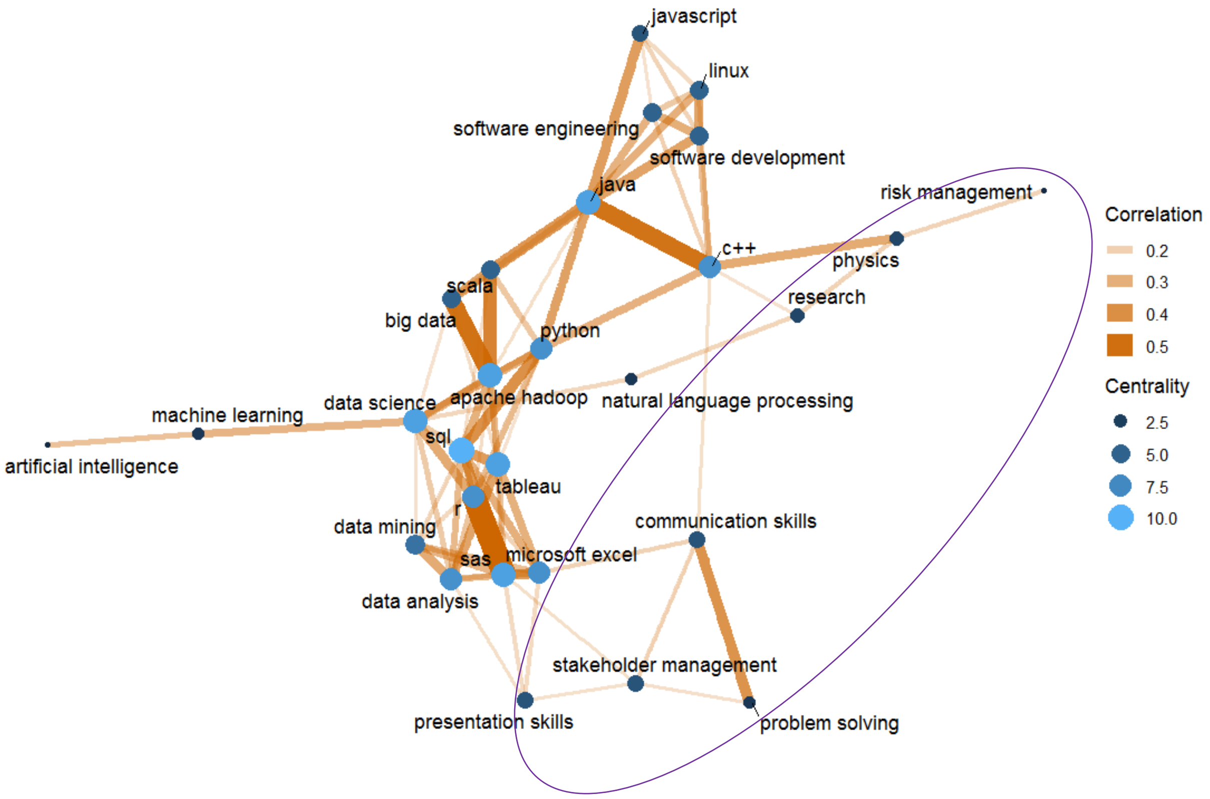
Note: Left axis shows the number of companies demanding x number of unique 1-digit ISCO occupations. The orange diamonds denote the average number of AI-related jobs demanded by companies posting vacancies related to the number of unique 1-digit ISCO occupations. The colours of the bars denote the occupational group that is demanded which are defined by 1-digit International Standard Classification of Occupations (ISCO) code representing: 1) Managers; 2) Professionals; 3) Technicians and associate professionals; 4) Clerical support workers; 5) Service and sales workers; 6) Skilled agricultural forestry and fishery workers; 7) Craft and related trades workers; 8) Plant and machine operators, and assemblers; 9) Elementary occupations. The diamond for 8 unique occupations falls outside the figure to allow better visibility of the other diamonds, but represents an average number of 400 jobs by company. The average number of jobs by company (the diamonds) varies from 2.2 for companies demanding one unique occupation to 400 jobs for companies demanding AI related jobs for 8 unique occupations.
Source: Authors' own compilation based on BGT data.

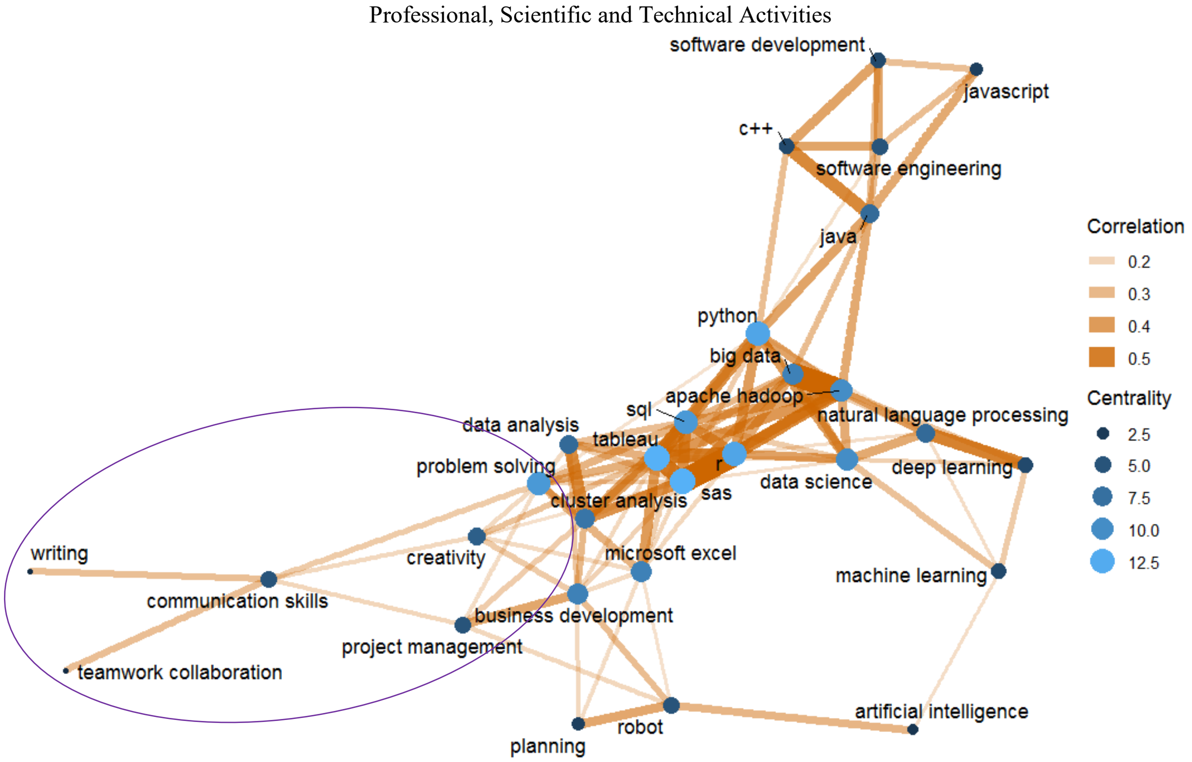
Figure A.12. Top 30 skills in AI-related jobs, United Kingdom, Business services, 2017-19

Information and Communication



Financial and Insurance Activities

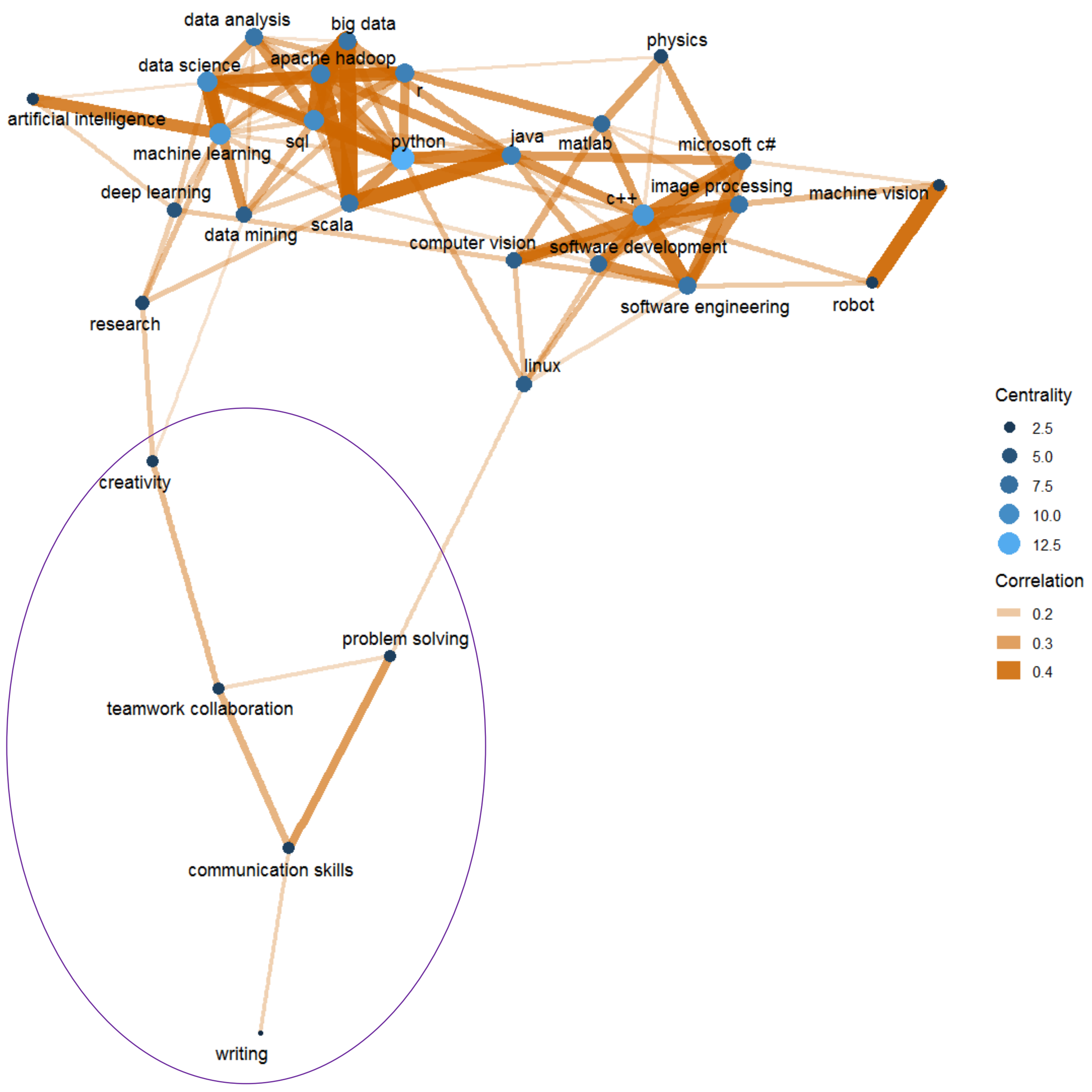




Note: Network of skills with correlation > 0.1; Information and Communication sector is defined by ISIC Rev 4 code J, Financial and Insurance Activities by code K and Professional, Scientific and Technical Activities by code M. The identified socio-emotional skill bundle is colour coded purple.
Source: Authors' own compilation based on BGT data.

Figure A.13. Top 30 skills in AI-related jobs, United Kingdom, Manufacturing, 2017-19

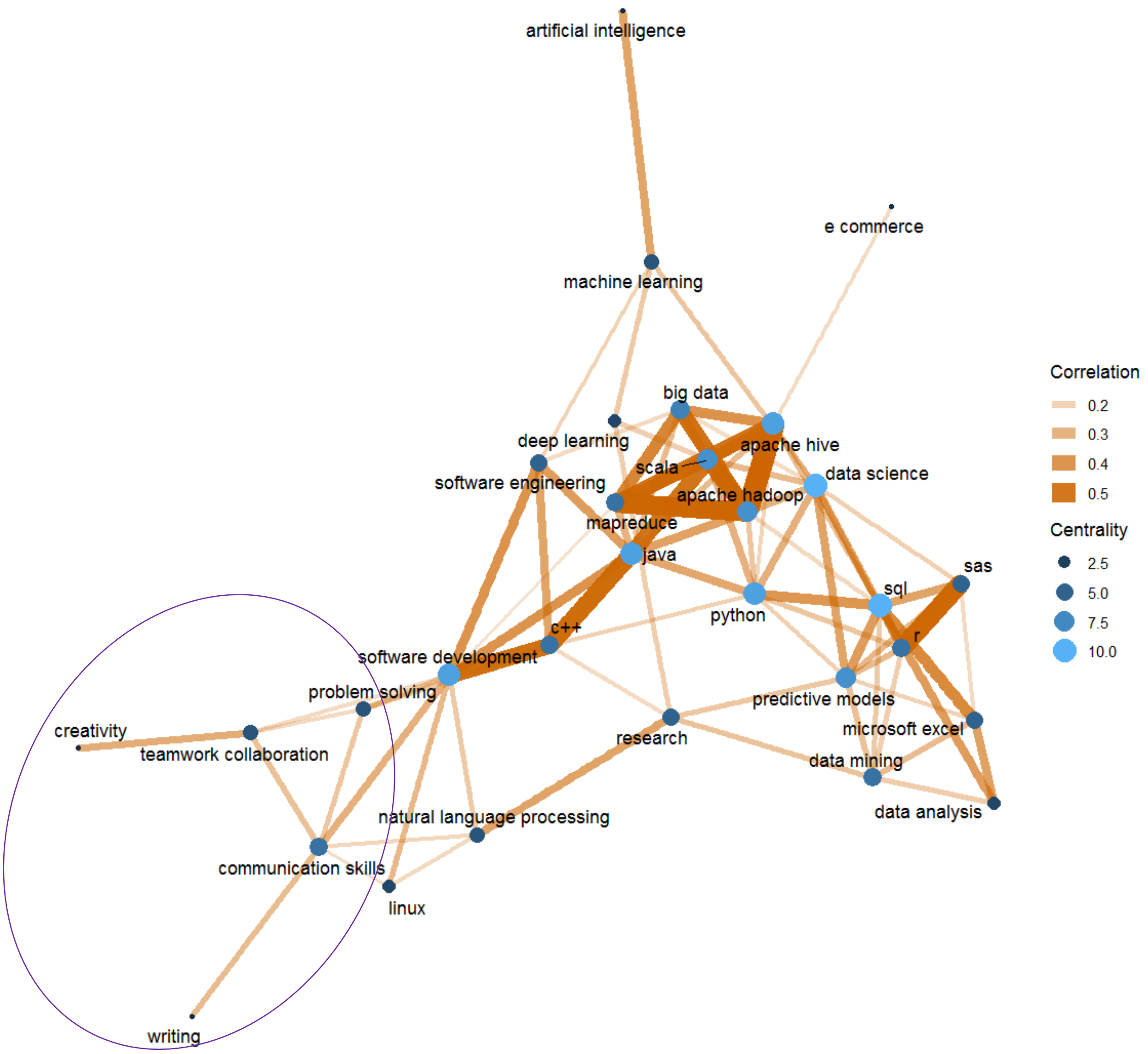
Network of skills with correlation > 0.1



Note: Manufacturing is defined by ISIC Rev 4 code C. The identified socio-emotional skill bundle is colour coded purple.
Source: Authors' own compilation based on BGT data.

Figure A.14. Top 30 skills in AI-related jobs, United Kingdom, Wholesale and Retail, 2017-19

Network of skills with correlation > 0.1



Note: Wholesale and Retail is defined by ISIC Rev 4 code G. The identified socio-emotional skill bundle is colour coded purple.
Source: Authors' own compilation based on BGT data.

Annex B. Hierarchical Clustering

The previous network analyses, which relied on correlations between skills, revealed a number of skill bundles in both, the United States and the United Kingdom. Using a different network feature that relies on hierarchical clustering, we can group nodes together if there is a higher density of edges within groups than between those groups. In other words, skills form a bundle if they are more frequently demanded together than with any of the skills outside of that bundle.

Although many algorithms have been created to construct different networks and address their respective characteristics, they tend to be demanding in terms of computational power and time. We therefore use a much less demanding and commonly employed algorithm (Newman, 2004[41]; Clauset, Newman and Moore, 2004[42]; Wakita and Tsurumi, 2007[43]), called community detection, which relies on modularity, i.e. a measure of the quality with which the network is partitioned into groups. The algorithm starts with each node being the only member of a community. Two communities are then joined together iteratively if their union yields the largest increase in the current modularity score, i.e. the union is locally optimal. The clustering is completed when modularity can no longer be improved.

Modularity is proportional to the number of links within a group, relative to what we would expect if we randomly rewired the network (thereby keeping the total number of nodes and edges constant).

$$Modularity = \frac{1}{2m}\sum_{C}\sum_{i\in C}\sum_{j\in C}\left(A_{ij} - \frac{k_i k_j}{2m}\right),$$

where A is the adjacency matrix or, in other words, the number of edges connecting two skills, m is the total number of edges in the network, k is the degree of the node and C is the community.

The network modularity score is usually between one and minus one where higher scores suggest a more pronounced community structure with scores exceeding 0.3 being considered as strong community structures. Scores around zero suggest that the partitioning has not picked up any community structure. As the following findings reveal, modularity scores of our skill clusters are just below 0.2 implying a weaker partitioning of skill bundles. However, this does not invalidate the existence of skill bundles or the demand for more specialised skills but merely shows that the composition of skills within bundles is not set in stone.

Figure B.1 shows the communities of AI-related skills found in AI-related jobs in the United States in the recent period covering 2017 to 2019. For clarity, only the most frequently appearing skill pairs are analysed, meaning that they have to appear more than 3,000 times in United States' job postings during that period to be included.

The skill bundles emerging in this network are very similar to the ones already identified in the previous network based on correlations. Here, we also find four skill bundles which distinguish skills necessary to apply AI (green) from advancing AI (yellow) as well as skills related to robotics (in red) and software (in blue).

Therefore, this analytical approach re-emphasises the fact that skills related to AI applications form an integral part in the skill profile of AI talent by permeating all skill bundles and hence the majority of AI-related jobs. This is also supported by the modularity score of 0.15, suggesting that the partitions between the identified community structures are not strong. Modularity increases slightly (0.18) when the AI application bundle is dissolved and its skill components are allocated to the remaining clusters.

When conducting the cluster analysis for the United Kingdom, as shown in Figure B.2, five skill clusters are revealed. Given the smaller number of online job vacancies in that country, we reduce the threshold and only analyse skill pairs appearing more than 450 times between 2017 and 2019.

For the United Kingdom, the skill composition of the AI application (pink), AI development (green) and AI-related software (blue) skill bundles is, in large, consistent with the skill mix observed in the correlation analysis and also in the cluster analysis carried out for the United States. The additional cluster in red emerges as a result of deep learning related competencies splitting from the robotics cluster (yellow). While it could be argued that deep learning and its frameworks form a bundle in itself, its connection to the remaining four skill bundles (e.g. natural language processing, robotics, (un)supervised learning, cluster analysis and data mining) and the network's relatively low modularity score of 0.16 rather indicate weak partitioning. That is to say, the skill bundles may not be as distinct or independent as the graph initially suggests.

Finally, the approach confirms, for both the United States and the United Kingdom, that Python and ML are at the centre, having direct links to (almost) all the skills presented in this network. However, it is worth reiterating that this approach is based on co-occurrences, i.e. pairwise skill counts, and so these results are not surprising. In the correlation network, which looks at how often skills appear together relative to appearing separately, competencies related to neural networks stood out linking the two skill bundles related to AI applications and AI developments. While the analysis here generally supports these observations, it also highlights that employers, who look for workers endowed with neural network related competencies, tend to also demand a wide range of skills necessary to advance AI. In fact, AI applications related to deep learning are the driving force, often in combination with robot related competencies.

Figure B.1. Communities of AI-related skills in AI-related jobs, United States, 2017 - 19

Co-occurrences > 3,000; modularity = 0.15

Note: The identified skill bundles are colour coded as follows: 1) Skills related to developing and advancing AI are yellow; 2) AI applications are green; 3) robotics are red; and 4) software is blue.
Source: Authors' own compilation based on BGT data.

Figure B.2. Communities of AI-related skills in AI-related jobs, United Kingdom, 2017 - 19

Co-occurrences > 450; modularity = 0.16)

Note: The identified skill bundles are colour coded as follows: 1) Skills related to developing and advancing AI are green; 2) AI applications are pink; 3) robotics are yellow; 4) software is blue; and 5) deep learning in red.
Source: Authors' own compilation based on BGT data.

This raises the question of the role socio-emotional and other less technical skills play and if/how skill clusters change when they are also taken into account. Figure B.3 and Figure B.4 show the skill clusters that emerge when looking at the top 30 most demanded skills over the period 2017 to 2019 in the United States and the United Kingdom, respectively. Given that the focus in this part of the analysis is on very frequently appearing skills, the threshold is increases significantly to display only skill pairs appearing more than 39,000 times in the United States and 5,500 times in the United Kingdom.

In both countries, four clusters emerge, which broadly speaking relate to big data (blue), software (red), programming (green) and socio-emotional (yellow) skills, being in line with the findings previously revealed by the correlation networks for the top 30 skills in Figure 6.3.

However, the previous analysis has also shown that socio-emotional skills build their own, very distinct skill bundle, which is only weakly correlated with AI-related skills. That is not to say that they are not important or that it is sufficient for AI talent to be solely endowed with technical skills. Instead, it merely showed that socio-emotional skills are increasingly demanded as a bundle, i.e. they are more often mentioned together in an online job posting than they are mentioned separately.

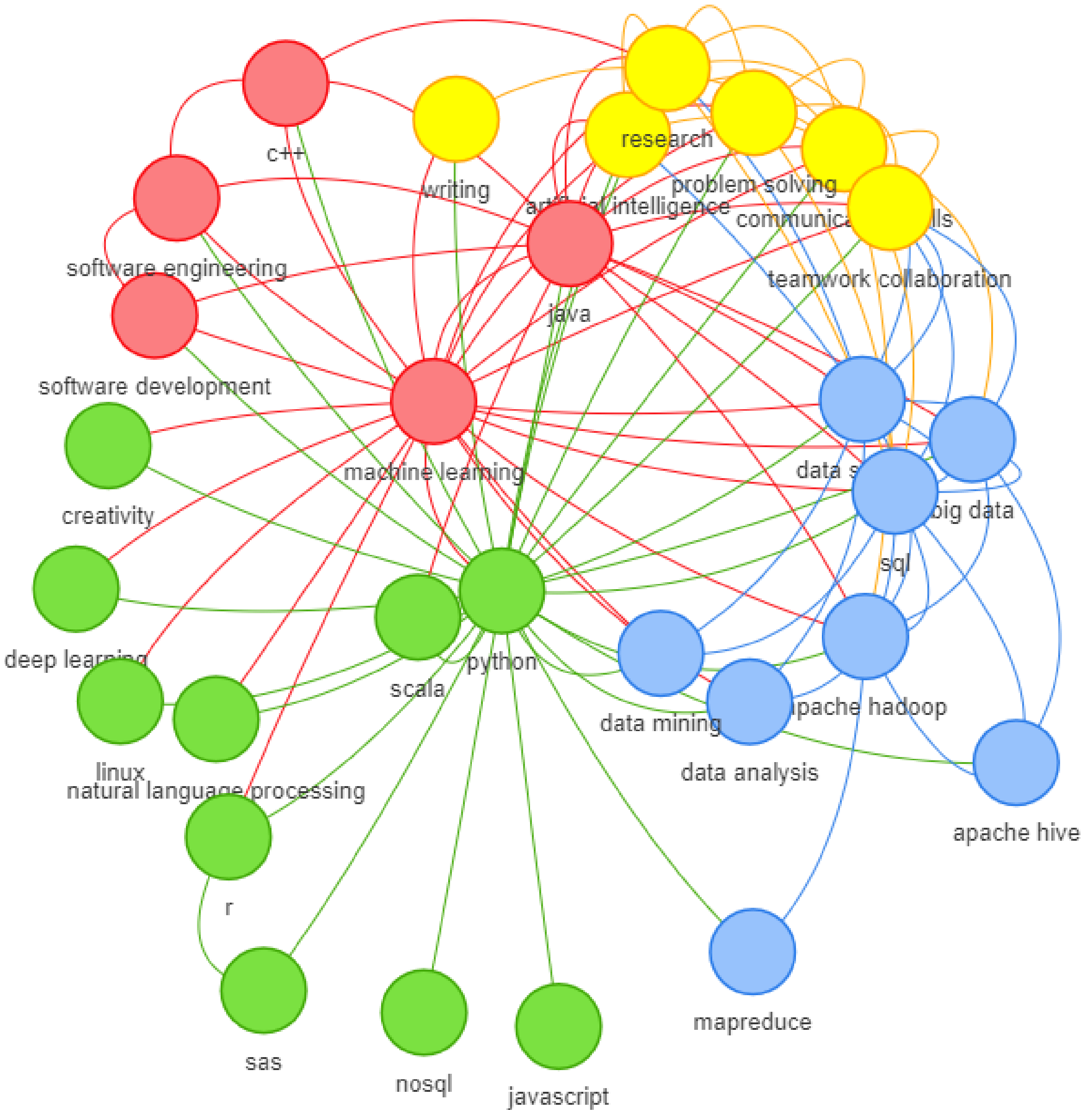
Building on these findings, the community cluster analysis shows that, while competencies related to communication, teamwork and research form their own cluster in both countries, creativity is rather associated with programming related skills; and so is problem solving in the United Kingdom.

Java and *data science* also constitute a considerable part of the skill profiles of AI-related jobs advertised online. As part of the software and big data related skill clusters, they are frequently demanded with *Python, ML* and socio-emotional skills.

The modularity scores of 0.17 and 0.19 for the United States and the United Kingdom respectively suggest that the identified community structure for the top 30 skills demanded in AI-related jobs is also relatively weak.

Figure B.3. Communities of the top 30 skills in AI-related jobs, United States, 2017 - 19

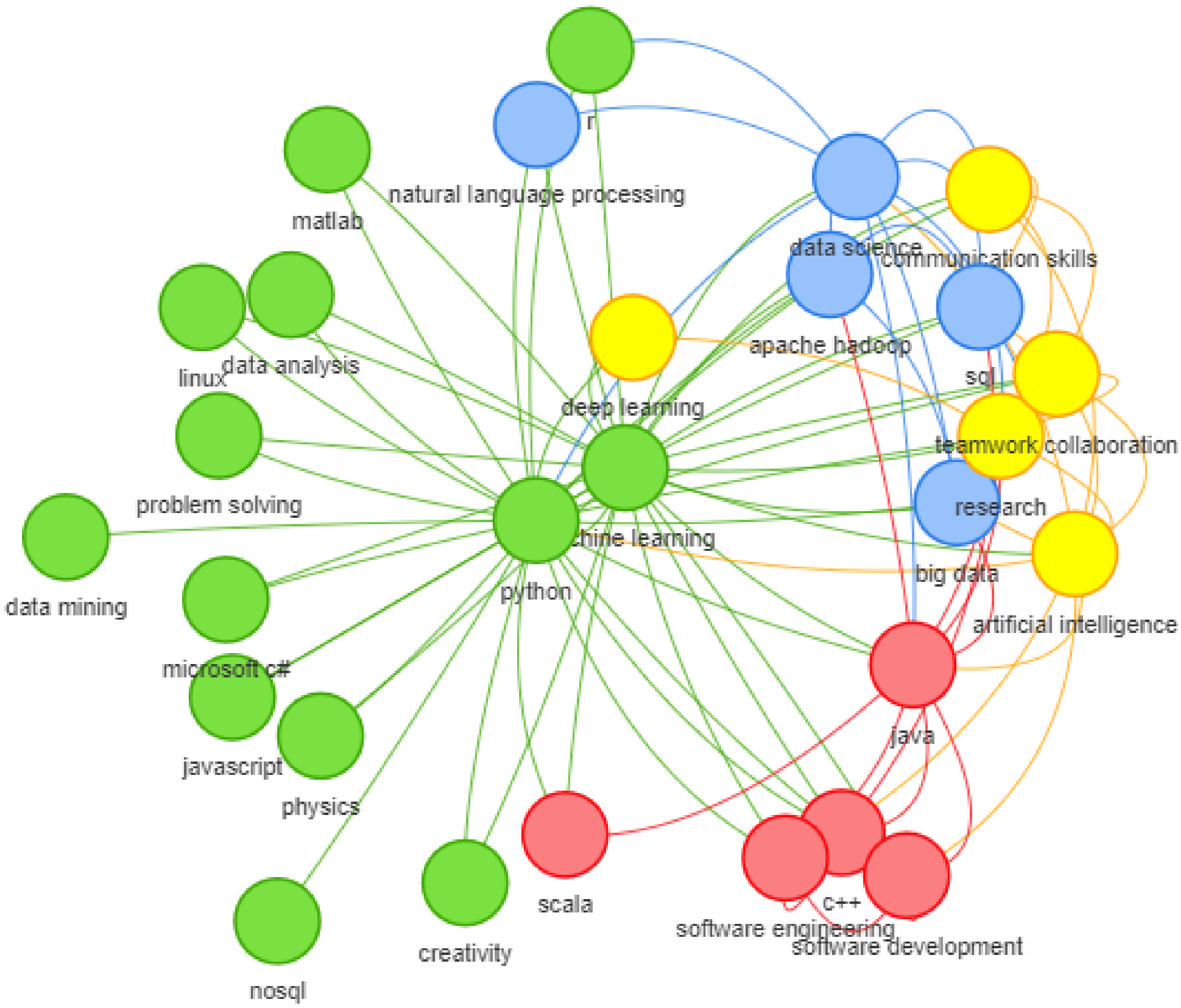
Co-occurrences > 39,000); modularity = 0.17



Note: The identified skill bundles are colour coded as follows: 1) programming skills are green; 2) management of big data is blue; 3) software skills are red; and 4) socio-emotional skills are yellow.
Source: Authors' own compilation based on BGT data.

Figure B.4. Communities of the top 30 skills in AI-related jobs, United Kingdom, 2017 – 19

Co-occurrences > 5,500; modularity = 0.19



Note: The identified skill bundles are colour coded as follows: 1) programming skills are green; 2) management of big data is blue; 3) software skills are red; and 4) socio-emotional skills are yellow.
Source: Authors' own compilation based on BGT data.