Dynamics of Skill Relatedness Density: Similarity and Complementarity Influencing Company Demand for AI Skills

Genghao Zhang, [a,*] Emmanouil Tranos, [a] and Rui Zhu[a]

[a] *School of Geographical Sciences, University of Bristol, Bristol, United Kingdom*

* *Corresponding author (Genghao Zhang): genghao.zhang@bristol.ac.uk*

Abstract

Demand for Artificial Intelligence (AI) skills is unevenly distributed among regions. This multi-scale study employs online job advertisements data to develop the measurement of skill relatedness density distinguishing between AI-complementary and fundamental skills. Multilevel logit regressions find that single-locational companies seeking AI skills are more likely to be spatially sorted into the labour markets specialised in more AI-complementary skills. In contrast, regions cultivate skill structures specialised in either more complementary or fundamental skills to stimulate AI skill demand among multi-locational companies. These geographical mechanisms promote regional policy debates about the diffusion and application of AI skills among regions.

Keywords: Skill relatedness density; Online job vacancies; Skill complementarity; Spatial sorting

JEL Classification: L86, R12, O33, J23

1. Introduction

Artificial intelligence (AI) technologies are widely expected to improve company and regional productivity (Barzotto and De Propris 2019; Brynjolfsson et al. 2021). However, the adoption of AI technologies remains highly uneven across different local and regional labour markets (Kalyani et al. 2025; Rouwendal et al. 2026; Zhang et al. 2025a). Such studies use the company demand for AI skills as the proxy of the adoption of AI technologies by companies. These geographical patterns reflect the location choices and hiring decisions of individual companies, contingent upon local capacities (Frigon and Rigby 2024; Neffke et al. 2018). For instance, the early demand for AI skills is disproportionately concentrated among large and economically advanced companies within specific knowledge-intensive sectors (Acemoglu et al. 2023; Alekseeva et al. 2021; Babina et al. 2024; Zhang et al. 2025a). Rather than being an isolated company-level effort searching for AI skills, the adoption of AI technologies is also deeply contingent upon the company's capabilities to recombine similar and complementary resources in the local environment, such as specialised digital skills and place-based expertise (Barzotto and De Propris 2019; Hunt et al. 2024). To avoid potential productivity disparities among regions, it is essential to further investigate the company demand for AI skills by integrating the regional and company-level and examine the dynamics of regional capacities over time as AI technologies are increasingly diffused.

In labour economics, the adoption of AI by companies is found to be correlated with internal resources, such as high-tech occupations (Draca et al. 2024), digital and computing capacities (McElheran et al. 2024; Rouwendal et al. 2026), company investment in research and development (R&D) activities, and business expansion (Acemoglu et al. 2023; Alekseeva et al. 2021). At the regional level, evolutionary economic geographers demonstrated that local capacities such as industrial structure (Zhang et al. 2025a), ICT-related patents (Xiao and Boschma 2023), and research-intensive universities (Hunt et al. 2024) influence regional

concentration of AI technologies. Nevertheless, these studies overlook the multi-scale processes of this phenomenon that the company demand for AI skills can be inter-related with the availability of existing skills in regional labour markets. Furthermore, limited research distinguishes regional skill structures between skills similar and fundamental to AI and the other skills complementary to AI (thereafter, AI-fundamental and AI-complementary skills), facilitating the development and application of AI technologies in labour markets. It is important to conduct such a multi-scale, skill similarity-complementarity study since the spatial patterns of the demand for AI skills are the joint outcome of concurrent regional and company-level dynamics.

A skill is defined as occupation-based requirements (Neffke 2019) or task-oriented capabilities (Gathmann and Schönberg 2010). As for the former, skills are accumulated by workers through official education in specific disciplines and can be similar or complementary to colleagues in occupations within any company (Neffke 2019). Skills in the same occupation are considered as similar and substitutable skills between workers in the same company, while skills from different occupations are defined as complementary skills among colleagues (Neffke 2019). As for the latter study, skills are developed and enhanced by hands-on experience or learning-by-doing in analytical or manual tasks (Gathmann and Schönberg 2010). These studies do not define a type of skills simply as an abstract qualification or a single occupation but as task-based proficiency that is interactive and communicable among colleagues, transferable among occupations by job switches, and accumulated over time. However, the former study ignores that skills are accumulated differently through practical tasks and in-house training even in the same occupation. There are also strong interactions outside single companies in regional labour markets (Barzotto and De Propris 2019; Chen et al., 2025; Deegan et al., 2024; Neffke et al., 2018). The latter study depends on static survey data collected in many years to measure self-reporting skills classified in a simplified scope of

capabilities. Building upon these definitions, our study further defines skills as worker capacities expected to accomplish various tasks required by companies in labour demand of each job position. This skill definition not only considers job requirements for initial endowment and essential abilities of workers but also expectations of new primary skills potentially learned and developed in future work.

The demand for AI skills refers to worker competencies required by companies to develop or adopt AI methods, tools, or solutions for problem-solving (Acemoglu et al. 2022; Hunt et al. 2024; Zhang et al. 2025a). According to the task-based approach (Gathmann and Schönberg 2010), workers in companies can utilise AI methods to predict processes of firm production and quality assurance and, of course, incorporate them in service and production activities. Such AI skills can both substitute and augment existing non-AI skills, such as coding, analytical thinking, or creativity in various occupations within industries (Acemoglu et al. 2022; Goldfarb et al. 2023; Mäkelä and Stephany 2024; Stephany and Teutloff 2024; Wang et al., 2026a). These integration effects such as skill substitution and augmentation are mainly achieved by AI workers performing tasks that AI skills can accomplish within companies, cities, or regional labour markets (Acemoglu et al. 2022; Neffke 2019; Wang et al., 2026a).

According to the skill relatedness literature (Buyukyazici and Coll-Martínez 2026; Chen et al. 2025; Fitjar and Timmermans 2016; Neffke et al. 2018), the geography of the demand for AI skills can be shaped by related skill structures. These local skill structures anchore primarily in regions already specialised in similar, fundamental, or complementary skills relative to AI. From a skill similarity perspective (Buarque et al. 2020; Xiao and Boschma 2023), companies may seek workers in regions with the specialisation in fundamental skills[1]

[1] Fundamental skills include information technology (IT) and mathematical modelling (Math) skills, the very varieties from which AI originates (Buarque et al. 2020).

to develop state-of-the-art AI algorithms or apply AI technologies in analytical tasks efficiently. These fundamental skills may be spatially concentrated in knowledge-intensive city-regions (Buarque et al. 2020; Hunt et al. 2024; Xiao and Boschma 2023; Zhang et al. 2025a). From a skill complementarity perspective, companies in regions specialised in AI-complementary skills[2] are also likely to attract or search for workers using AI skills for exploration of combinatorial potentials in various application domains, such as law, business management, customer services, manufacturing, biosciences, cultural and creative services (Mäkelä and Stephany 2024; Santoalha et al. 2021; Wang et al. 2026a). These AI-complementary skills can be more spatially concentrated in large, diverse city-regions (Balland et al. 2020; Neffke 2019). Thus, it is important to distinguish these different geographies of regional skill structures influencing the generation and concentration of AI skill demand for the development and application of AI technologies by local companies to a different extent.

Different types of companies with varying internal resources may utilise these two regional skill structures differently for generating the demand for AI skills. As demonstrated by Frigon and Rigby (2024) and Neffke et al. (2018), multi-locational companies facilitate the diffusion of novel technologies among regions by establishing new subsidiary firms based on internal resources. By comparison, single-locational companies rely heavily on existing regional resources, which further deepen the region's existing skill specialisations. As for the demand for AI skills, single-locational companies may considerably rely on local workers either with highly specialised IT and Mathematical modelling skills to support the adoption of AI services (McElheran et al. 2024). Or they can also rely on local workers specialised in the complementary skills to adopt AI methods in specialised application domains. In contrast,

[2] In contrast, AI-complementary skills are other non-AI, -IT, and -Math, skills with the varying degree of relatedness to AI across application sectors (Mäkelä and Stephany 2024).

multi-locational companies may be able to attract and redistribute workers with AI and fundamental similar skills among their firms to the regions specialised in the complementary skills for AI application or development in local sectors (Babina et al. 2024; Neffke et al. 2018). There is a lack of research further investigating and distinguishing how regional skill structures influence the demand for AI skills between these two types of companies differently.

To address these research gaps, this study examines how regional skill structures influence the company-level demand for AI skills. It operationalises the company demand for AI by using OJAs requiring AI skills, such as machine learning, computer vision, generative AI, or large language models (LLM). Building upon a skill relatedness framework, the study adopts multilevel logit models to regress the likelihood of local companies seeking AI skills in regional labour markets in Great Britain between 2017-2024 on regional skill relatedness density. More specifically, the study separates data samples into two groups, one for single-locational companies and the other for multi-locational companies. By doing so, models investigate how regional skill relatedness density of the AI-fundamental or AI-complementary skills correlates with the likelihood of single-locational companies searching for AI skills or multi-locational companies spatially concentrating AI skill demand in the region.

Research results indicate that regions spatially sort single-locational companies seeking AI skills to the regional labour market specialised in more complementary skills, especially during 2018-2019 and 2023-2024. Internal resources of single-locational companies may determine their decision of adopting and seeking AI skills. Regional capacities of AI-complementary skill structures may also facilitate the application of AI skills in local industries by single-locational companies. These single-locational companies searching for AI skills are geographically dispersed in Great Britain between 2017-2024, which indicates the pervasive diffusion of simple AI skills among regions over time (Kalyani et al. 2025). In contrast, regions acting as incubators can build and accumulate local capacities specialised in more either AI-

complementary or fundamental (IT and Math) skills to foster the demand for AI skills from multi-locational companies in the labour market. These multi-locational companies may utilise regional skill structures by combining both AI-complementary and fundamental capabilities to further develop or apply more complex AI skills in diverse industries. They spatially concentrated their demand for AI skills in large, knowledge-intensive, and diverse regions, which supports the theory of Hidalgo (2021) and empirical research of Balland et al. (2020) and Babina (2024). These diverging, dynamic effects between companies promote academic and policy discussions.

Contributions of this paper is three-fold. First, research findings talk to empirical debates about uneven geographies of AI skills adopted by companies, which are centered around labour economics, economic geography, and regional studies. Especially, the paper brings new light into how these notions of skill relatedness shape the demand for AI skills over time for single- and multi-locational companies. Diverging patterns for these two companies revisit the traditional theory of agglomeration economies in which small and single-locational companies cluster in large and dense regions to recruit competent workers, adopt emerging technologies, and learn new experience. Multi-locational companies utilise locally specialised capacities to foster their intensive adoption of AI skills, debating about corporate agency in regional development demonstrated by Zhang and Rigby (2022), Frigon and Rigby (2024), Neffke (2019), and Neffke et al. (2018).

Second, it offers a novel measurement of skill relatedness density about the AI-complementary and fundamental skills reflected in the OJA data. Third, separating relatedness between complementarity and similarity facilitates the formulation of more detailed place-based policies. For instance, one type of policy could be regional digitalisation and retraining programs to improve fundamental skills of local labour force. This policy could facilitate the spatial concentration of AI skills by multi-locational companies to further develop or apply

complex AI technologies. Another policy could be subsidizing regional investment in AI-complementary assets such as skilled workers and proprietary data in specialised sectors for diverse AI application. This type of regional policy can facilitate the extensive diffusion of AI skills among local companies across different application domains and potentially decrease economic disparities among regions.

The structure of this paper is shown as follows. The next section is a literature review discussing how skill relatedness density influences the demand for AI skills from single- and multi-locational companies. Four theoretical hypotheses are proposed. The third section introduces research data of OJAs and the multilevel models. The fourth section presents, interprets, and discusses regression results. The fifth section concludes this study by summarising research findings, implications, and limitations.

2. Literature review

Demand for AI skills is predominantly conceptualised in the literature as the human capital requirements that companies actively seek through job vacancies to adopt, maintain, and develop artificial intelligence technologies, methods, services, or tools (Acemoglu et al. 2022; Alekseeva et al. 2021; Rouwendal et al. 2026; Zhang et al. 2025a). Theoretical debates of the demand for AI center around labour economics, economic geography, and regional studies.

Labour economists focusing on internal resources justify how companies integrate AI skills into existing production inputs based on cost management and firm productivity (Acemoglu et al. 2022; Alekseeva et al. 2021). Furthermore, multi-locational companies can take advantage of internal pipelines to absorb and diffuse non-local technologies like AI among own establishments beyond the place-based effects of regional capacities (Acemoglu et al. 2023; Frigon and Rigby 2024; Zhang and Rigby 2022). The configuration and quality of company networks also influence the adoption and spatial diffusion of AI (Dahlke et al. 2024). Except for these internal resources, urban economists add that city-regions act as agglomerated,

competitive markets to share amenities, human capital, complex knowledge, and product markets among local companies (Balland et al. 2020; Rubinton 2025). In addition, local companies tend to imitate the adoption of AI technologies in the local environment with complex AI knowledge in the air (Dahlke et al. 2024). Evolutionary economic geographers further argue that technological (un)relatedness density of inventions shapes the regional development trajectory of emerging digital technologies and such AI-related demand (Boschma et al. 2023; Chen and Wu 2025). However, limited research investigates geographical mechanisms of the company-level demand for AI skills from the perspectives of multi-scale and skill relatedness. These processes of generating and spatially concentrating AI skill demand by local companies are not only the outcome of endogenous regional development but also individual selection of different companies.

A substantial body of empirical studies demonstrates an increase and diffusion of the demand for AI skills among companies. For instance, the adoption of AI technologies is positively correlated with large and cash-rich enterprises that heavily invest in R&D activities (Acemoglu et al. 2023; Alekseeva et al. 2021). The intensity of companies adopting machine learning has a positive association with their proportion of professionals from Science, Technology, Engineering, and Mathematics (STEM) occupations in the UK (Draca et al. 2024). That is to say, scale and functions of individual companies play crucial roles in influencing the demand for AI skills (Rouwendal et al. 2026). At the regional level, the literature highlights that the diffusion of AI skill demand is geographically uneven (Zhang et al. 2025a). It frequently clusters in knowledge-intensive hubs and urban areas that already possess a strong knowledge infrastructure or an early history of AI-related industries (Hunt et al. 2024; Xiao and Boschma 2023; Zhang et al. 2025a). Despite these insights, existing research fails to recognise that a company's demand for AI skills not only occur within companies but also is

intricately inter-related with the existing availability of related skills in regional labour markets (Park and Kim 2026; Santoalha et al. 2021; Wang et al. 2026b).

Skill relatedness fundamentally shapes the development trajectory of local labour demand. Skill relatedness density represents the extent to which a region's specialised skill structure lays the foundation of promoting the demand for new skills, as a proxy for the local capacity to absorb and support new related skills (Park and Kim 2026; Wang et al. 2026b). Previous research measured skill relatedness based on broad industry classifications or labour mobility patterns across sub-industries (Fitjar and Timmermans 2016; Neffke et al. 2018). Recent studies used industry-occupation co-occurrence in regions to compute skill relatedness density (Chen et al. 2025; Buyukyazici and Coll-Martínez 2026). However, AI as an emerging digital, general-purpose technology cannot be fully identified by any single industrial, technological, or occupational classification. In addition, these conventional definitions can risk conflating genuine skill relatedness with corporate network effects, institutional cultures, or historical geographical co-location. Thus, it would be more appropriate to analyse the extent of co-occurrence between AI and other non-AI skills from each job demand in regional labour markets, revealing the demand for AI skills in the future.

To understand how skill relatedness density can shape the demand for AI skills from local companies, it is crucial to conceptualise and distinguish between skill similarity and skill complementarity. Skill similarity between fundamental skills and AI indicates the level that skills from the same knowledge field of information technology, computing, and mathematics are required to complete the similar analytical tasks relative to AI technologies (Buarque et al. 2020; Verma et al. 2022). In contrast, AI-complementarity refers to proficiencies drawn from other skill groups with complementary capacities across diverse application domains and sectors, such as management, healthcare, or business services (Mäkelä and Stephany 2024; Stephany and Teutloff 2024).

Each type of relatedness drives company demand for AI skills through distinct mechanisms. fundamental skills similar to AI can extensively promote the demand for AI skills since companies require related technical expertise to directly build, programme, and refine AI algorithms and software architectures (Alekseeva et al. 2021; Rouwendal et al. 2026). Conversely, AI-complementary skills also fuel the demand for AI skills since AI acts as a general purpose technology that can be integrated with diverse domain-specific knowledge (Goldfarb et al. 2023; Santoalha et al. 2021; Wang et al. 2026a). Companies actively seek out these complementary skills since applying AI to business and production processes requires adaptive problem-solving, communication, and sector-specific expertise (Mäkelä and Stephany 2024; Stephany and Teutloff 2024). This recruitment decision also explains why employers offer substantial wage premiums for roles that combine AI capabilities with management or sector-specialised skills (Alekseeva et al. 2021; Stephany and Teutloff 2024).

These two relatedness densities influence the demand for AI skills from local companies by fundamentally lowering the barriers to the adoption of AI technologies (Park and Kim 2026). A dense cluster of fundamental skills similar to AI provides local companies with a readily accessible pool of technical talent to produce advanced digital services or adopt existing AI services. In contrast, a high density of AI-complementary skills supplies local companies with the crucial absorptive capacity required to effectively apply and commercialise AI tools across specialised industries.

Distinct spatial constraints of skill relatedness between single- and multi-locational companies fundamentally influence their recruitment strategies of AI skills in regions. Since single-locational companies are geographically bound to their local environment (Neffke et al. 2018), their likelihood of seeking any AI skill is directly dependent on the surrounding regional skill relatedness density (Rouwendal et al. 2026). Single-locational companies may search for local workers with highly specialised IT and mathematical modelling skills to support the

adoption of AI services or tools (Zhang et al. 2025a). This occurs in regions where the density of fundamental skills is pronounced. Alternatively, they can also rely on local workers specialised in complementary skills to adopt AI methods within specialised application domains (Santoalha et al. 2021). This integrative potential can be achieved by these companies drawing heavily on the local workforce's domain expertise when the region exhibits a high density of AI-complementary skills (Wang et al. 2026a, 2026b). Accordingly, the study proposes two hypotheses as follows.

Hypothesis 1: Single-locational companies are more likely to seek AI skills in the regions specialised in more complementary skills.

Hypothesis 2: Single-locational companies are more likely to seek AI skills in the regions specialised in more fundamental skills.

In contrast, multi-locational companies possess the organisational and geographic flexibility to bypass the constraints of a single local labour market (Zhang and Rigby 2022). By locating establishments in different regions, multi-locational companies choose to access heterogeneous labour pools, which are configurated by regional specialisations in various skills (Frigon and Rigby 2024; Neffke et al. 2018). Rather than depending solely on the pre-existing skill structure of one specific region, these companies may be able to attract and redistribute human capital (Zhang and Rigby 2022). For instance, they can re-locate workers with fundamental AI skills among their firms to the regions specialised in complementary skills for not only the application of AI technologies but also the production of AI services in local sectors.

This internal redistribution enables multi-locational companies to efficiently match mobile, IT specialists with place-based domain experts. By doing so, these companies are more likely to spatially concentrate their AI skill demand in large and knowledge-intensive regions to utilise locally dense, fundamental and AI-complementary skills (Balland et al. 2020; Hunt

et al. 2024; Rubinton 2025). In comparison, single-locational companies subject to both internal resources and place-based capacities may generate the demand for simpler AI skills among regions, for example, the adoption of AI tools or methods in local industries (Hidalgo 2021; Kalyani et al. 2025). Accordingly, the study proposes another two hypotheses as follows.

Hypothesis 3: Multi-locational companies are more likely to spatially concentrate AI skill demand in the regions specialised in more complementary skills.

Hypothesis 4: Multi-locational companies are more likely to spatially concentrate AI skill demand in the regions specialised in more fundamental skills.

3. Methodology

3.1 Data

To capture such patterns of the adoption of AI technologies, researchers have been relied, almost exclusively, on patent data (Boschma et al. 2023; Chen and Wu 2025; Santoalha et al. 2021; Xiao and Boschma 2023). Useful as such data is, patents only capture the tip of the iceberg in terms of technology usage. To overcome this issue, this study follows previous work from Acemoglu et al. (2022), Kalyani et al. (2025), Rouwendal et al. (2026) and Zhang et al. (2025a), and employ novel data from online job advertisements (OJA). OJAs provide more granular and broader coverage to investigate geographies of AI demand. This OJA dataset is not biased in comparison to employment data from the Office for National Statistics (ONS) in terms of broad occupation classifications (SOC2020) in the UK.[3]

This OJA dataset is useful because OJAs indicate company demand for specific skills in local economies (Draca et al. 2024; Kalyani et al. 2025). Adzuna is an online job search engine managing hundreds of millions of OJAs, which contain detailed job category and occupation labels (Zhang et al. 2025a). These OJAs posted on the Adzuna platform are mainly

[3] Comparison results can be provided upon a proper request.

retrieved from employer websites, online job boards, and third-party recruitment agencies (Adzuna 2025). This dataset has been preprocessed by Adzuna, and OJAs that are filled, expired, or are identical duplicates have been removed (Zhang et al. 2025a). Each Adzuna OJA includes an advert ID, a timestamp of each job posting, a company name, skills and job descriptions, longitude and latitude, a job category, and additional metadata.

This study focuses on OJAs requiring AI skills to capture the company demand for AI skills (Zhang et al. 2025). It defines an OJA as an AI OJA if it contains at least one general AI keyword and at least one specific AI keyword in its skill or job descriptions (Goldfarb et al. 2023). These two groups of (general and specific) AI keywords are classified by Maslej et al. (2025) in a Stanford AI 2025 report. General AI keywords represent clusters of AI skills such as generative AI and machine learning, while specific AI keywords refer to technical skills within each AI cluster, for instance, prompt engineering and reinforcement learning (see Appendix A).

After data cleaning, Figure 1 illustrates the number and share of AI OJAs in Great Britain during 2017-2024. The share of AI OJAs substantially increased between 2017-2022 (up to 0.56% in 2022) while slightly decreased in 2023 and then, increased to 0.6% in 2024. This sudden decrease in the share of AI OJAs may be attributed to the launch of ChatGPT in November 2022, which can substitute traditional data science or natural language processing skills and over time, increase the demand for large language modelling skills such as prompt engineering (Mäkelä and Stephany 2024). However, the shares of AI OJAs are generally stable and therefore, these data patterns do not significantly affect our regression results. Against this backdrop, the study conducts robustness tests by estimating yearly effects at the end of sub-sections 4.1 and 4.2 (see Appendix E: OJA Observations). Figure 2 shows the frequency distribution of AI keywords among all AI OJAs where automation, machine learning, robotics,

artificial intelligence, automation systems, and deep learning rank as the top 6 most frequent keywords during 2017-2024.

After identifying AI OJAs, the next step is to clean company names of OJAs. For instance, the study removes OJAs posted by third-party recruitment companies with its name containing any text related to ‘recruit’, ‘people’, ‘job’, ‘resourcing’, or ‘staff’. Then, the study distinguishes the company between single- and multi-locational companies according to the number of regional labour markets where a company post OJAs. For instance, a company is defined as a single-locational company if it posts OJAs only in one regional labour market during the study period between 2017-2024; otherwise, it is multi-locational. The regional labour market in Great Britain is defined as travel to work areas (TTWA) within which most workers reside and commute on a daily basis, and companies interact intensively.

Figure 3 illustrates that single-locational companies seeking AI skills is spatially dispersed during the study period. In the map, these single-locational companies adopting AI are spatially concentrated in not only large or knowledge-intensive regions like London, Oxford, and Cambridge, but also remote areas like Ullapool and small towns such as Minehead, Bude, Malton, Newtown and Welshpool. This geographical pattern indicates the diffusion outcome of AI technologies to single-locational companies among regions. Another map also illustrates a similar, geographically dispersed pattern, which shows the share of AI OJAs posted among these single-locational companies in Table A.1 in Appendix A. According to Hidalgo (2021) and Kalyani et al. (2025), these single-locational companies may tend to adopt simple AI technologies.

Figure 4 shows that the demand for AI skills from multi-locational companies is spatially concentrated in large, diverse, or knowledge-intensive regions and their neighbouring regions, including Cambridge, Stevenage and Welwyn, Oxford, London, Edinburgh, and Bristol. According to Balland et al. (2020) and Kalyani et al. (2025), these multi-locational

companies may intensively search for AI talent in these industrialised regions to develop or apply more complex AI technologies than single-locational companies.



Figure 1. Count of AI OJAs (in thousands, left) and share of AI OJAs (%, right) in each year between 2017-2024 in Great Britain.

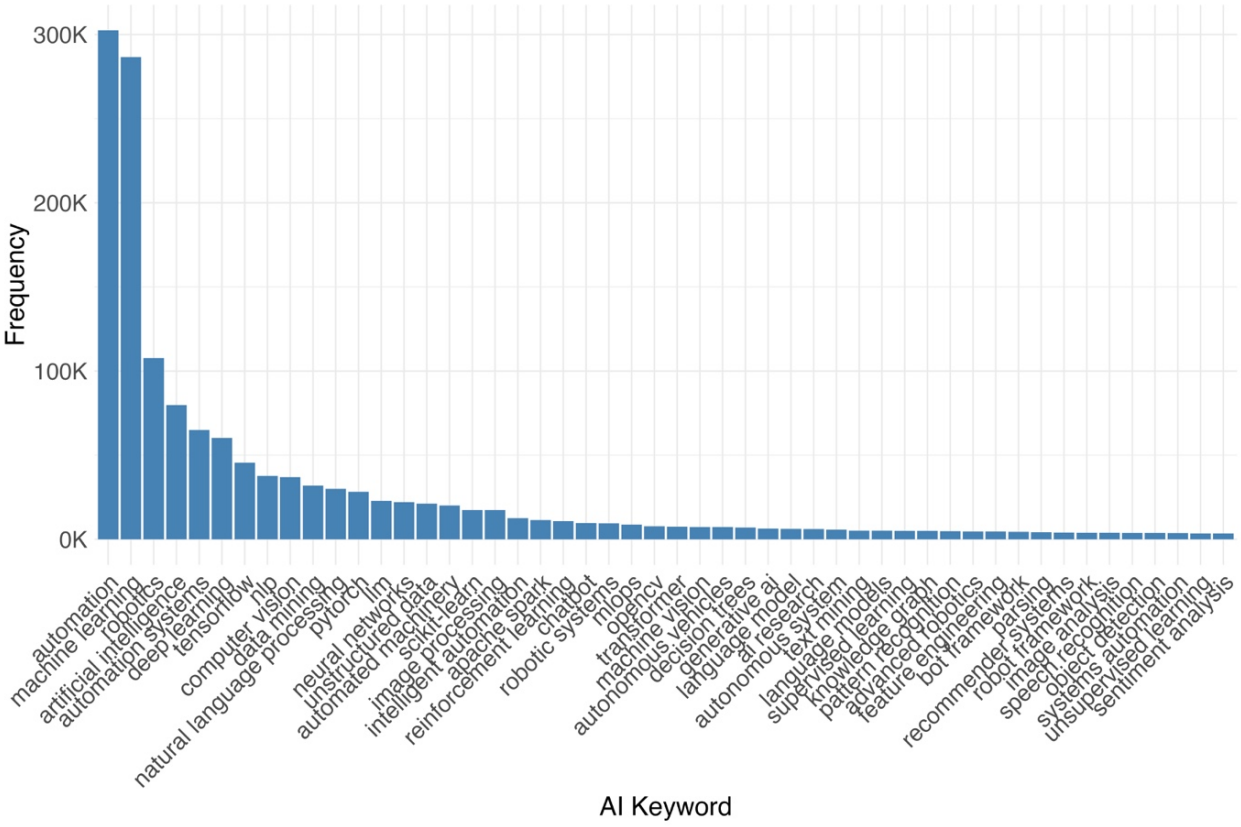


Figure 2. AI keywords frequency among AI OJAs during 2017-2024 in Great Britain.

Note: This figure removes AI keywords with the frequency less than 3,500 among all AI OJAs.

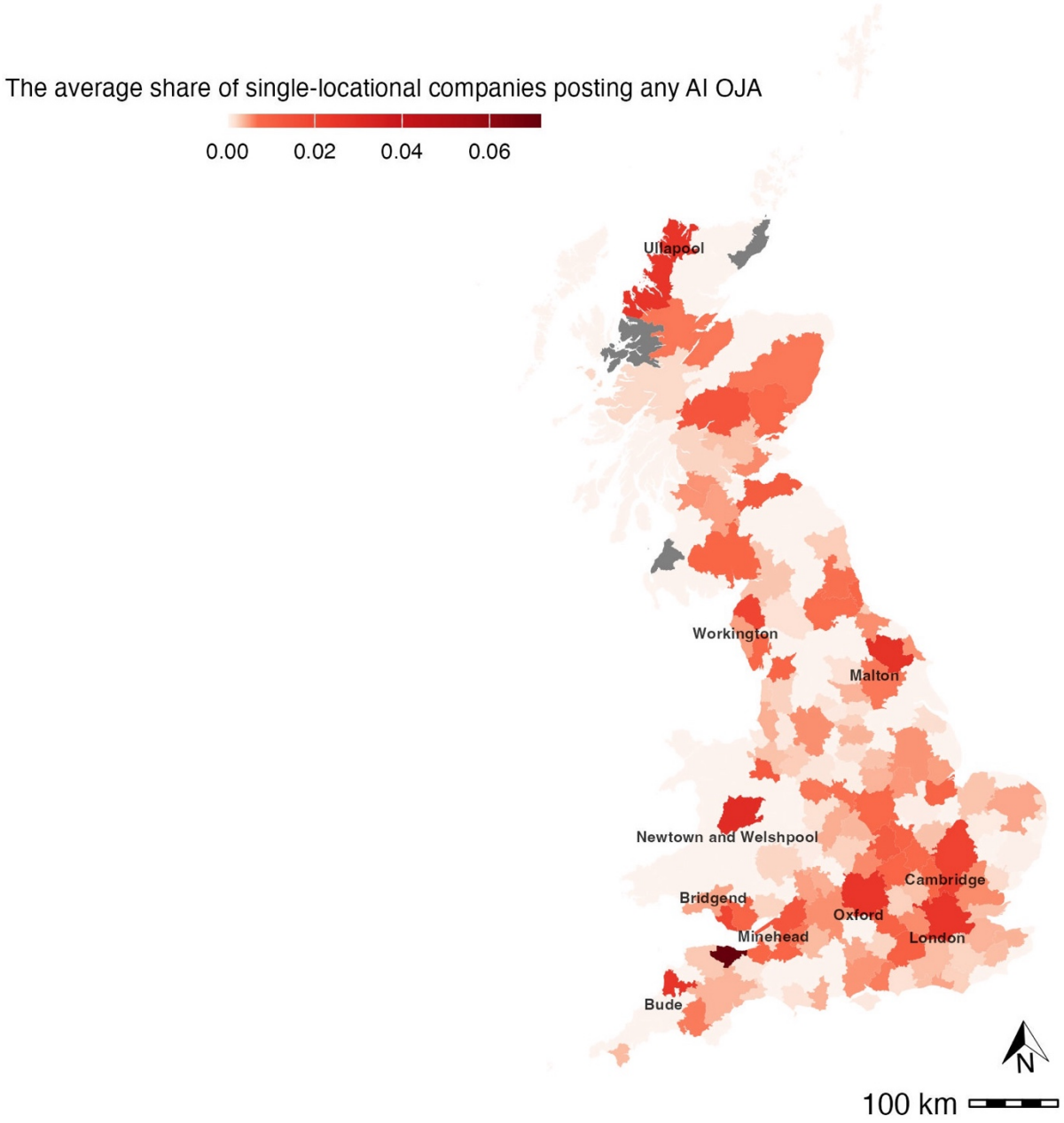


Figure 3. The average share of single-locational companies posting any AI OJA over all single-locational companies in Great Britain, 2017-2024

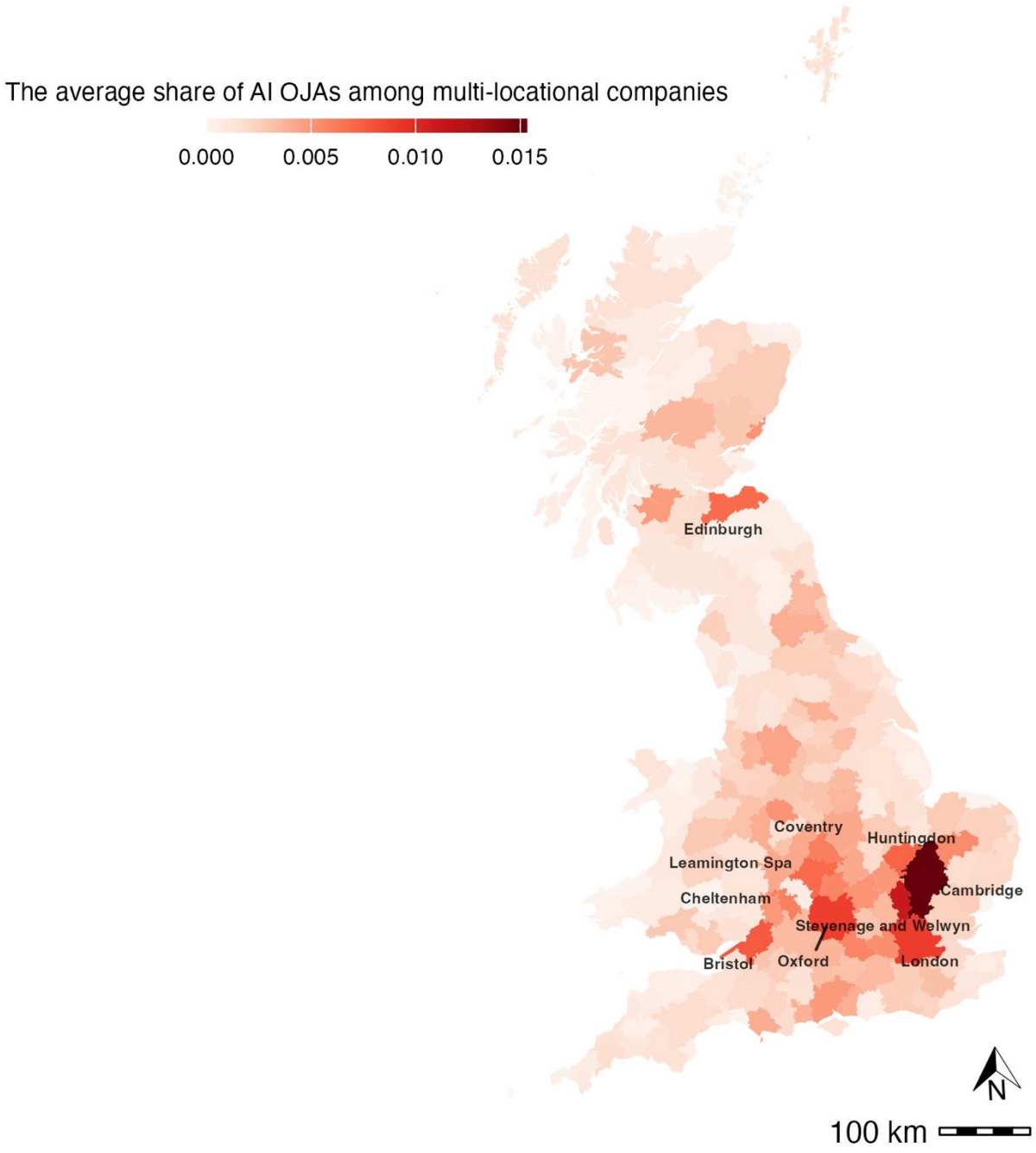


Figure 4. The average share of AI OJAs posted among multi-locational companies

3.2. Methods

According to the literature review, the adoption of AI by companies among regions is a multiscale process. Within regions, regional skill relatedness to AI influences the demand for AI skills from local companies. Among regions, spatial concentration of AI technologies also influences geographical patterns of the company demand for AI skills, for instance, the London effect (Draca et al. 2024) or the Cambridge effect (Zhang et al. 2025a). Because of these geographical mechanisms, a company-level fixed effect model cannot meet the assumption that each company is independent and identically distributed. A company-region-level fixed effect model also cannot investigate how regional skill structures influence the company demand for AI skills. Therefore, the study adopts a multilevel modelling approach to estimate the spatial diffusion and concentration patterns of demand for broad AI skills by single- and multi-locational companies over time.

The baseline model (Equation (1)) is a multilevel logit regression model at the company and TTWA levels. The model includes a company-level random intercept (v_{c0t}) to control heterogeneity among companies (see Equation (2)) and another random intercept conditional on TTWA-level variables (λ_{0dt}) (see Equation (3)). Regression analyses estimate parameters of this model in R (version 4.4.0) by using a "glmmTMB" function (Brooks et al. 2017).

$$\log\left(\frac{P(AI_{\mathrm{cdt}}=1)}{1-P(AI_{cdt}=1)}\right) = \beta_{0\mathrm{cd}} + \sum_{k=1}^{2} Z_{kcdt-1}R_k + v_{c0t} + \lambda_{0dt} + \tau_t \quad (1)$$

$$v_{c0t} = \alpha_{0c0} + \varepsilon_{c0t} \quad (2)$$

$$\lambda_{0dt} = \gamma_{00\mathrm{d}} + \gamma_{10\mathrm{dt}-1}AIRD_Complementary + \gamma_{20\mathrm{dt}-1}AIRD_Similar + \sum_{j=5}^{11} Z_{j0dt-1}R_j +$$

$$\gamma_{30\mathrm{dt}-1}AIRD_Complementary * \tau_t + \gamma_{40\mathrm{dt}-1}AIRD_Similar * \tau_t + \varepsilon_{0dt} \quad (3)$$

where, AI_{cdt} refers to each of the two binary dependent variables. One is AI_Demand_{cdt} with the value of 1 if a single-locational company (c) in each TTWA (d) has any AI OJA posted in a year (t) between 2017-2024. The other is $AI_Demand_LQ_{\mathrm{cdt}}$ with the value of 1 if AI OJAs posted by all establishments of a multi-locational company (c) are spatially concentrated in a specific TTWA (d). Equations (4)-(5) as follows show the computation of AI_Demand_{cdt} and $AI_Demand_LQ_{\mathrm{cdt}}$.

$$AI_Demand_{\mathrm{cdt}} = \begin{cases} 0, & if\ a\ company\ (c)\ does\ not\ post\ any\ AI\ OJA\ in\ TTWA\ (d) \\ 1, & if\ a\ company\ (c)\ posts\ at\ least\ 1\ AI\ OJA\ in\ TTWA\ (d) \end{cases} \quad (4)$$

$$AI_Demand_LQ_{\mathrm{cdt}} = \begin{cases} 0, & if\ \frac{\lambda_{\mathrm{cdt}}/T_{\mathrm{cdt}}}{\sum_d \lambda_{\mathrm{cdt}}/\sum_d T_{\mathrm{cdt}}} < 1 \\ 1, & if\ \frac{\lambda_{\mathrm{cdt}}/T_{\mathrm{cdt}}}{\sum_d \lambda_{\mathrm{cdt}}/\sum_d T_{\mathrm{cdt}}} \geq 1 \end{cases} \quad (5)$$

where, AI_Demand_{cdt} is a binary variable indicating any demand for AI skills by each single-locational company (c) in the TTWA (d) in year t, while $AI_Demand_LQ_{\mathrm{cdt}}$ is a binary variable of the location quotient of AI OJAs among each multi-locational company's establishments in every TTWA in year t. λ_{cdt} refers to the number of AI OJAs requiring AI skills by a multi-locational company (c) within a TTWA (d) in a year t between 2017-2024. $\sum_d \lambda_{\mathrm{cdt}}$ indicates the total number of AI OJAs by the same multi-locational company (c) in all TTWAs (Σ_d) in Great Britain in t. T_{cdt} is the number of all OJAs posted by the same multi-locational company (c) within the TTWA (d) in the year t. $\sum_d T_{\mathrm{cdt}}$ refers to the total number of all OJAs posted by the same multi-locational company (c) in all TTWAs (Σ_d) in Great Britain in t.

R_k refers to two control variables at the company-region-year levels (see the sub-section 3.4). Z_{kcdt-1} is the estimated effect of each of these two control variables. v_{c0t} is the random effect of each unique company in Equation (1), and its computation is shown in Equation (2). λ_{0dt} is the random intercept conditional on TTWA-level variables.

$AIRD_Complementary$ and $AIRD_Similar$ are two independent variables of skill relatedness density relative to AI skills (see the sub-section 3.3 for variable construction). $\gamma_{10\mathrm{dt}-1}$ and $\gamma_{20\mathrm{dt}-1}$ are their estimated coefficients, respectively. R_j is a vector of TTWA-level control variables in $t-1$ (see sub-section 3.4), while $Z_{0\mathrm{jdt}-1}$ is a vector of corresponding coefficients. τ_t is a year fixed effect. $\gamma_{30\mathrm{dt}-1}$ and $\gamma_{40\mathrm{dt}-1}$ are yearly interaction effects. ε_{0dt} is an error term for unobserved variations at the TTWA level, while ε_{c0t} is its counterpart for each company. $\beta_{0\mathrm{d}}$, α_{c0}, and γ_{00} are constant terms.

In the baseline model, a few continuous variables with strong skewness are log-transformed (excluding the share variables) and then, all variables are taken z-score normalisation for efficient estimation, model convergence, and between-variable comparison. The model uses one year lag period for all explanatory variables to cope with potential endogeneity issues. For instance, it should take a year for competent employees to fill online job vacancies requiring specific skills, for instance the AI-complementary skills, which would influence company demand for AI skills in the future. In addition, the demand for AI skills may also influence the demand for the complementary skills in reverse in the same year (Mäkelä and Stephany 2024).

3.3. Relatedness density variables

Based on the OJA data, this study develops the measurement of skill relatedness density distinguishing between similarity and complementarity relative to AI skills in regions to estimate the likelihood of the company demand for AI skills.

The relatedness density is the share of AI relatedness degrees of skills ($i \in r;\ i \neq a$) in which each TTWA (d) is specialised ($\sum_{i\in r, i\neq a}^{r} S_{\mathrm{idt}-1} * \phi_{\mathrm{iat}-1}$) over the aggregated AI relatedness degrees of all skills ($\sum_{i\in r, i\neq a}^{r} \phi_{\mathrm{iat}-1}$). The degree of AI relatedness for each skill ($\phi_{\mathrm{iat}-1}$) is computed based on the probability of its co-occurrence (i) with AI skills (a) in every OJA in each year ($\mathrm{t}-1$) in Great Britain (Balland 2017; Balland et al. 2019; Chen and Wu

2025). Each skill (i) belongs to the entire skill structure (r) in each year ($r = 1, \dots, n; i = 1, \dots, k; k < n$), while the skill ($i$) is not an AI skill ($a$). The AI relatedness density of existing skill structures derived from OJAs in each TTWA is computed based on Equation (6).

Based on this equation, we compute the two main independent variables that include $AIRD_Complementary_{cdt}$ and $AIRD_Similar_{cdt}$. The first variable refers to the AI relatedness density of regionally specialised skills to which AI is complementary in TTWAs in each year. This variable excludes IT and Mathematical Modelling skills from the regional skill structures. The other variable indicates the AI relatedness density of IT and Mathematical Modelling skills since most AI technologies originate from computing and mathematics (Acemoglu et al. 2022; Buarque et al. 2020; Hunt et al. 2024). We further explain the computation process of skill relatedness density in Appendix B in details and interpret each definition in Table C.1 in Appendix C.

The reason of distinguishing these two $AIRD$ variables is that the combination between AI skills and the complementary skills lays the foundation of adopting AI skills in various application domains (Goldfarb et al. 2023). In contrast, the combination of AI and IT or Mathematical modelling skills can facilitate the development and application of state-of-the-art AI algorithms or innovation (Hunt et al. 2024; Xiao and Boschma 2023). The $AIRD_Complementary$ variable is used to test Hypothesis 1 and 3, and the $AIRD_Similar$ variable to test Hypothesis 2 and 4 (see Equations (6) and (7)). Even if these two types of skill relatedness density are distinguished in the definition, there should be some technical skills in the group of complementary skills highly related to the fundamental skills similar to AI. Following Neffke (2019), this study further estimates the residual of regressing $AIRD_Complementary_{cdt}$ on $AIRD_Similar_{cdt}$ to create a new variable of $AIRD_Complementary_{cdt}$ orthogonal to $AIRD_Similar_{cdt}$. In this way, two skill relatedness density variables are clearly distinguished in terms of concepts and measurement.

$$AIRD_{\mathrm{dt-1}} = \frac{\sum_{i\in r, i\neq a}^{r} S_{\mathrm{idt-1}} * \phi_{\mathrm{iat-1}}}{\sum_{i\in r, i\neq a}^{r} \phi_{\mathrm{iat-1}}} \quad (6)$$

$$AIRD_{cdt-1} = \begin{cases} AIRD_Similar_{cdt-1}, & if\ i \in \{IT,\ Math\} \\ AIRD_Complementary_{cdt-1}, & if\ i \notin \{IT,\ Math\} \end{cases} \quad (7)$$

where $S_{\mathrm{idt-1}}$ is 1 if the TTWA (d) has a regional specialisation in the skill (i) in the year of $t-1$; otherwise, $S_{\mathrm{idt-1}}$ is 0. $\phi_{\mathrm{iat-1}}$ is the degree of relatedness of each skill (i) related to AI skills (a), which indicates the normalised probability of its co-occurrence with the AI skills in every OJA in $t-1$ (Balland 2017; Balland et al. 2019; Boschma et al. 2023). IT refers to the skills classified as information technology by Lightcast (2025) while similarly, $Math$ indicates skills of mathematical modelling. We compute the degree of AI relatedness of each skill (i), and AI skill relatedness density in each TTWA by using the EconGeo R package developed by Balland (2017).

3.4. Control variables

There are two company-level control variables. The first one ($Total_OJA$) is the total number of OJAs posted by the company (c) within the TTWA (d) in the last year ($t-1$). In this way, the model controls the size effect of the company in a region. The second one ($Mean_Total_OJA$) is the average of OJAs posted by the company (c) within the TTWA (d) in every year during 2016-2023. By controlling this time-invariant variable, the model further controls company-level unobservable relevant to the company size reflected by job vacancies, for instance, company investment in labour recruitment, business scale, management culture, internal resources, and the stage of business expansion (Acemoglu et al. 2023; Babina et al. 2024; McElheran et al. 2024). In addition, considering the functions of the company, the model further controls a variable of company types at the company-TTWA-year levels. However, this additional variable could lead to endogeneity issues, possibly acting as the mediator of the effect of regional skill relatedness density on the company demand for AI skills. So, this

variable is included for robustness tests. See the variable definition in Table C.1 in Appendix C and estimated results in Table E.1 in Appendix E.

At the level of regional labour markets, the model includes control variables such as $Human_Capital$, $Large_Com$, Job_Den, $Mean_AIRD_Similar$ and $Distance_London$. For instance, $Human_Capital$ indicates the share of human capital working as managers, professional, or technical occupations in high-tech industries, which influences the company demand for AI skills (Alekseeva et al. 2021; Draca et al. 2024). The following two control variables are the share of large companies (Acemoglu et al. 2023; Babina et al. 2024) and job density (Balland et al. 2020) to control agglomeration effects. $Mean_AIRD_Similar$ is the average of skill relatedness density of the fundamental skills similar to AI in the region in every year between 2016-2023. In this way, the model controls time-invariant unobservable relevant to the independent variable, for instance, the selection (sorting) bias of tech-savy companies, the regional level of technical-digital skills, and so on. In addition, $Distance_London$ is euclidean distance of TTWA centroids between London and each region. This time-invariant variable controls spatial structure of the geographical concentration and spillover of complex technology and high-tech investment in the London-Oxbridge triangle (Draca et al. 2024; Zhang et al. 2025a).

This study also controls the effects of regional employment specialisations in each industry on the generation and spatial concentration of AI skill demand by single- and multi-locational companies in TTWAs (McElheran et al. 2024; Zhang et al. 2025a). So, this group of control variables consists of industrial specialisations, which is computed as location quotients of employment in each industry. These industries include Information & Communication Technology (ICT), Professional, scientific & technical (Sci), Financial & insurance (Finance), Mining, quarrying & utilities (Energy), and Manufacturing (Manufacturing) sectors in TTWAs. However, ICT, Sci, and Finance are removed from the model because of potential mediator

biases and multicollinearity issues for independent variables. Table 1 presents descriptive statistics for all variables. All variables are described in Table C.1 in Appendix C. In addition, Table D.1 in Appendix D describes and summarises important variables for Top10 TTWAs with the greatest share of AI OJAs.

Table 1. Descriptive statistics of variables between 2016-2024.

Statistic	N	Mean	St. Dev.	Min	Max
AI_Demand	388,115	0.012	0.11	0	1
AI_Demand_LQ	3,398,807	0.016	0.12	0	1
AIRD_Complementary	1,742	0.00	0.08	-0.21	0.37
AIRD_Similar	1,742	0.001	0.0008	0.00	0.004
Mean_AIRD_Similar	1,742	0.001	0.0005	0.00	0.003
Energy (log)	1,742	-0.05	0.62	-2.40	2.98
Manufacturing (log)	1,742	0.12	0.52	-1.37	1.52
Human_Capital	1,742	0.13	0.09	0.00	0.43
Large_Com	1,742	0.003	0.002	0.00	0.007
Job_Den	1,742	0.83	0.12	0.54	1.22
Distance_London (log+1)	1,742	0.45	0.61	-3.71	1.55
Total_OJA[1] (log+1)	388,115	0.80	1.04	0.00	9.14
Total_OJA[2] (log+1)	3,398,807	1.28	1.55	0.00	13.41

Mean_total_OJA[1] (log+1)	388,115	1.02	0.93	0.00	8.45
Mean_total_OJA[2] (log+1)	3,398,807	1.58	1.48	0.00	11.94

Notes: [1]This variable is used for regression model of single-locational companies.

[2]This variable is used for regression model of multi-locational companies.

(log) indicates that the natural logarithm of that variable is used.

4. Results and Discussion

4.1. Spatial sorting of single-locational companies seeking AI skills

Table 2 presents the estimates of the likelihood that each single-locational company in any TTWA in any year posts at least one online job advert requiring AI skills. Model (3) includes random effects at both the company and TTWA levels and has the greatest explanatory power (1.1% for only fixed effects and 97.1% for both fixed and random effects). This model also shows the greatest goodness of fit (the lowest AIC value) among models in Table 2. Therefore, the following interpretations focus on Model (3).

Model (3) in Table 2 shows a significantly positive effect of regional AI relatedness density of the complementary skills in TTWAs. Importantly, this estimate remains consistent in all models. The estimate significantly supports the first theoretical hypothesis that regions specialised in more AI-complementary skills significantly increase the likelihood of single-locational companies seeking AI skills within the TTWA. The likelihood increases by 40.5% if regional AI relatedness density of the complementary skills increases by one standard deviation. This finding reflects that the company demand for AI skills may be influenced by regional labour markets cultivating specialised, complementary skills for diverse applications of AI in local industries. For instance, artificial neural networks are applied to detect food fraud

in cheesemaking.[4] Natural language processing, machine learning, and Chatbots are used to do legal reasoning and automate the legal segment of property transaction in the law industry. This result partly supports Mäkelä and Stephany (2024) and extends the findings of Draca et al. (2024) and Zhang et al. (2025) from a more granular perspective of labour skills.

Similar to the complementary skills, regional AI relatedness density of the fundamental skills shows a significantly positive effect in Model (3) of Table 2 as well. This estimation supports our second hypothesis at a 1% significance level. This finding indicates that regions specialised in more fundamental skills cognitively similar to AI reveal a greater likelihood for single-locational companies to seek AI skills. Its effect magnitude is smaller than that of the complementary skills. An explanation could be that it is more likely for single-locational companies to combine new AI skills with regionally specialised complementary skills than the fundamental skills.

A few control variables have significant and positive coefficients. At the regional level, job density has a significantly positive correlation with the likelihood of single-locational companies searching for AI skills. This effect supports the role of agglomeration economies or job centres in attracting single-locational companies adopting AI skills. This result is in line with Rouwendal et al. (2026). Other TTWA-level control variables are all insignificant in Model (3) of Table 2. At the company level, two size effects are significant and positive. These results align with Acemoglu et al. (2023) and Babina et al. (2024).

The Model (3) show that the TTWA-level unexplained variance of the outcome variable is close to 0 (i.e., $\sigma 2(\text{TTWA}) = 0.000$), while the company-level variance is up to 110 (i.e., $\sigma 2(\text{Company}) = 110.1$). These statistics indicate that this multi-level logit model (3) completely

[4] Cheesemaking is computed as the Top 2 skill group with the greatest AI relatedness index in 2019 in Table B.1 in Appendix B.

explains the baseline regional variation in AI skill demand among single-locational companies, but the company-level variation approximately determines their demand for AI skills. Significant effects of regional skill relatedness density do not exogenously facilitate these single-locational companies to seek and adopt AI skills. In contrast, these single-locational companies adopting AI skills spatially sort themselves into the TTWAs specialised in more complementary or fundamental skills.

Figure 5 further illustrates the effect dynamics of skill relatedness density between 2017-2024 (see Table E.2 in Appendix E for its full regression model). The regional effect of AI relatedness density of the complementary skills remains stable over time. In comparison, the relatedness effect of the fundamental skills fluctuates and decreases during the study period and even turns insignificant in 2024. The magnitude gap between these two effects widens to a greater extent after the year of 2022. This diverging pattern means that single-locational companies seeking AI skills are less likely to choose to locate in TTWAs specialised in the fundamental skills similar to AI. This phenomenon can be explained by the reason that an increasingly pervasive diffusion of AI tools such as ChatGPT can facilitate the adoption of simple AI skills among single-locational companies. More of them may choose to locate in TTWAs with place-based complementary skills for the application of AI skills in various local industries.

Table 2. Multilevel logit regressions of AI skill demand by each single-locational company in TTWAs, 2017-2024.

	Dependent variable:		
	AI_Demand		
	(1)	(2)	(3)
TTWA-level			
AIRD_Complementary	0.39***	0.39***	0.34**
	(0.08)	(0.09)	(0.14)
AIRD_Similar	0.13***	0.14***	0.28***
	(0.04)	(0.04)	(0.07)
Mean_AIRD_Similar	0.14*	0.14*	0.02
	(0.08)	(0.08)	(0.08)
Energy		-0.02	0.12
		(0.06)	(0.08)
Manufacturing		-0.25**	-0.17
		(0.11)	(0.16)
Human_Capital		-0.14**	-0.15
		(0.06)	(0.09)
Large_Com		-0.01	0.06

		(0.05)	(0.08)
Job_Den		0.15**	0.22**
		(0.07)	(0.10)
Distance_London		-0.07	-0.04
		(0.13)	(0.09)
Company-level			
Total_OJA		-0.04**	0.08***
		(0.02)	(0.03)
Mean_total_OJA		0.58***	0.35***
		(0.02)	(0.05)
Constant	-5.90***	-5.80***	-12.15***
	(0.13)	(0.16)	(0.18)
Year FEs	YES	YES	YES
Model summary			
Random Intercept	TTWA-level	TTWA-level	TTWA-level and Company-level
σ2(Company)	/	/	110.1
σ2(TTWA)	0.559	0.494	0.000

Marginal R-squared	0.087	0.257	0.011
Conditional R-squared	0.220	0.354	0.971
Observations	388,115	388,115	388,115
Akaike Inf. Cri.	46184.09	44166.77	26071.8

Notes: ***, **, * represent the significance level of 1%, 5%, 10%, respectively. Marginal R-squared values refer to the extent of the outcome variation is explained by fixed effects. Conditional R-squared values indicate the extent of the outcome variation is explained by all random and fixed effects. The last model (3) controls not only regional (TTWA-level) random effects but also company-level random intercept. There are 137,940 unique single-locational companies and 218 TTWA groups.

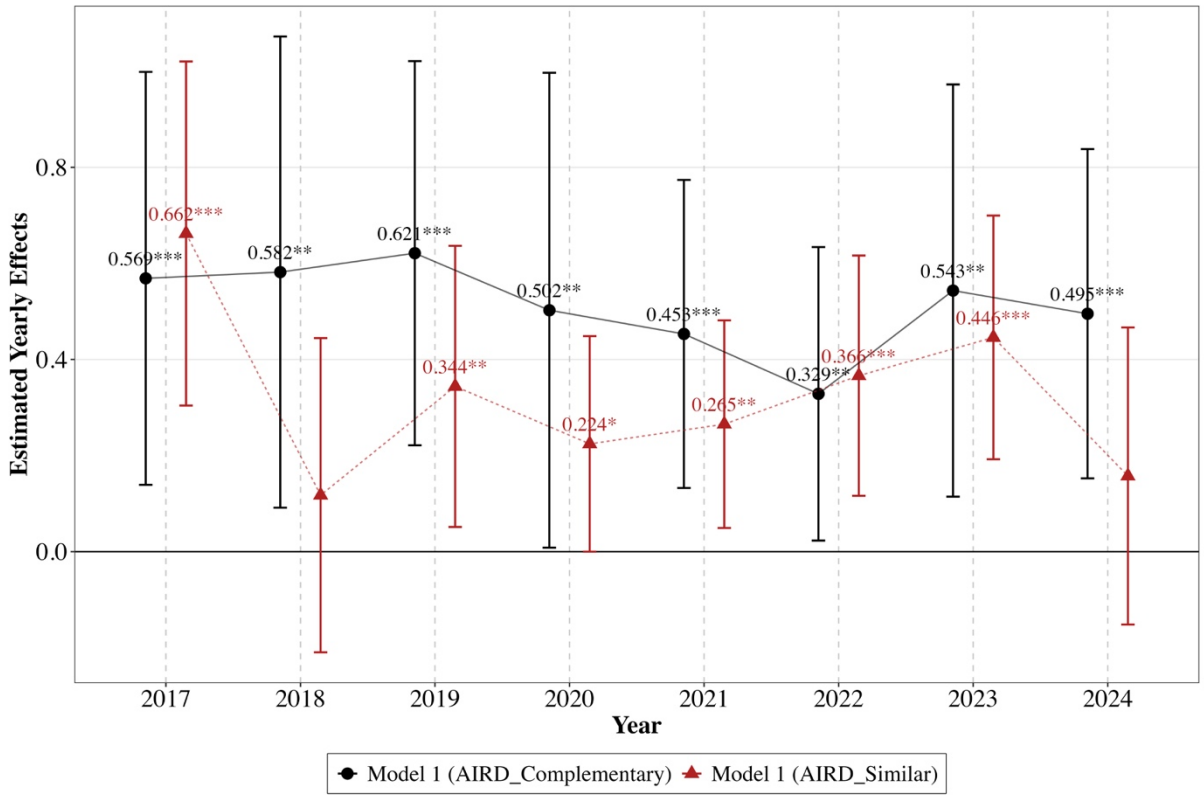


Figure 5. Significant yearly effects of AI relatedness density of the complementary or fundamental skills between 2017-2024 on single-locational companies.

4.2. Regional effects on multi-locational companies spatially concentrating AI skill demand

The multilevel logit models in Table 3 estimate how regional skill relatedness density affects the probability that each multi-locational company spatially concentrates its AI skill demand in a specific TTWA. Model (3) in this table provides the best explanatory power and goodness of fit. For instance, its random and fixed effects together explain up to 67 percent of the outcome variation (with 56 percent from the group-level effects). Model (3) has a lower AIC value, controlling both TTWA- and company-level random effects, than the other two models.

Model (3) in Table 3 shows that regional AI relatedness density of the complementary skills has a significant and positive effect. This effect suggests that TTWAs specialised in more complementary skills relative to AI can increase the likelihood of multi-locational companies spatially concentrating their AI skill demand in the TTWA. This positive effect supports our third hypothesis. One potential explanation could be that establishments of the multi-locational company may intensively search for workers with AI skills in the TTWA to combine AI with regionally specialised, AI-complementary skills in place-based application domains. This broad cross-field application enabled by AI is due to its general-purpose technology (Goldfarb et al. 2023).

Similarly, AI relatedness density of the fundamental skills also has a significantly positive effect. This result support the fourth hypothesis. The positive effect indicates that it is more likely for multi-locational companies to spatially concentrate their AI skill demand in TTWAs specialised in more fundamental skills similar to AI. By doing so, these companies may utilise locally specialised IT or mathematical modelling skills possibly to further develop or apply more state-of-the-art AI algorithms (Hunt et al. 2024; Xiao and Boschma 2023). However, this effect is less than half the magnitude of that observed for the complementary skills. This result indicates that unlike single-locational ones, these multi-locational companies

with sufficient internal resources do not heavily rely on regional capabilities of digital and math skills for the adoption of AI skills. Aiming for business expansion (Babina et al. 2024), multi-locational companies may value the complementary skills more for the application and development of advanced AI technologies in regional labour markets.

However, temporal analyses in Figure 6 illustrate that the gap of regional relatedness effects between the complementary skills and the fundamental skills decreases over time. More specifically, the effect of the complementary skills decreases during the Covid-19 period and after the public release of ChatGPT. It could be explained that other companies previously without such internal resources of IT or math capabilities can take advantage of generative AI tools after 2022 for various AI application in local industries. This new change may decrease the likelihood of multi-locational companies spatially concentrated AI skill demand in these regions. In contrast, the effect of the fundamental skills increases after 2020 while remains stable in general. This result indicates that in comparison to single-locational companies, multi-locational companies more intensively require and utilise these fundamental skills underlying AI technologies for its development or application.

For robustness tests, the study further controls a variable of the company type in Table E.1 in Appendix E. This additional variable is measured as the most frequent job category among OJAs posted by each company in each TTWA in each year. In this way, the new model (2) in Table E.1 controls the self-selection effect of multi-locational companies in terms of scope of economies. Estimates of two skill relatedness density variables remain robust. This model has its TTWA-level residuals normally distributed according to a Shapiro test ($W = 0.9889$, p-value = 0.0909).

The variance components of the outcome variable at the company and TTWA levels in Table 3 and Table E.1 indicate that regions have contextual effects of skill relatedness density on the spatial concentration of the demand for AI skills from multi-locational companies. In

sum, these regions act as incubators of AI skills among multi-locational companies. Both skill similarity and complementarity density relative to AI are important. In contrast, these regions act as containers attracting single-locational companies with the capabilities of adopting and seeking AI skills. Skill complementarity density relative to AI plays a more important role than skill similarity, especially after 2022.

Table 3. Multilevel logit regressions of the location quotient of AI skill demand within each multi- locational company among its establishments in TTWAs, 2017-2024.

	Dependent variable:		
	AI_Demand_LQ		
	(1)	(2)	(3)
TTWA-level			
AIRD_Complementary	0.13***	0.16***	0.12***
	(0.01)	(0.02)	(0.01)
AIRD_Similar	0.05***	0.06***	0.05***
	(0.01)	(0.01)	(0.01)
Mean_AIRD_Similar	0.38***	0.17***	0.17
	(0.05)	(0.04)	(0.15)
Energy		-0.05***	-0.05***
		(0.01)	(0.01)
Manufacturing		0.04	-0.00

		(0.03)	(0.04)
Human_Capital		-0.05***	-0.06***
		(0.01)	(0.02)
Large_Com		0.10***	0.04
		(0.02)	(0.02)
Job_Den		0.03	0.01
		(0.02)	(0.02)
Distance_London		-0.23***	-0.27
		(0.06)	(0.23)
Company-level			
Total_OJA		0.14***	0.18***
		(0.01)	(0.01)
Mean_total_OJA		0.62***	0.69***
		(0.01)	(0.01)
Constant	-5.15***	-5.19***	-5.40***
	(0.05)	(0.04)	(0.17)
Year FEs	YES	YES	YES
Model summary			
			TTWA-level

Random Intercept	TTWA-level	TTWA-level	and Company-level
σ2(Company)	/	/	2.02
σ2(TTWA)	0.38	0.21	3.57
Marginal R-squared	0.06	0.21	0.11
Conditional R-squared	0.16	0.25	0.67
Observations	3,398,807	3,398,807	3,398,807
Akaike Inf. Cri.	517074	477899	390242

Notes: ***, **, * represent the significance level of 1%, 5%, 10%, respectively. There are 136,294 unique multi-locational companies and 218 TTWA groups.

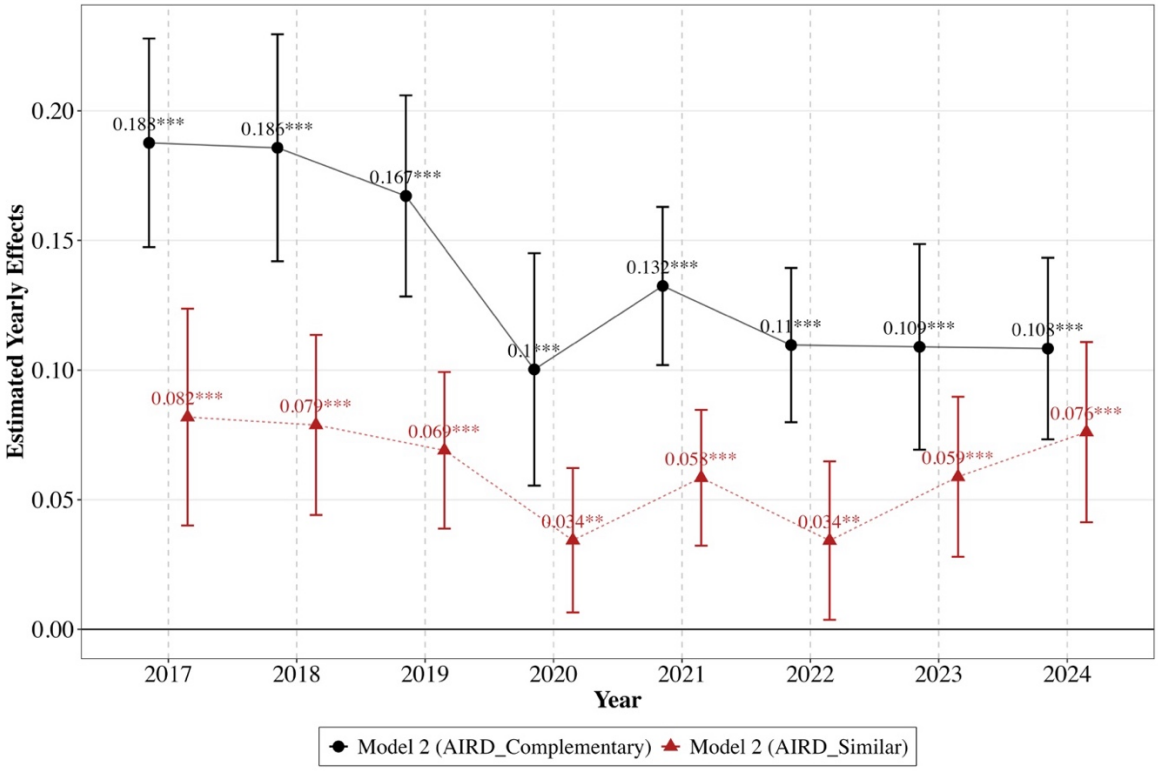


Figure 6. Significant yearly effects of AI relatedness density of the complementary or fundamental skills between 2017-2024 on multi-locational companies.

5. Conclusion

This study establishes a skill relatedness density framework distinguishing between skill similarity and complementarity relative to AI. It investigates how these two types of skill relatedness density influence the demand for AI skills from single-locational and multi-locational companies in regional labour markets from a multi-scale perspective. This study examines their associations with both the likelihood of single-locational companies seeking AI skills and multi-locational companies spatially concentrating AI skill demand in regions over time. Based on the literature review, the study proposes and tests four hypotheses. Empirical research employs Adzuna online job advertisements (OJA) requiring AI skills to reflect the company demand for AI skills as the proxy of the adoption of AI by companies. Regression results statistically support each of the four theoretical hypotheses.

Regions spatially sort single-locational companies seeking AI skills while locally build related skill structures supporting the demand for AI skills from multi-locational companies. Results of multilevel logit regressions significantly indicate that single-locational companies adopting and seeking AI skills are spatially sorted into regional labour markets specialised in more AI-complementary or fundamental skills. Furthermore, these companies adopting AI skills are less likely to rely on regional capacities of the fundamental skills (e.g. IT and mathematical modelling) after 2022. In comparison, their multi-locational counterparts may heavily utilise both regional capacities of AI skill complementarity and similarity density to foster and spatially concentrate their demand for AI skills in these regional labour markets.

Indeed, single-locational companies without sufficient internal resources likely depend on the regionally specialised, fundamental skills such as IT and Math to absorb and learn cognitively close skills like AI for imitative applications (Dahlke et al. 2024; Neffke et al. 2018). However, the roles of these fundamental, similar skills in diverse tasks could also be substituted by the adoption of AI methods or generative AI tools such as ChatGPT.

Furthermore, it should be more likely for single-locational companies to apply AI in diverse application domains across various tasks to which AI is complementary, rather than in the development or application of new AI methods based on IT and Math skills. These findings may be out of the common expectation that AI jobs should be more likely to be posted by companies in regions specialised in advanced digital skills. Single-locational companies without sufficient internal resources could search for workers to adopt simple AI technologies to accomplish tasks more efficiently across application domains according to Goldfarb et al. (2023), Kalyani et al. (2025) and Stephany and Teutloff (2024).

As illustrated in maps of this study, single-locational companies seeking AI skills are geographically dispersed in Great Britain. Multi-locational companies spatially concentrate most AI OJAs in large, diverse, and knowledge-intensive regional labour markets. Except for internal resources, they rely on the regional capacities of AI-complementary and fundamental skills to foster the demand possibly for complex AI skills. This diverging pattern of AI skill demand between these two groups of companies may generate different economic returns and re-produce existing geographical disparities as discussed by Babina et al. (2024), Dahlke et al. (2024), McElheran et al. (2024), and Kalyani et al. (2025).

In this study, the skill similarity-complementarity framework enables economic geographers to explain regional distribution of companies seeking and spatially concentrating their AI skill demand in diverse application domains. This study bridges the literature in labour economics and evolutionary economic geography to shed light on a new theoretical discussion that single- and multi-locational companies reveal diverging geographies of AI skill demand over time. Theoretical arguments may arise that a company with idiosyncratic characteristics and resources determines its own demand for emerging digital technologies such as AI mainly according to internal capacities, cost management, and technological trajectory. Furthermore, pipelines within large, multi-locational companies facilitate its diffusion and diversification of

non-local technologies beyond the so called “regional capabilities”. We agree that these companies with agency and internal resources do increasingly diffuse AI technologies and so, the demand for AI skills beyond and among regions. In contrast, regions as competitive markets, ecosystems, and places also enable single- and multi-locational companies to secure increasing returns to scale, to decrease their transport, searching, and transaction costs, and to utilise diverse networks of specialised ideas with unrelated varieties. Based on the explanatory framework, the generation and concentration of the demand for AI skills from various companies can co-evolve with regional capacities of skill relatedness density.

Research findings also contribute to regional policy debates. For instance, regional industrial strategies should consider and leverage regional skill structures with greater AI-complementarity or fundamental skills to facilitate various AI applications in specialised industries. Lagging regions without specialisations in IT and mathematical modelling skills are not necessarily destined for little likelihood of AI applications by local companies. These regions could diversify existing related specialisations through the diverse combination between AI and existing AI-complementary skills, for instance, new AI-enabled manufacturing facilities, agrifood and healthcare robots, AI-empowered clean energy, AI ethics and safety, and predictive analytics. In this way, regional institutions can develop or distribute potential productivity gains more broadly among different regions, industries, companies, and workers.

It is noticeable that research results in this study reflect correlations but not causality. The findings of this study should be interpreted considering its limitations. OJA-based skill demand does not reflect the actual skill supply. We also do not distinguish complex AI techniques from the broad adoption of basic AI tools and AI solution services. Future research could use employee profiles, occupational survey data, and company websites to examine how skill relatedness density of AI-empowered workers or products at the company level influences labour productivity and regional development.

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Appendix A. Keywords of AI Skills

An OJA is defined as an AI OJA if it requires at least one general AI skill and at least one specific AI skill (Goldfarb et al. 2023). These AI skills are widely retrieved and selected from an AI report of Maslej et al. (2025) and Lightcast (2025) open skill taxonomy. See lists as follows.

AI_General_Skills = ['Artificial intelligence', 'Machine learning', 'Natural language processing', 'NLP', 'Computer vision', 'Neural networks', 'Robotics', 'AI ethics', 'Autonomous driving', 'Generative AI', 'Generative artificial intelligence', 'Image recognition']

AI_Specific_Skills = ["ethical AI", "data sovereignty", "AI security", "agentic systems", "AI/ML inference", "AIOps", "AI personalization", "AI testing", "artificial general intelligence", "automated data cleaning", "Azure Cognitive Services", "Baidu", "cognitive automation", "cognitive computing", "computational intelligence", "Cortana", "Data Version Control", "Edge Intelligence", "embedded AI", "expert systems", "explainable AI", "intelligent control", "intelligent systems", "interactive kiosk", "IPSoft Amelia", "knowledge distillation", "knowledge engineering", "knowledge-based configuration", "knowledge-based systems", "knowledge representation", "multi-agent systems", "neuro-symbolic AI", "Open Neural Network Exchange", "OpenAI Gym", "operationalizing AI", "PineCone", "Qdrant", "reasoning systems", "swarm intelligence", "synthetic data generation", "Watson Conversation", "Watson Studio", "Weka Weaviate", "advanced driver-assistance systems", "autonomous cruise control systems", "autonomous system", "autonomous vehicles", "dynamic routing", "guidance navigation and control systems", "LiDAR", "light detection and ranging", "object tracking", "OpenCV", "path analysis", "path finding", "remote sensing", "scene understanding", "unmanned aerial systems", "Adobe Sensei", "ChatGPT", "CrewAI", "DALL-E image generator", "generative adversarial networks", "Google Bard", "image inpainting", "image super-resolution", "LangGraph", "large language modeling", "LLM", "Microsoft Copilot",

"multimodal learning", "multimodal models", "prompt engineering", "retrieval-augmented generation", "Stable Diffusion", "text summarization", "text to speech", "variational autoencoders", "AdaBoost", "adversarial machine learning", "Apache MADlib", "Apache Mahout", "Apache SINGA", "Apache Spark", "association rule learning", "attention mechanisms", "AutoGen", "automated machine learning", "autonomic computing", "AWS SageMaker", "Azure Machine Learning", "bagging techniques", "Bayesian belief networks", "Boltzmann Machine", "Chi-Squared Automatic Interaction Detection", "Classification and Regression Tree", "cluster analysis", "collaborative filtering", "concept drift detection", "confusion matrix", "cyber-physical systems", "Dask", "data classification", "Dbscan", "decision models", "decision-tree learning", "dimensionality reduction", "distributed machine learning", "Dlib", "embedded intelligence", "ensemble methods", "evolutionary programming", "expectation maximization algorithm", "feature engineering", "feature extraction", "feature learning", "feature selection", "federated learning", "game AI", "Gaussian process", "genetic algorithm", "Google AutoML", "Google Cloud ML Engine", "gradient boosting", "H2O.ai", "hidden Markov model", "hyperparameter optimization", "incremental learning", "inference engine", "k-means clustering", "kernel methods", "Kubeflow", "LIBSVM", "loss functions", "Markov chain", "matrix factorization", "meta learning", "Microsoft Cognitive Toolkit", "MLflow", "MLOps", "mlpack", "ModelOps", "Naive Bayes Classifier", "neural architecture compression", "neural architecture search", "objective function", "Oracle Autonomous Database", "Perceptron", "Predictionio", "predictive modeling", "programmatic media buying", "Pydata", "PyTorch", "PyTorch Lightning", "Random Forest Algorithm", "recommender systems", "Scikit-Learn", "semi-supervised learning", "soft computing", "sorting algorithm", "supervised learning", "support vector machines", "t-SNE", "t-distributed Stochastic Neighbor Embedding", "test datasets", "topological data analysis", "Torch", "training datasets", "transfer learning", "transformer", "unsupervised learning", "Vowpal Wabbit", "Xgboost", "Theano",

"AI copywriting", "Amazon Alexa", "Amazon Textract", "ANTLR", "Apache OpenNLP", "BERT", "chatbot", "computational linguistics", "conversational AI", "DeepSpeech", "dialog systems", "fastText", "fuzzy logic", "handwriting recognition", "Hugging Face", "intelligent agent", "intelligent virtual assistant", "Kaldi", "language model", "latent Dirichlet allocation", "Lexalytics", "machine translation", "Microsoft LUIS", "natural language generation", "natural language programming", "natural language toolkits", "natural language understanding", "natural language user interface", "nearest neighbour algorithm", "Nuance Mix", "optical character recognition", "screen reader", "semantic analysis", "semantic kernel", "semantic search", "sentence transformers", "sentiment analysis", "Seq2Seq", "Shogun", "small language model", "speech recognition", "speech synthesis", "statistical language acquisition", "summarization methods", "text mining", "text retrieval systems", "tokenization", "Vespa", "voice assistant technology", "voice interaction", "voice user interface", "word embedding", "Word2Vec", "Apache MXNet", "artificial neural networks", "Caffe2", "Chainer", "convolutional neural networks", "Cudnn", "deep learning", "Deeplearning4j", "deep reinforcement learning", "evolutionary acquisition of neural topologies", "Fast.AI", "graph neural networks", "Keras", "Long Short-Term Memory", "neural ordinary differential equations", "OpenVINO", "PaddlePaddle", "Pybrain", "recurrent neural network", "residual networks", "sequence-to-sequence models", "spiking neural networks", "TensorFlow", "advanced robotics", "bot framework", "cognitive robotics", "motion planning", "Nvidia Jetson", "OpenAI Gym environments", "reinforcement learning from human feedback", "robot framework", "robot operating systems", "robotic automation software", "robotic liquid handling systems", "robotic programming", "robotic systems", "servomotor", "SLAM algorithms", "Simultaneous Localization and Mapping", "3D reconstruction", "activity recognition", "contextual image classification", "Deck.gl", "digital image processing", "digital twin technology", "eye tracking", "face detection", "facial recognition", "general-purpose

computing on graphics processing units", "gesture recognition", "image analysis", "image captioning", "image matching", "image recognition", "image segmentation", "image sensor", "ImageNet", "instance segmentation", "machine vision", "MNIST", "motion analysis", "object recognition", "OmniPage", "pose estimation", "RealSense", "thermal imaging analysis", "Parsing","Visual Odometry",'Predictive Text','Word Recognition','Knowledge Graph','Document Classification','Obstacle Avoidance','Bayes Classifier','RDF','Buildbot','VisualVM','Automated Machinery','Robotc','Mechanical Reasoning','Autonomous Underwater Vehicle','Fingerprint Recognition','Regular Expressions','Automation','Structured Text','Semantics','Unstructured Data', "Visual Recognition","Named Entity Recognition", "Generative Design","Text Processing","Decision Tree Learning", 'Three Degrees Of Freedom','Six Degrees Of Freedom', 'Object Detection', "Backpropagation", "Text Classification", "Feature Detection", "Decision Trees", "Image Processing", "WordNet","Robotic Components","Knowledge Discovery","Information Extraction","Pattern Recognition", "Ontologies","Data Mining","LSTM","Relation Extraction","Support Vector Machine" , "Data Mining Methods","Speech Processing","Automatic Target Recognition","Image Generation" , "Automated Reasoning","Robots.txt", "Visual Objects","Text Extraction", "Semantic Web", "Conditional Random Fields","Relationship Extraction", "Artificial Consciousness", "Amazon Polly", "Bonsai", "AI Agents","AI Alignment", "AI Innovation","AI Research","AI Safety", "AWS Bedrock","AWS Certified Machine Learning Specialty", "Aforge","Agentic AI", "Amazon Forecast","Amazon Personalize","Amazon Transcribe", "Autoencoders", "Automated Planning And Scheduling","Automation Systems","Automation Systems Design","Azure AI Studio", "Azure OpenAI", "Building Automation Software", "CatBoost", "ChatGPT Integration", "ChatGPT Prompt", "Decision-Matrix Method", "Few Shot Learning", "Fuzzy Set", "Generative AI Agents", "Genetic Programming", "GitHub Copilot", "Google Assistant",

"Google Colaboratory", "Haystack", "Human AI Interaction", "Intelligent Automation", "Intelligent Character Recognition", "Intertec Superbrain", "Isaac SDK", "K-Nearest Neighbors Algorithm", "LangChain", "Language Models", "LightGBM","Linear Prediction", "ML.NET" , "Machine Learning Algorithms", "Machine Learning Methods", "Machine Learning Model Monitoring And Evaluation", "Machine Learning Model Training", "Markov Decision Process", "Markov Process","Meta-Learning", "Microsoft Delve", "Multimodal Learning", "NeuroSolutions", "Nuance Nina Virtual Assistant", "OPS5", "Open Mind Common Sense", "Orthogonal Projections", "Partially Observable Markov Decision Process", "Particle Swarm Optimization", "Pattern Mining", "Probably Approximately Correct Learning", "PyCaret", "Q Learning", "Quote Generators", "Recurrent Neural Networks", "RLHF", "ResNet", "Residual Networks", "Retrieval Augmented Generation", "S Voice", "SAS Certified ModelOps Specialist", "Sequence Detector", "Sframe", "Skflow", "SpamBayes", "Systems Automation", "Vertex AI", "Weaviate", "Weka", "Wit.ai", "XLISP", "Zero Shot Learning", 'Amazon Comprehend', 'Amazon Lex', 'Artificial Linguistic Internet Computer Entity', 'Dialogflow', 'Disambiguation', 'Doc2vec', 'GPT-3', 'Generative Grammar', 'GluonNLP', 'Grammatical Framework', 'Language Identification', 'Lemmatization', 'Lexical Analysis', 'Lingpipe', 'N Gram', 'NLTK', 'NetBase Quid', 'Parser Generators', 'Part-of-Speech Tagging', 'Porter Stemmer', 'Question Answering', 'Refal', 'Relationship Extraction', 'Semantic Analysis', 'Semantic Reasoner', 'Sirikit', 'Speech Enhancement', 'Speech Technology', 'Stemming', 'SyntaxNet', 'Tilde', 'Voice Technology', 'Sphero', 'SCARA Robot', 'SACA Certified Industry 4.0 Associate Robot System Operations', 'Robotic Machines','Robot End Effector', 'Remotely Operated Underwater Vehicle', 'Paint Robot', 'PX4 Autopilot', 'Motion Estimation', 'Mobile Robot Programming Toolkit', 'Mobile Robot Navigation', 'Microsoft Robotics Developer Studio', 'Linear Encoder', 'Lego Mindstorms NXT', 'Inverse Kinematics', 'Industrial Robotics', 'Forward Kinematics', 'Flownet', 'Automated Guided Vehicle Operation

and Maintenance', 'Automated Guided Vehicle', 'Unmanned Ground Vehicles', 'ArduPilot', 'Autopilot System']

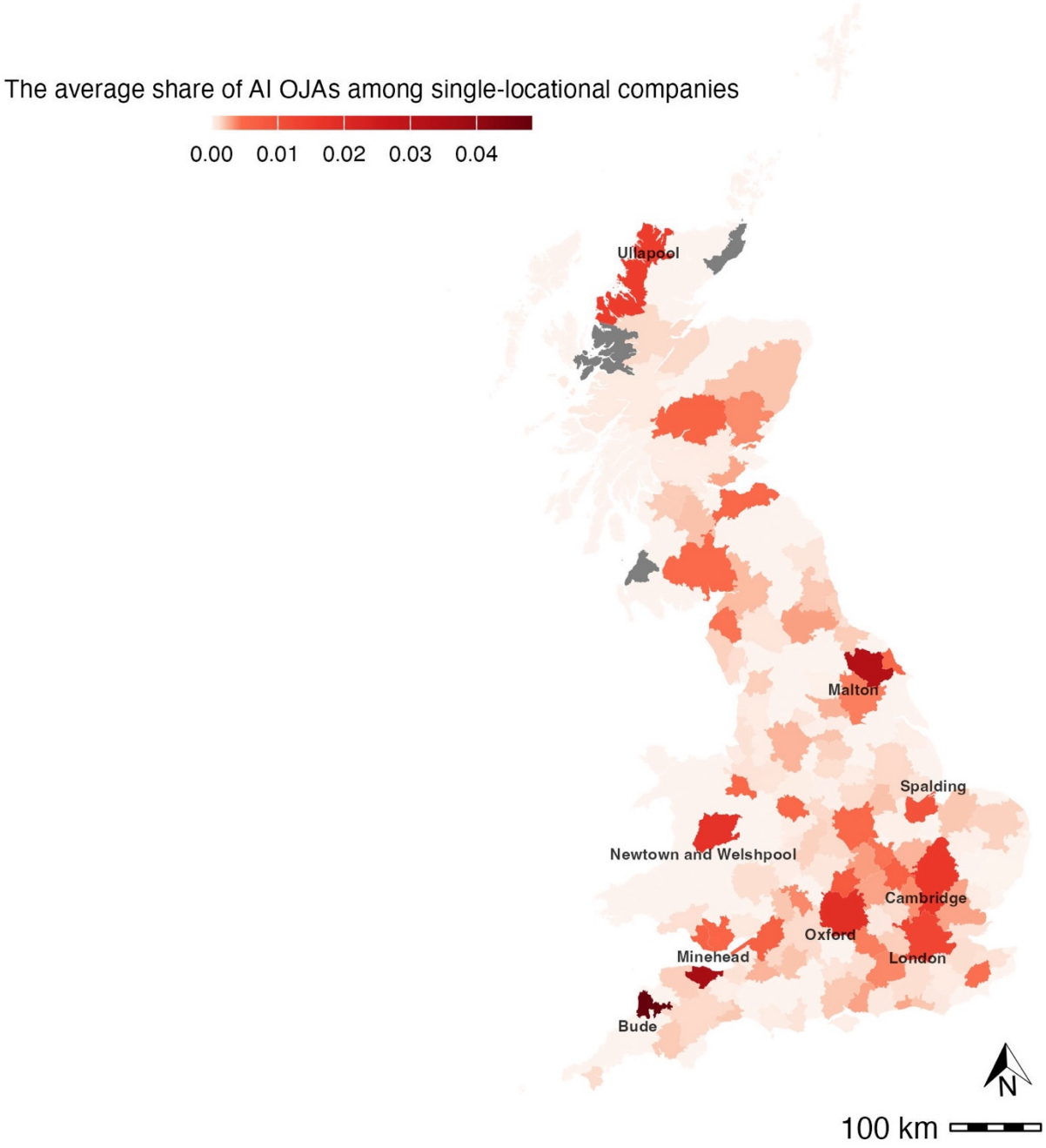


Figure A.1. The average share of AI OJAs posted among single-locational companies

Appendix B. AI Relatedness Density of Skills

Skill relatedness density is a conceptual framework which our research aims to build upon and contributes to in the field of evolutionary economic geography. Balland et al. (2017) develop an EconGeo package in R to compute AI relatedness density in regions. This package enables researchers to conveniently create a relatedness matrix between technologies or skills, a matrix of regional specialisation in these technologies, and the regional relatedness density of existing specialised technologies related to any emerging technology (e.g. AI) researchers are interested in.

Our research analyses a vast skills landscape, encompassing around 26,400 unique skills extracted from online job advertisements annually in Great Britain, which requires considerable computing power. Thus, before using the EconGeo package to create the variable of AI relatedness density, we decide to reduce dimensionality of skill keywords of the OJA dataset. We adopt a sentence transformer function named "Agglomerative Clustering" to cluster the unique skills in each year's OJA data based on a pre-trained model of "job-cv-multi-datasets" in Python. This agglomerative clustering function facilitates researchers to decide how fine-grained or coarse-grained clusters of skill portfolios could be. The pre-trained model is developed and shared by other researchers on HuggingFace (Reimers 2019). After using this transformer function, we successfully group the around 26,400 skills into around 1,200 clusters in each year based on their semantic similarity with "distance_threshold" equal to 8.0, reducing the dimensionality of the skill portfolios. We calculate skill relatedness between AI technologies and any other skill group (i.e., the share of the co-occurrence between AI and each skill group in all OJAs) in each year by using a "relatedness" function from the EconGeo package based on a probability normalisation procedure.

We further distinguish skill groups between AI-complementary and fundamental skills based on whether each skill group is IT and Mathematical modelling skills or not. Table B.1

shows the Top 5 AI-complementary skill groups highly related to the AI technologies in each year between 2016-2024. Results indicate that AI technologies diffuse among and are combined with more and more diverse skill groups as shown in the decreased AI relatedness index in these Top 5 skill groups year on year. These AI relatedness values change from the range between 16.6 and 55.3 in 2016 to a considerably lower range between 7.5 and 11.7 in 2024. Additionally, these AI-complementary skills with the greatest AI relatedness are mainly from engineering, materials science, media, design, video production, education and training, inferential statistics analysis, clinical medicine, business management, food production, finance, logistics, and so on. In contrast, Table B.2 lists the AI relatedness index and the rank of IT and Mathematical modelling skills in each year. Findings indicate that IT and Math skills were less and less related to AI skills after 2019. More and more AI-complementary skills exhibit greater AI relatedness than the IT and Math (fundamental) skills.

Based on a regional skill specialisation matrix and an AI relatedness vector, we compute the independent variable: The regional relatedness density of AI-complementary (excluding IT and Math skills) or fundamental (only IT and Math) skill structures among OJAs posted in 2016-2024 in TTWAs. We compute this variable by using a function named "relatedness.density" from the EconGeo package in R (Version 2024.04.1+748). Maps as follows (Figure B.1-B.9) illustrate spatial patterns of the relatedness density of AI-complementary skills in each year. Specific TTWAs obtain a great level of the relatedness density of AI-complementary skills, spatially concentrated around Cambridge, London, Oxford, Bristol, and Edinburgh between 2016-2022. During 2022 and 2024, some TTWAs emerge as new pioneering hotspots of the AI relatedness density, such as Manchester, Birmingham, and Glasgow. Another map in Figure B.10 illustrates regional patterns of AI relatedness density of the fundamental skills. This map illustrates that knowledge-intensive

regions are specialised in more fundamental skills similar to AI, for instance, Cambridge, Cheltenham, Manchester, Leamington Spa, Oxford, Newcastle, and Leeds.

Table B.1. Skill groups with the greatest AI relatedness of complementary skills (excluding IT and Mathematical Modelling skills) among OJAs in each year between 2016-2024, Great Britain.

Year	Rank	Skills Group	AI Relatedness Index
2016	Top 1	Dublin Core	55.359
	Top 2	RAM Structural System	52.445
	Top 3	Nonlinear Regression, Linear Regression, Multiple Linear Regression, Polynomial, Regression, Multivariate Linear Regression, Linear Model, General Linear Models, Generalized Linear Model	28.397
	Top 4	Spotfire, BB FlashBack	16.831
	Top 5	OpenGL	16.603
2017	Top 1	NumPy, NUC, NueMD, Numerology, Nucleo, Nucleation, Nucleofection	24.679
	Top 2	Spark, Adobe Fireworks, Sparkr, Sparklines, BrightEdge, Brightcove, Brightspace	14.287
	Top 3	OpenGL	12.600

	Top 4	HIV, HIVE, Learning Aids, Finding Aids	8.971
	Top 5	UserZoom, Simscape, Mastopexy, Matlab Simulink, Matlab, Matplotlib, MATHLAB, MeshLab, Collabnet, Matrigel	8.770
2018	Top 1	RAM Structural System	24.818
	Top 2	OpenGL	10.804
	Top 3	Spark, Adobe Fireworks, Sparkr, Sparklines, BrightEdge, Brightcove, Brightspace	9.989
	Top 4	Dublin Core	9.933
	Top 5	Logility, Certified Professional Logistician, Well Logging, SWOT Analysis, Logistic Regression	8.775
2019	Top 1	NumPy, Nucleation, NUC, Numerology, Nucleo, Numeric Distribution, Sequence Alignment, Multiple Sequence Alignment, Numerical Sequences, Rapid Sequence Induction	18.103
	Top 2	Cheesemaking, Cheese Industry	15.457
	Top 3	Spark, Sparkr, Adobe Fireworks, Sparklines, BrightEdge, Brightspace, Brightcove	9.809

	Top 4	Moving Average, Forward Rate, Forward Rate Agreement, Trend Analysis, Trend Following, Trendwatching, Trend Line, Progress Indicator, Digital Indicators	8.432
	Top 5	OpenGL	8.406
2020	Top 1	Clarabridge	20.801
	Top 2	FL Studio	20.318
	Top 3	Dublin Core	19.299
	Top 4	NumPy, NUC, Numerology, Nucleation, Nucleo, ZBrush, ZigBee, ZFS, Zotero, Tinnitus, TinkerCAD	10.957
	Top 5	RAM Structural System	10.875
2021	Top 1	Dublin Core	16.253
	Top 2	Nucleation, Nucleofection, Nucleo, NumPy, Numerology, NUC	11.634
	Top 3	Linear Regression, Robust Regression, Regression Analysis, Nonlinear Regression, Multiple Linear Regression, Multivariate Linear Regression, General Linear Models, Linear Model, Generalized Linear Model	9.529

	Top 4	Software-In-The-Loop, DipTrace, Query Builder, Query Designer, Microsoft Query	9.266
	Top 5	Steiner Principles, Amag Symmetry, Quark, Quarries, QuantLib, Quantile, Quantum Technology, Quantum Mechanics, Quantum Computing, Quantum Information, Quantum Phase Transition, Quantum ESPRESSO	7.380
2022	Top 1	Dublin Core	10.935
	Top 2	Nucleation, Nucleo, Nucleofection, NumPy, NUC, Numerology	9.279
	Top 3	Steiner Principles, Amag Symmetry, Quantum Computing, Quantum Mechanics, Quantum Information, Quantum Technology, Quantum ESPRESSO, Quarries, Quark, Quantile, QuantLib	7.240
	Top 4	OpenGL	6.860
	Top 5	Regression Analysis, Linear Regression, Robust Regression, Nonlinear Regression, Multiple Linear Regression, Polynomial Regression, Multivariate Linear Regression, Linear Model, General Linear Models, Generalized Linear Model	6.628

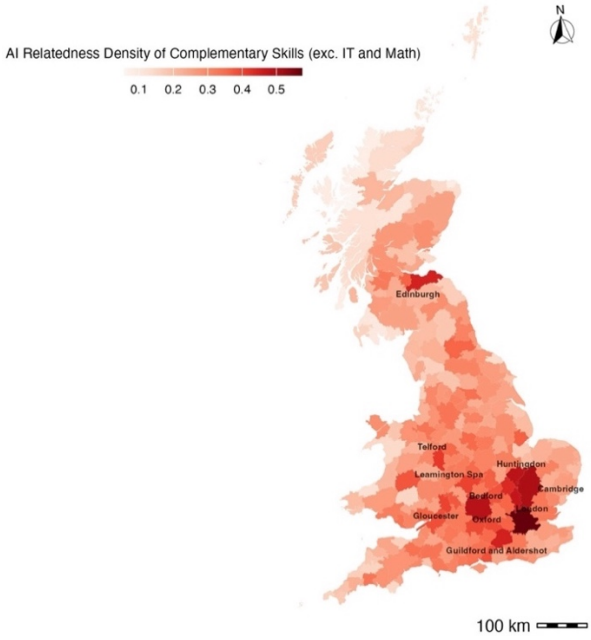
2023	Top 1	RAM Structural System	18.158
	Top 2	Firefox Extensions	15.264
	Top 3	NumPy, NUC, Numerology, Numeric Distribution, Nucleo, Nucleation, Nucleofection	12.243
	Top 4	Dublin Core	12.212
	Top 5	Xerox, Xerography	9.402
2024	Top 1	Lottery Equipment	11.767
	Top 2	Nucleation, Nucleofection, Nucleo, NumPy, NUC, Numerology	11.006
	Top 3	Joint Replacement, Joint Value, Joint Manipulation	9.215
	Top 4	Regression Analysis, Linear Regression, Robust Regression, Multivariate Linear Regression, Nonlinear Regression, Linear Model, General Linear Models, Generalized Linear Model	8.149
	Top 5	Steiner Principles, Amag Symmetry, Quarries, Quark, Quantile, QuantLib, Quantum Computing, Quantum Information, Quantum	7.585

		Technology, Quantum Mechanics, Quantum ESPRESSO	

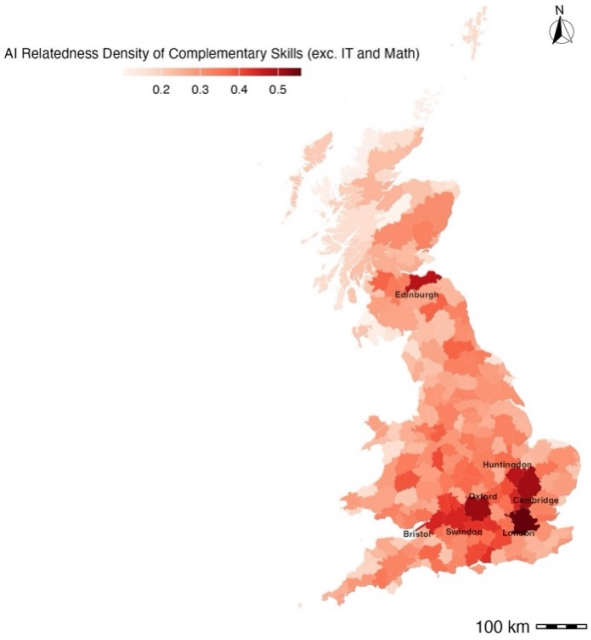
Table B.2. Skill groups with the greatest AI relatedness index of the fundamental skills (only IT and Mathematical Modelling skills) among OJAs in each year between 2016-2024, Great Britain.

Year	Rank	Skills Group	AI Relatedness Index
2016	166th	Information technology (.NET Development, AWS Certified Developer, Cloud Services, Communications Protocols, Database Servers, Extended Sql, HTTP Cookie, IBM Spufi, JQuery, Network Troubleshooting, Zendesk API, Web Service Protocol, etc.)	1.987
	182th	Mathematical modelling (Analytic Geometry, Boolean Networks, Differential Calculus, Fractal Geometry, Linear Algebra, Multivariable Calculus, Random Walk, Stochastic Process, Variance Reduction, etc.)	1.900
2017	138th	Information technology	2.025
	158th	Mathematical modelling	1.856
	122th	Information technology	1.967

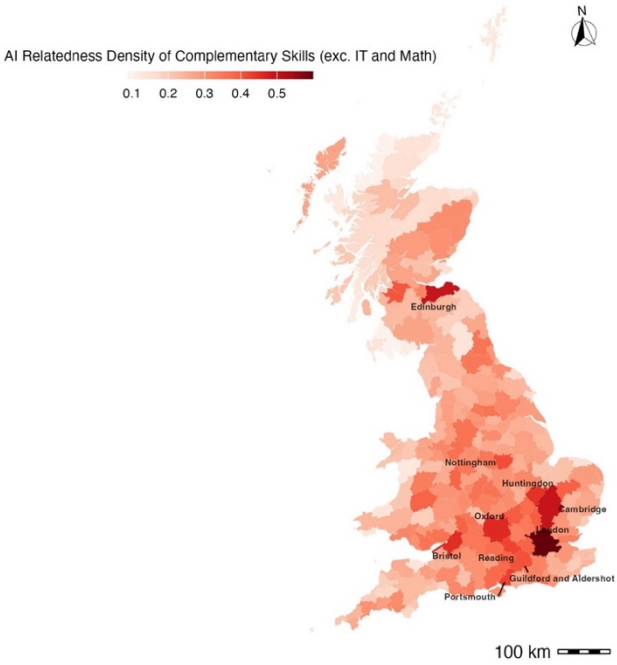
2018	159th	Mathematical modelling	1.692
2019	109th	Information technology	2.077
	131th	Mathematical modelling	1.888
2020	117th	Information technology	1.979
	198th	Mathematical modelling	1.527
2021	115th	Information technology	1.856
	232th	Mathematical modelling	1.380
2022	144th	Information technology	1.700
	270th	Mathematical modelling	1.303
2023	128th	Information technology	1.831
	358th	Mathematical modelling	1.213
2024	139th	Information technology	1.843
	458th	Mathematical modelling	1.029



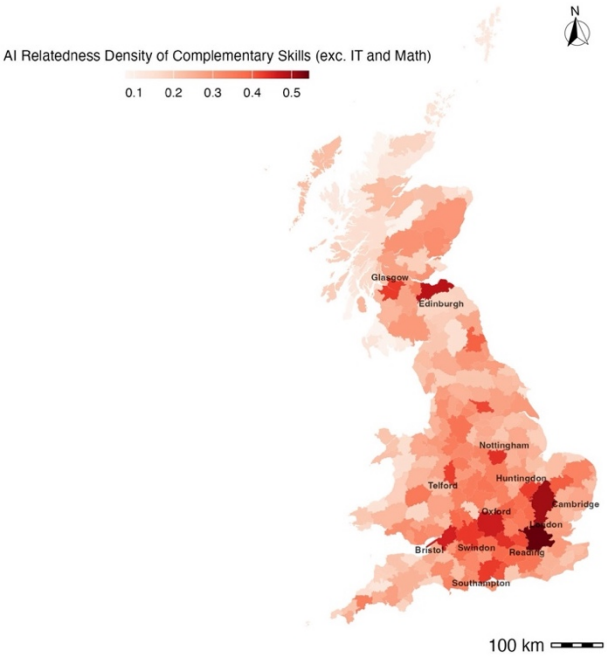
B.1. 2016



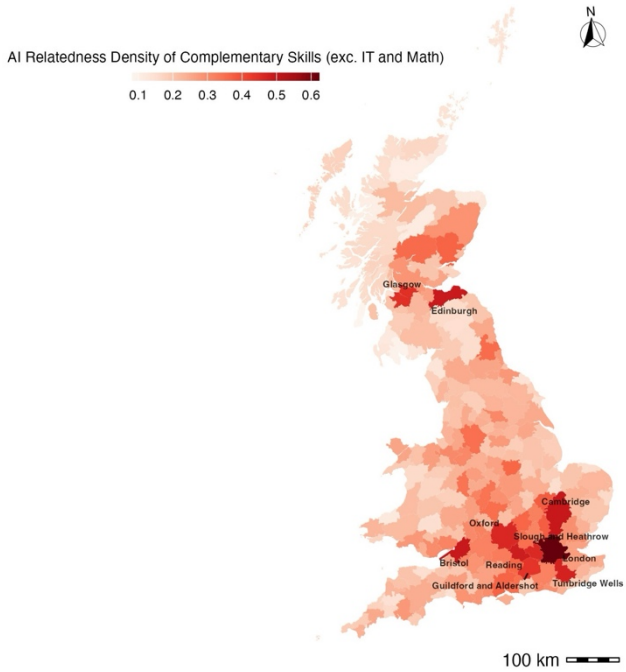
B.2. 2017



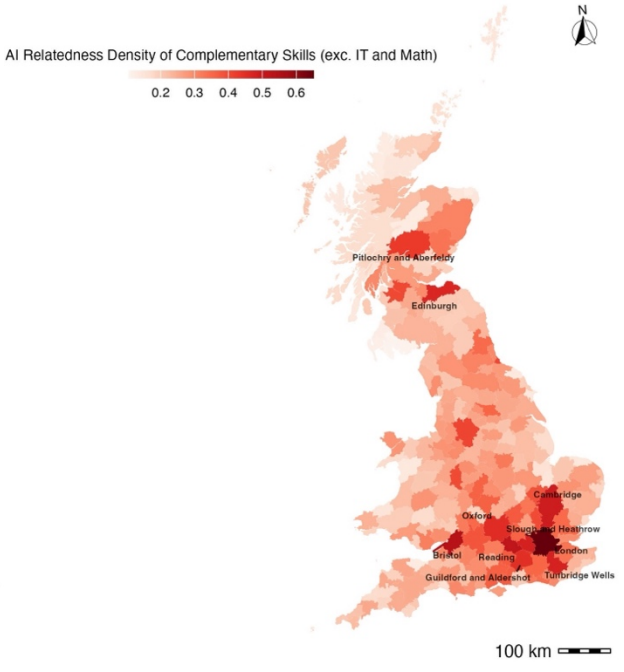
B.3. 2018



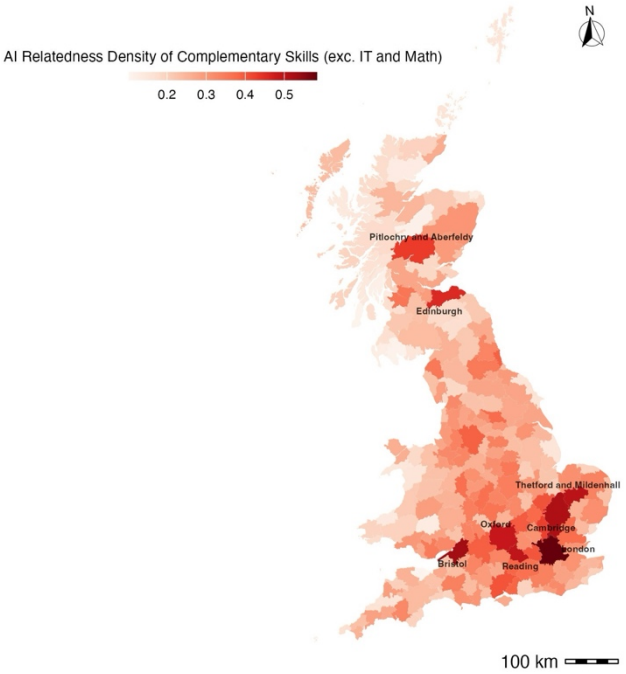
B.4. 2019



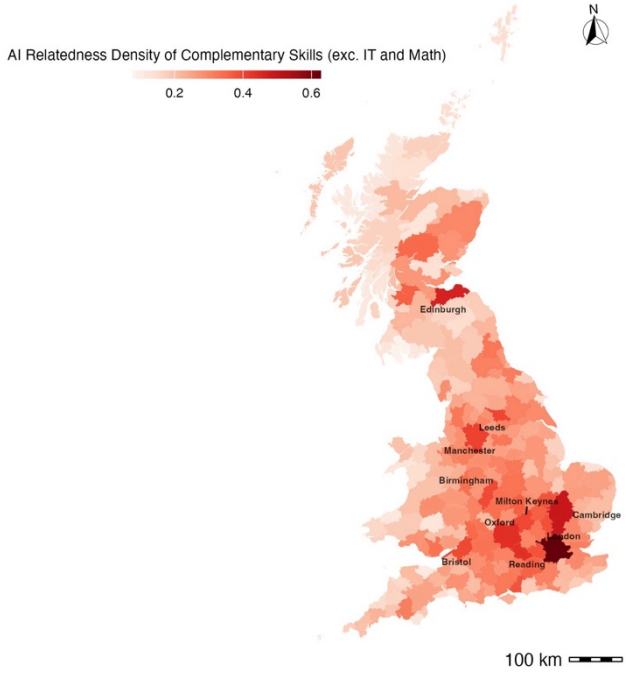
B.5. 2020



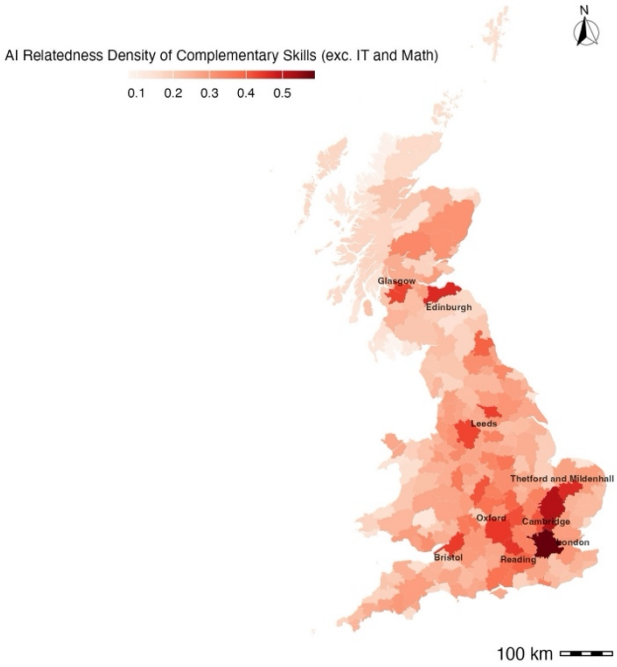
B.6. 2021



B.7. 2022



B.8. 2023



B.9. 2024

Figure B. Map of the relatedness density of AI-complementary skills (exc. IT and Math) between 2016-2024 in TTWAs, Great Britain.

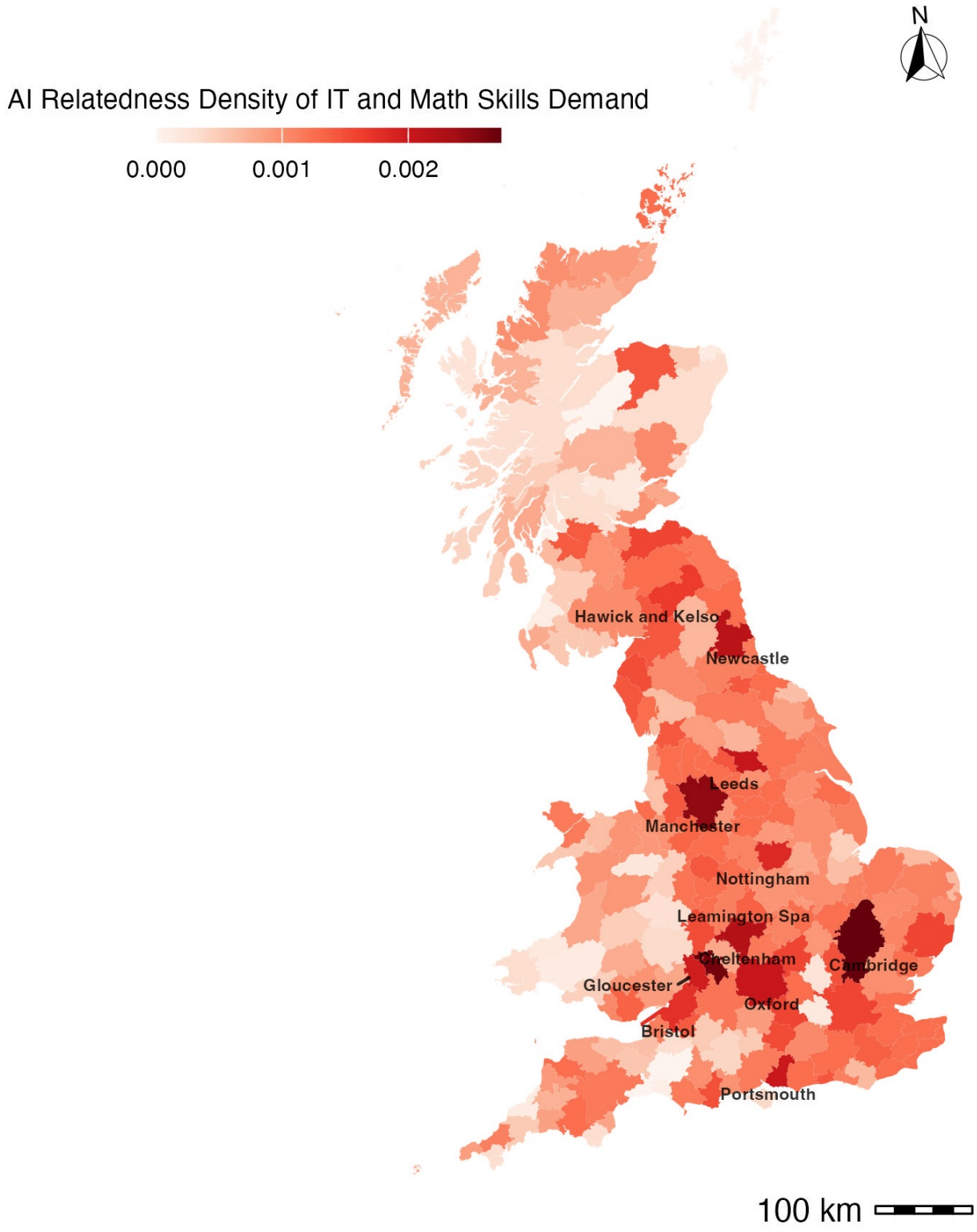


Figure B.10. Map of the average AI relatedness density of the fundamental skills (only IT and Math) between 2016-2024 in TTWAs in Great Britain.

Appendix C. Variables

Table C.1. Description of variables.

Scale	Data	Variables	Definition	Literature
Company	Adzuna (Dependent variables)	AI_Demand	A binary variable indicates whether a single-locational company in a TTWA has any OJA requiring AI skills or not in the year t between 2017-2024.	Technology diffusion
		AI_Demand_LQ	A binary variable of the location quotient regarding AI OJAs indicates whether each multi-locational company's establishments in a region have a larger share of AI OJAs than its company-level average share (AI_Demand_LQ = 1) or not (AI_ Demand_LQ = 0) in the year of t. The average share of AI OJAs is computed by dividing AI OJAs over total OJAs posted by the multi-locational company's all establishments among all TTWAs in Great Britain in each year t.	Spatial divisions of labour
			AI Relatedness density of complementary skills in each TTWA indicates a share: the sum of the probability of skill co-occurrence among all OJAs between AI skills and each skill in which the region	

Travel To Work Areas (TTWA)	Adzuna (Independent variables)	AIRD_Complementary	(TTWA) is specialised, over the sum of the co-occurrence probability for every skill relative to AI skills in the year of t-1 in Great Britain. Complementary skills refer to the skills which AI technologies are complementary to but are not IT and Mathematical modeling skills (Lightcast 2025). The combination between AI skills and the complementary skills lays the foundation of adopting AI technologies in various application domains (Goldfarb et al. 2023). In order to clearly distinguish skill relatedness between similarity and complementarity, the study further regress skill relatedness density of the complementary skills on that of the fundamental skills and estimate the regression residuals. By doing so, the study uses the regression residual to create a new AIRD_Complementary variable orthogonal to another independent variable of AIRD_Similar.	Technological relatedness
			This continuous variable (AIRD_Similar) is defined and computed similarly as AIRD_Complementary, but the one	

		AIRD_Similar	difference is that this variable only measures the AI Relatedness density of IT and Mathematical skills in each TTWA. These skills of IT and Mathematical Modelling are retrieved from Lightcast (2025) skill taxonomy. The combination between AI skills and the IT as well as Math skills should lay the foundation of developing or applying AI technologies for state-of-the-art algorithms or inventions (Hunt et al. 2024; Xiao and Boschma 2023).	
	NOMIS (Independent variables)	Energy	A continuous variable - location quotient – indicates employment specialisation in the Mining, quarrying & utilities (B, D and E) industry in TTWAs in the year of t-1.	Industrial specialisation and comparative advantages
		Manufacturing	A continuous variable - location quotient – indicates employment specialisation in the Manufacturing (C) industry in TTWAs in the year of t-1.	
			Human capital is measured as the proportion of managers, senior officials, professionals, and tech occupations in high-tech industries over total	

	NOMIS (Control variables)	Human_Capital	employment in TTWAs in the year t-1. These high-tech industries include (B,D,E) Energy & water, (C) Manufacturing, (H,J) Transport & communication, (K-N) Banking finance & insurance.	Human capital
		Large_Com	Large company: The proportion of companies with 250+ employees over all companies in TTWAs in t-1.	Agglomeration externalities
		Job_Den	Job density: The share of the number of jobs over residents aged 16-64 in TTWAs in t-1.	
Company		Company_Type	This variable is the job category of the most OJAs posted by each company in each TTWA in the last year t-1. There are 30 job categories in the Adzuna OJA dataset, including Accounting & Finance Jobs, IT Jobs, Sales Jobs, Customer Services Jobs, Engineering Jobs, HR & Recruitment Jobs, Healthcare & Nursing Jobs, Hospitality & Catering Jobs, PR, Advertising & Marketing Jobs, Logistics & Warehouse Jobs, Teaching Jobs, Trade & Construction Jobs, Admin Jobs, Legal	

	Adzuna (Control variable)		Jobs, Creative & Design Jobs, Graduate Jobs, Retail Jobs, Consultancy Jobs, Manufacturing Jobs, Scientific & QA Jobs, Social work Jobs, Travel Jobs, Energy, Oil & Gas Jobs, Property Jobs, Voluntary Jobs, Domestic help & Cleaning Jobs, Maintenance Jobs, Part time Jobs, Other/General Jobs, and Unknown. We exclude the last category in the model to avoid any multicollinearity issue.	Internal resources of companies

Appendix D. Descriptive analysis

Table D.1. Top 10 travel to work areas with the largest average share of AI OJAs, 2016-2024.

TTWA11CD	TTWA Name	AI OJAs	Total OJAs	AI Share (%)	AIRD_ Complementary (orthogonal)	AIRD_ Similar	ICT
E30000186	Cambridge	2,832	212,658	1.332	1.091	0.0029	1.294
E30000272	Stevenage and Welwyn Garden City	1,284	140,709	0.974	0.761	0.0015	1.042
E30000250	Oxford	1,956	213,446	0.902	1.086	0.0022	1.343
E30000234	London	24,423	3,305,404	0.773	2.734	0.0016	1.844
E30000180	Bristol	1,996	306,587	0.645	1.191	0.0018	1.238
E30000221	Huntingdon	448	73,180	0.607	1.001	0.0013	0.760
E30000228	Leamington Spa	495	89,967	0.584	-0.177	0.0023	1.251
S22000059	Edinburgh	1,051	176,061	0.583	1.405	0.0016	1.174
E30000195	Coventry	671	127,366	0.538	0.084	0.0012	0.618
E30000189	Cheltenham	267	56,180	0.514	-0.386	0.0027	1.300

Notes: Numeric values of each column are taken average between 2016-2024 in TTWAs in Great Britain, including the number of AI OJAs, the number of all OJAs, the share of AI OJAs,

the AI relatedness density of complementary skills (exc. IT and Mathematical modelling skills), and the AIRD of fundamental (IT and Math) skills, and employment specialisation in ICT industries. We select the Top 10 TTWAs with the highest average share of AI OJAs.

Appendix E. Robustness tests

Table E.1. Robustness tests of Model (3) in Table 3 for multi-locational companies.

	Dependent variable:	
	(1)	(2)
	AI_Demand_LQ	AI_Demand_LQ
TTWA-level		
AIRD_Complementary	0.12***	0.10***
	(0.01)	(0.01)
AIRD_Similar	0.05***	0.04***
	(0.01)	(0.01)
Controls	YES	YES
Company-level		
Company type	NO	YES
Controls	YES	YES
Year FEs	YES	YES
Model summary		
Random Intercept	TTWA-level and Company-level	TTWA-level and Company-level

σ2(Company)	2.02	1.85
σ2(TTWA)	3.57	0.36
Marginal R-squared	0.11	0.37
Conditional R-squared	0.67	0.62
Observations	3,398,807	3,398,807
Akaike Inf. Cri.	390242	362958

Notes: See notes in Table 2. While Model (1) in this table is the baseline model, but Model (2) further controls the company type, which is the most frequent job category of OJAs posted by each company in each region in each year (see variable description in Table C.1 in Appendix C).

OJA Observations

The number of OJAs considerably decreases in the Adzuna dataset after the pervasive adoption of ChatGPT at the end of 2022. Furthermore, there are lower proportions of unique OJAs in 2023 and 2024 compared to 2022 (see computation in Equations E.1-E.3). Thus, the study adds yearly interaction terms of the two independent variables between 2017-2024. Table E.2 as follows shows robust estimates of independent variables.

Share of unique OJAs in 2022: $18604809 / 54840336 = 0.339254$ (E.1)

Share of unique OJAs in 2023: $13649129 / 45785893 = 0.298108$ (E.2)

Share of unique OJAs in 2024: $10137514 / 34376612 = 0.294896$ (E.3)

Table E.2. Yearly interaction effects of AI relatedness density for Model (3) in Table 2 & 3.

	Dependent variable:	
	(1)	(2)
	AI_Demand	AI_Demand_LQ
TTWA-level		
AIRD_Complementary	0.58***	0.19***
	(0.20)	(0.02)
AIRD_Similar	0.66***	0.08***
	(0.18)	(0.02)
AIRD_Complementary*Year(2018)	0.01	-0.00
	(0.20)	(0.02)

AIRD_Complementary*Year(2019)	0.05	-0.02
	(0.17)	(0.02)
AIRD_Complementary*Year(2020)	-0.06	-0.09***
	(0.20)	(0.02)
AIRD_Complementary*Year(2021)	-0.12	-0.06***
	(0.16)	(0.02)
AIRD_Complementary*Year(2022)	-0.24	-0.08***
	(0.16)	(0.02)
AIRD_Complementary*Year(2023)	-0.02	-0.08***
	(0.18)	(0.02)
AIRD_Complementary*Year(2024)	-0.08	-0.08***
	(0.17)	(0.02)
AIRD_Similar*Year(2018)	-0.54**	-0.00
	(0.23)	(0.03)
AIRD_ Similar*Year(2019)	-0.32	-0.01
	(0.22)	(0.02)
AIRD_Similar*Year(2020)	-0.44**	-0.05**
	(0.20)	(0.02)
AIRD_Similar*Year(2021)	-0.40**	-0.02

	(0.20)	(0.02)
AIRD_Similar*Year(2022)	-0.30	-0.05*
	(0.21)	(0.02)
AIRD_Similar*Year(2023)	-0.22	-0.02
	(0.21)	(0.02)
AIRD_Similar*Year(2024)	-0.50**	-0.01
	(0.22)	(0.03)
Controls	YES	YES
Year FEs	YES	YES

Model summary

Random Intercept	TTWA-level and Company-level	TTWA-level and Company-level
σ2(Company)	110.2	4.21
σ2(TTWA)	0.000	0.86
Marginal R-squared	0.012	0.117
Conditional R-squared	0.971	0.652
Observations	388,115	3,398,807
Akaike Inf. Cri.	26082	390911

Notes: See notes in Table 2. In models (1) and (2), the reference year is 2017.