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Demand for Creativity and AI Skills in the Post-ChatGPT Labour Market: Evidence from UK Job Vacancies

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Contents

Abstract

Drawing on Adzuna UK job vacancy data comprising over 168 million job postings from 2016 to 2024, this study examines the evolving relationship between employer demand for creativity and AI skills in the UK labour market. Using the public release of ChatGPT 3.5 in November 2022 as a critical inflection point marking the widespread accessibility of Generative AI (GenAI), we adopt a pre- and post-event study design to empirically assess how this relationship has changed. Our findings reveal that labour markets with greater demand for AI skills also tend to exhibit greater demand for creativity. Notably, the co-occurrence of these two skill sets in job postings has intensified following the launch of ChatGPT, particularly in high-skilled roles located within creative clusters, where concentrations of creative industries firms and workers compete and collaborate with each other. We conclude by highlighting the importance of multi-level policy interventions, while also cautioning against the risk of GenAI in further entrenching regional disparities in left-behind regions.

Keywords: job vacancy data, GenAI, human creativity, labour market demand

JEL: J23, J24, O33, R23

Introduction

For centuries, technological progress has been defined by the automation of routine tasks. From steam engines to industrial machinery, successive waves of innovation have surpassed human capabilities in dimensions such as power, speed, productivity, quality, accuracy, reliability, durability, and often, in cost (Autor, 2015; Chui et al., 2016), leading to the displacement of human labour towards less automatable work (Dixon et al., 2020). In recent years, the future of work has been further reshaped by rapid advancements in Artificial Intelligence (AI), which extend beyond the automation of codified, routine tasks (Acemoglu and Restrepo, 2019; Frey and Osborne, 2017).

AI technologies have increasingly been adopted to perform tasks beyond traditional technical domains (Acemoglu et al., 2022; Bonfiglioli et al., 2025). Most recently, large language model-based generative AI (GenAI) systems such as ChatGPT, trained on massive datasets and refined through user feedback, are emerging as powerful tools for ideation and complex problem-solving (Rafner et al., 2023). Although still in their early stages of development, they already demonstrate considerable potential to automate non-routine and creative tasks ranging from ideation to content creation, selection and evaluation, domains historically considered uniquely human (Grilli and Pedota, 2024; Lysyakov and Viswanathan, 2023; Zhou and Lee, 2024). Owing to their general-purpose functionality, low cost (often free), and wide accessibility, GenAI tools are poised to significantly reshape labour market dynamics where historically creative skills have been at a premium (Costa et al., 2024; Demirci et al., 2025; Liu et al., 2023). The potential for technology to interact with creativity has led to governments to prioritise investment in sectors such as 'createch', which bring together creative activities with R&D-led technology (Government, 2025; Siepel et al., 2022) and which are seen as sources of future economic growth.

Yet, the implications of these developments for labour markets remain uncertain. The adoption of AI technologies by firms is inherently associated with an increased demand for AI skills, which are capabilities associated with developing, deploying, or working alongside AI systems (e.g., machine learning, natural language processing, and algorithmic modelling) (Acemoglu et al., 2022; Babina et al., 2023; Maslej et al., 2025; Zhang et al., 2025), as firms seek workers capable of implementing these technologies effectively (Acemoglu et al., 2022; Alekseeva et al., 2021). However, with the rapid proliferation of GenAI, concerns are mounting that employers may begin to prioritise AI skills at the expense of human creativity, which are capabilities to intentionally generate new and useful ideas, methods, or practices to solve problems (Anderson et al., 2014; Sleuwaegen and Boiardi, 2014), potentially diminishing its value across a broad spectrum of economic activities (Wilson and Daugherty, 2018). These concerns are potentially exacerbated by geographical inequalities, with AI adoption, like other disruptive technologies often occurring in more technologically advanced regions (Bessen et al., 2021; Bloom et al., 2021; McElheran et al., 2024). With creative activities, particularly in the creative industries, also tending to cluster in urban areas (Casadei et al., 2023; Gutierrez-Posada et al., 2022), this trend could further strain existing regional inequalities. This raises a central question for both scholars and policymakers alike: in an era where GenAI tools like ChatGPT are widely accessible and increasingly embedded into workflows, do employers still seek creativity as a skill requirement when hiring? And is employers' desire for creativity linked to geography? It is to these questions that this paper turns.

To date, the discourse on AI's impact on creativity remains predominantly theoretical, with nascent empirical investigations exploring whether their relationship is complementary or substitutive. Existing empirical research is still in its early stages and tends to be narrow in scope, often relying on experimental designs conducted in controlled environments (Noy and Zhang, 2023) or focusing on micro-level analyses of particular tasks (Arntz et al., 2016; Eloundou et al., 2023), occupations (Lysyakov and Viswanathan, 2023; Teutloff et al., 2025) or job designs within particular organisational contexts (Jia et al., 2024; Liu et al., 2017). Consequently, a significant gap persists in our understanding of how the relationship between AI and creativity manifests at the broader labour market level (Teutloff et al., 2025).

This study addresses the key gap by leveraging a large-scale, granular dataset comprising over 168 million Adzuna job postings from 2016 to 2024 to capture the evolving relationship between the demand for creativity and AI skills within the UK labour market. Moving beyond traditional approaches that rely on pre-defined keyword lists, we build on the method adopted by Schmidt et al. (2024) and employ a more comprehensive natural language processing (NLP) method to capture both explicit and implicit references to creativity and AI skills within job postings. As AI may particularly reshape how work is organised and tasks are performed within occupations (Albanesi et al., 2023; Brynjolfsson and Mitchell, 2017; Costa et al., 2024; Hui et al., 2024), we aggregate all job postings by occupation and Travel to Work Area (TTWA), which serve as proxies for local labour market units. To examine temporal shifts in skill demand, we employ a pre- and post-event study design, using the public release of ChatGPT in December 2022 as a pivotal inflection point that marks the widespread accessibility of powerful GenAI. This design enables us to empirically assess how the relationship between employer demand for creativity and AI skills evolves in response to the introduction of GenAI. Our analysis reveals an overall increase in demand for both AI skills and creativity following this launch. More importantly, we identify a positive association between the two – labour market units with higher demand for AI skills also tend to exhibit greater demand for creativity. This relationship has strengthened post-ChatGPT, particularly within high-skilled roles located within creative clusters. These patterns suggest that rather than displacing creativity, the accessible GenAI has increased demand for workers who can leverage both skill sets, especially in high-skilled labour markets with dense concentrations of creative industry employers.

This study offers several contributions. First, we contribute to the ongoing debate on the relationship between creativity and AI skills in the workplace (De Cremer et al., 2023; Wilson and Daugherty, 2018). By incorporating insights from labour market demand across different geographical dimensions, we broaden the theoretical scope beyond firm-level or task-based analyses (Jia et al., 2024). Second, this study bridges theoretical inquiry with policy relevance by providing quantitatively grounded insights to inform skills policy. Critically, we also draw attention to the potential *dark side* of the observed AI–creativity co-occurrence: it may intensify existing regional inequalities, particularly disadvantaging left-behind UK regions that lack both a highly skilled workforce and the agglomeration benefits of creative clusters, warranting targeted policy interventions. Finally, the study joins a growing number of papers making methodological contributions to the study of AI and labour market demands (Schmidt et al., 2024; Zhang et al., 2025): we leverage granular, real-time job vacancy data to construct a micro-level view of labour market demand, complemented by the application of advanced NLP techniques, allowing for the systematic and scalable identification of job postings that require both creativity and AI skills.

The remainder of this paper is organised as follows. The next section presents the theoretical framework and hypotheses. Section 3 outlines the methodological approach. Section 4 reports and discusses the empirical findings. Section 5 examines the policy implications arising from the findings. Finally, Section 6 concludes.

Theory and Hypotheses

Theoretical Tension between Creativity and AI

In organisational research, creativity is commonly defined as the capacity to intentionally generate new and useful ideas, methods, or practices to address problems (Anderson et al., 2014; Sleuwaegen and Boiardi, 2014). Its significance spans multiple domains: it is recognised as an important predictor of occupational growth (Easton and Djumalieva, 2018), a micro-foundation of firm innovation (Anderson et al., 2014; Bakhshi and McVittie, 2014), and an important driver of local economic development (Florida, 2019; Gutierrez-Posada et al., 2022). Consequently, creativity has been identified as one of the most sought-after and desirable skills in the workplace (Casner-Lotto et al., 2009; Puccio and Cabra, 2010). However, rooted in a fundamental capacity for autonomous judgement and genuine creative intent, creativity is widely regarded as a uniquely human cognitive process (Amabile, 1996; De Cremer et al., 2023). For this reason, it has historically been seen as inherently constrained by limited scalability and a 'bottleneck' to automation (Frey and Osborne, 2017; Bakhshi, Frey and Osborne, 2015). Consistent with this, while creativity is in high demand across the labour market, it remains a skill that is often scarce and difficult to identify in job applicants (Otani, 2015).

In recent years, the rapid advancement and widespread accessibility of AI technologies, particularly mostly free access GenAI applications such as ChatGPT, have introduced new dynamics into the workplace, however, fundamentally altering how creativity is enacted (Brem and Hörauf, 2025). Trained on massive datasets and user feedback, GenAI models are increasingly capable of producing content in text, image, audio, or multimodal forms. These tools have emerged as powerful instruments for ideation and complex problem-solving (Rafner et al., 2023), capable of generating creative outputs at unprecedented speed and scale – often surpassing human capabilities in terms of volume and efficiency (Grilli and Pedota, 2024). Although still in the early stages of development, GenAI technologies already show considerable potential to automate creative tasks traditionally performed by humans, such as writing, visual design, programming, and other knowledge- and information-intensive activities (Grilli and Pedota, 2024; Jia et al., 2024; Zhou and Lee, 2024).

However, an important component of creativity lies in the availability of cognitive and personality processes that enable individuals to think creatively, such as divergent thinking, cognitive flexibility, and a willingness to take risks (Amabile, 1996). These qualities to some extent suggest the inherent limitations of AI, particularly its lack of intrinsic creative thinking capacity (Runco, 2023). While AI has been shown to enhance human creative productivity and efficiency, arguably it has not generated fundamentally new ideas or breakthroughs (Financial Times, 2025). Current GenAI applications are unable to exercise autonomous judgement or genuine creative intent, their outputs remain bounded by pre-defined algorithms, protocols, and scripts (Berente et al., 2021; Choudhury et al., 2020), and ultimately require human interpretation and evaluation (Joosten et al., 2024). These limitations become especially apparent in unscripted, higher-order, and unstructured tasks (Brynjolfsson and McAfee, 2014), precisely the domains where human creativity retains a distinctive and irreplaceable role.

Therefore, the widespread adoption of GenAI in the workplace may be unlikely to altogether replace unstructured critical thinking, contextual awareness, originality and high-level problem-solving, which are key elements underpinning the cognitive process of creativity. While GenAI may substitute for some specific creative tasks (e.g., editing a script, denoising a visual effect), at the more aggregated level, it is more likely to serve as a complementary tool (OECD, 2017). As such, far from rendering human creativity obsolete, the increasing integration of GenAI within work processes may in fact enhance the value of creativity (Zhou and Lee, 2024), thus increasing the demand for roles requiring creativity skills. As employers increasingly demand broader skill bundles in tandem (Petersen et al., 2025), we therefore expect that within the labour market, job postings that demand AI skills are likely to demand creativity at the same time. And as the emergence of ChatGPT marks a significant turning point in the widespread accessibility and adoption of GenAI, we anticipate that this co-occurrence in labour market demands becomes more pronounced following its launch. Based on this reasoning, we formulate our first hypothesis:

H1: Demand for creativity and AI skills co-occurs within the labour market, and this positive association is strengthened after the public launch of ChatGPT.

The Regional Dimension: Creative Clusters

Geography plays a crucial role in shaping labour market demands, as skilled labour and knowledge spillovers are inherently spatial and influenced by the geographic concentration of interconnected firms, workers, and institutions (Bratanova et al., 2022; Chapain and Comunian, 2009; Diodato et al., 2018). The agglomeration literature highlights that labour market dynamics often differ significantly within and outside agglomerations (Di Addario, 2011). In his seminal work on the spatial concentration of economic activity, Marshall (1890) identified pooled labour market benefits as one of the core advantages of agglomeration economies. Agglomerations, particularly in the form of thick labour markets, provide stable and consistent demand for a wide range of skills, facilitating more efficient matching between supply and demand (Corradini et al., 2025).

In line with this, the co-occurrence of demand for creativity and AI skills is likely to be influenced by the broader local context in which firms and workers operate. Across occupations and sectors, demand for creativity tends to be higher in creative occupations and industries. Firms and institutions operating in creativity-intensive domains often agglomerate spatially, forming *creative clusters* (Casadei et al., 2023; Gutierrez-Posada et al., 2022).

Creative clusters are characterised by specialised labour markets, dense networks of collaboration and competition, and rich ecosystems that support knowledge exchange and talent attraction (Bakhshi and Dorsett, 2023). These clusters benefit from thick labour markets, shared infrastructures, and sectoral specialisation, which not only sustain a consistently high proportion of creative roles but also foster broader creative activity across the workforce through informal social interactions and localised knowledge spillovers (Sleuwaegen and Boiardi, 2014). As such, they offer more stable and sustained demand for creative work, as firms embedded in these ecosystems continually require new content, design, branding, and creative outputs to stay competitive.

Importantly, AI technologies are not adopted homogeneously across space (Acemoglu et al., 2023). A growing body of research shows that agglomerations accelerate the adoption and diffusion of advanced technologies through local knowledge-sharing (Sleuwaegen and Boiardi, 2014; Tambe and Hitt, 2014). These environments may promote experimentation and early uptake of frontier technologies. Therefore, creative clusters, being both creativity-intensive and early adopters of AI, are likely to demand creativity and AI skills in tandem. Consequently, the labour market effects of AI on creativity demand may be further amplified following the launch of ChatGPT. Based on this reasoning, we formulate our second hypothesis:

H2: The positive association between demand for creativity and AI skills is more pronounced in creative clusters after the public launch of ChatGPT.

Skill-biased Impact of GenAI on Human Creativity

Technological change is often associated with skill-biased demand shifts, whereby advancements in technology increase the demand for more highly skilled workers (Acemoglu and Autor, 2011). This may be particularly relevant for creative roles, which, according to the componential theory of creativity, require a sufficient level of domain-specific expertise and knowledge as a fundamental prerequisite (Amabile, 1996). These domain-specific resources determine how effectively individuals address challenges in their work and thus play a central role in enabling job-relevant creative performance. Higher levels of domain expertise and knowledge also strengthen cognitive capacity, allowing employees to better identify opportunities for creative problem-solving and to engage effectively with complex, non-routine tasks that demand innovative thinking (Liu et al., 2017).

As AI technologies become increasingly integrated into workplace processes, a sequential division of labour emerges. AI takes on routine, codifiable, and structured components of work governed by pre-defined algorithms and scripts, which produces outputs that creative talent with high levels of domain expertise and knowledge can utilise when exercising their divergent thinking and human judgement for higher-level, less codifiable tasks (Lysyakov and Viswanathan, 2023). As such, we expect the relationship between demand for AI skills and creativity to be skill biased. At the labour market level, demand for AI skills is more likely to co-occur with demand for creativity in high-skilled jobs, where workers possess the necessary capabilities to manage novel, abstract, and cognitively complex tasks (Jia et al., 2024; Lysyakov and Viswanathan, 2023). Based on this reasoning, we formulate our third hypothesis:

H3: The positive association between demand for creativity and AI skills is more pronounced for high-skilled jobs after the public launch of ChatGPT.

Methodologies

Data Sources

This study joins an emerging strand of research that leverages job vacancy data to examine the evolution and spatial patterns of labour market demands (Acemoglu et al., 2022; Alekseeva et al., 2021; Costa et al., 2024; Draca et al., 2024). We employ Adzuna online job vacancy data spanning 2016 to 2024, offering timely and granular insights into UK labour market dynamics. Adzuna is an online job search engine that aggregates job advertisements from various sources (e.g., employer websites, recruitment software providers, and traditional job boards), and generates weekly snapshots that capture over 90% of all jobs advertised in the UK (Bassier et al., 2025). The dataset includes information on the posting firm, job title, wage, location, Standard Occupational Classification (SOC), Standard Industrial Classification (SIC), a free-text job description, and required skills. Recognised as an indicator of UK economic activity by the Office for National Statistics (ONS, 2021), Adzuna data is increasingly used in research examining labour market dynamics (Bratanova et al., 2022; Costa et al., 2024; Petersen et al., 2025).

Given that technological change, and AI in particular, reshape how work is organised and tasks are performed *within occupations* (Albanesi et al., 2023; Brynjolfsson and Mitchell, 2017; Costa et al., 2024; Hui et al., 2024), our analysis focuses on occupationally disaggregated patterns of labour market demand. To operationalise this, we first deduplicate the job postings by retaining a single unique occurrence per ad ID, as postings may appear multiple times within a month due to Adzuna's algorithmic capture. This yields 202,090,938 unique job postings. We exclude vacancies lacking essential information (i.e., job descriptions, required skills, SOC codes, or location data), resulting in a final analytical sample of 168,349,704 postings. We then aggregate them to our final unit of analysis at the SOC-TTWA-month level, providing a fine-grained and geographically localised view of labour demand. The final dataset comprises 4,192,719 SOC–TTWA–month observations.

Labour Market Demand for Creativity Skills and AI Skills

Moving beyond traditional approaches that rely on pre-defined key word/term lists to identify creativity and AI skills, we build on the method adopted by Schmidt et al. (2024) and employ a more comprehensive NLP method capable of capturing both direct and indirect references to creativity and AI skills.

To capture labour market demand for creativity and AI skills, we identify job postings that are creativity- or AI-related. For creativity-related postings, we first construct a compendium of terms encompassing both *generic* and *specific* forms of creativity, drawing on established contributions from the creativity literature (Chen et al., 2025; Osborn, 1953; Pollok et al., 2021; Runco and Jaeger, 2012). We then extract noun chunks from job descriptions using NLP techniques and transform them into vectorised representations suitable for quantitative analysis. Using our compendium as seed terms, we systematically scan for generic creativity in the free-text job descriptions and specific creativity in the structured skill requirement fields. Cosine similarity is used to assess the semantic closeness between extracted noun chunks and the seed terms, applying a similarity threshold of 30%. A job posting is classified as creativity-related if it contains at least one generic creativity and one specific creativity requirement (Goldfarb et al., 2023; Zhang et al., 2025).

We adopt the same methodological framework to identify AI-related job postings. One group of seed terms captures *generic AI* skills such as machine learning, computer vision, and natural language processing, while a second group identifies *specific AI* skills, including AdaBoost, Hidden Markov Models, and Word2Vec (Acemoglu et al., 2022; Babina et al., 2023; Maslej et al., 2025; Zhang et al., 2025). For further technical details on the construction of skill taxonomies and threshold selection, see Appendix A.1.

Model Specifications and Variable Construction

Model Specification

We estimate a triple interaction event study specification, using December 2022 (the release of ChatGPT) as the event of interest. The baseline specification is as follows:

$$\begin{aligned}\textit{Creativity Demand Share}_{o,t,m} = {} & \beta_1 \textit{AI Demand Share}_{o,t,m} + \beta_2 \textit{Post-ChatGPT}_{m} + \beta_3 \textit{High-skilled Share}_{o,t,m} + \beta_4 \textit{AI Demand Share} \times \textit{Post-ChatGPT}_{o,t,m} \\ & + \beta_5 \textit{AI Demand Share} \times \textit{High-skilled Share}_{o,t,m} + \beta_6 \textit{Post-ChatGPT} \times \textit{High-skilled Share}_{o,t,m} \\ & + \beta_7 \textit{AI Demand Share} \times \textit{Post-ChatGPT} \times \textit{High-skilled Share}_{o,t,m} + \beta_8 \textit{Time Trend}_{m} + \beta_9 \textit{Posting Length (log)}_{o,t,m} \\ & + \beta_{10} \textit{Permanent Position}_{o,t,m} + \beta_{11} \textit{Average Salary (log)}_{o,t,m} + \rho_t + \iota_o + \varepsilon_{o,t,m} \qquad (1)\end{aligned}$$

Our unit of analysis is at the SOC-TTWA-month level. We include a set of control variables, a dummy variable to capture the launch of ChatGPT, and a series of interaction terms to examine how the association between demand for AI skills and creativity shifts in the post-ChatGPT period. We also include fixed effects for occupations *o* and TTWAs *t* to account for unobserved heterogeneity across occupation and location. Regressions are weighted by the number of job postings in each TTWA-SOC unit to account for variation in job posting volumes. To compare the effects across creative and non-creative clusters, we split the sample into two subsamples and conduct the analysis separately for each group. The classification of creative clusters follows the list of 55 TTWAs identified by the UK Department for Digital, Culture, Media and Sport (DCMS) as creative clusters, often referred to as the 'DCMS-55' list (DCMS, 2022). Of the 4,192,719 SOC-TTWA-month observations, 1,590,593 belong to creative clusters and 2,602,126 to non-creative clusters.

Dependent Variable

Creativity Demand Share. To measure labour market demand for creativity, we construct *Creativity Demand*

Share, defined as the proportion of job postings that are creativity-related within a labour market unit.

Independent Variables

AI Demand Share. To measure labour market demand for AI skills, we construct *AI Demand Share*, defined as the proportion of AI-related job postings within a labour market unit.

Post-ChatGPT. A binary indicator representing the period after the public launch of ChatGPT 3.5. The event is dated to December 2022[1] (= 1 for months ≥ December 2022, 0 otherwise).

High-skilled Share. This variable measures the proportion of job postings that can be classified as high-skilled. We construct it using three indicators: (1) the share of job postings explicitly requiring higher education qualifications above the level of a bachelor's degree, drawing on previous literature that highlights higher educational attainment as an indirect proxy for higher skill levels (Berlingieri, 2019; Frey and Osborne, 2017; Leknes et al., 2022); (2) the share of postings classified as senior-level positions, as they typically require more advanced and comprehensive skill sets (Indeed, 2025; Mumford et al., 2007); and (3) the share of postings that are not apprenticeships, as apprenticeships tend to focus on initial skill acquisition rather than the application of higher-level specialised knowledge (Kuczera, 2017). These three proxies are combined using Principal Component Analysis (PCA) to compute an index of high-skilled demand at the labour market level.

Control Variables

Time Trend. This variable represents the year-month of each observation and is included in the model to control for underlying linear time trends that may influence the creativity demand share over time. By accounting for these temporal dynamics, we try to ensure that the estimated effect associated with the release of ChatGPT is not confounded by general upward or downward drift in the demand for creativity that are unrelated to the event.

Posting Length (log). We control for the logarithm of the average job posting length within each labour market unit, as longer postings are more likely to contain detailed descriptions and thus increase the likelihood of referencing creativity and AI skills.

Permanent Position. This binary control variable captures the proportion of job postings within each labour market unit that are classified as permanent positions (1 = permanent positions, 0 otherwise), to account for variation in contract types[2] (Teutloff et al., 2025), as skill requirements may differ between permanent roles and short-term positions.

Average Salary (log). We also control for the logarithm of the average advertised salary within each labour market unit to ensure that the observed variation in demand for creativity and AI skills is not simply driven by higher-paying jobs that typically require more advanced skills (Alekseeva et al., 2021; Garcia-Lazaro et al., 2025).

Details of the summary descriptive statistics, including Variance Inflation Factors (VIF), and pairwise correlation coefficients are presented in Table 1. Our analyses confirm that issues of multicollinearity do not distort our estimations.

[1] Given that ChatGPT 3.5 was launched on 30 November 2022, the earliest month in which its labour market impact could plausibly begin to appear is December 2022.
[2] Due to data limitations, we are unable to distinguish freelancing roles within the non-permanent category, despite freelancers accounting for a large proportion of labour in creative industries (Mould et al., 2013).

Table 1. Descriptive Statistics, VIF and Correlation Matrix

Variable		Obs.	Mean	Std. dev.	Min	Max	VIF	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Creativity Demand Share	(1)	4192719	0.006	0.053	0	1	NA	1						
AI Demand Share	(2)	4192719	0.009	0.064	0	1	1.989	0.017	1					
Post-ChatGPT	(3)	4192719	0.239	0. 426	0	1	1.491	0.001	0.018	1				
High-skilled	(4)	4192719	0.222	0.416	0	1	1.532	0.044	0.067	0.024	1			
Posting Length	(5)	4192719	318.702	174.739	1	9369	1.088	0.062	0.080	0.194	0.135	1		
Average Salary	(6)	4192719	27275.330	9966.943	5336.49	174415	1.311	0.038	0.101	0.304	0.347	0.180	1	
Permanent Position	(7)	4192719	0.265	0.304	0	1	1.053	0.008	0.018	0.182	0.063	0.105	0.120	1

Table 2. Regression Results

	Creativity Demand Share											
	Creative Clusters						Non-Creative Clusters					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Time Trend	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Posting Length (log)		0.005***	0.005***	0.005***	0.005***	0.005***		0.004***	0.004***	0.004***	0.004***	0.004***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Permanent Position		-0.001***	-0.000***	-0.001***	-0.001***	-0.001***		-0.000	-0.000	-0.000**	-0.000**	-0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Salary (log)		0.001***	0.001***	0.001***	0.001***	0.002***		-0.000	-0.000	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AI Demand Share			0.008***	0.008***	0.003***	0.001			0.004***	0.004***	0.004***	0.004***
			(0.001)	(0.001)	(0.001)	(0.001)			(0.000)	(0.000)	(0.001)	(0.001)
Post-ChatGPT				0.000***	0.000	-0.001***				0.000***	0.000***	0.000***
				(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
AI Demand Share × Post-ChatGPT					0.017***	-0.004*					0.002**	-0.002
					(0.001)	(0.002)					(0.001)	(0.001)
High-skilled						0.000						0.000***
						(0.000)						(0.000)
AI Demand Share × High-skilled						0.005***						0.000
						(0.001)						(0.001)
High-skilled × Post-ChatGPT						0.002***						0.001***
						(0.000)						(0.000)
AI Demand Share × Post-ChatGPT × High-skilled						0.017***						0.007***
						(0.002)						(0.002)
Constant	-0.011***	-0.038***	-0.037***	-0.033***	-0.036***	-0.040***	0.001*	-0.010***	-0.009***	-0.002	-0.002	-0.001
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	1590593	1590593	1590593	1590593	1590593	1590593	2602126	2602126	2602126	2602126	2602126	2602126

Note: Robust standard errors clustered at the TTWA–SOC level are in parentheses. All specifications include fixed effects for TTWA and occupation. * p < 0.10; ** p < 0.05; *** p < 0.01.

Results and Discussions

Equation (1) is estimated using a hierarchical regression framework incorporating triple interaction terms to explore the relationship between demand for creativity skills and AI skills before and after the release of ChatGPT. The dependent variable is first regressed on *Time Trend* and control variables, followed by the inclusion of *AI Demand Share*, and finally, the interaction terms. The complete results are presented in Table 2. To explore heterogeneity across local labour market contexts, we estimate the models separately for creative clusters (Models 1–6) and non-creative clusters (Models 7–12).

Across all specifications, *Time Trend* is consistently positive and highly significant in creative clusters (Models 1–6), indicating a sustained upward trajectory in demand for creativity over the study period. In contrast, non-creative clusters exhibit a significantly negative time trend (Models 8–12), suggesting stagnation or decline in creativity skills demand. This divergence reflects a growing spatial concentration of creativity demand within creative clusters.

In both clusters and non-clusters, *AI Demand Share* is positively and significantly associated with *Creativity Demand Share* across all model specifications. This suggests that local labour markets with greater demand for AI skills are also more likely to demand creativity. This pattern supports the view that AI adoption does not diminish the value of creativity skills at the aggregate level but rather amplifies the need for human creative input. These findings align with those existing studies which identify creativity as one of the core complementary skills to AI competencies (Squicciarini and Nachtigall, 2021). In creative clusters, the coefficient on *AI Demand Share* is 0.008 (Model 3), indicating that a 1 percentage-point increase in the share of AI-related job postings is associated with a 0.008 percentage-point increase in the share of creativity-related postings. In contrast, in non-creative clusters, the coefficient is 0.004 (Model 9) – half the magnitude, suggesting that the co-occurrence between creativity and AI skills is significantly more pronounced in creative clusters.

The *Post-ChatGPT* dummy provides evidence of a further shift in creativity skills demand. The positive and significant coefficient suggests an overall rise in creative job demand after the launch of ChatGPT (Model 4 and 10). Moreover, the interaction *AI Demand Share* × *Post-ChatGPT* is significantly positive in both groups (Model 5 and 11). This pattern confirms H1, suggesting that after ChatGPT, the co-occurrence between creativity and AI skills in job postings strengthened. However, we notice differing magnitudes. In creative clusters, the coefficient is 0.017, indicating that the marginal effect of AI demand on creativity demand increased by 0.017 percentage points after ChatGPT. Adding this to the pre-ChatGPT effect (β = 0.008), the total post-ChatGPT marginal effect becomes 0.025 percentage points, more than three times the pre-ChatGPT effect. In non-creative clusters, by contrast, the interaction effect is much smaller (β = 0.002). This finding supports H2, confirming that creative agglomeration amplifies AI–creativity linkages within the labour market.

Turning to the triple interaction, *AI Demand Share* × *Post-ChatGPT* × *High-skilled Share* is strongly positive and significant in creative clusters (β = 0.017, Model 6) and also significant, though smaller in magnitude, in non-creative clusters (β = 0.007, Model 12). This supports H3 and demonstrates that the co-occurrence between creativity and AI skills is most pronounced in high-skill labour markets. Notably, in creative clusters, the combined marginal effect after ChatGPT is 0.042[3], meaning that a 10 percentage-point increase in AI-

[3] To interpret this effect, the combined marginal effect after ChatGPT is the sum of the main effect and both interaction terms in a high-skilled creative cluster: 0.008 (AI Demand Share) + 0.017 (AI × Post-ChatGPT) + 0.017 (AI × Post-ChatGPT × High-skilled) = 0.042.

demanded job postings corresponds to a 0.42 percentage-point increase in creativity-demanded postings in high-skilled creative clusters, compared to just 0.08 percentage points before ChatGPT. This finding is consistent with Acemoglu and Autor (2011), who argue that technological change is inherently skill biased: the positive association between demand for creativity and AI skills is stronger in the higher-skilled labour markets following the release of ChatGPT.

Policy Implications

Our findings carry potentially important policy implications across multiple levels. Broadly, the intensified co-occurrence between creativity and AI skills in the post-ChatGPT era highlights the need to foster more integrated skills development approaches that bring together human creativity and emerging AI technologies. Such integration is likely to be central to the development of new creative workflows in the age of GenAI (Zhou and Lee, 2024).

For policymakers, the convergence of technology and creativity, sometimes referred to as *Createch*, represents an emerging engine of economic growth, productivity, and employment in the UK (Government, 2025). As part of this, education and training providers, including universities and further education institutions, must adapt by embedding interdisciplinary curricula that reflect the increasing convergence of creativity and AI (Davenport et al., 2019; Morrison and Rooney, 2017; UKCES, 2015). Aligning skills provision more closely with labour market demands is essential to reduce skill mismatch (Corradini et al., 2025), and ensure the future workforce is equipped to thrive in technology-enhanced creative jobs.

Our findings also point to the important role of place for the co-occurrence of AI and creativity. Existing research has shown that the adoption of AI technologies has already contributed to skill-biased inequalities in the labour market (Dahlke et al., 2024; Draca et al., 2024; Shi and Dorling, 2020). As the demand for AI and creativity skills increasingly grows in tandem, there is a risk that this complementarity may further exacerbate such inequalities.

Our results show that the strongest creativity-AI skills co-occurrence is found in creative clusters. The performance of the UK's world-leading creative industries sector is largely driven by its clusters (Siepel et al., 2023), suggesting that these clusters are well-positioned to take advantage of the opportunities presented by AI and the potential for 'createch' to drive further growth. But the creativity-AI co-occurrence also echoes growing concerns in the literature about the uneven spatial distribution of skills (Balland et al., 2020; Draca et al., 2024), reflecting the *Matthew Effect*[4] (Merton, 1968), whereby advanced regions with a strong skills base and thick labour markets reap disproportionate benefits from technological advancements, while left-behind regions struggle to keep pace (Corradini et al., 2025; Gutierrez-Posada et al., 2022).

Supporting left-behind regions that lack both a high-skilled workforce and the critical mass of creative clusters requires a more inclusive and geographically sensitive approach across multiple levels of intervention (Lee, 2024). Within firms and organisations, complementary investments in human capital are essential to ensure that the adoption of AI technologies does not exacerbate inequalities. This may involve providing targeted, on-the-job training for lower-skilled employees, enabling them to adapt to AI-enhanced workflows and reducing the risk of displacement (Jia et al., 2024). At the broader regional level, there is a need to foster place-based ecosystems in which AI skills and creativity can co-evolve, leveraging smaller, creative 'microclusters' (Siepel et al., 2020; Velez-Ospina et al., 2023) to strengthen local institutional

[4] 'For to everyone who has, more will be given, and he will have abundance; but from him who has not, even what he has will be taken away' (Matthew 25:29) (Merton, 1968).

capacity. A suite of targeted interventions (such as coworking spaces, innovation hubs and fabrication laboratories) (Bailey et al., 2018; Barzotto et al., 2020) can help to ensure that the transformative potential of AI–creativity complementarities is distributed more equitably, benefiting not only thick labour markets but the wider economy.

Conclusion

In this paper, we investigate real-world labour market dynamics surrounding the demand for creativity and AI skills, focusing on the period before and after the launch of ChatGPT 3.5 as a key inflection point to capture the impact of GenAI. We highlight three main results. First, our analysis reveals a consistent and significant co-occurrence between creativity and AI skills in job postings, indicating that employers seek these two skillsets in tandem. Second, this co-occurrence has intensified since the public release of ChatGPT, suggesting that the accessibility and widespread adoption of GenAI tools may have further elevated the demand for creativity alongside AI skills. Third, the post-ChatGPT co-occurrence is skill-biased and spatially uneven, particularly pronounced in high-skilled roles located within creative clusters.

Together, these findings offer timely empirical evidence to inform ongoing debates about the impact of AI on human creativity. Despite the rapid advancement of GenAI, our results suggest that employers continue to highly value human creativity. Rather than replacing creativity with AI, employers appear to be seeking hybrid skill profiles that integrate both skillsets. This pattern points to a growing synergy between creativity and AI in the labour market and suggests that AI is not displacing creativity but rather is redefining its role and expanding its relevance in increasingly AI-augmented workplaces.

While our paper offers valuable insights, we acknowledge some caveats and suggest avenues for future research. First, this study adopts a demand-side perspective by analysing job vacancy data to infer labour market preferences. However, job postings reflect employers' intentions rather than realised hiring outcomes. Future research could triangulate these findings with supply-side data, such as worker surveys or matched employer-employee datasets, to assess how AI and creativity interact in practice. Second, due to data limitations, we are unable to distinguish freelancing roles within non-permanent positions from the job postings (Teutloff et al., 2025), despite their significance in creative work (Mould et al., 2013). Future research could address this gap by incorporating survey data collected from selected employers to better capture the skill demands associated with freelancing roles. Third, our analysis considers creativity and AI skills at an aggregated level, without disaggregating into specific sub-skill-types. Future studies could explore this potential heterogeneity to uncover more insights into the demands for different types of creativity and AI skills. Moreover, our NLP-based identification strategy relies on pre-defined seed terms and a threshold-based cosine similarity approach, which may fail to capture more implicit, nuanced, or context-dependent mentions of creativity and AI skills. Future research could explore more advanced machine learning techniques, such as contextual word embeddings (e.g. BERT) or fine-tuned classification models, to enhance detection accuracy and capture a broader spectrum of skill references embedded in job descriptions. Lastly, this study uses the public release of ChatGPT 3.5 as a critical inflection point signalling the widespread accessibility of GenAI. It is important to acknowledge that this is only one of several pivotal events shaping the trajectory of GenAI development. Future studies could explore alternative or additional temporal markers for more insights.

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Appendix A

In this paper, we investigate real-world labour market dynamics surrounding the demand for creativity and AI skills, focusing on the period before and after the launch of ChatGPT 3.5 as a key inflection point to capture the impact of GenAI. We highlight three main results. First, our analysis reveals a consistent and significant co-occurrence between creativity and AI skills in job postings, indicating that employers seek these two skillsets in tandem. Second, this co-occurrence has intensified since the public release of ChatGPT, suggesting that the accessibility and widespread adoption of GenAI tools may have further elevated the demand for creativity alongside AI skills. Third, the post-ChatGPT co-occurrence is skill-biased and spatially uneven, particularly pronounced in high-skilled roles located within creative clusters.

A.1 Key Terms for Creativity and AI Skills

Table A1. Compendium for Creativity

Creativity (Chen et al., 2025; Osborn, 1953; Pollok et al., 2021; Runco and Jaeger, 2012)	**Keywords and Phrases**
Generic Creativity	creativity, brainstorm, ideation, imagination, inspiration, curiosity, novelty, originality, conceptual thinking, divergent thinking, convergent thinking, non-linear thinking, blue-sky thinking, creative thinking, lateral thinking, thinking outside the box, creative concepts, design concepts, creative design, creative problem-solving
Specific Creativity	Photoshop, Illustrator, Figma, Sketch, Adobe Creative Suite, Adobe Creative Cloud, Adobe Indesign, After Effects, InDesign, typography, layout design, composition, grid systems, design principles, wireframing, prototyping, user flows, UX design, interactive design, mockups, design iteration, motion design, Motion Graphics, responsive design, animation, visual effects, pixel-perfect, refined design, high-fidelity output

Table A2. Compendium for AI Skills

AI (Acemoglu et al., 2022; Babina et al., 2023; Maslej et al., 2025; Zhang et al., 2025)	**Keywords and Phrases**
Generic AI	machine learning, supervised learning, unsupervised learning, reinforcement learning, predictive modelling, model training, ML, feature engineering, data preprocessing, statistical modelling, cross-validation, neural networks, deep learning, feedforward networks, CNN, RNN, transformer, autoencoder, backpropagation, gradient descent, natural language processing, text mining, text analytics, NLP, language modelling, semantic analysis, text classification, tokenization, generative AI, text generation, image generation, LLM, large language model, GAN, prompt engineering, foundation model, autonomous driving, self-driving, autonomous vehicle, ADAS, sensor fusion, path planning, perception, localization, mapping, image recognition, object detection, image classification, computer vision, OCR, segmentation, bounding box, visual perception, robotics, robotic system, robot arm, autonomous robot, motion planning, control systems, mechanical kinematics, AI ethics, responsible AI, fairness, algorithmic bias, transparency, explainability, accountability, AI governance, AI regulation, trustworthy AI, AI Act, compliance, oversight, data privacy
Specific AI	scikit-learn, XGBoost, LightGBM, CatBoost, tensorflow, keras, pandas, numpy, PyTorch, TensorFlow, Keras, MXNet, HuggingFace Transformers, TorchVision, spaCy, NLTK, AllenNLP, Gensim, BERT, GPT-2, GPT-3, RoBERTa, T5, GPT-4, DALL·E, Stable Diffusion, Midjourney, VQ-VAE, StyleGAN, CLIP, ROS, ROS2, Autoware, Apollo, lidar, radar, camera calibration, OpenCV, YOLO, ResNet, EfficientNet, Mask R-CNN, Detectron2, Gazebo, MoveIt!, URDF, Webots, Fairlearn, Aequitas, IBM AI Fairness 360, GDPR, CCPA, ISO/IEC 27001, NIST AI Risk Management