1 Abstract

The adoption of AI technologies leads to socio-economic inequality issues within and among cities to some extent (Pinheiro et al. 2022, Rodríguez-Pose 2018). On the one hand, complex technologies tend to be spatially concentrated in large cities due to local accumulation of economic activities, human capital, knowledge, urban infrastructure and research institutions (Balland et al. 2020, Duranton & Puga 2004, Bloom et al. 2021). In this way, complex technologies are intertwined with further urban agglomeration over time, while simple technologies are spatially distributed more evenly across space (Bloom et al. 2021). On the other hand, AI-exposed enterprises replace non-AI tasks with AI occupations (Acemoglu et al. 2022). For instance, it is more likely for rural areas with higher proportions of low-skilled workers performing routine tasks to be influenced by AI technologies (Brekelmans & Petropoulos 2020).

Thus, it is important for economic geographers to map the evolution of spatial patterns regarding AI adoption and investigate its driving forces. Limited studies investigate how place characteristics influence the AI spatial concentration within and among cities over time (Bloom et al. 2021). My research estimates heterogeneous, compositional and contextual effects of local places' characteristics on AI location quotients at the LSOA (Lower Layer Super Output Areas) and TTWA (Travel To Work Areas) level in Great Britain, using data of AI online job vacancies between 2016-2021. Firstly, place characteristics mean that local places shape and are shaped by local contexts (e.g. local demographics, socio-economic levels, public amenities as well as governance), network structure among local places (e.g. ICT infrastructure and urban transport) and public perceptions (Di Zhu & Liu 2020). In our research, these place characteristics are proxied mainly by socio-economic indicators such as urban productivity, population density and points of interest (POIs) (e.g. transport stations) in local areas. Secondly, the spatial concentration indicates that similar economic activities are co-located in local areas within regions. Furthermore, these local areas are specialised in AI adoption (i.e., AI online job advertisements), which is represented by AI location quotients. Thirdly, the location quotient is a relative rate of the AI online job proportion in local areas (i.e., LSOAs) over the AI job proportion in the entire study area (i.e., Great Britain). Descriptions of all variables are given in the Appendix.

Research findings of linear multilevel models indicate that new yearly AI online jobs become more and more spatially concentrated in specific local areas over time at the early stage of AI adoption. This remarkable phenomenon illustrates potential inequality issues of urban and regional economic development in Great Britain. For one thing, local intensive AI online hiring activities have a significant and positive correlation with place characteristics, for instance, urban productivity and points of interest of cultural amenities, local governance, urban transport as well as intellectual resources. For another, developed regions with more universities and better internet speed manifest labor demands for AI skills to a relatively greater extent on average across Great Britain. However, these linear models have autocorrelation and non-normality issues of residuals despite robust effects estimated in another two-level mixed-effect logit model. In addition, the LSOA-level estimated fixed effects do not indicate heterogeneous effects across LSOAs but assume spatial homogeneity, which is not the case according to the literature. It would be more appropriate to combine the current model with a GWR (Geographically Weighted Regression) model, which uncovers local variation of the estimated effects (Hu et al. 2022).

Based on current results, two policy recommendations are provided. Specifically, local areas could regenerate communities around local governments by increasing public transport stations, improving ICT infrastructure, and incentivising more R&D and technical services to establish local businesses for place making. Furthermore, revenues generated by local new businesses should be reinvested partly to renovate historic buildings as well as cultural facilities close to the renovated communities as training centres for low-skilled workers. In sum, maintaining and improving place characteristics is one of the most potential ways for lagging regions in Great Britain to alter this unequal phenomenon of the consistent AI spatial concentration in developed areas. As for my future research, it is promising to investigate how the AI spatial concentration influences urban green transitions, for instance, green jobs (Larsen et al. 2022).

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Appendix

Type	Symbol	Meaning
Dependent variable (LSOAs level)	$LQ_{lw,t}$	Location quotients of online AI job advertisements requiring both general and specific AI skills.
Control variables (LSOAs level)	$GVA_{lw,t-1}$	Total amount of local gross value added (GVA) estimates indicates the level of economic contribution of local industries to gross domestic products. (see: Website)
	$Pop\_den_{lw,t-1}$	The rate of local population per square kilometer in LSOA (Lower Layer Super Output areas) in England, Wales and Scotland in mid-2015,-2016,-2017,-2018,-2019,-2020
	$PoI_{lw,t-1}$	$PoI\_Fin_{lw,t-1}$: The number of commercial services of finance as well as insurance in each LSOA, including 'Credit Reference Agencies', 'Financial Advice Services', 'Insurers and Support Activities', 'Mortgage and Financial Lenders', 'Stocks, Shares and Unit Trusts' and 'Pension and Fund Management'. (see: Website)
		$PoI\_ICT_{lw,t-1}$: The number of commercial services of information technology in each LSOA, including 'Computer Security', 'Computer Systems Services', 'Database Services', 'Film and Video Services', 'General Computer Services', 'Internet Services' and 'Mailing and Other Information Services'. (see: Website)
		$PoI\_Uni_{lw,t-1}$: The number of higher education establishments in each LSOA. (see: Website)
		$PoI\_LG_{lw,t-1}$ and $PoI\_CG_{lw,t-1}$: The number of central or local governments on which social capital is created based in each LSOA. (see: Website)
		$PoI\_Culture_{lw,t-1}$: The number of 'Historic Buildings Including Castles, Forts and Abbeys', and 'Museums' as cultural characteristics of LSOAs.
		$PoI\_RD_{lw,t-1}$: The number of research & design businesses, including $PoI\_RDr_{lw,t-1}$ ('Research Services'), $PoI\_RDd_{lw,t-1}$ ('Design Services'), and $PoI\_RDt_{lw,t-1}$ ('Testing and Analysis Services').
		$PoI\_Headquarters_{lw,t-1}$: The number of 'Headquarters, Administration and Central Offices' as business characteristics of LSOAs.
		$PoI\_Transport_{lw,t-1}$: The number of each transport facility such as coach, metro and railway stations, which decrease transport costs of

		companies/employees travelling between local areas. (see: Website)
	$London_{lw}$	A dummy variable indicates whether each LSOA is located within the London TTWA or inner London.
Control variables (TTWAs level)	$Emp_{w,t-1}$	$Emp\_Rate_{w,t-1}$: The employment rate (see: Website)
		$Emp\_STEM_{w,t-1}$: The proportion of managers, senior officials, professionals, and tech occupations in high-tech industries over total employment. These high-tech industries are defined according to SIC 2007, including (B,D,E) Energy & water, (C) Manufacturing, (H,J) Transport & Communication, (K-N) Banking finance & insurance etc. (see: Website)
	$Business_{w,t-1}$	The proportion of all enterprises in TTWAs over economically active population. (see: Website)
	$Large\_Com_{w,t-1}$	The proportion of large companies with more than 250 employees over the total number of companies in each TTWA. (see: Website)
	$ICT_{w,t-1}$	ICT infrastructure indicates regional capacities of disseminating and receiving information. $ICT\_download_{w,t-1}$: Users' experiences of broadband download speeds.
		$ICT\_upload_{w,t-1}$: Users' experiences of broadband upload speeds.
	$Airport_{w,t-1}$	The rate of airports over economically active population in each TTWA. (see: Website)
	$University_w$	The number of universities in each TTWA. (see: Website)
	$TTWA\_area_w$	The area of each TTWA as a proxy of socio-economic levels and regional transport infrastructure in general.
	$Distance_w$	Spatial distance between each TTWA and London.

Figure 1: Variable descriptions