# Digital skill demand by region and industry in the UK

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**Abstract**

This paper proposes a new approach to quantifying digital skill demands using job platform data, focusing on regions of the UK, and on industries identified by the UK government as of strategic importance. The analysis shows a concentration of the highest-level digital skills required for innovation in regions around London known as the Golden Triangle, but skills required for “business as usual” are important everywhere and growing over time. Job adverts requiring AI related skills are even more concentrated. Areas outside the Golden Triangle, especially in the second-tier cities, are more likely to hire non-graduates to fill their digital skills needs. High-level digital skills are in much greater demand in strategic industries than in other sectors.

# 1 Introduction

The significant decline in labour productivity growth in advanced countries including the UK since the financial crisis has been the focus of extensive research. Explanations range from a focus on cyclical factors and financial constraints to more structural weaknesses. The UK's productivity growth slowdown has deep, long-standing roots in regional disparities (HM Treasury, 2001), which have persisted due to weak internal equalization mechanisms (Rice and Venables, 2021). These include limited wage adjustments and have been exacerbated by the out-migration of young and skilled individuals, which has depleted local labour forces.

Despite steadily increasing employment since 2011, the UK labour market faces significant challenges, including widespread skill shortages in many occupations, low worker mobility across regions and sectors, and a substantial proportion of employees in mismatched roles, (Joyce et al., 2022). The widespread diffusion of new digital technologies should predominantly benefit high-skilled workers, particularly those in Science, Technology, Engineering and Mathematics (STEM)-related occupations (Black et al., 2021), but there is evidence of a decline in the graduate wage premium (O'Mahony et al., 2026). Examining skill trends that go beyond a narrow focus on graduates is crucial in understanding both the aggregate slowdown and regional differentials.

The purpose of this paper is to examine digital technical skills both by region and industry using job platform data. A companion paper combines these data with measures of skill supply by region. The remainder of this paper is organised as follows. The next section summarises the existing literature on measuring skills. Section 3 presents an overview of the datasets we use in our analysis. Section 4 outlines the methodology used in determining demand for digital skills by type. Section 5 presents a descriptive analysis of these skills by region and section 6 includes an analysis by industry. Section 7 briefly describes soft skills co-occurring with digital skills. Section 8 concludes.

# 2 Skills and Qualifications

The disruptive effects on the labour market associated with the diffusion of new digital technologies are complex. Most of the attention in the recent literature has been paid to Artificial Intelligence (AI). This technology is argued to affect the labour demand differently than robots and software, mostly adversely affecting high-skilled workers and more generally those performing high level cognitive tasks. Online job vacancy data is frequently used to track the demand for new skills, as it provides a real-time overview of firm requirements, even though it does not indicate whether the advertised positions are ultimately filled. Borgonovi et al. (2023) offers one of the first broad international comparisons of AI skill demand, examining OECD country data from 2019 to 2022. On average, 0.5% of online vacancies in the UK require AI skills, placing it just behind the US and Canada. Approximately 40% of AI-related vacancies in the UK are concentrated in the Manufacturing, ICT, and Professional Services sectors. This proportion is significantly lower compared to other OECD countries, suggesting that AI deployment in the UK is more evenly distributed across sectors. Schmidt et al. (2024a) show that AI intensity ranges from 30% to 40% of total vacancies in Finance and Information and Communication, and from 20% to 30% in Mining, Electricity, and Professional Services.

However, focusing solely on AI-related labour demand overlooks broader trends in the demand for new digital skills. AI can lead jobs to vanish, but at the same time, firms may struggle to find workers with the skills required for newly created roles (Stephany and Teutloff, 2024). Schmidt et al. (2023) estimates that in the UK, online job postings requiring data expertise far exceed those requiring AI skills, peaking at 4% of total vacancies during the pandemic years. Among occupations with the largest increase in demand for new digital skills, roles such as financial quantitative analysts, biochemists, and social science researchers saw their degree of data intensity surge in recent years. Going beyond these new digital skills, as highlighted in this paper below, demand for more general digital skills required for using software has been increasing.

Structural change and post-recession recovery may also be influential, as individuals seek jobs in declining sectors, while hiring concentrates in emerging segments of the economy (Patterson et al., 2016). Also new digital technologies are reshaping job requirements, increasing demand for social, high-cognitive, and technological skills, a set of characteristics that cannot be easily found in the current workforce.

These labour market trends also have a regional dimension. Stansbury et al. (2023) show that the graduate wage premium (the ratio of wages of graduates to those whose highest qualification is A-levels) has been declining in all regions of the UK, except for London. They conclude from this that the expansion of higher education has helped alleviate the prior scarcity of graduate skills relative to demand. However, when they examine STEM skills, they find that the wage premium for university-level STEM skills has hardly fallen – and even, in some regions, has risen, at a time when STEM attainment has been rising rapidly (Vignoles et al., 2011). This suggests demand for STEM skills among graduates appears to have risen as fast as supply. Therefore, a general trend in overeducation due to supply of graduates outstripping demand, can co-exist with shortages for particular types of skills.

In this paper, we develop a way of classifying types of skills that goes beyond a focus on qualifications, in line with recent advances in skill measurement. There are a large and growing number of skill taxonomies available for researchers to classify skill types. The European Commission's ESCO (European Skills, Competences, and Occupations) classification identifies and categorizes skills, competences, and occupations relevant for the EU labour market and education and training[1]. Related to this is the European Commission's Digital Competence framework (DigComp)[2]. Lightcast itself has developed a skill taxonomy mainly to inform job seekers and employers on the skill requirements for particular jobs[3]. Nesta has produced an occupation skills taxonomy using job platform data[4].

More recently there is a growing literature delineating skills related to AI, with much of this associated with research undertaken at the OECD (see Squicciarini and Nachtigall, 2021; Schmidt et al., 2024b). This work presented new evidence about occupations requiring AI-related competencies, based on online job posting data. Building on work assessing AI-related developments in science and technology (Baruffaldi, 2020), Squicciarini and Nachtigall (2021) suggested rapid change in the skills and competencies required for using AI. In 2012, those related to software engineering and development as well as operating systems, but by 2018, AI-related skills such as Natural Language Processing (NLP), deep and big data analysis grew in importance, as did skills related to communication, problem solving, creativity and teamwork. However, AI related skills are utilised in only a small percentage of firms. In the UK context, Schmidt et al. (2024b) show that these skills are very concentrated around the London area - see also Calvino et al. (2022) on the geographical location of AI adopters.

# 3 Data

The focus of this paper is on digital technical skills, as defined in more detail below. A commonly and increasingly used measure capturing demand is the number of new jobs that are advertised by firms. We use the data supplied by the company Lightcast (previously Burning Glass Technologies) on job adverts by region and industry. We distinguish types of skills whose common feature is that they involve software skills for innovation, including programming and scripting, AI, data science and large language models, but also software skills for instigating more efficient business processes. Lightcast web scrapes job advertisements from a range of sources and currently provides information on virtually all job advertisements in the UK. The sample period considered in this paper is 2014 to 2025. Our data consists of approximately 9 million job adverts on average per year. It is important to note that job advertisements are measures of firms' desired demands for new hires, and do not say anything about who is actually hired by the firm, and is a measure of flows rather than the stock of workers.

The coverage of job adverts in the Lightcast data is shown in Table 1. This shows no trend over time from 2015 but is somewhat lower in the first year of our sample period. The total number of adverts fluctuates over time. While we would expect a decline in 2020 due to

[1]https://esco.ec.europa.eu/en
[2]https://joint-research-centre.ec.europa.eu/oldpage-digcomp/digcomp-framework_en
[3]https://lightcast.io/products/data/our-taxonomies
[4]https://data-viz.nesta.org.uk/skills-taxonomy/index.html

the COVID-19 pandemic, the number of adverts has an unusual dip in 2019 which predates the pandemic and has abnormally high numbers in 2022 and 2023 followed by a pronounced decline in 2024, and to a lesser extent in 2025. Explanations for these time patterns are likely to reflect both changes in the sources used for the web scraping and the extent to which firms advertise online. This means that the data are not very useful for looking at the absolute levels of job vacancies. They are, however, useful for examining differing intensities and trends across regions and industries, which is the focus of our work.

Table 1: Number of job adverts, UK, 2014-2025.

| Year | Total |
|---|---|
| 2014 | 6,441,728 |
| 2015 | 8,346,991 |
| 2016 | 9,343,194 |
| 2017 | 10,056,626 |
| 2018 | 9,140,803 |
| 2019 | 7,222,659 |
| 2020 | 6,564,387 |
| 2021 | 9,435,400 |
| 2022 | 12,578,573 |
| 2023 | 12,074,712 |
| 2024 | 8,922,564 |
| 2025 | 8,416,712 |

*Source:* Authors tabulations using Lightcast data.

As well as the body of the advertisement, useful for text analysis, Lightcast presents summary data on the job advert characteristics, such as job location, occupation, industry, education and other summary measures such as years experience required, type of contract (full-time, part-time, permanent, temporary) and if the job has the flexibility to work from home. It also includes lists of skill keywords which are explained more fully below. Although this represents rich data that can be used in analysis, the coverage varies significantly by characteristic with geography and occupation having high coverage whereas industry is only identified in about 50% of job adverts.

The geographical location of the job is identified in about 75% of the adverts. Lightcast summarises the data according to a number of geographic typologies, including Travel to Work Area (TTWA), Local Authority Unit (LAU) and various levels of The International Territorial Levels (ITLs). In this paper, we focus on TTWA as this is the closest definition to a local labour market. The share where TTWA is identified is stable around 73% for years up to 2023, except for a small dip in 2021, but is about 80% in the final two years. To exclude selectivity problems in the data used in our analysis, we extracted adverts where geography was not identified and checked that this sample did not behave differently from the main sample in the measures we construct below.

Education requirements are identified by Lightcast in less than 20% of job adverts. In an earlier paper, Andrieu and Kuczera (2023) use the text body of the advertisements to try to increase the proportion of adverts where education requirements can be identified. This relies on direct keyword matching with additional cleaning strategies. They retrieve all vacancies that clearly mention the minimum educational requirement for the job from the set of Lightcast adverts by using the text of the job vacancy and directly matching some specific keywords related to qualifications. In addition, employers might not mention explicitly the educational requirement for some occupations because it is straightforward that a specific qualification or a legal education requirement is needed. For example, registered nurses are required to have a specific level of education and lawyers need to take a Legal Practice Course for which you need to have a bachelor degree. Therefore, they manually annotate the adverts for those jobs where a degree or higher are formally required. For this paper, we employed the same methodology as Andrieu and Kuczera (2023) but included some additional cleaning to identify false positives. The end result is that we were able to identify educational requirements in about 40% of job adverts.

In addition to the lower sample size, there are other reasons to be cautious about using qualifications as a measure of skill requirements, especially looking across time. A number of recent papers have highlighted a downward trend in job adverts that require a university degree. This may represent a real reduction but could also (partially) be due to changes over time in the way companies recruit. Ensuring diversity and inclusion in hiring has become more important as part of firms' ESG (Environmental, Social, and Governance) strategies, and not mentioning qualifications is one way human resources specialists have identified as helping to hire a more diverse workforce. In addition, many larger companies nowadays recruit using multiple step procedures, with earlier steps involving AI generated tests and requests for CVs coming later in the process. This is likely to mean that firms do not see a need to mention qualifications at the initial job advertising stage.

Therefore, the traditional measures used in skill mismatch research, based on qualifications, are not ideal when using job platform data. Instead, the advantages that these data have over other sources is the very rich information on actual skills required in the job. Much of the earlier literature match tasks to occupations using sources such as O*NET and labour force surveys to identify high skilled jobs. Job platform data provide an alternative to this method.

# 4 Measuring Digital Technical Skills

Our approach examines firms' desire to hire workers with "Digital Technical Skills", which are defined below. Much of the existing literature on skill mismatches uses occupation-based measures cross-classified by broad education groups. In this paper, we use an alternative approach by examining the skills that firms desire when hiring, focusing on technical skills that both develop and use software. There is a vast and growing recent literature on firms' use of AI skills or digital skills more broadly defined; our measure of digital technical skills is broader than AI but narrower than many measures of digital skills, and is based on keywords in our job postings data. Most are 'software' keywords identified by Lightcast, but also include some 'specialized skills' keywords.

## 4.1 Defining Digital Technical Skills

Much of the previous literature on measuring digital skills is broad based, outlining competencies and proficiency levels and linking to particular types of qualifications, often based on a broad range of data sources and expert advice. In this paper, we use the keywords available in the Lightcast data to examine demand for the technical skills required for digital technologies.

Our Lightcast data distinguishes about 28,000 skill keywords that appeared in at least one job advert in our time period. Note that skill keywords can be a single word such as 'Python' or consist of several words required to describe a skill such as 'Key Performance Indicators'. They are a mix of specific knowledge such as the Salesforce software packages or International Financial Reporting Standards; tasks such as Triage or Database Administration; and generic skills such as Leadership.

Lightcast divides these skills into Software skills (approx 6,700 keywords), specialized skills (about 19,000 excluding Software) and General skills (about 2,500 in addition to Software and specialized). In this paper, we attempt to define digital technical skills based on the list of Software skills and some specialized skills keywords, giving approximately 8,000 keywords. It is tempting to term this as just "digital skills" but that term is often used not only to describe the use of software but also more general skills, as in the previous work by the European Commission mentioned above. Therefore we use the term 'digital technical skills' (DTS).

We divide our digital technical skills into three groups, namely *Advanced*, *Intermediate* and *Basic* skills. Advanced are those that involve knowledge of programming language, artificial intelligence or data science, which facilitate change and innovation in firms. Intermediate skills are those that involve employing standard software packages in business processes but do not require any knowledge of programming, or advanced statistics, or mathematics. We also decided to place a limited number of keywords such as Microsoft Office into a basic category, which we define as those required for a broad range of tasks. These basic skills represent only a few hundred of the Lightcast keywords but a much greater share of mentions in adverts. This division into three groups is similar to that employed by Carvella et al. (2023), who divide skills into user, practitioner and developer.[5]

We categorized all Software keywords into one of the three groups. The starting point for this was the keywords that appeared in IT, Engineering and Research occupations. We initially designated a keyword as Advanced if these keywords appeared in adverts for more than 50% of these occupations. However, our initial sift through the data suggested that this criteria was insufficient to identify all digital skills. Therefore, we manually examined all approximately 6,700 keywords, with the help of a computer scientist[6], using particular phrases such as scripting, SQL, Java, etc., and if the share in technical occupations was very high. This led to nearly 5,000 of the Software skills being categorized as Advanced. The Intermediate group was based on phrases such as customer relationship management (CRM), enterprise resource planning (ERP) and accounting and auditing, about 2,500 keywords. The Basic group consisted of keywords that are widely used and/or require low levels of technical knowledge such as Microsoft Office, Google Docs and Zoom. These amounted to about 400 keywords.

We then looked at the specialized skills list and picked out about 1,200 keywords that did not appear in the Software Skills list. Again, our starting point was IT, Engineering and Research occupations. Most of these specialized skills referred to use of AI, Machine Learning, Large Language Models and Data Science and their associated mathematical and statistical skills. All of these skill keywords were allocated to the Advanced group.

Table 2 shows examples of popular keywords for each of the three groups. In the Advanced category, the highest job advert requirements are for knowledge of well known programming languages. Interestingly, the highest counts overall are for a couple of basic skills, Microsoft Excel and Office.

[5]In Carvella et al. (2023) users require basic knowledge on using technology for specific purposes, practitioners require some expertise to tailor technologies and developers require significant expertise to design and modify technologies.

[6]We are grateful to Conor O'Mahony for reviewing our classifications into the three groups.

Table 2: Software skills: examples among the most popular

| | Software | Count | | Software | Count |
|---|---|---|---|---|---|
| A | SQL (Programming Language) | 2,816,885 | I | SAP Applications | 1,255,488 |
| A | JavaScript (Programming Language) | 2,323,256 | I | Salesforce | 521,821 |
| A | C# (Programming Language) | 1,775,040 | I | Microsoft Dynamics CRM | 151,073 |
| A | Java (Programming Language) | 1,613,566 | I | Sage 50 (Accounting Software) | 122,199 |
| A | Cascading Style Sheets (CSS) | 1,417,609 | I | Google Workspace | 94,648 |
| A | Python (Programming Language) | 1,304,573 | B | Microsoft Excel | 4,273,949 |
| A | C++ (Programming Language) | 820,473 | B | Microsoft Office | 3,470,386 |
| A | AutoCAD | 790,131 | B | Microsoft Word | 1,013,334 |
| A | Ruby (Programming Language) | 224,494 | B | Zoom (Video Conferencing Tool) | 107,201 |

## 4.2 From Keywords to Classifying Adverts

Many adverts contain mixes of Advanced, Intermediate and Basic keywords, so it is necessary to devise criteria to decide when a complete job advert should be classified into one of the three groups, plus a residual category where there is no mention of digital technical skills. We used a range of methods based on the number of occurrences of the keywords, or their share in total keywords in the advertisement. We also checked correlations across TTWA for each method and found correlation coefficients of more than 0.95, both for the sample as a whole and by year.

Given this we decided to go for the method that classified adverts into the groups if they had at least one relevant keyword as follows:

- *Advanced*: if the advert had at least one Advanced keyword and at least one other Advanced, Intermediate, or Basic keyword.
- *Intermediate*: if there is at least one Intermediate and no Advanced keywords.
- *Basic*: if there is at least one Basic keyword and Advanced and Intermediate are both zero.

The criteria for Advanced skills is stricter than for the other two categories to minimise the occurrence of false positives. This is where a keyword is erroneously included in an advert that does not require these skills, for example, an advert for a cleaner requiring SQL. Adverts that included Advanced skills usually specified a range of these and/or intermediate and basic skills.

The criteria for Intermediate and Basic skills are less strict as some keywords describe single software packages and some describe combinations of packages. The most obvious example is that Microsoft Excel is a separate keyword to Microsoft Office, but the latter includes the former. Therefore, going for a stricter criteria such as at least two keywords would knock out many adverts that specify Microsoft Office. A similar issue arises for many CRM and EPL software packages. The downside is that there may be some false positives for these two categories. We examined a sample of adverts to check for false positives and found these were minimal.

By specifying that Intermediate skilled adverts do not include any Advanced keywords, and Basic do not include either Advanced or Intermediate, we also mitigate the issue that some of these software packages will have advanced features. For example, Excel can perform very advanced functions and permits coding and creating macros. If a job posting only mentions Excel, it's likely to be used only for basic spreadsheet tasks, whereas if it is meant for advanced usage it is likely to occur simultaneously with Advanced keywords in an advert.

Advanced DTS represent a much greater share of the number of keywords than job counts - this is due to a large number of keywords with less than 10 observations which are primarily very specific software skills. In contrast, Basic DTS represents a small fraction of keywords but a much greater share of counts due to some very basic skills such as Microsoft Excel having very large counts.

One issue that cannot easily be addressed is cases where skills are used in the job, but there is an assumption that the pool of applicants will possess those skills, for example, job adverts for academics or lawyers that may not list Microsoft Office as a required skill, even though it is needed. In many of these cases some digital skills are likely to be mentioned in the advert, and so are captured in our measures. However, this may lead to an underestimation, especially for Basic and Intermediate. In the analysis below we are implicitly assuming that these cases do not systematically vary by region or industry.

Table 3 shows the time pattern of job advert shares for the three digital technical skill categories and the total. The latter shows no obvious trend and this is true also for Advanced, which shows increases across the years affected by the COVID-19 pandemic and then a sharp decline in the final three years. This is consistent with anecdotal evidence that firms increased their hiring of workers with advanced software skills to deal with many activities going online once the pandemic hit, but reduced hiring these types of workers subsequently. This decline may also reflect firms moving to using AI to substitute for some advanced skills. The fall in the share of Advanced from 2015-2019 is more difficult to understand. This may reflect the coverage of jobs adverts in the earlier years which may have been more skewed towards IT tasks. By the end of the decade, most jobs were advertised online but it is not known when that occurred. There are clear upward trends for the other two categories, Intermediate and Basic, although their combined share is much lower than Advanced.

Table 4 shows the shares of the three digital technical skill groups by occupation. The highest shares of Advanced skills are for professional and technical occupations, as expected, and for associate professional and technical staff. The advanced shares are also relatively high for managers and administrative staff. The latter dominate the intermediate category and basic skill shares are very high also for this occupation group. Basic skills are also relatively important for sales and customer services.

Table 3: Shares of digital technical skills in job adverts, UK, 2014-2025.

| Year | Advanced (%) | Intermediate (%) | Basic (%) | Total DTS (%) |
|---|---|---|---|---|
| 2014 | 24.4 | 2.9 | 3.9 | 31.2 |
| 2015 | 26.1 | 2.8 | 3.9 | 32.8 |
| 2016 | 24.2 | 3.0 | 4.3 | 31.6 |
| 2017 | 24.1 | 3.3 | 4.1 | 31.5 |
| 2018 | 21.3 | 3.2 | 4.3 | 28.7 |
| 2019 | 20.9 | 3.5 | 4.6 | 29.0 |
| 2020 | 22.2 | 3.5 | 4.2 | 29.9 |
| 2021 | 24.1 | 3.9 | 4.8 | 32.7 |
| 2022 | 24.9 | 4.4 | 4.8 | 34.1 |
| 2023 | 17.9 | 4.2 | 5.2 | 27.3 |
| 2024 | 17.0 | 4.3 | 5.2 | 26.4 |
| 2025 | 17.9 | 4.4 | 4.9 | 27.1 |

*Source:* Authors tabulations using Lightcast data.

Looking across TTWAs, the correlation between the shares of Advanced DTS and Professional and Technical occupations is high at 0.61, but by no means a perfect correlation. Administration and secretarial is correlated with Intermediate DTS (0.48) but not with Basic DTS (0.09). Sales and customer services is slightly more correlated with Basic DTS (0.13). Therefore, our digital technical skills measures are capturing something other than occupations.

Finally, in this section it is worth examining how this division into DTS types varies by education. As noted above we could only identify education requirements in about 40% of adverts. Table 5 shows the shares of the three skill groups for adverts explicitly requiring graduates, non-graduates and where the education requirement was unknown. The share of

Table 4: Shares of digital technical skills by occupation, 1-digit SOC groups

| Occupations | Advanced | Intermediate | Basic |
|---|---|---|---|
| Managers and directors | 16.3 | 4.3 | 5.3 |
| Professionals and technical | 36.8 | 3.0 | 2.5 |
| Associate professionals and technical | 26.9 | 4.9 | 5.3 |
| Administrative and secretarial | 14.2 | 10.2 | 15.6 |
| Skilled trades | 7.6 | 1.4 | 1.9 |
| Caring, leisure and other services | 3.4 | 0.6 | 2.2 |
| Sales and customer services | 10.2 | 3.1 | 6.2 |
| Process and machinery operatives | 9.2 | 1.5 | 1.5 |
| Elementary occupations | 4.6 | 1.5 | 2.1 |

Advanced DTS is significantly higher for graduates than non-graduates. In contrast, Basic DTS are more in demand for non-graduates. This might be affected by employer assumptions on the pool of applicants, e.g. that employers assume that graduates can use basic software. However, non-graduate qualifications identified in job adverts are often high level ones, if they also require digital technical skills, and so may also assume knowledge of more basic software.

Table 5: Shares of skill types by education.

| Education | Advanced (%) | Intermediate (%) | Basic (%) | Total DTS (%) |
|---|---|---|---|---|
| Graduates | 25.3 | 4.3 | 3.9 | 33.4 |
| Non-graduates | 13.9 | 2.9 | 5.9 | 22.7 |
| Education unknown | 22.3 | 3.5 | 4.6 | 30.4 |

*Notes:* Shares based on entire sample, 2014-2025.
*Source:* Authors tabulations using Lightcast data.

# 5 Skill Demand by UK Region

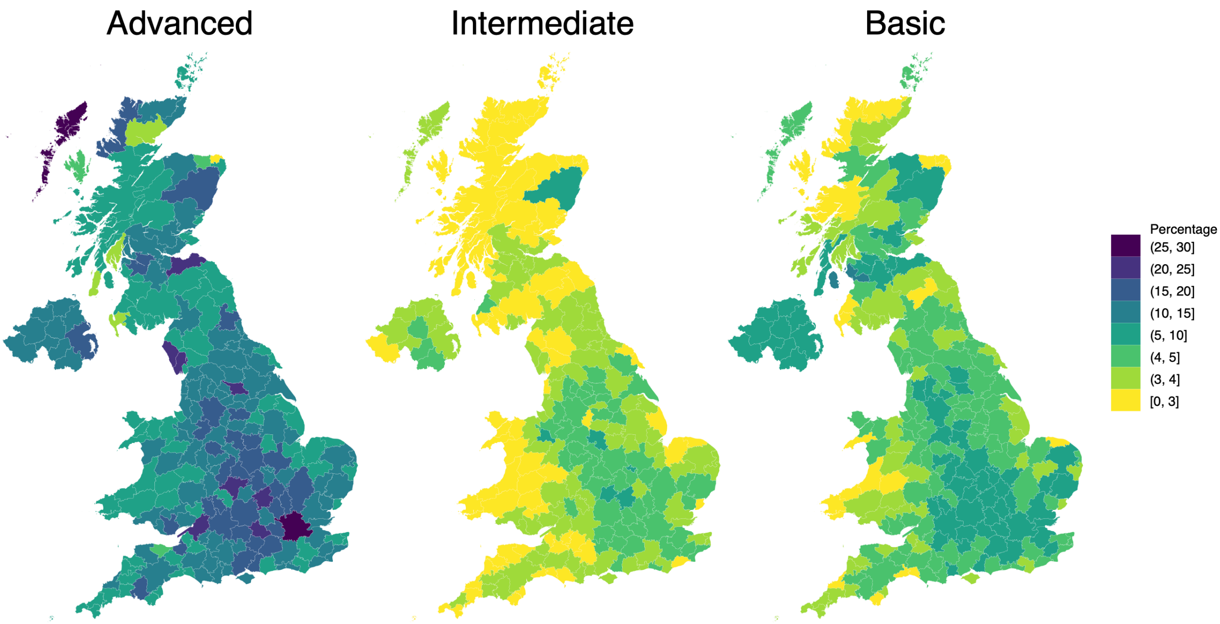
## 5.1 Digital Technical Skills

In this section, we describe the geographic distribution of our measures of digital technical skills, looking both at recent years and changes through time. These are shown as a series of maps, Figures 1-7 below.

Figure 1 shows the average percent of jobs accounted for by our three digital technical skill groups in 2023-25. It is clear that Advanced represent a much higher share of adverts than either Intermediate or Basic in almost all regions. Nearly 95% of TTWAs have higher shares of advanced than the combined share of intermediate and basic. The TTWAs where this is not true are all in rural or coastal areas. The share of job adverts requiring Advanced DTS is concentrated in a small number of areas, especially in London and its surrounding areas such as Reading, in the Golden Triangle areas of Cambridge and Oxford and in Bristol. The shares are smaller but still sizeable in larger cities such as Manchester, Birmingham, and Leeds. The shares are relatively smaller for mid-sized cities such as Ipswich and Leicester, lower still in Northern cities such as Middlesbrough and Preston and very small in more rural and coastal areas such as Kendal, Bridport and Minehead. These findings mirror those in much of the economic geography literature that emphasize the dominance of the London area and the relatively poor performance of many of our medium sized cities (McCann, 2016; Overman and Xu, 2024).

In contrast, the demand for Intermediate and Basic digital technical skills are much more spread out. The coefficient of variation is lower for the Intermediate and Basic groups (0.29), than for Advanced (0.37). Some areas such as Huntingdon and Worksop have relatively high shares of Intermediate while having low shares of Advanced. Regions vary much more on the relative importance of Intermediate versus Basic DTS shares. Therefore, firms across the country require workers with the skills to use software in their business processes, and sales and customer service, even in areas where the demand for more advanced digital technical skills is relatively low.

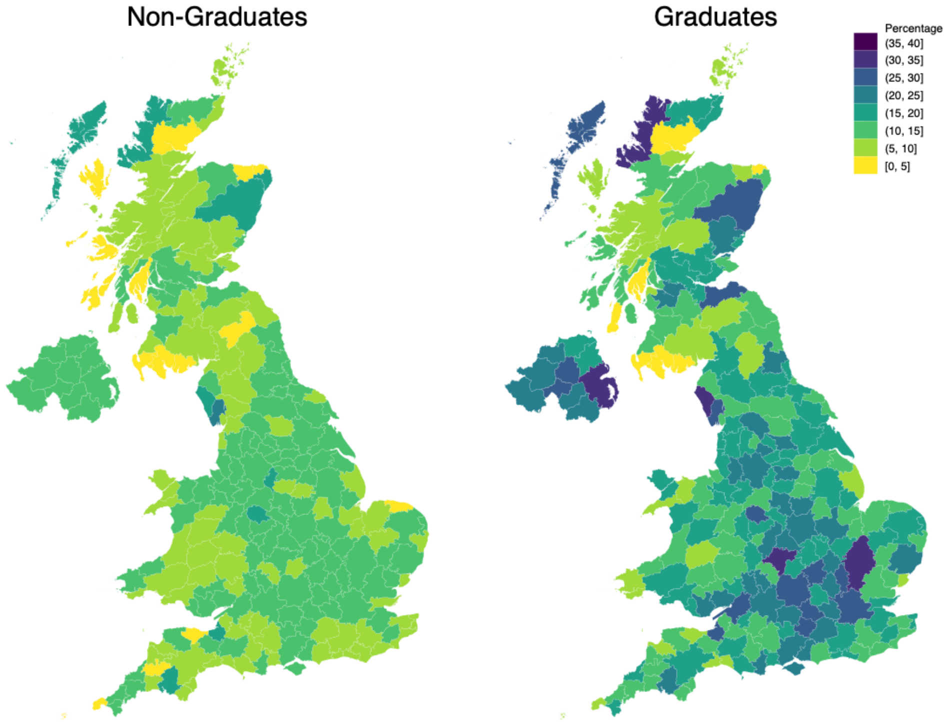
Figure 1: Share of digital technical skills in all job adverts - Average 2023-25




*Notes:* The maps show the average percent of all job adverts in 2023-25 for each of our three digital technical skill groups: Basic, Intermediate and Advanced. Darker colours represent higher intensities. TTWAs with fewer than ten job advertisements in any given year were excluded from the analysis; these are indicated in grey. *Source:* Authors' calculations using Lightcast data.

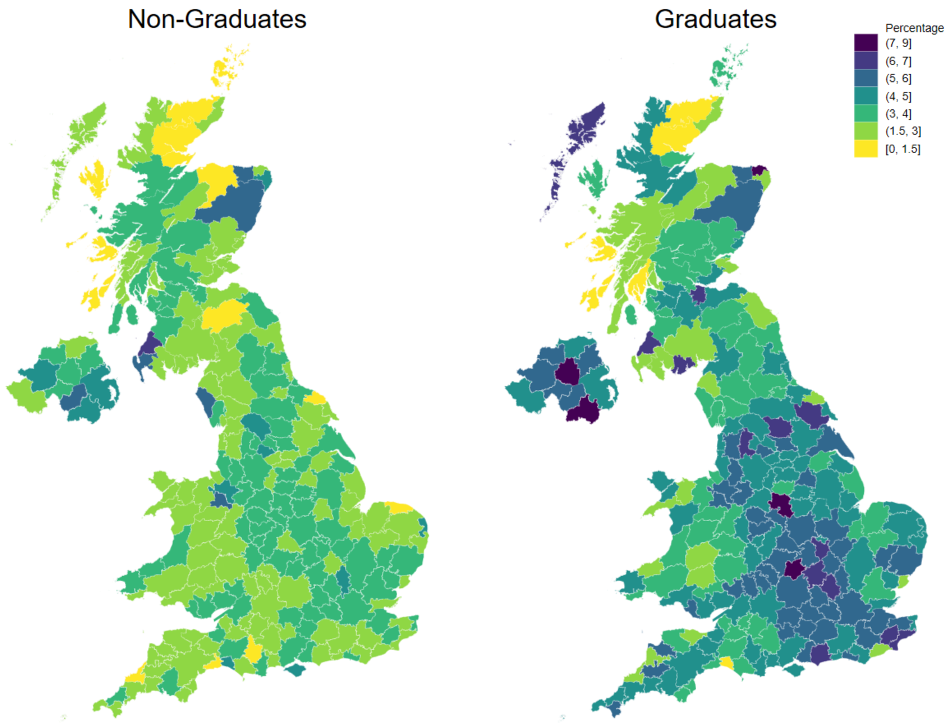
Figures 2-4 present the job advert shares of the three groups for graduates and non-graduates. As highlighted above, we could only identify education in about 40% of job adverts (25% graduates, 15% non-graduates). Here we see a pronounced concentration of adverts for graduates with Advanced DTS in the Golden Triangle, although Leamington Spa (the UK centre of the games industry) has the highest share of graduates jobs that required Advanced DTS. London and its surrounding areas, Cambridge and Oxford have graduate Advanced shares ranging around 30%, as do Edinburgh and Belfast. But other large cities such as Birmingham and Manchester have much lower shares, just above 20%. In contrast, the latter two cities have well above average shares of non-graduate Advanced DTS and this is true for many cities outside the Golden Triangle. For example, non-graduate adverts requiring Advanced DTS is significantly higher in Plymouth than in London and Cambridge. About 6% of TTWAs have a greater share of Advanced DTS in non-graduate than graduate job adverts.

Figure 2: Share of Advanced digital technical skills in job adverts - Average 2023-25




*Notes:* See footnote to Figure 1.

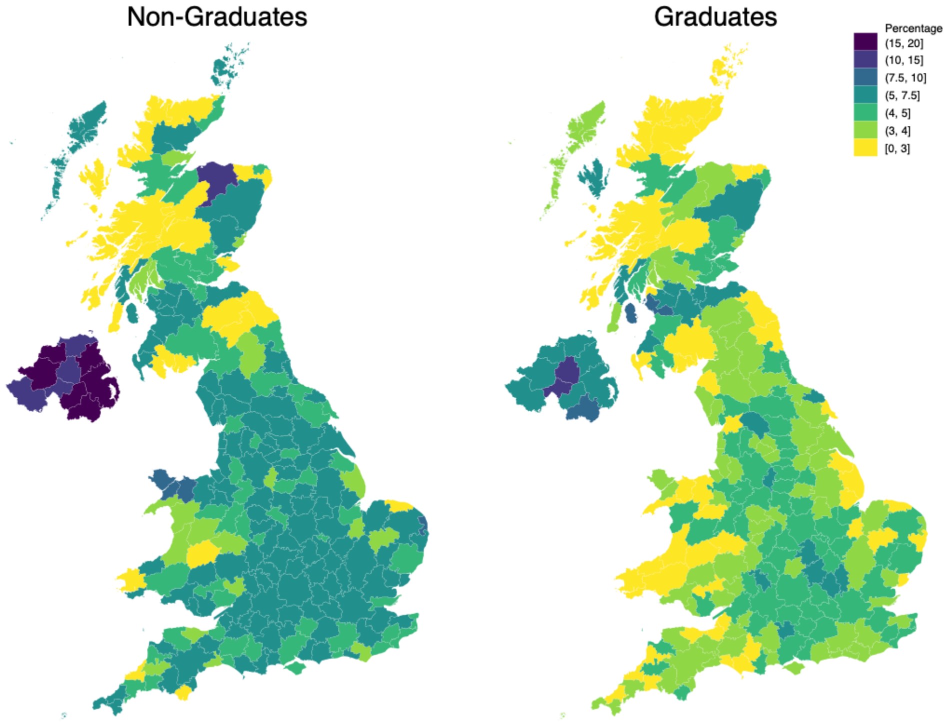
Figure 3: Share of Intermediate digital technical skills in job adverts - Average 2023-25




*Notes:* See footnote to Figure 1.

Similarly to Advanced, the share of graduate jobs requiring Intermediate DTS is generally greater than non-graduates with these skills (Figure 3). For both education types, the Intermediate shares tend to be more spread out across the country, than was the case for

Figure 4: Share of Basic digital technical skills in job adverts - Average 2023-25



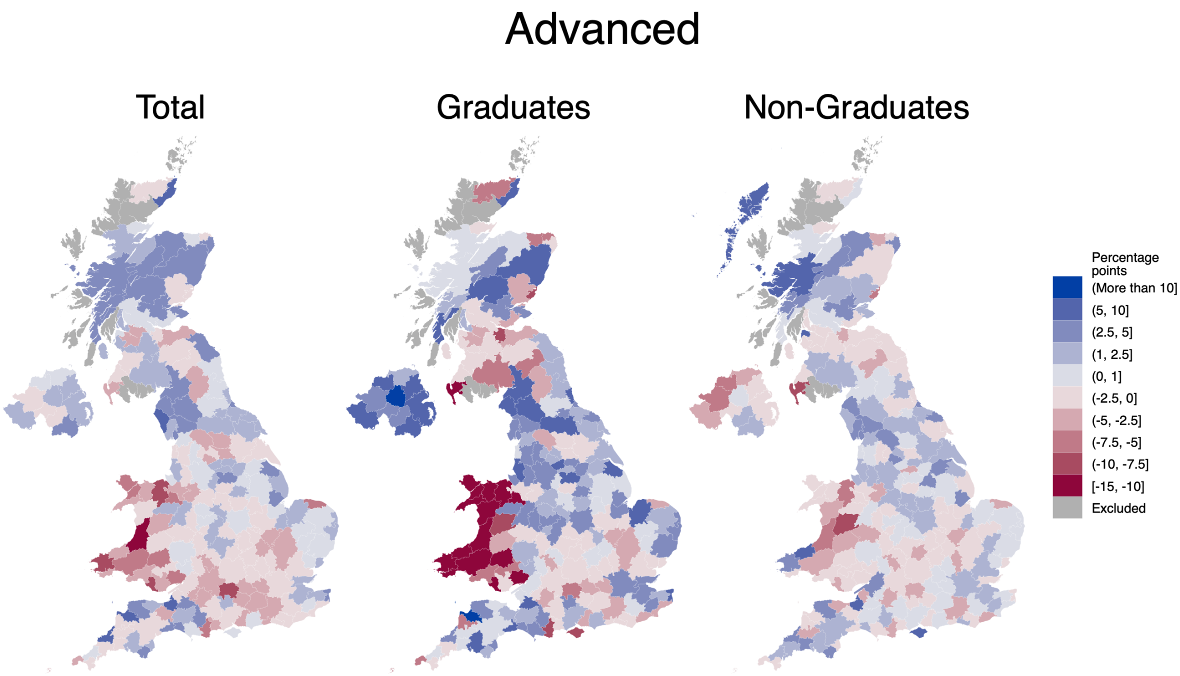

*Notes:* See footnote to Figure 1.

Advanced. This is also true for Basic skills, but here the share of non-graduate job adverts that require these skills (but not Advanced or Intermediate) is greater than for graduates (Figure 4). Over 95% of TTWAs have higher shares of non-graduate adverts requiring Basic DTS than graduate adverts.

Overall, these figures paint a picture of high demand for all three types of skills across regions but with skills required for "business as usual" important everywhere and relatively more important outside the Golden Triangle. These areas appear also to be more likely to hire non-graduates to fill their needs.

We next examine how demand for the three groups of digital technical skills has changed over time. Specifically, we compute the change in skill shares between 2014-2019 and 2020-2025 for each TTWA. For the Advanced skills DTS, we demean the changes by subtracting the UK-wide average change, shown in Figure 5. As discussed above, the Advanced DTS shares shows high variability across time so is more informative to show region-specific deviations from the national trend. In Figures 5, decreases relative to the mean are shown in red and increases in blue.

Figure 5: Difference in the average shares of digital technical skill demand in advanced job adverts (2020-2025 minus 2014-2019, demeaned)

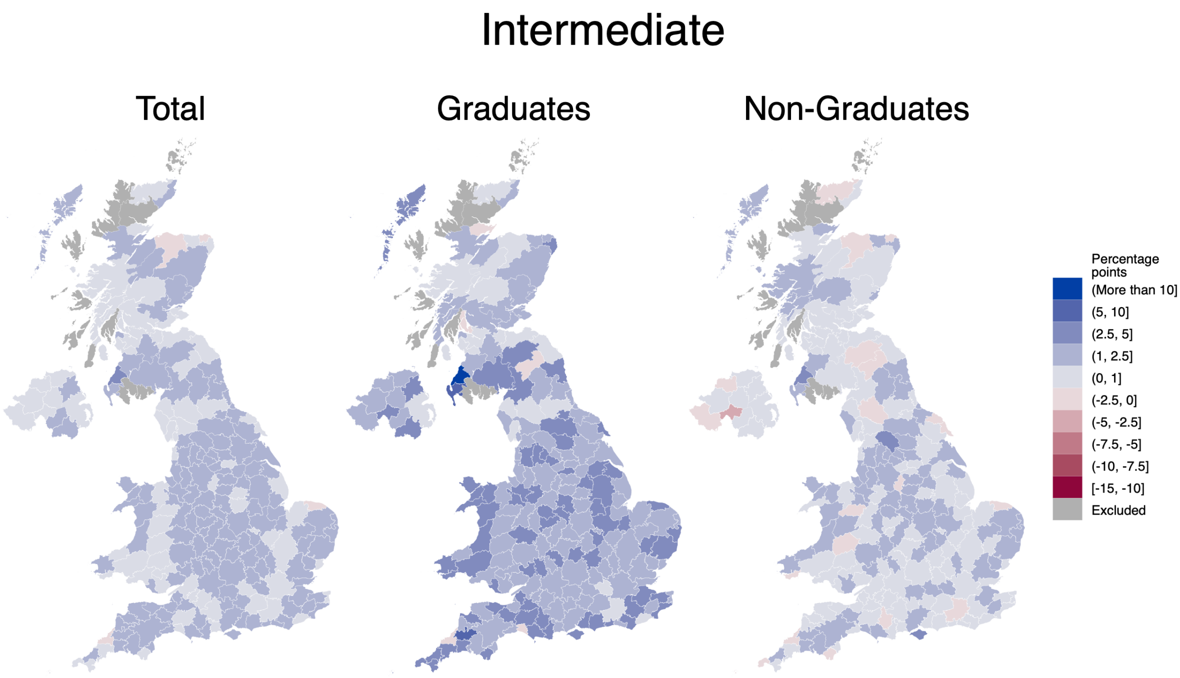



*Notes:* The figure shows the difference in shares of digital technical skills between the pre-pandemic period (2014-2019) and the post-pandemic period (2020-2025). Red shades indicate declines in skill shares, with darker red representing larger declines. Blue shades indicate increases in skill shares, with darker blue representing larger increases. TTWAs with fewer than ten job advertisements in any given year were excluded from the analysis; these are indicated in grey. *Source:* Authors' calculations using Lightcast data.

In Figure 5 some of the areas with the highest shares of Advanced DTS such as London, Oxford and Cambridge, show declines relative to the average, whereas Birmingham, Liverpool and Manchester show above average growth, suggesting some progress in moving towards the more advanced areas in these larger cities. But many of the second tier cities in England show little progress. The graduate demands largely mirror those for the whole sample, although London shows above average growth, but this is not the case for its surrounding areas. The changes in non-graduate shares tend to be show less variation with a much smaller coefficient of variation.

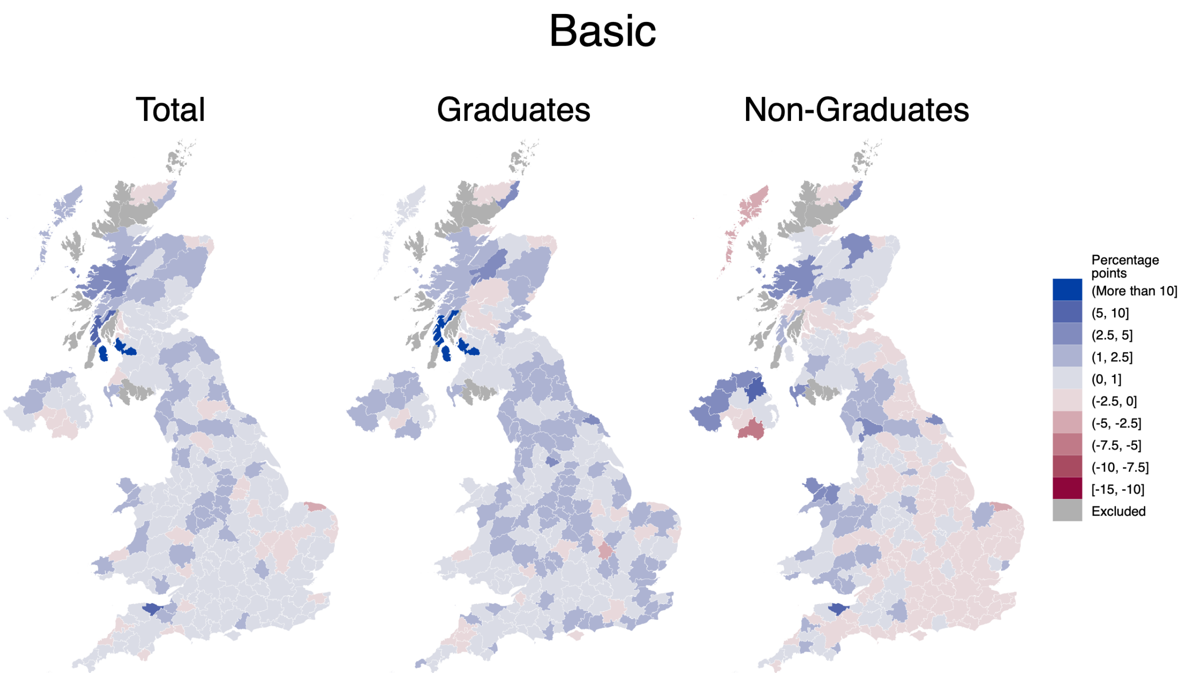
Figures 6 and 7 show the maps for Intermediate and Basic DTS. Here it makes more

Figure 6: Difference in the average shares of digital technical skill demand in intermediate job adverts (2020-2025 relative to 2014-2019)




*Notes:* See footnote to Figure 5.

Figure 7: Difference in the average shares of digital technical skill demand in basic job adverts (2020-2025 relative to 2014-2019)




*Notes:* See footnote to Figure 5.

sense to show the absolute variation, as these shares have been growing steadily. In Figure 6 it is immediately apparent that, in almost all regions (98%), the shares of Intermediate DTS has increased. These shares are increasing for both graduates and non-graduates in the majority of TTWAs, but more so for graduates. For Basic DTS (Figure 7), there is more variation with a larger number of TTWAs showing declining shares, especially for non-graduates. Demand for graduates whose only digital skills are Basic shows growth in many TTWAs, although this tends to in urban areas. Since Basic skills are more concentrated in non-graduates, the growing graduate share may relate to the literature on the growing incidence of overeducation in the UK (Vecchi et al., 2021). Firms hiring graduates to do non-graduate jobs may prefer those with at least some Basic DTS rather than those with no digital skills.

In summary, there is considerable heterogenity in the time pattern of digital technical skills demand across regions, with a hint of some convergence at the Advanced skills level, at least for the larger cities. This preliminary look at the data is not able to distinguish the causes of these changes. These are likely to be affected by differences in industrial structure across regions, for example, the software sector is concentrated in London and the South East. A more detailed analysis of industry structure is discussed below.

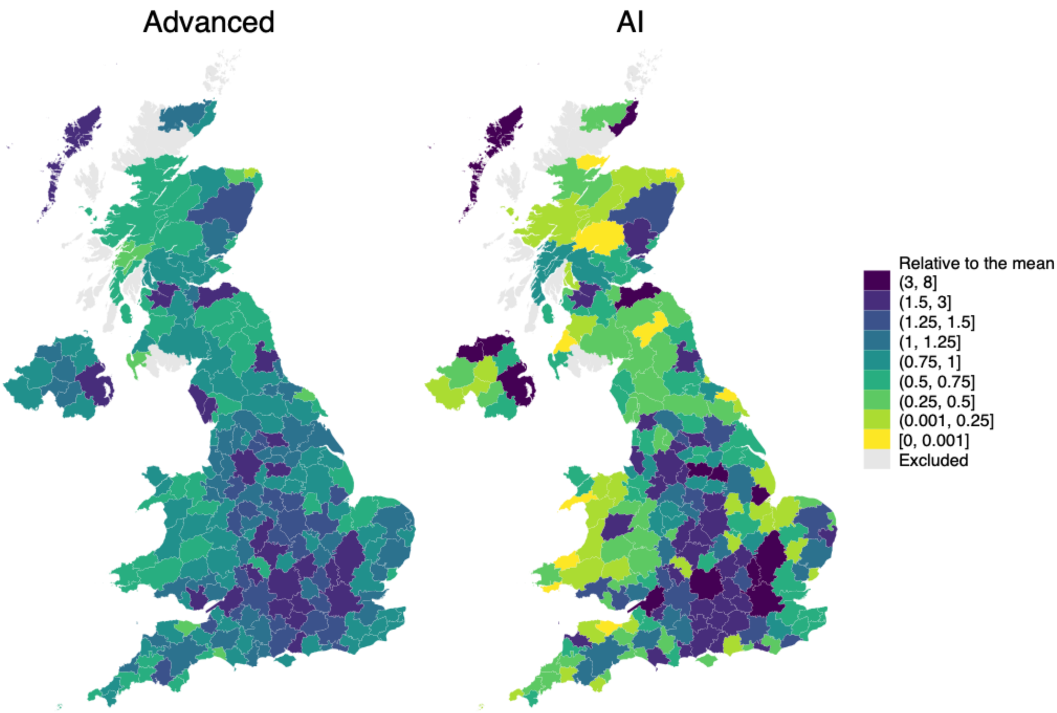
## 5.2 AI Skills

Much of the current literature on skill requirements in the workplace is focused on AI and its impacts, so this section looks specifically at these skills. Work at the OECD identified a list of AI specific keywords which are commonly used in the literature on this topic (Borgonovi et al., 2023). We matched these to the Lightcast skills keywords, with the exception of a couple of very generic descriptors. All of these AI keywords were contained in our Advanced grouping. A major issue with looking at AI specific words in job platform data is that they appear in only about 1% of adverts. This is well known in the literature and is the case regardless of whether researchers use the full text of the advert or if they use lists of keywords, as in this study.

Given the small number of AI skill adverts we aggregated 2020-2025. Figure 8 compares the cross regional pattern of Advanced and AI skills, relative to mean shares to aid the comparison. It is obvious from the Figure 8 that AI skill shares are much more concentrated than Advanced skill. The coefficient of variation of AI skills is about 3 times that of Advanced skills. The TTWAs with the highest concentrations of AI skills tend to be similar to those for Advanced skills, with a correlation coefficient of 0.71. Cambridge, London and Oxford all have AI skill shares more than four times the average and there are many areas where AI skill shares are effectively zero.

It is interesting to examine the co-occurrence of the AI skill keywords with other digital technical skills. For all the job adverts that we designate as AI job postings, we calculated

Figure 8: Advanced and AI in job adverts, relative to the mean

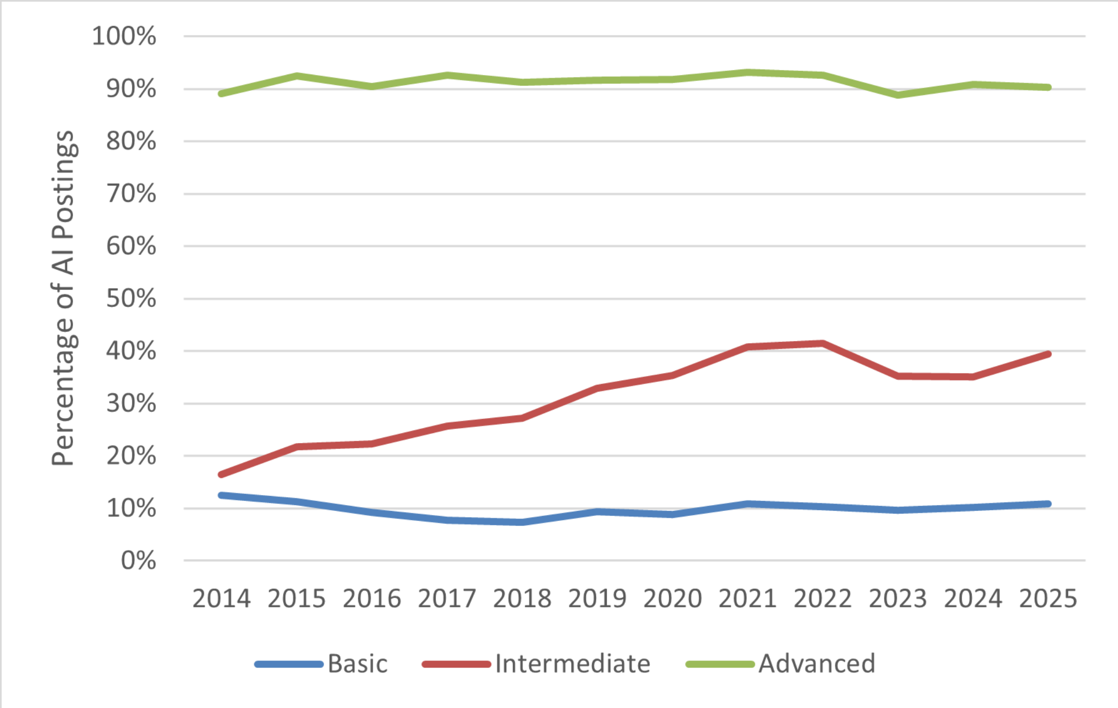



*Notes:* TTWAs with fewer than ten job advertisements in any given year were excluded from the analysis, these are indicated in grey. Note that there is a larger number of TTWAs in which AI activity is negligible. These have been set to zero in the analysis and are presented in bright yellow.

how many times at least one other digital technical skill shows up by category and by year. This is shown in Figure 9 for all job adverts. The small sample sizes prohibit examining this at the level of TTWA.

The percent of AI job postings that require at least one other Advanced digital technical skill is roughly constant at 90% throughout the time period, highlighting that AI and Advanced digital skills are closely related. Given that the share of adverts requiring Advanced digital skills has been declining in the last few years, but co-occurrences with AI job postings have not seen a similar decline, reinforces the importance of the need for both types of skills. The most surprising finding in Figure 9, however, is the rising co-occurrence of Intermediate and AI keywords, from about 20% at the start of the period, to 40% by 2025. This could reflect an increasing focus by firms of deploying AI capabilities across the business and integrating it with specific application software. The share of AI job posting that also require basic digital skills is small and stable at about 10%. About 8% of AI adverts do not require any additional digital technical skills and this has not changed through time.

Figure 9: Co-occurrence of AI and Digital Technical skills.



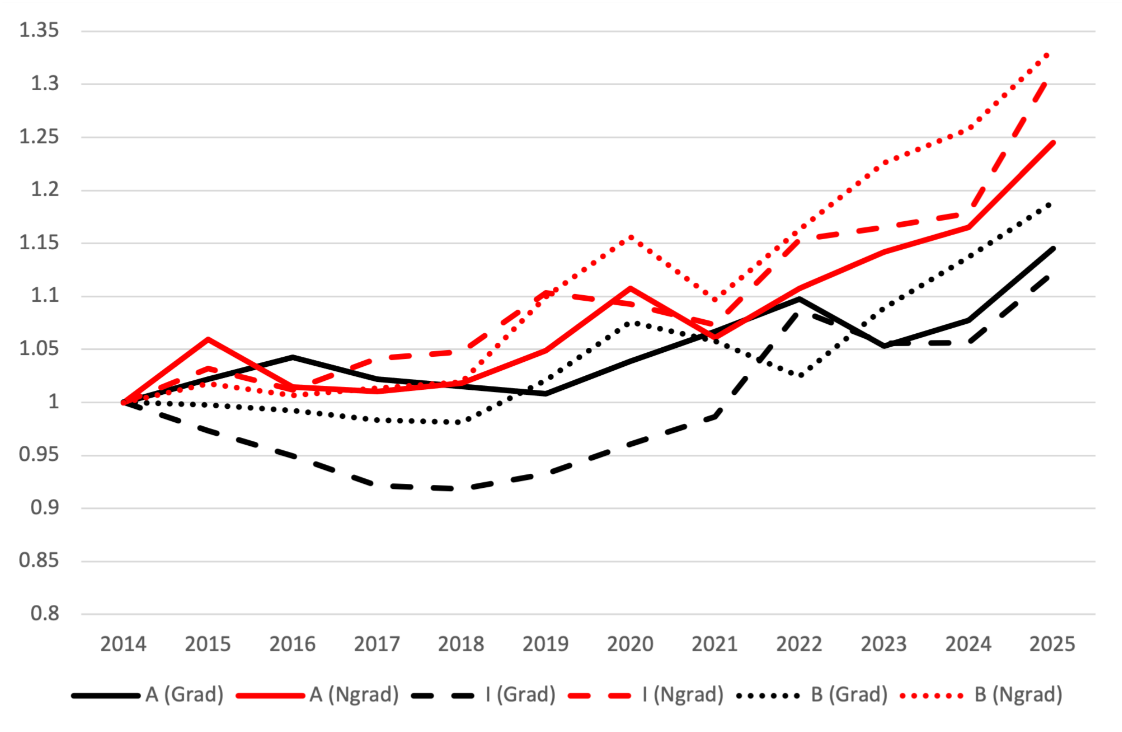

*Notes:* Per cent of AI jobs requiring other digital technical skills. Authors' calculations using Lightcast data. Since many AI adverts include all 3 types of DTS, the numbers do not add to 100.

## 5.3 Advertised Pay

We also examined trends in advertised pay for the three skill groups. Information on pay is only available for about 40% of job adverts. The mid point is used when there is a range of pay scales in the advert. On average over our sample period, those with Advanced DTS earn about 30% more than Intermediate and over 60% more than Basic, although this advantage declined during the final few years, coinciding with the declining shares of Advanced DTS. The earnings in adverts requiring Advanced DTS is also about 40% higher than in adverts that require no digital skills, although this residual group is very heterogeneous.

Figure 10 shows the growth in pay since 2014, where red depicts non-graduates and black depicts graduates. For Advanced skills growth in pay comparing graduates and non-graduates (the solid lines) roughly follow each other up to 2022 but non-graduate advertised pay grows faster in the final three years. In contrast, pay grows faster for non-graduate adverts that require Intermediate and especially Basic digital technical skills than for graduates requiring these skills.

Figure 10: Advertised pay for digital technical skills - Non-graduates and graduates



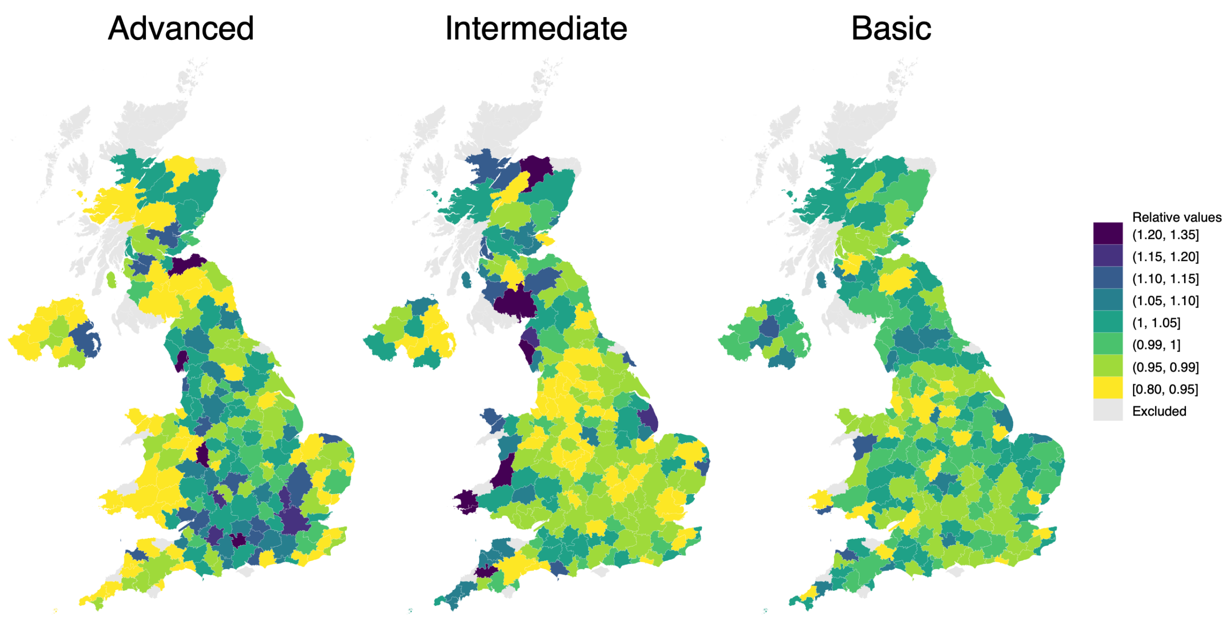

*Notes:* 40% of job adverts. *Source:* Authors' calculations using Lightcast data.

Figure 11 shows earnings relative to jobs requiring no digital technical skills for the three groups by TTWA, averaged across 2020-2025. Note in this case the number of observations was unreliably small for a greater number of TTWA than in previous maps - these are greyed out in the maps. To aid the comparison across skill groups we show values relative to the mean.

Virtually all TTWAs advertise higher wages for Advanced and Intermediate digital technical skills than for jobs that require no digital skills. However, the majority of TTWAs pay relatively lower wages for those requiring only Basic DTS. There is less concentration in these maps than for the number of adverts, which is to be expected as wages should show more commonality across labour markets. Nevertheless, there are some pockets of high values, notably for Advanced skills in the London-Cambridge corridor and in regional urban centers such as Edinburgh and Belfast. There is a slight suggestion in the map that some regions that pay lower than average for Advanced skills pay more than average for Intermediate skills. The correlation between these measure is negative, but small at -0.21.

We also examined the graduate relative to non-graduate pay by TTWA but here the sample sizes were very small in many areas. There is a suggestion that areas with lower demand for graduates with Advanced DTS pay their non-graduates with these skills relatively more. For example, graduate relative to non-graduate advertised pay for Advanced skills was much higher in areas of high demand such as London, and Cambridge than in cities such as Birmingham and Manchester where demand for non-graduates is relatively high. However,

Figure 11: Relative wages of Digital Technical Skills Compared to Other Adverts




*Notes:* The maps show the wages of the three Digital Technical Skills groups relative to all other adverts, with all values relative to mean for each group. Darker colours represent higher intensities. TTWAs with small sample sizes were excluded from the analysis; these are indicated in grey.

relative pay is likely to be affected by occupation and industry compositions, and it is difficult to adjust for these given sample sizes.

# 6 Analysis by Industry

## 6.1 Industry Composition

Some of the variation across regions is likely to reflect industry composition differences. Table 6 shows the shares of our three digital technical skills groups by industry, sorting by those with the highest share of Advanced DTS. As expected, Information and Communications has by far the highest share of Advanced, followed by Finance and Insurance. There is large variation in this type of skill with Information and Communication having shares of Advanced skills nearly six times larger than Accommodation and Food. The variation in the Intermediate category is lower, although the highest share (Water Supply, Sewerage and Waste) is more than four times that of Accommodation and Food. The latter sector, however, has similar shares of Basic skills to a number of industries. The coefficient of variation is highest for Advanced DTS shares, at 0.45, greater than Intermediate at 0.31 and nearly twice the coefficient of variation for Basic (0.23).

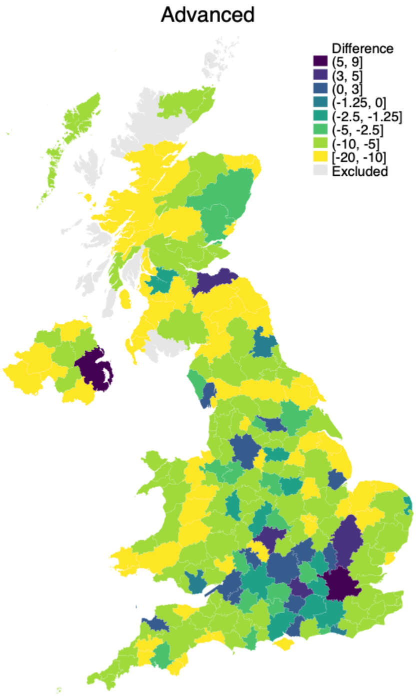
We calculated the expected shares of Advanced, Intermediate and Basic digital technical skills that would occur for each TTWA, based on their industry composition of job adverts

Table 6: Industry Shares of job adverts

| Industry | Advanced (%) | Intermediate (%) | Basic (%) |
|---|---|---|---|
| INFORMATION AND COMMUNICATION | 47.6 | 5.4 | 3.6 |
| FINANCE AND INSURANCE | 40.9 | 4.5 | 6.5 |
| MINING AND QUARRYING | 38.3 | 4.3 | 4.2 |
| ELECTRICITY, GAS, STEAM | 33.9 | 5.1 | 5.4 |
| MANUFACTURING | 30.7 | 6.6 | 5.8 |
| PROFESSIONAL, SCIENTIFIC AND TECHNICAL | 29.5 | 5.7 | 5.3 |
| ADMINISTRATIVE AND SUPPORT SERVICES | 24.3 | 5.1 | 4.1 |
| OTHER SERVICE ACTIVITIES | 23.1 | 4.3 | 5.1 |
| WATER SUPPLY; SEWERAGE, WASTE | 23.6 | 7.4 | 7.1 |
| EDUCATION | 31.0 | 3.6 | 5.1 |
| TRANSPORTATION AND STORAGE | 19.9 | 5.3 | 4.8 |
| REAL ESTATE ACTIVITIES | 18.7 | 5.8 | 6.7 |
| CONSTRUCTION | 18.4 | 5.5 | 7.0 |
| ARTS, ENTERTAINMENT, RECREATION | 17.1 | 3.2 | 3.6 |
| PUBLIC ADMINISTRATION | 15.6 | 2.2 | 6.0 |
| AGRICULTURE, FORESTRY, FISHING | 14.5 | 3.5 | 4.3 |
| WHOLESALE AND RETAIL TRADE | 14.1 | 3.7 | 5.0 |
| HEALTH AND SOCIAL WORK | 9.7 | 3.7 | 3.6 |
| ACCOMMODATION AND FOOD | 8.5 | 1.8 | 3.6 |

and using aggregate economy advert shares for each type and industry. We then took the difference between the actual and expected shares. This difference is even more concentrated across regions than the raw share data, especially for Advanced DTS, as illustrated in Figure 12. The actual shares of adverts requiring Advanced DTS in London and Cambridge are much higher than their expected shares whereas the opposite is true for cities like Middlesborough and Lincoln. Industry composition matters but it is not the whole story.

Figure 12: Industry Composition: actual minus expected shares, Advanced skills




*Notes:* The maps show the difference between the actual and the expected shares for advanced skills. Darker colours represent higher intensities. TTWAs with fewer than ten job advertisements in any given year were excluded from the analysis; these are indicated in grey. *Source:* Authors' calculations using Lightcast data.

## 6.2 Skills for Industrial Strategy

The government's industrial strategy identified 8 sectors that are likely to drive growth (IS-8).[7] These are: Advanced Manufacturing; Clean Energy Industries; Creative Industries; Defence; Digital and Technologies; Financial Services; Life Sciences; and Professional and Business Services.

In order to examine demand for digital technical skills for these sectors, they need to be translated into SIC codes. The Department for Business and Trade (DBT) developed a SIC matching[8] for seven of these sectors but Clean Energy Industries cut across too many SIC groups to be identified on this basis. In addition, only part of the Defence sector matches SIC codes. Some SIC codes appear in more than one IS-8 sector so the total IS sectors in the tables and figures below remove these duplicates. DBT also defined frontier sectors within the seven IS sectors so results are also shown for these. The number of adverts for some IS sectors are very small, especially when we divide by region. Therefore, in what follows we take a cautious approach, frequently aggregating across years.

Table 7 shows the shares of our three types of digital skills for the total IS sectors, the subset of frontier industries, and all other industries. The shares of Advanced DTS are much

[7]See https://www.gov.uk/government/publications/industrial-strategy for the associated policy reports.
[8]https://www.gov.uk/government/publications/industrial-strategy/industrial-strategy-sector-definitions-list

higher for IS sectors, and even more so for IS frontier sectors, than for other industries but shows a similar decline in the final few years. Intermediate shares are also greater in IS total and Frontier sectors but Basic skills seem equally in demand in total IS sectors as for other industries. However, surprisingly the frontier sectors show the highest shares of Basic skills, especially towards the end of the period.

Table 7: Shares of Digital Technical Skills

| | IS Sectors | | | Frontier IS sectors | | | Other Industries | | |
|---|---|---|---|---|---|---|---|---|---|
| | Advanced | Intermediate | Basic | Advanced | Intermediate | Basic | Advanced | Intermediate | Basic |
| 2014 | 32.5 | 3.6 | 4.2 | 32.0 | 4.1 | 6.6 | 16.5 | 2.3 | 4.2 |
| 2015 | 35.0 | 3.3 | 3.9 | 31.0 | 3.4 | 5.1 | 15.2 | 2.3 | 3.8 |
| 2016 | 31.7 | 3.6 | 4.1 | 31.4 | 3.9 | 5.5 | 15.2 | 2.4 | 4.0 |
| 2017 | 31.7 | 4.1 | 4.4 | 34.9 | 4.1 | 6.0 | 16.0 | 2.6 | 4.1 |
| 2018 | 26.8 | 4.0 | 4.6 | 32.4 | 4.3 | 6.1 | 14.6 | 2.3 | 4.0 |
| 2019 | 27.0 | 4.3 | 4.8 | 33.7 | 4.7 | 6.5 | 14.1 | 2.5 | 4.2 |
| 2020 | 29.9 | 4.3 | 4.1 | 38.1 | 4.5 | 5.9 | 14.6 | 2.5 | 4.4 |
| 2021 | 31.5 | 4.8 | 4.8 | 37.4 | 5.3 | 6.6 | 16.2 | 2.9 | 5.3 |
| 2022 | 31.8 | 4.9 | 5.1 | 38.9 | 5.1 | 6.3 | 15.5 | 3.5 | 4.8 |
| 2023 | 23.5 | 5.1 | 5.6 | 29.4 | 5.7 | 7.2 | 12.8 | 3.0 | 5.0 |
| 2024 | 22.3 | 5.5 | 5.6 | 28.4 | 6.2 | 7.3 | 12.9 | 3.1 | 5.0 |
| 2025 | 23.5 | 5.6 | 5.3 | 31.6 | 5.8 | 6.7 | 13.7 | 3.4 | 4.8 |

Table 8 shows the skill shares for the seven IS sectors where we could identify the SIC codes. The first column, showing the number of job adverts, is clearly dominated by Professional and Business Services, which is also the sector with the lowest shares of digital technical skills for all three types. Defence has by far the largest share of Advanced but this is based on only a subset of the sector and only about 60,000 adverts over the entire period. The other sectors all show shares of Advanced skills significantly higher than for Professional and Business Services. Intermediate and Basic skills are relatively important in Advanced Manufacturing and Life Sciences. Four of the sectors show increasing shares of Advanced skills across the time periods, bucking the trends discussed in previous sections - these are Advanced Manufacturing, Digital and Technologies, Financial Services and Life Sciences.

Table 9 shows the skill shares for the IS frontier sectors. For Advanced skills, these shares are higher than their corresponding IS sector in Table 8 in Advanced Manufacturing and Professional and Business Services, with not much difference for Financial services. However, for creative industries, the frontier sectors have lower shares. In the 2020-25 period the shares of Intermediate and Basic skills in the frontier creative industries are significantly greater than for the sector as a whole. In all four sectors, the share of Advanced DTS increases over the time periods, but only marginally for Professional and Business Services.

Table 10 shows information by occupation in IS sectors relative to all other sectors. For IS sectors, Advanced and Intermediate DTS shares are higher for the majority of occupations,

Table 8: Skill shares IS Sectors

| | | 2014-19 | | | 2020-25 | | |
|---|---|---|---|---|---|---|---|
| | Ads (millions) | Advanced | Intermediate | Basic | Advanced | Intermediate | Basic |
| Advanced Manufacturing | 0.78 | 37.1 | 5.7 | 6.0 | 43.3 | 7.0 | 6.4 |
| Creative Industries | 2.32 | 41.9 | 4.2 | 4.1 | 39.3 | 4.8 | 4.8 |
| Defence sector | 0.06 | 62.8 | 5.2 | 2.5 | 60.3 | 4.2 | 2.2 |
| Digital and Technologies | 3.75 | 46.9 | 4.5 | 4.2 | 47.5 | 5.3 | 4.7 |
| Financial services | 1.68 | 37.1 | 3.2 | 6.5 | 40.0 | 4.0 | 7.3 |
| Life Sciences | 0.20 | 38.6 | 6.8 | 6.9 | 44.5 | 8.8 | 7.2 |
| Professional and Business Services | 36.9 | 28.8 | 3.8 | 4.3 | 24.3 | 5.1 | 5.1 |
| IS Total | | 30.7 | 3.9 | 4.3 | 27.2 | 5.1 | 5.1 |
| Other Industries | | 15.2 | 2.4 | 4.1 | 14.1 | 3.1 | 4.9 |

Table 9: Skill Shares, IS Frontier Sectors

| | Ads (millions) | 2014-19 | | | 2020-25 | | |
|---|---|---|---|---|---|---|---|
| | Frontier IS | Advanced | Intermediate | Basic | Advanced | Intermediate | Basic |
| Frontier Advanced Manufacturing | 0.21 | 41.9 | 4.6 | 6.6 | 49.1 | 5.0 | 6.0 |
| Frontier Creative Industries | 0.62 | 26.9 | 4.5 | 5.1 | 28.8 | 5.7 | 6.3 |
| Frontier Financial services | 0.83 | 38.9 | 3.7 | 7.3 | 37.6 | 4.9 | 7.5 |
| Frontier Professional and Business Services | 1.33 | 30.9 | 4.0 | 5.5 | 31.0 | 5.9 | 6.5 |
| IS Frontier Total | | 32.7 | 4.1 | 5.9 | 33.9 | 5.5 | 6.7 |
| IS Total | | 30.7 | 3.9 | 4.3 | 27.2 | 5.1 | 5.1 |

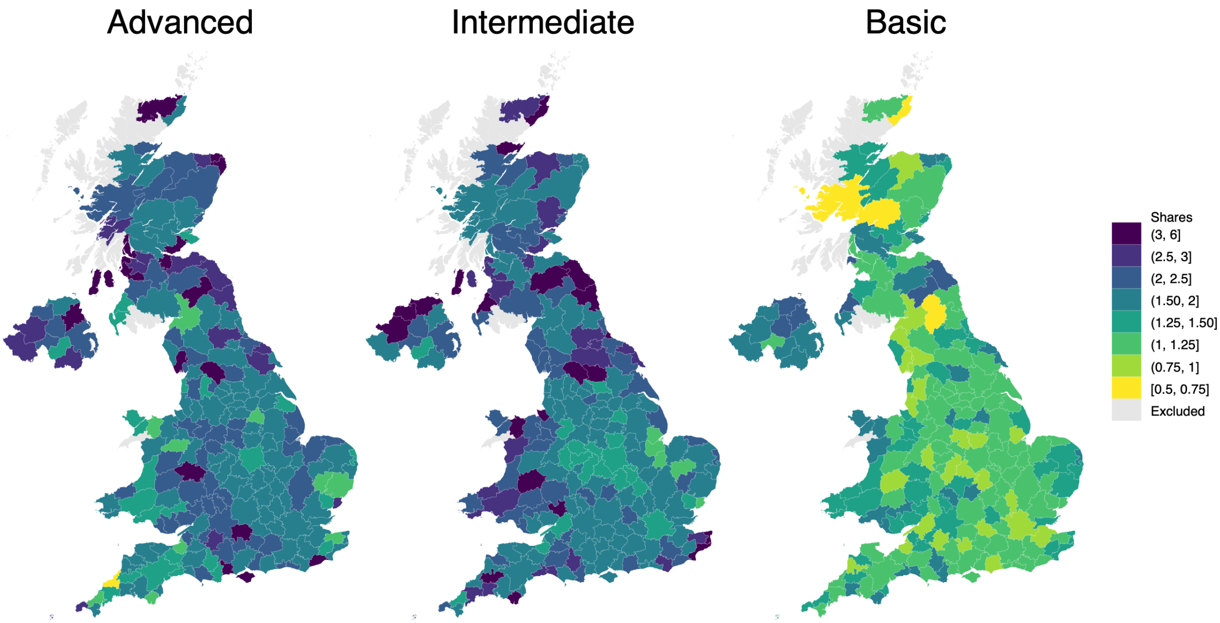
the exceptions being administrative and secretarial for Advanced skills and caring, leisure and other services for both. However, there is more variation for Basic DTS. All occupations show higher skill shares for all three skill types in IS Frontier sectors.

We now turn to the geographic distribution of the digital skill shares in IS sectors. Given the small number of observations in many TTWA we aggregated the job adverts over the period 2020 to 2025. Figure 13 shows the ratio of shares of digital technical skills in IS sectors relative to other sectors. This shows a remarkable uniformity. For Advanced DTS all bar one TWWA, and for Intermediate skills all TTWAs show shares higher in IS sectors. Even for Basic the majority of TTWAs (86%) show higher shares in IS sectors. For Advanced DTS Barrow-in-Furness stands out, but this is due to its association with BAE Systems. Bournemouth, a center for the creative industries, and Newbury also stand out.

Table 10: Skill shares by occupation

| | IS Sectors/Other | | | IS Frontier/Other | | |
|---|---|---|---|---|---|---|
| Occupations | Advanced | Intermediate | Basic | Advanced | Intermediate | Basic |
| Managers and directors | 1.2 | 1.6 | 1.0 | 1.7 | 1.8 | 1.3 |
| Professionals and technical | 1.6 | 1.3 | 0.9 | 2.3 | 1.5 | 1.4 |
| Associate professionals and technical | 1.4 | 1.4 | 0.9 | 1.7 | 1.5 | 1.2 |
| Administrative and secretarial | 0.9 | 1.8 | 1.1 | 1.1 | 1.8 | 1.1 |
| Skilled trades | 1.6 | 1.6 | 0.7 | 1.6 | 1.6 | 1.2 |
| Caring, leisure and other services | 0.9 | 0.7 | 0.9 | 1.4 | 1.2 | 1.9 |
| Sales and customer services | 2.2 | 2.4 | 2.2 | 2.4 | 2.2 | 2.0 |
| Process and machinery operatives | 1.6 | 1.1 | 0.9 | 1.7 | 1.4 | 1.2 |
| Elementary occupations | 1.8 | 2.6 | 1.5 | 2.0 | 2.1 | 1.1 |

Figure 13: Shares IS Total/Other Industries, 2020-25




*Notes:* The maps show the average shares of total IS job adverts over other industries in 2020-25 for each of our three digital technical skill groups: Basic, Intermediate and Advanced. Darker colours represent higher intensities. TTWAs with fewer than ten job advertisements in any given year were excluded from the analysis; these are indicated in grey. *Source:* Authors' calculations using Lightcast data.

Table 11 shows the average advertised pay for IS sectors relative to other sectors for the three skill groups. IS sectors advertise on average 25% higher pay than in other sectors for Advanced DTS. There is also a pay premium in these sectors for Intermediate and Basic skills, although that has reduced over time, and is now lower than in job adverts that do not require any digital technical skills. Somewhat surprisingly, given the higher shares discussed above, IS Frontier sectors pay premium is lower than for the IS sectors as a whole, although still substantial for Advanced DTS.

Overall, this section highlights the importance of digital technical skills in sectors identified in the Industrial Strategy as likely to grow significantly.

Table 11: Average advertised pay, IS sectors relative to other industries

| | Advanced | Intermediate | Basic | No DTS skills |
|---|---|---|---|---|
| *IS Sectors* | | | | |
| 2014-19 | 1.25 | 1.19 | 1.17 | 1.13 |
| 2020-25 | 1.26 | 1.09 | 1.09 | 1.18 |
| *Frontier IS Sectors* | | | | |
| 2014-19 | 1.20 | 1.13 | 1.14 | 1.15 |
| 2020-25 | 1.17 | 1.00 | 1.04 | 1.09 |

# 7 Soft Skills

In this section we look briefly at 'soft' skills associated with the three types of digital technical skills. We extracted data for generic keywords by advert count that we could classify into five groups of skills, communications, personal organisation skills, general management, people and team management and generic skills. We then calculated the share of adverts which we classify as Advanced, Intermediate and Basic that also include these keywords. We also include these shares for all other job adverts that do not require any digital skills, which we label 'residual'. These shares are shown in Table 12. In all cases the digital technical skill adverts are more likely to contain these keywords, suggesting that a combination of technical and soft skills matter.

Much of the literature on AI emphasizes the need for communication skills alongside digital ones. Our job platform data does show that these skills co-occur with digital skills but more for Intermediate and Basic than for Advanced. However, about 40% of adverts include something relevant to communications and this term is probably too broad to accurately capture the type of skills required. Similar remarks apply to the keyword 'Management' in the general managerial skills group.

In the group of personal organizational skills, jobs requiring Advanced digital technical skills are more likely to require problem solving than other adverts, especially relative to the residual category. In contrast, Advanced requires less detail oriented, organizational skills or time management than Intermediate of Basic.

General managerial skills such as leadership, influencing, decision making and consulting are more likely to be required in Advanced skills adverts. This is also the case for mentorship among the people and team management skills group. Team management and the two generic skills are more likely to appear in adverts for Intermediate and Basic.

Table 12: Occurrence of ‘soft skill’ keywords in job postings, per cent, average 2023-2024.

| | Advanced | Intermediate | Basic | Residual |
|---|---|---|---|---|
| *Communication skills* | | | | |
| Communication | 39.6 | 44.7 | 51.4 | 24.1 |
| Interpersonal Communications | 7.2 | 9.7 | 11.0 | 4.6 |
| Verbal Communication Skills | 4.6 | 4.9 | 7.7 | 1.6 |
| Persausive Communication Skills | 0.8 | 0.8 | 0.8 | 0.3 |
| *Personal Organizational skills* | | | | |
| Detail Oriented | 13.2 | 25.7 | 28.7 | 7.5 |
| Problem Solving | 14.6 | 12.2 | 11.7 | 4.0 |
| Organizational Skills | 6.7 | 12.4 | 16.9 | 4.1 |
| Teamwork | 5.6 | 5.0 | 5.9 | 3.3 |
| Time Management | 5.5 | 8.9 | 12.0 | 3.0 |
| Multitasking | 2.9 | 6.0 | 8.8 | 1.6 |
| *General Managerial skills* | | | | |
| Management | 28.4 | 32.1 | 30.5 | 15.2 |
| Planning* | 14.7 | 14.3 | 13.3 | 7.1 |
| Leadership** | 12.6 | 10.0 | 8.1 | 6.4 |
| Influencing Skills | 6.3 | 4.0 | 4.2 | 1.8 |
| Decision Making | 5.2 | 3.8 | 3.3 | 1.6 |
| Coordinating | 4.7 | 5.6 | 5.5 | 1.4 |
| Consulting | 2.2 | 1.1 | 0.8 | 0.5 |
| Program Management | 1.0 | 0.6 | 0.4 | 0.2 |
| Strategic Thinking | 0.9 | 0.6 | 0.4 | 0.2 |
| *People and Team Management skills* | | | | |
| Mentorship | 5.3 | 2.9 | 2.8 | 2.2 |
| People Management | 1.5 | 1.4 | 1.4 | 0.7 |
| Relationship Management | 1.6 | 1.5 | 1.4 | 0.5 |
| Team Management*** | 1.6 | 2.9 | 2.1 | 1.3 |
| Team Building, Team Motivation and Delegation skills | 1.1 | 1.1 | 1.0 | 0.5 |
| *Generic skills* | | | | |
| Self-Motivation | 5.6 | 6.8 | 9.1 | 3.5 |
| Enthusiasm | 4.0 | 4.2 | 6.5 | 4.3 |

*Notes: *includes strategic planning; **includes leadership development; *** includes team leadership and team performance management.*

We carried out the same calculation for 2016-17, to investigate how these shares change over time. In general, the occurrence of these soft skill keywords increased over time, but this may merely reflect the increasing sophistication and details contained in job adverts. There are a few instances where the keywords shares decline, in particular, self-motivation shows a decline for all skill types. The keyword shares increased more than average for Advanced digital technical skills, in particular for leadership, decision making, strategic planning and strategic thinking. Similarly the keyword shares in Intermediate digital technical skills also increased by more than for Basic or the residual. Here organizational skills and multi-tasking show high growth. Adverts that just require Basic digital technical skills show about average growth, although mentorship and teamwork appear much more frequently in 2023-24 than in 2016-17.

This brief overview of 'soft' skills suggests there may be some differences across the digital skill types that are worth exploring further. However, as pointed out by a reviewer, what kinds of skills are specified in job adverts are likely to depend on expectations by the firms who are hiring on the target applicant group. For example, 'Detailed Oriented' skills are much more likely to be required in adverts for Intermediate and Basic than for Advanced digital technical skills. This might indicate that those doing jobs such as general administration are required to pay more attention to detail than those using specialized programming languages, but would also be consistent with detail orientation being assumed for the latter target population. Similar concerns apply to many of the keywords listed in Table 12. It is likely that reliance on keywords alone is not sufficient to differentiate soft skills by digital skill type. An analysis of the advert text which can capture the nuances of how these skills are combined, is likely required. We leave this for future work.

# 8 Conclusions

This study highlights the significant regional disparities in digital technical skills demand across the UK. This shows a concentration of high-level digital technical skills within the Golden Triangle, and even more so for job adverts that specifically request AI skills. However, areas outside of this region, particularly second-tier cities, demonstrate a greater likelihood of employing non-graduates to meet their Advanced digital skills needs. This is consistent with a shift in employer preferences away from traditional graduate pathways towards alternative forms of skill acquisition that has been noted in recent media reports. The findings suggest greater concentration of AI skills across regions than for other Advanced DTS, and that the extent to which AI keywords co-occur with Intermediate DTS keywords has been growing over time, suggestive of a use of AI across business functions. The analysis by industry suggests that the industrial composition of regions alone does not explain the differences observed and that digital technical skills are more in demand in the high growth sectors identified by the government's Industrial Strategy.

This paper only considers firms' desired hires but this begs the question of whether there is sufficient supply to meet these demands. In a forthcoming companion paper we produce measures of the supply of skills coming from the education system, and by combining these with the demand side, identify regions where skill mismatch is particularly binding.

Finally, it should be noted that Generative AI is likely to have significant impacts on future digital skill demands, in ways that are difficult to predict. There are suggestions that

AI will displace many programming/data science tasks, and this has particularly affected younger workers. This points to the need for further research that looks beneath our three measures, linking also to soft skills.

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